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 a worker's education, cognitive skills, personality traits and other demographic characteristics. The model is estimated using data from 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 (10.7% and 12.0%) of the gender wage gap and that their effect operates largely through the reduction of women's bargaining power.

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1 Introduction

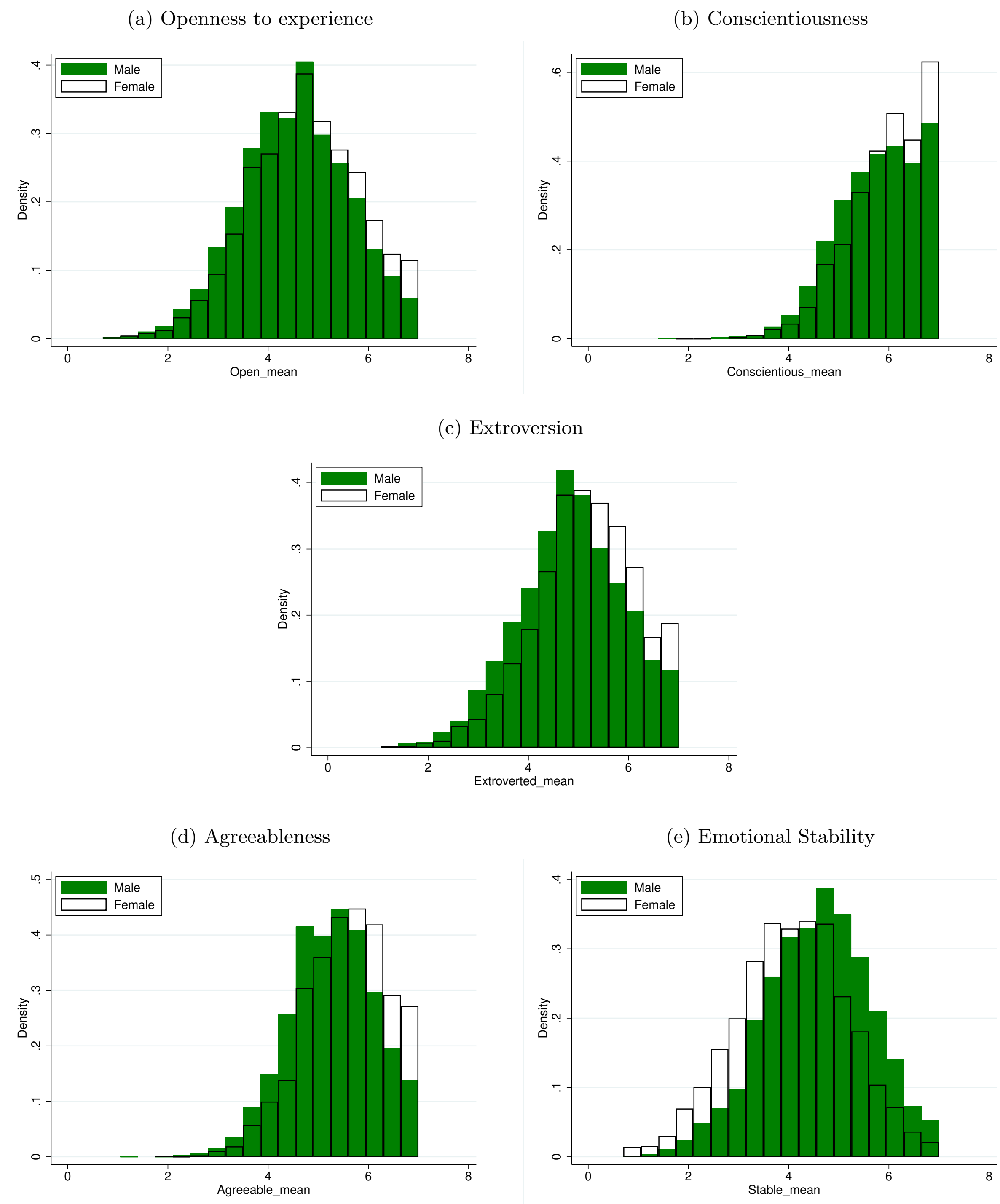
Despite substantial convergence in gender wage and employment differentials over the 1970s and 1980s, significant differences remain with women earning on average 25 percent less than men (Blau and Kahn (2006), Flabbi (2010b)). A large empirical literature uses data from the US and Europe to investigate 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, extroversion, 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, extroversion 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 seldom been 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, randomly receive employment opportunities from firms characterized in terms of idiosyncratic match productivity values. Workers' human capital accumulates while employed and depreciates while 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 labor market disparities arise is important for designing effective labor market policies aimed at reducing these disparities.

[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



Note: The distributions are derived from individuals aged 25 to 60 who report personality traits in the GSOEP. Each trait is measured on a scale of 1 to 7.

This paper contributes to a relatively small literature in which job search models are used 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 paper differs in several respects from these papers, principally due to our focus on personality traits as partial drivers of gender differences. Unlike Flabbi (2010a), for example, we do not explicitly incorporate gender discrimination in our model. Rather, the existence of gender discrimination may be indirectly indicated by gender differences in the "returns" to various observed characteristics of labor market participants.

The distribution of work experience differs notably between genders in most countries, a trend that is also evident in the German labor market. Previous analyses of gender differences using a search framework most often assumed that there is no accumulation of additional human capital once individuals enter the labor market.[2] Building upon the traditional Bertrand competition model with bargaining (e.g. Cahuc et al. (2006) and Dey and Flinn (2005)) and inspired by the approaches of Burdett et al. (2016), Bagger et al. (2014), Flinn et al. (2017), and Amano-Patino et al. (2020), our model incorporates human capital appreciation and depreciation. One important difference, however, between our approach and those of previous studies is our wage-setting mechanism. For example, the Bagger et al. (2014) study assumes that workers receive a fixed share of the expected match surplus, and this condition is used to solve for a piece rate offer. In their model, the worker's wage increases at a job due to learning-by-doing and potentially due to receiving alternative offers that lead to a renegotiation of the piece rate but not job dissolution. Alternatively, Burdett et al. (2016) assume a wage-posting equilibrium in which firms post a constant piece rate offer, with the wage at any moment in time determined by the fixed piece rate and the individual's continuously increasing level of general human capital. Our approach largely builds upon the human capital and search framework of Burdett et al. (2016), but, given our interest in exploring the impact of personality and gender on bargaining outcomes, we found it essential to adopt a search framework that features worker-firm bargaining over wages.

An advantage of the matching and bargaining framework with Bertrand competition that we implement is that the wage determination function is tractable, as in Cahuc et al. (2006); Bagger et al. (2014). However, it markedly departs from previous research by introducing flexibility in how job search parameters are influenced by a larger set of observed characteristics that include cognitive ability measures and the Big-Five personality traits.[3] Through our use of this framework, we are able to quantify the significance of workers' characteristics on the gender wage gap through four distinct channels: initial human capital levels, job finding rates, job loss rates, and bargaining power.

Model parameters are estimated by maximum likelihood using data from the German Socioe-

[2] One notable exception is Amano-Patino et al. (2020), whose model features wage-posting and human capital accumulation and expands upon the framework developed by Burdett et al. (2016).

[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. In this sense, each individual inhabits their own personal frictional labor market.

conomic 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. 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, model specifications 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 indexes, on a comprehensive set of measured 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 restrictive version, we only allow parameters to vary by gender. Likelihood ratio tests overwhelmingly reject the more restrictive specifications in favor of the one that allows for the highest degree of heterogeneity, and that model also provides a better visual fit 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 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 2.5 percent and 1.2 percent increase in average wages for men and women, respectively. An increase of similar magnitude in emotional stability increases average wages by 4.9 percent for men and 3.5 percent for women. However, a one standard deviation increase in agreeableness decreases average wages by 3.3 for both men and women.

In order 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 19.8 percent. Equalizing average personality traits would reduce the wage gap by 19.2 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.

Our decomposition also indicates that part of the gender pay gap is explained by the fact that women's educational attainment and personality traits are valued less than those of men. Giving women the return to education estimated for men reduces the wage gap by 3.9 percent. Similarly, giving women men's estimated personality trait coefficients reduces the wage gap by 6.1 percent. Thus, a hypothetical policy that equalized the returns on both cognitive and non-cognitive skills for men and women would reduce the gender pay gap by 10 percent. Among the Big-5 personality traits, the gender difference in the estimated parameters associated with agreeableness stands out as the most significant contributor to the gender wage gap. Being agreeable lowers wages for both genders, but the penalty is more pronounced for women, predominantly via the bargaining channel (5.0 percent). Consequently, women, who generally exhibit higher levels of agreeableness than men, receive a double penalty in the labor market, both because agreeableness typically correlates with lower bargaining power, and because the penalty for being agreeable is harsher for women than for men. Nonetheless, we find that the major part of the impact of differences in personality characteristics and labor market experience is due to differences in the values of the characteristics, not the gender-specific parameters associated with them.

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. We treat personality traits as time-invariant individual characteristics, in line with empirical evidence that finds personality traits to be relatively stable after age 25 (e.g. Costa Jr and McCrae (1988); McCrae and Costa Jr (1994)) and 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)).

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 differences in the levels of agreeableness and emotional stability contribute significantly to gender gaps, with differential returns to these traits mattering 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,

[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))

rather than human capital accumulation or job search behavior. Our paper also contributes to a small literature incorporating personality traits into 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 laboratory 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 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. 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 show through a bargaining experiment that increasing 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.

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, and 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

[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 characteristics when we estimate the model.

with cumulative employment experience S_E and unemployment experience S_U has a human capital level equal to[6]

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

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 match-specific productivity, which is determined by an i.i.d. draw from the distribution $G_z(\theta)$ with support R_+.[7] The flow utility of unemployment to the individual is assumed to be $a \times b$, where $a = a(z, S_E, S_U)$ and b are both 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 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, which is 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 $\alpha(z)$.

[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, and the interpretation of θ is that it is a firm productivity parameter that is shared by all workers at the same firm. Given that they have observations of many workers at each firm, they are able to estimate 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 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 since the (ρ, b) are not individually identified in the canonical search framework (Flinn and Heckman (1982)).

2.2 Job search and wage determination

2.2.1 Worker and firm value functions

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-specific 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 two competing firms, and assume that $\theta > \theta'$. We will refer to θ as the *dominant* match productivity and θ' as the *dominated* match productivity. When the firms engage in Bertrand competition in terms of wage negotiations, the firm 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 productivity 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 θ.

In order 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, suppose that an individual leaves unemployment to accept a job at a firm with match productivity θ'. While working at that firm, the worker's productivity continuously grows at the rate $\psi(z)$. 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 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 the remainder of their employment spell implies that their wage at the new firm will grow at a rate of $\psi(z)$, reflecting their increasing outside option value. This can be seen as a continuous renegotiation process during their employment spell, which leads to consistent wage growth at a rate $\psi(z)$ across all jobs in the employment spell 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

[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.

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 productivity 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 productivity. 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 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

$$\rho V_E(\theta',\theta',z,a) = a\theta' + a\psi(z)\tfrac{\partial V_E(\theta',\theta',z,a)}{\partial a}$$
$$+\lambda_E(z)\textstyle\int_{\theta'}\left(V_E(x,\theta',z,a)-V_E(\theta',\theta',z,a)\right)dG_z(x)+\eta(z)\left(V_U(z,a)-V_E(\theta',\theta',z,a)\right). \quad (2)$$

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

[12] If offers were withdrawn as soon as they are rejected, then wages would only be renegotiated to reflect productivity gains due to human capital accumulation at the time when the worker encounters another potential employer and a renewed round of bargaining begins. Our model assumes that workers keep their external job offers, which grow in value as their human capital develops. This leads to continuous wage increases at their current employer as well due to continuous Bertrand competition.

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

at wage w, is

(3)
$$\rho V_F(\theta,\theta',z,a;w) = a\theta - w + a\psi(z)\frac{\partial V_F(\theta,\theta',z,a)}{\partial a} + \lambda_E(z)\int_{\theta'}^{\theta}(V_F(\theta,x,z,a)-V_F(\theta,\theta',z,a))\,dG_z(x)$$
$$+\lambda_E(z)\int_{\theta}(0-V_F(\theta,\theta',z,a))\,dG_z(x)+\eta(z)(0-V_F(\theta,\theta',z,a))$$

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 (that will vary only by gender).[15] The value of unemployment is

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

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

2.2.2 The bargained wage

The Nash-bargained wage for an employed worker is

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

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 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, $a = a(z,S_E,S_U)$, increases wages proportionally. The

[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" in a search framework.

[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).

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 is an increasing function of the bargaining power parameter $\alpha(z)$. 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 productivity θ' to a job with higher match productivity x. This option value increases with the difference between the two competing offers $(\theta - \theta')$.

From equation (6), we can observe the following. 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. However, if $\lambda_E(z) = 0$, then with probability 1 the worker will not have contacted any other employer during the employment spell, so the outside option will be the reservation match productivity associated with unemployed search, $\theta^*(z)$. Lastly, the wage also increases with the value of the dominated offer θ' and bargaining power $\alpha(z)$, because Bertrand competition and Nash bargaining both work to increase wages.

For a worker with human capital a hired directly out of unemployment, the bargained wage is

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

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 productivity $V_E(\theta^*, \theta^*, z, a) = V_U(z, a)$, 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 productivity $\theta^*(z, a)$ from the following fixed point problem (see Section A.1.1 for the derivation):

(8)

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

The reservation match productivity 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 with 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 describe the manner in which we allow search parameters to depend on worker characteristics (z, τ). 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 l that map linear index functions into the primitive parameters of the model as follows:

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

[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 $E(\theta) = \exp(\mu_\theta + 0.5\sigma_\theta^2) = 1$.

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 associated with 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 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 cycle but observe that the rate of change is modest, which allows 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. Respon-

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

[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.

dents were asked to indicate their 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 contrary 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 the 2012, 2013, 2017 and 2019 GSOEP waves. Our analysis includes individuals for whom personality traits were measured at least once. When there are multiple measurements, we average the values.[21] We standardize personality traits and use Z-scores in estimating our job search model.[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 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 as

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

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 different employment statuses, and we aggregate the information into three distinct categories: unemployed, employed and out of labor force. A person is defined as unemployed (a

[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 on the value of the index function.

[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 of cognitive ability.

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

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
Extroversion	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 corresponds to a two-sided t-test of equality of means. Observations in the upper panel are the 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.

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 in detail below, our model is estimated based on observed employment cycles, which do not include out of labor force spells. If an individual leaves the labor force, then their employment cycle is considered to have ended. If the same person eventually reenters the labor force, then a new employment cycle begins. If a job A directly follows a job B in the same employment spell, we code such an 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. In estimation, we drop individuals who are out of the labor force during the entire observation period (and therefore do not have any employment cycles) or those who are missing information on key variables (education, age, gender, personality traits, cognitive ability). The final sample contains data on 6,540 individuals.[25]

As seen in 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). They are also the same age on average (42). Men are more likely to be married (66 percent versus 59 percent)

[25]Appendix section A.4.1 discusses the sample selection criteria in greater detail. Table A1 compares the full sample and the final estimation sample.

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 and is the largest gender disparity observed for any of the traits. As previously mentioned, similar gender trait differences 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 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, from 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. The average hourly wage is €16.65 for men in comparison to €14.00 for women. This 18.9 percent gender wage gap is substantial considering that men and women have nearly the same years of education and cognitive skill levels. Blau and Kahn (2000) found a 32 percent gender hourly wage gap in West Germany, which was the sixth largest in a ranking of 22 industrialized countries. The gap we find is consistent with reports from the German Federal Statistical Office that showed 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).

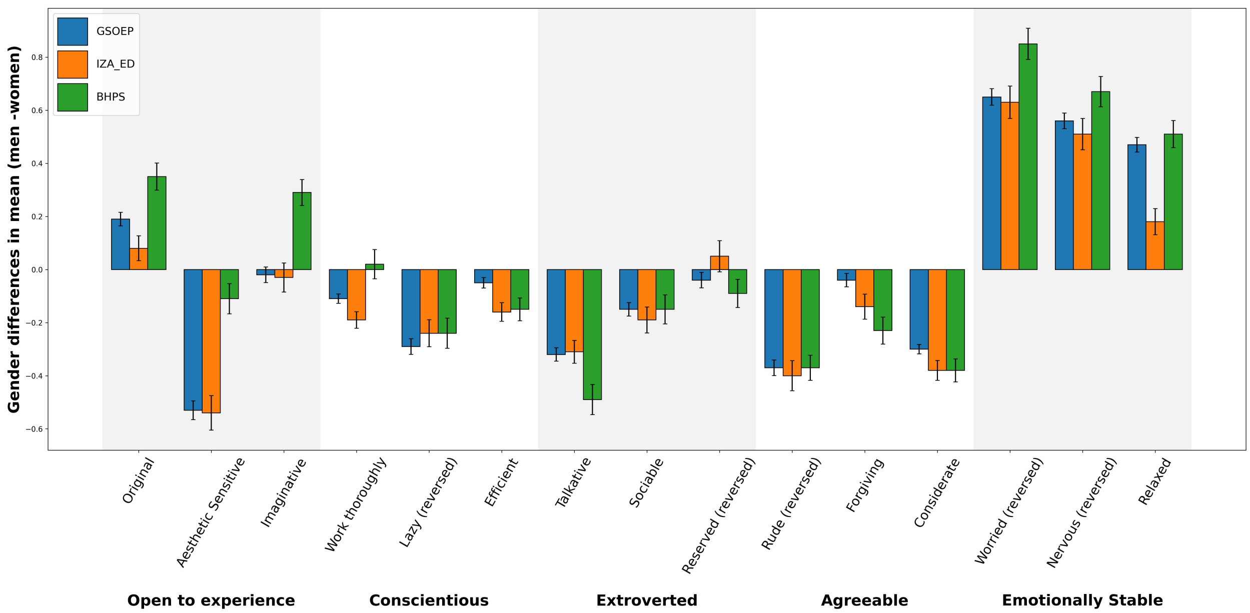
3.1 Robustness and reliability of gender differences in personality traits

Table 1 shows significant gender differences in personality traits. A natural question is whether the observed gender differences are unique to the GSOEP dataset or reflect a more general pattern across different populations. To examine this question, we compared gender differences in personality traits in three different datasets: the GSOEP, the IZA Evaluation Dataset Survey (IZA-ED), and the United Kingdom Household Longitudinal Study (UKHLS). All of these surveys collect personality trait information using a highly comparable short 15-item Big Five Inventory (BFI–S). Figure 2 shows the cross-dataset comparison. Despite the varied samples (which include a representative sample of the German population (GSOEP), individuals registered as unemployed in Germany (IZA-ED), and a representative sample of the UK population (UKHLS)), the gender differences are highly similar, even at the survey item level. Women are systematically found to be more agreeable and less emotionally stable than men, a robust pattern across the three datasets

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

and for the specific items used to measure these traits.[27]

Figure 2: Cross-Dataset Comparison of Measured Gender Differences in Personality Traits By Items



Note: Based on data from the GSOEP for 2012, 2013, 2017, and 2019; the IZA-ED; and UKHLS (Wave 3). Each dataset utilizes the 15-item Big Five Inventory (BFI–S) to assess personality traits. Responses for each item are recorded on a 7-point scale. For individuals appearing in multiple waves, average values for each item are calculated. Each bar represents the average gender difference between men and women, categorized by datasets and items. The vertical square brackets indicate their 95% confidence intervals. Sample sizes: 18,710 males and 19,896 females from SOEP, 6,137 males and 5,590 females from IZA-ED, and 6,282 males and 7,543 females from UKHLS.

3.2 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 in this section can be viewed as a linear approximation to that equation. The hazard model estimates the rate 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 display gender-specific coefficients, and columns 7-9 report coefficients based on a pooled sample of men and women, including a male indicator variable. Columns 1, 4, and 7 report

[27] In another paper (Flinn et al. (2018)), we analyze data from the Household, Income and Labour Dynamics in Australia (HILDA) Survey, which measures personality traits using a more comprehensive scale with 28 items. In the HILDA data, women display comparable levels of agreeableness to those observed in the GSOEP data. However, the HILDA data reveals a smaller gender gap in emotional stability. This difference can be attributed to the survey's expanded set of items that assess emotional stability and include questions about jealousy and moodiness in addition to the anxiety-related items typically found in the other surveys.

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 analogous results but add the Big-5 personality traits as covariates. Columns 3, 6, and 9 include, in addition, marital status and the number of dependent children in the household.

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 and to unemployment experience are similar for men and women. With regard to personality traits, agreeableness and emotional stability are significantly associated 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 and positively related to wages, with similar estimated coefficients for men and women. 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 shows that personality traits explain a significant portion of the wage gap within this linear regression specification. Lastly, both the younger cohort (age 25-37) and older cohort (age 49-60) have lower wages compared to the reference group (age 37-48).

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 their inclusion does not affect the explanatory power of personality traits in a major way. 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 our stationary model does not easily incorporate time-varying characteristics and because they are not typically considered to be direct determinants of wages.

Figure 3 displays estimated Kaplan-Meier survival functions for unemployment duration by gender. Women exit unemployment more slowly and exit employment more rapidly than men. We also estimated a Cox proportional hazards model, shown in Table 3, to analyze how employment transition rates are related 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 promote job stability for men by reducing the exit rate from employment.

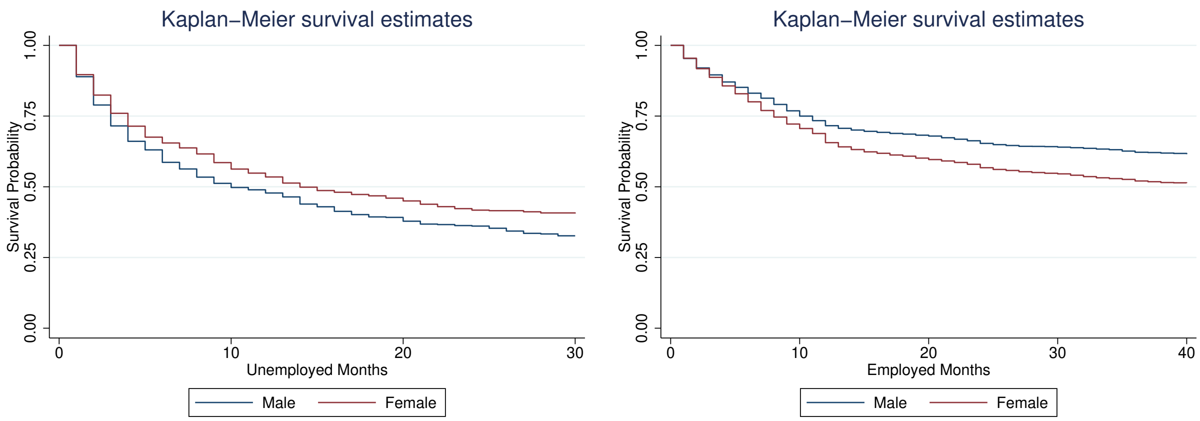
Table 2: The association between individual traits and hourly wages (by gender)†

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)
Extroversion		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 3: Kaplan-Meier survival estimates by gender

(a) Unemployment duration (b) Employment duration



Source: GSOEP data.

As seen in Table 3, all five personality traits (except agreeableness) are related to labor market transitions. For both men and women, higher conscientiousness and emotional stability scores are associated with lower rates of leaving employment and higher rates of exiting unemployment. This means that these traits are beneficial, because they improve the chances of finding a job and promote job stability. On the other hand, openness to experience increases the rate of leaving employment for both men and women. Agreeableness is also associated with a higher rate of exiting employment for men.

In summary, our analysis of hourly wages and employment transitions using regression and hazard rate statistical models indicates that both cognitive and noncognitive traits are significant determinants of these outcomes. Ignoring personality traits can potentially lead to misleading inferences regarding the sources of gender disparities in labor market outcomes. To gain a more holistic understanding of how personality traits affect 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 fairly 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 (general) human capital from the bargaining and matching processes. We will then turn to the specification of our maximum likelihood estimator.

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)
Extroversion	-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

4.1 Measurement error

The endogenous processes in the model are wages and the timing of changes in labor market state. As is virtually always the case, we will assume that there is no measurement error in the timing of labor market state changes.[28] In terms of the measurement error in wages, we make a fairly standard assumption that is consistent with most Mincerian wage equation specifications. 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:

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

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 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

[28]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.

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. In order 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 (once again, ignoring the $\ln \chi$ term for the moment).

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 since they are required to have their pay statements on hand at the time of the interview. 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 job spells for which repeated wage measurements are available. With two-sided measurement error, the likelihood of observing a wage decrease is strictly positive. It is worth noting that our model can 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 when moving between jobs than implied by the model (given reasonable parameter values) and measurement error in wages helps to account for this feature.

In addition, and perhaps most crucially, measurement error can reconcile cases where the model predicts a reservation wage that is higher than the wage that we observe a worker accepting out of unemployment. In our model, every individual inhabits their own labor market since most primitive parameters are a function of a linear index the value of which varies continuously across individuals. As a result, the reservation match productivity $\theta^*(z, \tau)$ differs across individuals. The lower bound of the theoretical wage distribution for a given individual with state variables $\{z, \tau\}$ 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 likelihood to such occurrences.

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

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

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. In this case the density of ε is

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

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 $E(\varepsilon|w) = 1$.[29] The expectation of the observed wage is equal to the true wage since

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

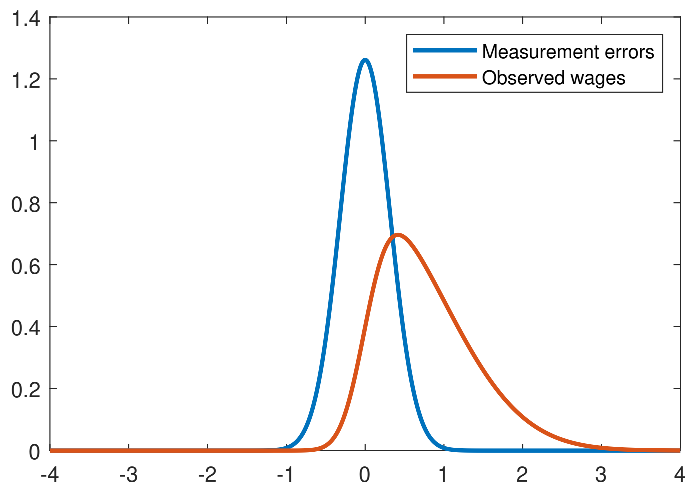
The measurement error dispersion parameter, σ_ε, can be identified from multiple wage measures within the same job spell. To see this, let $\tilde{w}_k^{t_1}$ and $\tilde{w}_k^{t_2}$ be two wage measures at two different periods, t_1 and t_2, in the same job k with a match productivity θ. Denote the "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 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 4. 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

[29] 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, Equation (10) is not actually used in estimating the model, it is only a device to make our identification arguments more intuitive.

Figure 4: An graphical illustration of how measurement error is identified



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 11-12 percent. However, for lower quantiles the wage changes are negative, consistent with measurement error.

4.2 Identification and Estimation

We now examine how our model 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 groups (1)-(3) are allowed to also vary by the observable individual characteristics. Further details and more rigorous arguments concerning identification are provided in Appendix A.5.

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 $\alpha = 1$.[30] 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 λ_U, η, and the parameters characterizing the population wage offer distribution can be identified using monthly Current Population Survey data. These data have information on wages for

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

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.

employed individuals and on the duration of on-going unemployment spells for individuals who are 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 for 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 job to another, given our mapping from (z, τ) into $\lambda_E(z, \tau)$, has the following expression:

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

Job-to-job 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 modestly-sized 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.[31] Because we observe these transitions in the data and

[31] This premise of independence is a widely accepted convention in the literature. For those interested in exploring potential modifications or extensions to this assumption, see Yamaguchi (2010).

this hazard rate appears explicitly in the likelihood, 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 productivity 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 γ_a^τ (the parameters associated with the constant ability level). 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 the (b_τ,ρ) parameters are not separately identified, which is why 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 challenging 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.[32] 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 the distribution $G(\theta)$ does not belong to a parametric location-scale family. Under the lognormality assumption, the match distribution is not location-scale (although $\ln\theta$ is), and the nonlinearity enables identification of α, at least in theory.[33]

An important difference between the case investigated in Flinn (2006) and the model estimated in this paper is that we allow for model parameters to depend on the vector of individual characteristics z. Introducing this heterogeneity considerably aids model parameter identification, but at the cost of having to make parametric assumptions on the nature of the dependence. We illustrate this through an example in which the matching distribution $G(\theta)$ belongs to a *location-scale family*. Flinn (2006) shows that the location and scale parameters $\{\mu,\sigma\}$ and bargaining power α in this case cannot be separately identified in a homogeneous labor market. We revisit the same setting as in Flinn (2006), in which there was an absence of on-the-job search, heterogeneous worker productivity (a), and measurement error. Allowing for the presence of heterogeneity z, the Nash-bargained

[32]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 regarding the production process.

[33]In addition to the functional form of $G(\theta)$, the identification argument of the bargaining power parameter is further strengthened in our model with on-the-job search and renegotiation by exploiting the variation from multiple wages within the same job spell, as is discussed below.

wage at a match productivity value of θ is given by

$$w(\theta; z) = \alpha(z)\theta + (1 - \alpha(z))\theta^*(z).$$

For our example, consider z to be a scalar characteristic that takes one of J possible values, with the j^{th} value denoted by $z(j)$. We will say that an individual i is type j if $z_i = z(j)$. Let J be small and fixed, so that as sample size N increases so do the number of observations in each subpopulation $z(j)$. Estimation could proceed conditionally on each value $z(j)$, with no restrictions on $\alpha(z(j))$, $\mu(z(j))$, and $\sigma(z(j))$ across the J subpopulations. If the parameters were not identified within any given subgroup, then they would not be identified in other subgroup, which is the case if the match productivity distribution belongs to a location-scale family as in our example.

Now suppose we assume that across-group parameter heterogeneity satisfies the restrictions $\alpha(z(j)) = q(\gamma_0^\alpha + \gamma_1^\alpha z(j))$, $\mu(z(j)) = \gamma_0^\mu + \gamma_1^\mu z(j)$, and $\sigma(z(j)) = \exp(\gamma_0^\sigma + \gamma_1^\sigma z(j))$, where $q(\cdot)$ is the logit mapping.[34] If $\gamma_1^\alpha = \gamma_1^\mu = \gamma_1^\sigma = 0$, then we are in the homogeneous case in which there is no heterogeneity in parameter values across the subpopulations. Because G is assumed to belong to a location-scale family, we know that the common values of α, μ, and σ are not individually identified in this case. Identification requires that each of the three parameters α, μ, and σ be functions of $z(j)$. The assumption that $G(\theta; \mu(z(j)), \sigma(z(j)))$ belongs to a *location-scale* family implies that the distribution of match quality can be written as

$$G(\theta; \mu(z(j)), \sigma(z(j))) = G_0\left(\frac{\theta - \mu(z(j))}{\sigma(z(j))}\right)$$

where $\{\mu(z(j)), \sigma(z(j))\}$ are the location and scale parameters, respectively, and G_0 is a known function (e.g. a standard normal distribution). Its associated (observed) wage distribution can be written as the following truncated *location-scale* distribution, with the lower truncation point at $\theta^*(z(j))$:

$$f(w|z(j)) = \frac{\frac{1}{\sigma'(z(j))} g_0\left(\frac{w - \mu'(z(j))}{\sigma'(z(j))}\right)}{1 - G_0\left(\frac{\theta^*(z(j)) - \mu'(z(j))}{\sigma'(z(j))}\right)}$$

where $\mu'(z(j))$ is the "new" location parameter and $\sigma'(z(j))$ is the "new" scale parameter:

$$\mu'(z(j)) = (1 - \alpha(z(j)))\theta^*(z(j)) + \alpha(z(j))\mu(z(j))$$
$$\sigma'(z(j)) = \alpha(z(j))\sigma(z(j))$$

Consistent estimators for $\mu'(z(j))$ and $\sigma'(z(j))$ are available, but these parameters are functions of the three primitive parameters $\mu(j)$, $\sigma(j)$, and $\alpha(j)$. With 2 equations and three unknowns, the model parameters are not identified without further restrictions when $J = 1$, which corresponds to

[34] Note also that we specify different mappings from the same index function into the different parameters of the wage determination equation. These are required to map the index, which takes values on R, into the appropriate space for each parameter. Although the explicit form of the mapping is arbitrary, the ones we use are the ones most commonly used as *link functions* for this purpose.

the homogeneous labor market case.

Now, assume that the number of values of $z(j)$ are $J = 3$. Then for each of the 3 types, we can obtain consistent estimates of the location and scale parameters $\hat{\mu}'(z(j))$ and $\hat{\sigma}'(z(j))$, $j = 1, 2, 3$). In addition, the lowest observed wage for type j is a consistent estimator for $\theta^*(j)$, that is

$$\hat{\theta}^*(z(j)) = \min\{w_i\}_{i \in S(j)}, \tag{13}$$

where $S(j)$ contains the set of indices of sample members of type $z(j)$. For each type we have consistent estimates of the location and scale parameters, and we have 6 unknown parameters to estimate (conditional on our super-consistent estimates $\hat{\theta}^*(j)$, $j = 1, 2, 3$). When $J = 3$ the model is exactly identified and produces unique estimates of each of the six β parameters.

If there are more than 3 types the model is over-identified, so to obtain unique estimates of the β parameters we need to define a proper estimator with a well-defined sampling distribution. In our case, due to the fact that some of the covariates in the index function are continuous, there are a continuum of types in the population. Each individual, characterized by z_i, essentially inhabits their own labor market, with the links between the individual labor markets being the common β parameters.[35]

Another key difference between the model estimated in this paper and models developed in the earlier literature (which have been cited in this section) is the inclusion of the human capital parameter a. Our identification argument for this parameter 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, $\chi\left(\theta, \theta', z, \tau; \gamma_{-a}^\tau\right)$, is facilitated by incorporat-

[35] The idea is no different than representing the conditional expectation of an endogenous variable as a linear index formed from covariates z_i. Particularly when using cross-sectional data in which one observation of the dependent variable is observed for each i, nonparametric estimation of the conditional mean function is not possible. The assumption that all population members share the same parameter vector β is required to obtain consistent estimates of the conditional mean function.

ing 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^{τ}_{-a}.

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 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.5 demonstrates identification within our likelihood framework for our most general model specification. 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^{τ}_{j} 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 and overall likelihood

We estimate the model parameters using a maximum likelihood estimator. We first describe how we construct each individual likelihood conditional on the individual-specific set of parameter values Ω_i, accounting for data censoring. We begin by considering the problem of right censoring that occurs when there are incomplete unemployment or employment spells. Later, we also consider the more difficult problem of left-censoring, which occurs when spells are in progress at the start of the observation period. After characterizing the individual likelihood contribution, we 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 discussion of the individual likelihood suppresses the dependence of the parameters on (z_i, τ_i), 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), for example, 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 labor force 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.[36] That is, an employment cycle can consist of

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

In the above definition, T_U represents the unemployment spell duration. The indicator variable r_U is equal to 1 if the unemployment spell is right-censored. If we observe subsequent employment spells, up to two jobs, T_k denotes the duration of job spell k within the employment spell, $k \in \{1, 2\}$. Within each job spell, wages are sequentially reported n_k times, at time periods $\{t_{k1}, t_{k2}, ..., t_{kn_k}\}$. We use the notation $\tilde{w}_k^{t_{kj}}$ to denote the wage reported at period t_{kj} within job spell k. The indicator variable $r_k = 1$ signifies that the duration of job k is right-censored. The indicator variable q_k equals 1 when the job k is dissolved at the end of the job spell, corresponding to a transition to unemployment, and it equals 0 when the individual transitions immediately from one job to another job. Each individual may contribute information on multiple ECs to the likelihood. Note that an EC ends if an individual enters the out-of-labor force state; we could observe a second EC if the individual reenters the labor force.[37]

We now address the left-censoring issue, which is unique to the first Employment Cycle. This occurs when individuals are already in the midst of their unemployment or employment spells at the beginning of our observation period.[38] In order to deal with this issue, we need to incorporate the individuals' labor market histories prior to the observation period. For those unemployed at the

[36] 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.

[37] Appendix A.4.2 describes our treatment of out-of-labor force and part-time work in greater detail.

[38] 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 the choice of jobs.

start, their initial unemployment status acts as a sufficient statistic of their labor market history. This is 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 is independent of the time already spent searching.[39] The likelihood of this duration is conditional on the individual being sampled while in the unemployment state. In order to form the joint likelihood of the duration of the left-censored unemployment spell and the likelihood of being sampled in the unemployment state, we must multiply the conditional density of the observed unemployment duration times given unemployment by the likelihood of finding the individual in an unemployment spell in the steady state at a randomly selected point in time.

For individuals who are employed at the beginning of the observation period, their initial condition hinges not only on their employment status but also on the current job match value, θ, and the dominated match value that represents the outside option, θ'. This pair (θ,θ') jointly determines the current wage. As described in detail below, we assume the initial match value and the dominated outside option match value are drawn from the steady-state distribution of these variables. These draws of the initial distribution are integrated out during the calculation of the likelihood function value for an employment cycle that begins with an on-going employment spell. This produces the conditional distribution of wages for the first left-censored job spell given that the individual was found in the employment state when first observed. To form the joint likelihood of wages in the first left-censored job spell and being initially sampled in the employment state we multiply the conditional likelihood given employment by the likelihood of being employed at a randomly sampled time in the steady state.

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 ($r_2 = 0, q_2 = 0$)

[39] In a stationary model like ours (strictly speaking, our model is stationary only after conditioning on ability a), length-bias isn't a concern. The distribution of forward recurrence times in length-biased spells (i.e. those in progress at the time when the sample window begins) is the same as the population distribution of the completed spells (that are not length-biased).

We will write one likelihood expression that nests 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 job 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 likelihood contribution for individuals whose ECs begin with unemployment is given by

(14)

$$\begin{aligned} l(t_U, r_U, \{\tilde{w}_1^{t_{1k}}\}_{k=1}^{n_1}, T_1, r_1, q_1, \{\tilde{w}_2^{t_{2k}}\}_{k=1}^{n_2}, T_2, r_2, q_2) = \int_{\theta^*}\int_{\theta_1} h_U^{(1-r_U)} \exp(-h_U t_U) \\ \times \left\{ \exp\left(-h_E(\theta_1)T_1\right) \left[\left(\lambda_E \bar{G}(\theta_1)\right)^{1-q_1} \eta^{q_1} \right]^{1-r_1} f_{w_1}(\tilde{w}_1^{t_{11}}, \tilde{w}_1^{t_{12}}, \tilde{w}_1^{t_{13}}, ..., \tilde{w}_1^{t_{1n_1}}, T_1 | \theta_1; \theta^*) \right\}^{1-r_U} \\ \times \left\{ \exp\left(-h_E(\theta_2)T_2\right) \left[\left(\lambda_E \bar{G}(\theta_2)\right)^{1-q_2} \eta^{q_2} \right]^{1-r_2} f_{w_2}(\tilde{w}_2^{t_{21}}, \tilde{w}_2^{t_{22}}, \tilde{w}_2^{t_{23}}, ..., \tilde{w}_2^{t_{2n_2}}, T_2 | \theta_1, \theta_2) \right\}^{1-r_1} \frac{dG(\theta_2)}{\bar{G}(\theta_1)} \frac{dG(\theta_1)}{\bar{G}(\theta^*)} \end{aligned}$$

An employment cycle that starts with an employment spell can be one of the following 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 likelihood for individuals whose ECs begin with employment needs to include all of the above cases. In addition, for workers who are employed at the start of the observation period, there is the complication that their match value at the current job and their best dominated match value are not observed. The pair of match values $\{\theta_1, \theta_1^{'}\}$ serves as a sufficient statistic for job history. We posit that the initial match productivity value θ is a random draw from the unconditional cdf $L(\theta)$, while the initial best dominated match productivity value is a random draw from the conditional steady-state cdf $S(\theta_1^{'}|\theta_1)$, both of which are derived in Appendix A.1.2. Consequently, our "unconditonal" likelihood function needs to integrate out $\theta_1^{'}$ and θ_1 based on their distributions

$S(\theta_1^{'}|\theta_1)$ and $L(\theta_1)$, using Monte Carlo integration (as described below).
(15)

$$l(\{\tilde{w}_1^{t_{1k}}\}_{k=1}^{n_1}, T_1, r_1, q_1, \{\tilde{w}_2^{t_{2k}}\}_{k=1}^{n_2}, T_2, r_2, q_2) =$$
$$\int_{\theta^*}\int_{\theta^*}^{\theta_1}\int_{\theta_1} \exp\left(-h_E(\theta_1)t_1\right)\left[\left(\lambda_E\bar{G}(\theta_1)\right)^{1-q_1}\eta^{q_1}\right]^{1-r_1} f_{w_1}(\tilde{w}_1^{t_{11}}, \tilde{w}_1^{t_{12}}, \tilde{w}_1^{t_{13}}, ..., \tilde{w}_1^{t_{1n_1}}, T_1|\theta_1^{'}, \theta_1)$$
$$\left\{\exp(-h_E(\theta_2)t_2)\left[\left(\lambda_E\bar{G}(\theta_2)\right)^{1-q_2}\eta^{q_2}\right]^{1-r_2} f_{w_2}(\tilde{w}_2^{t_{21}}, \tilde{w}_2^{t_{22}}, \tilde{w}_2^{t_{23}}, ..., \tilde{w}_2^{t_{2n_2}}, T_2|\theta_1, \theta_2)\right\}^{1-r_1} \frac{dG(\theta_2)}{\bar{G}(\theta_1)} dS(\theta_1^{'}|\theta_1)dL(\theta_1)$$

As shown in Appendix A.1.2, the steady-state distributions have a closed form:

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

We calculate the likelihood functions specified in equations 14 and 15 using closed form expressions when feasible, but to calculate some components of the likelihood requires the use of simulation methods. For each employment cycle that begins in an on-going employment spell, we first draw $r = \{1, 2, .., R\}$ sample paths as follows. From the steady state joint distribution of current match productivity and the current outside option productivity levels, we take R draws of $\{\theta_1(r), \theta_1^{'}(r)\}$, where θ is the current match productivity and $\theta^{'}$ is the best dominated productivity value (the outside option) used as a basis for wage-setting. If there is a second job in this EC, from the model we know that the outside option for that job corresponds to match productivity of the first job in the EC, so that $\theta_2^{'}(r) = \theta_1(r)$ on the sample path r. The match productivity at the second job on sample path r is determined by a draw from the truncated match quality distribution $G(\theta|\theta > \theta_1(r))$, with this draw denoted $\theta_2(r)$.

Because a series of sequential wage observations are available over the course of these job spells, we need to generate sample paths of wages within each job spell. Although the match productivity does not change over a job spell at a given employer, the best dominated match value may change. The sampling period is one month, and the number of months in job i in the EC is given by T_i. The probability of meeting another firm in a one-month period of time frame is given by $1 - \exp\left(-\lambda_E \times 1\right)$.[40] The probability that a match draw is no greater than the current job productivity level of $\theta_i(r)$ is $G(\theta_i(r))$, so that the probability of meeting another firm with a match productivity less than current match productivity is $(1 - \exp\left(-\lambda_E\right) \times G(\theta_i(r)))$. For each job spell, we generate M sample paths of the possible best dominated job offers, which we denote $\left\{\{\theta_{i=1}^{'}(t, r, m)\}_{t=1}^{T_1}\right\}_{m=1}^{M}$ for the first job spell and $\left\{\{\theta_{i=2}^{'}(t, r, m)\}_{t=1}^{T_2}\right\}_{m=1}^{M}$ for the second job spell. For each of the M sample paths and for each month, we draw a uniform random number to determine whether the individual received an offer from a firm with a match productivity less

[40]This is an approximation to the actual continuous-time process. In a one month period of time, in theory a countable infinity of contacts with potential employers could occur, and we are limiting the number of contacts to be at most 1 in a month. Given that the estimate of the rate of meeting alternative employers while employed, λ_E, is low for virtually all sample members, the likelihood of meeting 2 or more potential employers in a one-month period is low as well. This feature of the data suggests that the approximation is satisfactory. On the other hand, our estimates of λ_E are also based on this approximation, so that our claim is subject to this caveat.

than the current value. If so, we draw from the truncated distribution of match values with upper truncation point $\theta_i(r)$. If this draw is greater than the current outside option match value, it becomes the new outside option. In this way, the sample path m of outside options is generated. Given $\theta_i(r)$ and the best dominated match productivity in month t, $\theta_i'(t,r,m)$, the wage in that month is determined based on the wage determination Equation 6. We then average these M wage trajectories, which corresponds to a Monte Carlo integration over the joint density functions $f_{w_1}(\cdot)$ from the first job spell and $f_{w_2}(\cdot)$ from the second job spell. Lastly, we average the R sample paths to get the likelihood value corresponding to equations 14 and 15. A detailed description of our simulation approach for the various types of employment cycles that occur in the data can be found in Appendix A.3.

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

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

The individual likelihood function l_i is then calculated based on their multiple employment cycles over the observation period:

$$l_i = \sum_{k\in\{0,1\}} \Pr(E_i = k_i|\Omega(z_i,\tau_i))[\Pi_{j=1}^{J} \ln \ell_j(\text{Employment cycle}_{ij}|\Omega(z_i,\tau_i), E_i = k_i)] \tag{16}$$

where $\Pr(E_i = k_i|\Omega(z_i,\tau_i))$ denotes the probability of observing the initial employment status $E_i = k_i$, given individual i's characteristics $\Omega(z_i,\tau_i)$.[41] $\ell_j(\text{Employment cycle}_{ij}|\Omega(z_i,\tau_i), E_i = k)$ is the likelihood function for the j^{th} employment cycle for individual i, which corresponds to either equation 14 or 15 depending on the type of employment cycle. 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 $\theta^*(z_i,\tau_i)$. The overall log likelihood function $\ln L$ is given by

$$\ln L = \sum_{i=1}^{N} \ln l_i$$

[41] As detailed in Equation 18 in the Appendix (see subsection A.1.2), the probability of being unemployed when initially sampled is given by $\Pr(E_i = 0|z_i,\tau_i) = \frac{\eta(z_i,\tau_i)}{\eta(z_i,\tau_i)+\lambda_U\bar{G}(\theta^*(z_i,\tau_i))}$ in the steady state. Conversely, the probability of being employed when sampled is given by $\Pr(E_i = 1|z_i,\tau_i) = \frac{\lambda_U\bar{G}(\theta^*(z_i,\tau_i)}{\eta(z_i,\tau_i)+\lambda_U\bar{G}(\theta^*(z_i,\tau_i))}$.

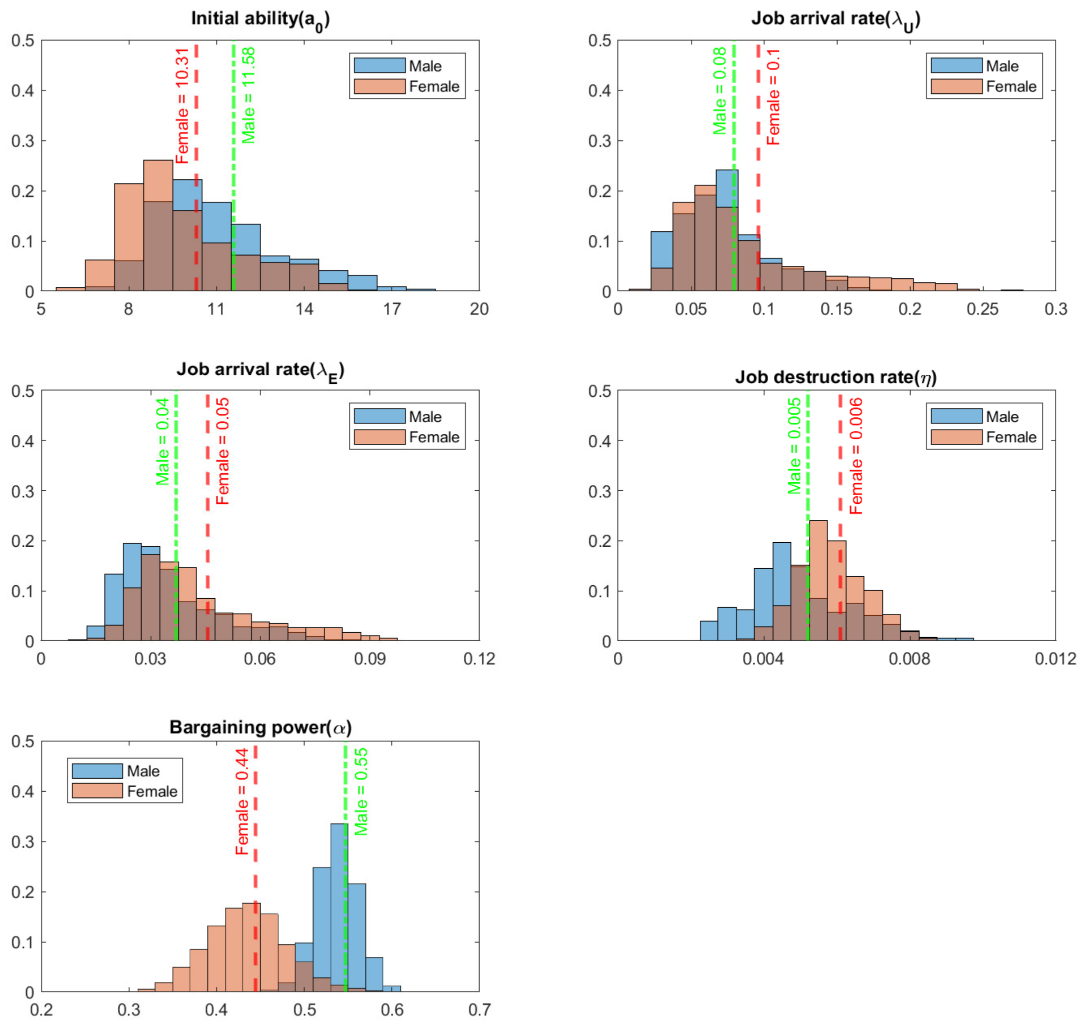
5 Model estimates

5.1 Estimated model parameters under alternative specifications

Previous papers that estimate search models usually incorporate covariates such as age, gender, education and race by dividing the sample into subgroups and estimating separate models for each subgroup (e.g. Bowlus (1997), Bowlus and Grogan (2008), Flabbi (2010a), Liu (2016), Morchio and Moser (2020), Amano-Patino et al. (2020)). However, the number of covariates used is often restricted to maintain a sufficient sample size within every subgroup, which is necessary for the reliable estimation of parameters for each of them. The index formulation we introduce 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 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 "fully 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 of the individual characteristics with the exception of personality traits. Figure 5 shows the distributions of the estimated parameter values for males and females under the "fully heterogeneous" model and Table 5 displays 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 the estimates for the "fully heterogeneous" and "without personality" specifications highlight the role of personality traits in the model's ability to match the data. Under the fully heterogeneous model, the estimated initial human capital endowment parameters (a_0) indicate that, on average, males possess a higher innate human capital endowment than females. The average human capital endowment for males is 11.60, compared to 10.31 for females in the fully heterogeneous model. Figure 5 illustrates the significant variability in the estimated human capital endowment parameters (a_0), with considerable overlap between the male and female distributions. This gender gap of approximately 11 percent in average human capital endowment is notably smaller than the productivity disparities reported in other studies. For example, Bowlus (1997) finds women's productivity is 20 to 41 percent lower than men's productivity in similar jobs. This discrepancy can be attributed to differences in accumulated work experiences (S_E) and unemployment experiences (S_U) between genders, rather than to innate human capital (a_0). Because women typically spend more time out of the labor force or in part-time employment, their S_E values tend to be lower compared to their male counterparts.[42] This factor contributes to a wider gap in overall productivity (a) compared to the initial human

[42]Note that we count part-time past work as half a year experience when calculating the accumulated working experience S_E.

Figure 5: The distribution of search parameters $\{a_0, \alpha, \lambda_U, \lambda_E, \eta\}$



Note: This graph presents the distribution of search parameters across genders under the "fully heterogeneous" specification. Blue bars represent male workers and red bars correspond to female workers. Vertical dashed lines indicate the mean values for each distribution-red for female and green for male-aligning with the mean values reported in Table 5 under the columns for "fully heterogeneous" specifications.

capital difference (a_0).

With regard to bargaining, men are estimated to have a higher bargaining parameter (α) and therefore receive a larger initial share of the job surplus on average than do women.[43] The estimated parameter values range from 0.44-0.55, 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 5 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 5), meaning that most people have low rates of finding a job opening, while a small fraction have higher values. Once employed, the job arrival rate, λ_E, is lower than when the individual is unemployed. The estimated job separation rate, η, is generally small in magnitude, and is slightly lower for men in comparison with women. It's worth noting that jobs may also end due to workers leaving for jobs at other employers. Men tend to have lower flow utility, b, 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" one and the "fully heterogeneous" specification against the "without personality" one. The models are nested and the likelihood ratio tests reject the more restrictive specifications. Models that allow for a greater degree of heterogeneity provide a better fit to the data. It is notable that the dispersion in the initial ability distribution is wider with the "fully heterogeneous" specification compared to the "without personality" specification. This difference is due to personality traits substantially accounting for the initial ability differences across both genders.

In addition to performing the formal tests, we also graphically examine the model's goodness of fit by comparing the distributions of wages and of unemployment/employment spell durations from the data and from model simulations. Figure 6 presents the distribution of first and last wages for employment spells of junior workers with work experience $\leq$ 12 years and senior workers with work experience $>$ 12 years. The estimated model fits the wage distributions and the growth in wages for both junior and senior workers. In Figure 7, 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.[44]

[43]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.

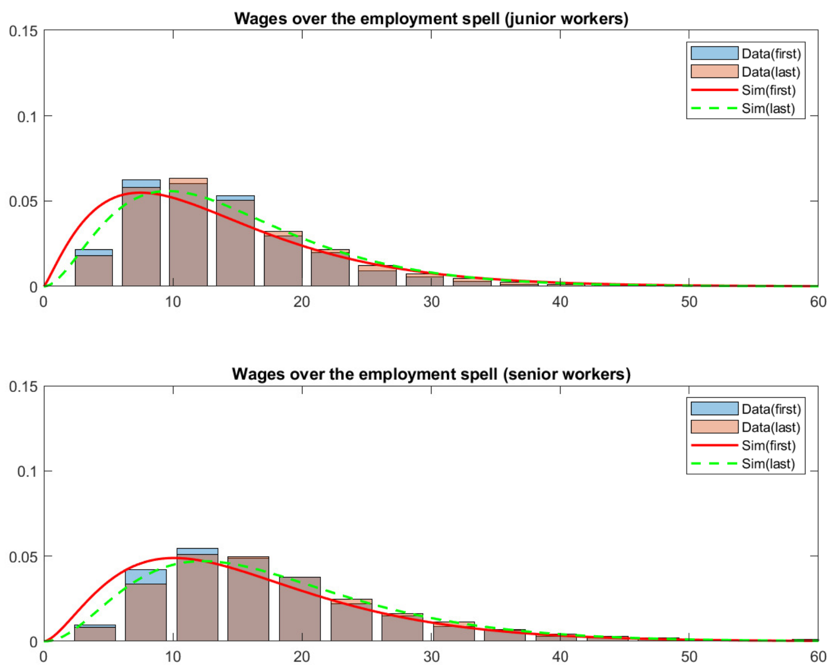
[44]We fully account for right-censoring in implementing the maximum likelihood estimator.

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	12.50	13.16	11.85	11.20	11.60	10.31
		(0.03)	(0.04)	[1.63]	[1.42]	[2.12]	[1.97]
α	bargaining	0.55	0.47	0.55	0.46	0.55	0.44
		(0.002)	(0.002)	[0.03]	[0.02]	[0.02]	[0.05]
η	separation rate	0.004	0.010	0.005	0.007	0.005	0.006
		(2.3e-05)	(5.2e-05)	[0.001]	[0.001]	[0.001]	[0.001]
λ_U	offer arrival rate, in unemp.	0.09	0.08	0.09	0.09	0.08	0.10
		(0.0002)	(0.0001)	[0.03]	[0.04]	[0.03]	[0.05]
λ_E	offer arrival rate, in emp.	0.04	0.04	0.04	0.04	0.04	0.05
		(0.0001)	(0.0001)	[0.01]	[0.01]	[0.01]	[0.01]
b	flow utility when unemp.	0.10	0.30	0.10	0.39	0.10	0.36
		(0.007)	(0.005)	(0.008)	(0.007)	(0.006)	(0.007)
ψ	human cap. acc.(monthly)	0.0007	0.0007	0.0008	0.0007	0.0009	0.0008
		(1.0e-5)	(1.1e-5)	(1.3e-5)	(1.6e-5)	(1.2e-5)	(1.0e-5)
δ	human cap. dep.(monthly)	0.004	0.003	0.004	0.004	0.004	0.004
		(3.4e-5)	(3.0e-5)	(3.3e-5)	(4.1e-5)	(5.1e-5)	(3.0e-5)
σ_θ	$\theta \sim \log N\left(-\frac{\sigma_\theta^2}{2}, \sigma_\theta\right)$	0.27	0.29	0.27	0.28	0.27	0.28
		(0.0006)	(0.0006)	(0.0007)	(0.0007)	(0.0007)	(0.0007)
σ_ε	$\varepsilon \sim \log N\left(-\frac{\sigma_\varepsilon^2}{2}, \sigma_\epsilon\right)$	0.21	0.21	0.20	0.21	0.20	0.21
		(0.0005)	(0.0004)	(0.0005)	(0.0005)	(0.0005)	(0.0005)
$\log L$		-56,280		-52,599		-52,049	
LR tests‡				(1) & (2) ($P < 0.001$)		(2) & (3) ($P < 0.001$)	

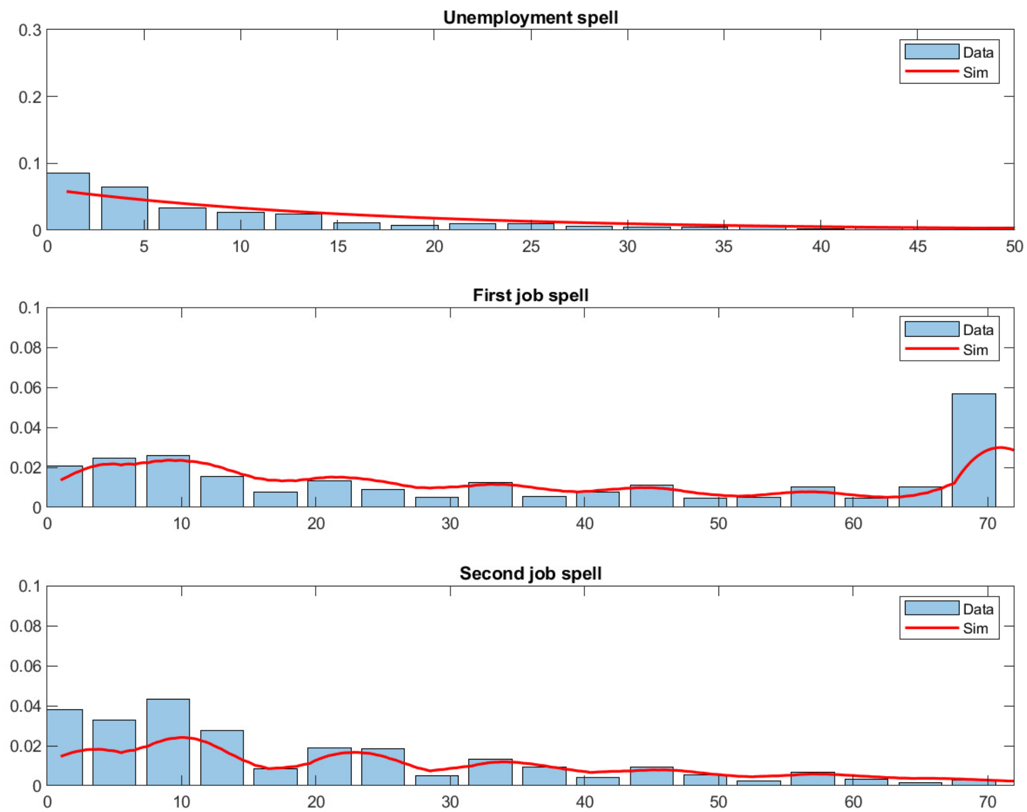
†In the *without personality* and *fully heterogeneous* specifications, the parameters $\{a_0, \alpha, \lambda_U, \lambda_E, \eta\}$ depend on indices of individual characteristics. For these parameters, we report the standard deviations of the parameter distribution in square brackets. For all other 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 one in the previous column. The monthly discount rate is set at 0.006.

Figure 6: Model goodness of fit to wage distributions



Note: 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 7: Model goodness of model fit to spell length distributions



Note: The histograms show the distribution of unemployment spell lengths and the spell lengths of the first and second job spells. The curve represents the fitted distributions from the simulations. The fitted curve is specified as an exponential for unemployment spell lengths and estimated nonparametrically for employment spell lengths, using an Epanechnikov kernel with a bandwidth of 2 months.

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 heterogeneous 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 rates in general (both λ_U and λ_E) 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 studies as the two traits most strongly associated with superior labor market outcomes. Consistent with these findings, our estimates indicate that conscientiousness increases job offer arrival rates while unemployed and decreases job separation rates. It also increases bargaining power for both men and women. These estimated effects generally contribute to higher wage levels and more stable employment. For men only, it also increases initial ability and decreases the job offer arrival rate while employed. Emotional stability is also clearly a desirable labor market trait. For both men and women, it increases the initial human capital endowment, the unemployment job arrival rate, and the bargaining power. It also increases their employment job arrival rate for women and lowers the job exit rate for men.

The remaining three traits - openness to experience, extroversion and agreeableness - are not necessarily desirable characteristics from a labor market perspective. On the one hand, openness to experience increases job offer arrival rates for both men and women. However, it also significantly increases the job separation rate for women and decreases the bargaining power parameter for both men and women. For women, extroversion increases the unemployment job offer arrival rate and increases initial human capital, but it decreases bargaining power. For men, extroversion has a uniformly positive effect, increasing the job arrival rate when employed and increasing bargaining power. Lastly, agreeableness has a uniformly negative effect on labor market parameters for both men and women, significantly decreasing job offer arrival rates while unemployed, lowering bargaining power (especially for women), reducing the initial human capital endowment, and increasing the job separation rate.

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 vector. However, we do allow there to be differences in the

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

	$\log a_0$		$\log \lambda_U$		$\log \lambda_E$		$\log \eta$		$\log\left(\frac{\alpha}{1-\alpha}\right)$	
	Male	Female	Male	Female	Male	Female	Male	Female	Male	Female
Constant	2.51	2.38	-2.44	-2.33	-3.28	-3.10	-5.37	-5.13	0.20	-0.14
	(0.004)	(0.004)	(0.006)	(0.003)	(0.006)	(0.004)	(0.009)	(0.008)	(0.011)	(0.010)
Education	0.13	0.16	0.23	0.39	0.25	0.27	-0.21	-0.12	0.06	0.05
	(0.002)	(0.003)	(0.003)	(0.004)	(0.003)	(0.005)	(0.007)	(0.008)	(0.007)	(0.007)
Cognitive ability	0.04	0.04	0.04	0.10	0.07	0.12	0.02	0.04	-0.02	-0.03
	(0.002)	(0.003)	(0.004)	(0.004)	(0.004)	(0.004)	(0.008)	(0.004)	(0.006)	(0.007)
Openness	0.00	0.01	0.07	0.06	0.06	0.05	0.01	0.05	-0.07	-0.09
	(0.002)	(0.003)	(0.003)	(0.004)	(0.002)	(0.003)	(0.008)	(0.009)	(0.005)	(0.005)
Conscientiousness	0.01	-0.003	0.07	0.03	-0.02	0.0005	-0.04	-0.02	0.03	0.05
	(0.002)	(0.003)	(0.004)	(0.004)	(0.003)	(0.003)	(0.006)	(0.007)	(0.006)	(0.007)
Extroversion	-0.002	0.02	-0.005	0.02	0.03	0.01	0.01	0.01	0.02	-0.03
	(0.002)	(0.002)	(0.004)	(0.004)	(0.003)	(0.004)	(0.005)	(0.007)	(0.006)	(0.007)
Agreeableness	-0.03	-0.02	-0.003	-0.02	0.004	0.004	0.01	0.01	-0.01	-0.14
	(0.002)	(0.003)	(0.004)	(0.004)	(0.004)	(0.003)	(0.002)	(0.008)	(0.006)	(0.006)
Emotional stability	0.04	0.02	0.02	0.05	-0.003	0.03	-0.02	0.01	0.03	0.10
	(0.002)	(0.002)	(0.004)	(0.003)	(0.003)	(0.002)	(0.008)	(0.007)	(0.005)	(0.005)
Cohort (ref group: 37-48)										
25-36	-0.10	-0.08	0.09	-0.12	0.08	-0.02	0.29	0.13	-0.04	-0.03
	(0.005)	(0.005)	(0.005)	(0.005)	(0.006)	(0.004)	(0.019)	(0.014)	(0.015)	(0.011)
49-60	-0.15	-0.10	-0.52	-0.26	-0.24	-0.15	-0.11	-0.08	0.02	-0.06
	(0.005)	(0.005)	(0.007)	(0.007)	(0.007)	(0.006)	(0.019)	(0.010)	(0.012)	(0.011)

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

labor market parameters for different birth cohort indicators by including birth cohort indicators in the vector z. Of course, these cohort members are different ages at the beginning of the observation period. As shown in the bottom rows of Table 6, individuals from the most recent cohort have lower ability compared to middle-aged workers (which is the reference cohort, aged 37-48 at the beginning of the sample period). For men, the youngest cohort members have significantly higher job offer arrival rates both on and off the job, while women in this cohort experience lower job offer rates. These most recent labor market entrants also have less bargaining power. The oldest cohort (aged 49-60 at the beginning of the sample period) have lower initial human capital endowments and job offer rates as well as lower job exit rates. Additionally, women in this cohort have lower bargaining power compared to the reference cohort and compared to men.

6 Interpreting the model estimates

We now use the estimated model to investigate the manner in which 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, the time varying component of a that captures the impact of labor market experience. The initial 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 match value and the best dominated match value received during the current employment spell), $\{\theta', \theta\}$, are drawn from the steady-state distribution, as described in Appendix A.1.

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 average labor market outcomes in the baseline case, where all the traits are set at the mean values observed in the data. The model simulations reveal significant gender gaps in both wages and working opportunities. Men tend to have higher wages, shorter unemployment spells, and longer job spells relative to women.

We also calculate the average share of the surplus by gender, using a definition given in Cahuc et al. (2006):

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

where θ denotes the match productivity and θ' denotes the best dominated match value, which is given by θ^* if the worker is hired directly from unemployment. The average share calculated this way tends to be higher than the share indicated by the bargaining parameter due to the between-firm Bertrand competition for workers. Between-firm competition has a greater impact on the share of the surplus received by women, increasing it by 69 percent (from 0.45 to 0.76), compared to the impact on the share of surplus received by men, which increased by 47 percent (from 0.55 to 0.81). Despite similar job arrival rates for employed men and women, counter-offers tend to benefit women more, enhancing their surplus share from a relatively lower starting point.

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 23-27 percent for both men and women, reduces unemployment, and increases job spell length, particularly for men. It also increases the average share of the surplus by 4.0 percent for men and 3.8 percent for women. Increasing cognitive ability has similar, albeit 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 due to the arrival of superior outside offers.

Conscientiousness and emotional stability are key contributors to favorable labor market outcomes. For both men and women, higher conscientiousness is associated with increased wages, longer job tenure, and shorter unemployment spells. Enhanced emotional stability leads to higher wages, a greater share of surplus, and reduced unemployment duration, although its effects on job duration vary by gender, increasing it for men but decreasing it for women. Openness to experi-

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

	Average wage		Unemp. spell		Job spell		Surplus division	
	Men	Women	Men	Women	Men	Women	Men	Women
Baseline	16.1	12.8	14.2	12.6	117.0	95.2	0.81	0.76
Education (+1SD)	23.6%	26.8%	-20.7%	-31.9%	18.6%	9.1%	4.0%	3.8%
Cognitive ability (+1SD)	4.6%	5.4%	-3.9%	-9.9%	-2.5%	-4.7%	0.1%	1.1%
Openness (+1 SD)	-0.1%	-0.3%	-6.4%	-5.4%	-1.6%	-5.2%	-0.8%	-0.1%
Conscientiousness (+1 SD)	2.5%	1.2%	-6.8%	-3.2%	3.7%	2.3%	0.3%	0.5%
Extroversion (+1 SD)	0.3%	1.4%	0.5%	-2.0%	-1.0%	-1.2%	0.7%	-0.2%
Agreeableness (+1 SD)	-3.3%	-3.3%	0.3%	1.6%	-1.2%	-1.1%	-0.3%	0.4%
Emotional stability (+1 SD)	4.9%	3.5%	-2.0%	-4.7%	2.3%	-1.4%	0.6%	0.7%
Work exp (+1 SD)	12.3%	10.8%	-	-	-	-	-	-
Unemp. exp (+1 SD)	-13.8%	-13.3%	-	-	-	-	-	-

†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.

ence tends to shorten both unemployment and job spells for both men and women. For women, extroversion boosts wages and shortens both unemployment spells and job spells. For men, extroversion has a lesser impact, decreasing the length of job spells and slightly increasing surplus. Agreeableness significantly lowers wages, increases unemployment spell durations and decreases job spell durations. Overall, it has a negative effect for both men and women.

These findings underscore the importance of both cognitive and noncognitive traits in shaping labor market careers. As expected, education and cognitive ability both enhance labor market outcomes and lead to a higher surplus share. Among the Big Five personality traits, conscientiousness and emotional stability consistently are associated with positive labor market outcomes, such as higher wages, shorter unemployment duration, and stable employment. In contrast, agreeableness tends to have a significant negative influence, marked by lower wages and reduced job finding rates for both men and women.

The last two rows of the table report the impact of changes in work experience on labor market outcomes. Increasing work experience by one standard deviation (approximately 11 years) increases wages by 11-12 percent, whereas increasing unemployment experience by one standard deviation (approximately 3 years) lowers wages by 13-14 percent for both men and women.

There are a number of reasons why personality traits might influence labor market outcomes. As seen in Table 6, 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

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	23.6%	14.2%	0.7%	1.3%	3.2%	3.7%
	F	26.8%	16.9%	0.6%	2.8%	5.2%	2.3%
Cognitive ability (+1SD)	M	4.6%	4.2%	-0.2%	0.2%	0.8%	-0.4%
	F	5.4%	4.4%	-0.3%	0.9%	1.6%	-0.7%
Openness (+1 SD)	M	-0.1%	-0.2%	-0.8%	0.3%	0.8%	-0.2%
	F	-0.3%	0.7%	-0.9%	0.5%	0.7%	-1.0%
Conscientiousness (+1 SD)	M	2.5%	1.3%	0.4%	0.4%	-0.2%	0.6%
	F	1.2%	-0.3%	0.7%	0.3%	0.0%	0.5%
Extroversion (+1 SD)	M	0.3%	-0.2%	0.3%	0.0%	0.3%	-0.1%
	F	1.4%	1.8%	-0.3%	0.2%	0.1%	-0.2%
Agreeableness (+1 SD)	M	-3.3%	-3.0%	-0.2%	0.0%	0.1%	-0.2%
	F	-3.3%	-1.6%	-1.4%	-0.1%	0.1%	-0.2%
Emotional stability (+1 SD)	M	4.9%	4.0%	0.4%	0.1%	0.0%	0.4%
	F	3.5%	1.7%	1.4%	0.4%	0.3%	-0.2%

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

Anger (2010); Risse et al. (2018)), the mechanisms through which they operate have not been explored.[45]

Table 8 shows the contribution of each personality 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 impact of openness to experience on wages is nearly negligible. Similarly, the effect of extroversion on wages is close to zero for men, yet it shows a modest positive effect for women. This positive impact on women primarily occurs through the initial human capital channel. In summary, three of the Big Five traits - conscientiousness, emotional stability, and agreeableness - are the most important determinants of labor market outcomes.

[45]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.

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 regression model settings to analyze the sources of gender or racial wage gaps. In this section, we adapt the method to our nonlinear model. To generate Table 9, we simulate outcomes (under the fully heterogeneous specification) in two ways. First, we perform a simulation in which we keep the parameter values as estimated but adjust the female trait levels upward or downward by adding a constant term (for each trait) to make the mean trait levels equal to those of males.[46] Second, we perform a simulation in which we keep female traits at the mean values in the data but assign females the estimated male parameter values. We denote the result of the first simulation by $w_f(\Omega_f, \bar{z}_m)$ and that of the second simulation by $w_f(\Omega_m, \bar{z}_f)$. This decomposition shows the extent to which the wage gap occurs due to women having different mean characteristics levels or due to differences in the valuations of these characteristics. Both factors are likely to be important, so that we examine their relative importance. The decomposition is performed separately for cognitive and noncognitive traits. In Table 9, for the case in which female characteristics are adjusted to have the same means as those of males, we label the result $\bar{z}_f = \bar{z}_m$, which corresponds to

$$\frac{w_f(\Omega_f, \bar{z}_m) - w_f(\Omega_f, \bar{z}_f)}{w_m(\Omega_m, \bar{z}_m) - w_f(\Omega_f, \bar{z}_f)}.$$

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

$$\frac{w_f(\Omega_m, \bar{z}_f) - w_f(\Omega_f, \bar{z}_f)}{w_m(\Omega_m, \bar{z}_m) - w_f(\Omega_f, \bar{z}_f)}.$$

The numbers in Table 9 are expressed as percentages.

As seen in Table 9, mean differences in the levels of education and cognitive ability do not account for the gender wage gap. When we simulate labor market outcomes using female-specific parameters, but replace women's years of education with men's, the results show a 9.3 percent increase in the average wage gap, indicating a widening pay gap. This occurs because women, on average, have more years of education than men. However, giving women the male-estimated education parameters narrows the wage gap by 3.9 percent. As seen in the Table, the effect occurs mainly because of a gender disparity in the unemployment job offer arrival rate parameter. Gender differences in cognitive ability, either in levels or in terms of estimated parameter values, have little effect on the gender wage gap.

Rows 5 and 6 of Table 9 show 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 19.2 percent. Comparing the magnitudes in the last five columns,

[46] That is, we add the constant $\bar{z}_m - \bar{z}_f$ to each value of the vector z_f.

the bargaining power model channel accounts for the majority of the decrease in the wage gap (15.2 percent). That is, females have personality traits that on average lead to lower bargaining power. Gender differences in the estimated personality trait parameters, specifically those associated with the bargaining parameter, also account for a notable part of the observed wage gap (10.1 percent).

Examining each of the personality traits separately, we see that two traits play a large role in generating the gender wage gap: agreeableness and emotional stability. As was seen in Table 1, the average values of these traits differ substantially for men and women. In Table 8 we see that agreeableness is negatively remunerated whereas emotional stability is positively remunerated. The fact that women on average have higher levels of agreeableness and lower levels of emotional stability results in a significant labor market disadvantage. The portion of the gender wage gap accounted for by differences in agreeableness and emotional stability is 10.7 percent and 12.0 percent, respectively. 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 reduce 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 do gender differences in the "return" to personality traits. Parameter value differences also contribute, but their effects are much smaller in magnitude.

The gender disparities in our estimated model coefficients imply that women would receive different wage offers, receive offers at different rates and receive a different bargaining share surplus than men, even if their mean trait levels were equalized ($\bar{z}_m = \bar{z}_f$). Two key findings are that women are rewarded less for their education and that they receive a harsher penalty than men for being agreeable, which primarily comes through the bargaining channel. Agreeable women face a double penalty in the labor market in that the agreeableness trait reduces bargaining power and the penalty for having this trait is greater for women than for men.

The last four rows of the table examine the relevance of work experience, unemployment experience and age in accounting for gender wage gaps.[47] The portion of the wage gap accounted for by work experience and unemployment experience is large, 19.8 percent and 3.8 percent, respectively. 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 in our sample face a smaller age penalty compared to men in the same birth cohort. If older women were assigned the same cohort coefficients as their male counterparts, the wage gap would increase by 11.1 percent.

To explore the connection between our model's estimates and the descriptive evidence presented in Section 4, in Table 10 we compare the model-based decomposition results with results from a standard Oaxaca-Blinder decomposition based on a log wage regression. Our model's estimation

[47]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	$\bar{z}_f = \bar{z}_m$	-9.3%	-5.1%	-0.6%	-4.9%	2.2%	-0.8%
	$\Omega_f = \Omega_m$	3.9%	-0.4%	-0.7%	5.2%	-1.2%	0.7%
Cognitive ability	$\bar{z}_f = \bar{z}_m$	0.5%	0.7%	-0.2%	0.7%	-0.6%	-0.1%
	$\Omega_f = \Omega_m$	-0.004%	0.02%	0.1%	0.4%	0.8%	-0.1%
Big Five personality traits	$\bar{z}_f = \bar{z}_m$	19.2%	2.9%	15.2%	0.6%	0.2%	0.6%
	$\Omega_f = \Omega_m$	6.1%	-3.8%	10.1%	1.6%	1.8%	0.2%
Openness to experience	$\bar{z}_f = \bar{z}_m$	2.5%	-0.6%	3.0%	-2.0%	1.1%	0.9%
	$\Omega_f = \Omega_m$	1.1%	-0.3%	1.1%	0.6%	-1.3%	0.3%
Conscientiousness	$\bar{z}_f = \bar{z}_m$	-3.6%	0.2%	-1.9%	-1.3%	0.0%	-0.5%
	$\Omega_f = \Omega_m$	2.2%	0.7%	0.0%	-0.1%	-0.7%	0.2%
Extroversion	$\bar{z}_f = \bar{z}_m$	-1.0%	-2.1%	1.6%	-1.0%	0.2%	0.3%
	$\Omega_f = \Omega_m$	-0.1%	-1.1%	1.6%	-0.9%	-0.6%	0.1%
Agreeableness	$\bar{z}_f = \bar{z}_m$	10.7%	2.2%	7.3%	1.0%	0.2%	0.3%
	$\Omega_f = \Omega_m$	4.2%	-1.0%	5.0%	0.8%	-0.001%	-0.009%
Emotional stability	$\bar{z}_f = \bar{z}_m$	12.0%	3.2%	7.1%	3.7%	-1.4%	-0.5%
	$\Omega_f = \Omega_m$	1.1%	-2.1%	3.7%	1.3%	0.5%	-0.5%
Work experience	$\bar{z}_f = \bar{z}_m$	19.8%	19.8%	-	-	-	-
	$\Omega_f = \Omega_m$	1.4%	1.4%	-	-	-	-
Unemployment experience	$\bar{z}_f = \bar{z}_m$	3.8%	3.8%	-	-	-	-
	$\Omega_f = \Omega_m$	-4.9%	-4.9%	-	-	-	-
Cohort 1	$\bar{z}_f = \bar{z}_m$	1.2%	0.6%	0.1%	0.4%	-0.03%	0.2%
	$\Omega_f = \Omega_m$	-0.9%	-3.0%	-1.3%	9.2%	2.1%	-5.4%
Cohort 3	$\bar{z}_f = \bar{z}_m$	0.04%	0.02%	0.01%	0.03%	-0.01%	-0.003%
	$\Omega_f = \Omega_m$	-11.1%	-5.9%	3.7%	-11.9%	2.6%	0.9%

†Rows labeled $\bar{z}_m = \bar{z}_f$ capture the proportion of the observed male-female wage gap accounted for by differences in the covariate values. The numbers in these rows are calculated by $\frac{w_f(\Omega_f,\bar{z}_m)-w_f(\Omega_f,\bar{z}_f)}{w_m(\Omega_m,\bar{z}_m)-w_f(\Omega_f,\bar{z}_f)}$. Rows labeled $\Omega_f = \Omega_m$ capture the proportion of the wage gap accounted for by differences in the male and female parameter estimates. The numbers in these rows are calculated by $\frac{w_f(\Omega_m,\bar{z}_f)-w_f(\Omega_f,\bar{z}_f)}{w_m(\Omega_m,\bar{z}_m)-w_f(\Omega_f,\bar{z}_f)}$.

uses data on unemployment and employment spells in addition to wage data, whereas the wage regression is based only on wage data for employed persons. Although the results are qualitatively similar, the model-based decomposition assigns a larger role to personality traits. For instance, our model suggests that gender differences in agreeableness and emotional stability account for 8.8 percent and 11.6 percent of the wage gap, while the log wage regression-based decomposition indicates that these traits account for only 2.8 percent and 5.8 percent of the gap. The quantitative discrepancy most likely arises because our model captures the non-linear effects of these characteristics on log wages. Recall the model-based log wage equation (10),

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

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, $\ln \chi \left(\theta, \theta', z_i, \tau_i; \gamma_{-a}^{\tau_i}\right)$, are non-linear and appear in the term $\ln \chi$. Ignoring the term $\ln \chi$ in the Mincer regression means that it is included in the disturbance term, implying that the assumption of mean independence is violated.

Because of this, the OLS estimates of γ_a^g will be biased and inconsistent.[48]

The effects of work experience and unemployment experience on the wage gap are 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 large proportion of the gender wage gap is not accounted for under either approach. 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 accounting for 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.

7 Conclusions

This paper extends a canonical partial equilibrium 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 disparities in labor market outcomes. 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 the greatest degree of individual heterogeneity, and indicate that personality characteristics play an important role in accounting for variation in labor market outcomes over the life cycle. The model estimates indicate 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, including higher wages and shorter durations of unemployment. One trait, agreeableness, systematically worsens labor market outcomes for both genders.

We develop a Oaxaca-Blinder type decomposition, adapted to our nonlinear model setting, in order to assess the relative contributions of individual traits and model channels in accounting for the gender wage gap. We find that differences in work experience and in personality traits are primary factors. Interestingly, education levels and estimated returns to education cannot account for the gap. When we simulate the model in the steady state, we find that equalizing average work experience by gender reduces the wage gap by 19.8 percent. Personality traits also play a crucial role, particularly as they operate through the bargaining channel of the model. Our model estimates indicate 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. The wage gap would decrease by 19.2 percent if women had the same average personality trait levels as men.

[48] The conditional expectation of the disturbance term in the Mincer regression under our model specification is $E(\ln \chi\left(\theta, \theta', z_i, \tau_i; \gamma_{-a}^{\tau_i}\right)|z_i) + E(\xi_i|z_i) \neq 0$ since $E(\ln \chi\left(\theta, \theta', z_i, \tau_i; \gamma_{-a}^{\tau_i}\right)|z_i) \neq 0$.

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

	Model-based	Regression-based	
	(1)	(2)	(3)
Differences in endowments: $\bar{z}_f = \bar{z}_m$			
Education	-9.3%	-9.2%	-9.2%
Cognitive ability	0.5%	1.3%	1.3%
Openness to experience	2.5%	0.9%	0.7%
Conscientiousness	-3.6%	0.1%	0.4%
Extroversion	-1.0%	-1.1%	-0.9%
Agreeableness	10.7%	2.8%	2.8%
Emotional stability	12.0%	5.8%	6.1%
Cohort1	1.2%	-0.8%	-0.6%
Cohort3	0.04%	1.5%	1.0%
Working experience	19.8%	25.2%	26.7%
Unemployment experience	3.8%	1.4%	1.3%
Marriage			1.5%
Children			3.2%
Differences in coefficients: $\Omega_f = \Omega_m$			
Education	3.9%	-1.2%	-1.1%
Cognitive ability	-0.004%	0.0%	0.1%
Openness to experience	1.1%	-0.1%	-0.1%
Conscientiousness	2.2%	0.0%	-0.1%
Extroversion	-0.1%	0.0%	0.0%
Agreeableness	4.2%	0.1%	0.1%
Emotional stability	1.1%	0.3%	0.3%
Cohort1	-0.9%	-0.9%	1.0%
Cohort3	-11.1%	-13.7%	-11.7%
Working experience	1.4%	3.9%	-5.9%
Unemployment experience	-4.9%	-2.2%	-2.2%
Marriage			23.5%
Children			-1.0%
Intercept	92.6%	85.9%	62.9%

†Our regression-based results are derived from the two-fold division method, which is articulated as: $\bar{w}_m - \bar{w}_f = (\bar{z}_m - \bar{z}_f)'\Omega^* + [\bar{z}'_m(\hat{\Omega}_m - \Omega^*) + \bar{z}'_f(\Omega^* - \hat{\Omega}_f)]$. Here, Ω^* represents the coefficients derived from the pooled sample, as described in Neumark (1988).

We also find gender differences in how traits are valued. Since we do not attempt to model the mechanisms that could produce these coefficient differences between the genders, we cannot claim that this represents labor market discrimination as opposed to reflecting the different occupational or educational choices made by men and women. We find that these differences in the valuation of characteristics by gender accounts for 6.1 percent of the wage gap and mainly operate through the bargaining channel. Particularly notable is the fact that women receive a higher penalty than men for being agreeable.

Our results suggest that policies that focus on equalizing bargaining power by gender, such as negotiation training, or policies that reduce the bargaining element in wage determination, may be effective in reducing gender wage disparities. Flinn and Mullins (2021), using data described in Hall and Krueger (2012), find that women are less likely than men to bargain during the wage-setting process at the beginning of a job. The authors estimate a general equilibrium search model that, consistent with empirical observation, allows some jobs to have negotiable wages set via bargaining and other jobs to specify a non-negotiable wage, considered to be wage posting. Through model simulations, the authors find that eliminating the possibility of bargaining reduces the gender wage gap by 6 percent, although this comes at the cost of an overall reduction in workers' welfare. Many states and localities have recently enacted laws that prohibit former employers from sharing an individual's wage history with prospective employers, which could severely limit workers' ability to bargain with firms when setting wages. The results of this paper and of Flinn and Mullins (2021) suggest that a better policy choice may be to improve the negotiating skills of highly agreeable workers, who are more likely to be women, so as to level the playing field.

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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 $w(\theta,\theta',z,\tau,a)$ and the reservation match productivity $\theta^*(z,\tau,a)$. For notational simplicity, we suppress the notation that shows the dependence of the parameters on the vector of individual characteristics $\{z,\tau\}$ in this section. We start with the equation that specifies the value function for an employed individual:

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

Under the Nash bargaining protocol described in section two, we obtain

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

Substituting this expression into the previous equation yields

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

From Proposition 1 in Burdett et al. (2016), we know that the Bellman equation can be written as follows:

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

Therefore,

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

Thus, we can write the above Bellmen equation as

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

Now, consider the case $\theta'=\theta$ and $w=a\theta$ and take the derivative of the above equation to get:

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

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

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

Using the condition $V_E(\theta, \theta', a) = \alpha V_E(\theta, \theta, a) + (1-\alpha) V_E(\theta', \theta', a), \theta > \theta'$, the bargained wage has the following expression:

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

The third term inside the square brackets captures how much the worker is willing to sacrifice lower wages today for the promise of future wage appreciation.

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

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

Again invoking Proposition 1 of Burdett et al. (2016), we have that $a\delta \frac{\partial V_U(a)}{\partial a} = \delta a \frac{\partial (a V_U(a=1))}{\partial a} = \delta V_U(a)$. Substituting into the value function expression gives

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

Recall the definition of $V_E(\theta^*, \theta^*, a)$

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

The reservation match quality makes a person just indifferent between working and not working. It is obtained be setting $V_E(\theta^*, \theta^*, a) = V_U(a)$ and solving a fixed point problem for θ^*:

$$\theta^*(a) = \frac{\rho - \psi}{\rho + \delta} b + \alpha \left(\frac{\rho - \psi}{\rho + \delta} \lambda_U - \lambda_E \right) \int_{\theta^*} \frac{\bar{G}(x)}{\rho + \eta - \psi + \lambda_E \alpha \bar{G}(x)} dx \tag{17}$$

As seen in (17), there is no direct dependence of $\theta^*(.)$ on a.

A.1.2 How to derive the steady state distribution

We next derive the steady state conditional distribution of the best dominated offer given the current job offer, which is used in constructing the likelihood (equation 15).[49] The derivation is similar to the calculation of the equilibrium wage distribution shown in Appendix C in Cahuc et al. (2006). In the steady-state, the equilibrium unemployment rate is

$$u = \frac{\eta}{\eta + \lambda_U \bar{G}(\theta^*)} \Rightarrow (1-u)\eta = u \lambda_U \bar{G}(\theta^*). \tag{18}$$

[49] Specifically, this distribution is used in simulating the initial match productivities for individuals who are employed in the initial sample period.

Let $s(\theta'|\theta)$ denote the steady state pdf of θ' conditional on θ, and $S(\theta'|\theta)$ the corresponding cdf:

$$S(\theta'|\theta) = \int_{\theta^*}^{\theta'} s(x|\theta)dx.$$

Let $l(\theta)$ denote the steady state unconditional pdf of θ and $L(\theta)$ the cdf. Consider a group of workers whose match productivity at their current firm is θ and whose best dominated match productivity is less than or equal to θ'. In steady-state, the size of this group needs to be to be time-invariant. On the inflow side, workers enter this group either by being hired out of unemployment or being hired from another firm with match productivity less than or equal to θ'. On the outflow side, workers can leave this group either by becoming unemployed (at rate η) or by receiving an offer from some firm with match productivity greater than θ'. In steady state, inflows are equated with outflows:

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

Plugging $(1-u)\eta = u\lambda_U \bar{G}(\theta^*)$ (equation 18) into equation 19 gives

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

To derive an expression for $l(\theta)$, we can set $\theta' = \theta$ and use the fact that $S(\theta' = \theta|\theta) = 1$ (i.e. $\Pr(\theta' \leq \theta|\theta) = 1$ because θ' is by definition the best dominated offer), which gives:

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

Solving for $l(\theta)$ we get

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

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

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

(22) $$L(\theta) = \int_{\theta^*}^{\theta} l(x)dx = \frac{G(\theta)}{1+\kappa_1 \bar{G}(\theta)}, \kappa_1 = \frac{\lambda_E}{\eta}$$

Plugging equation 21 into equation 20 and solving for $S(\theta'|\theta)$ yields

(23) $$S(\theta'|\theta) = \left(\frac{1+\kappa_1 \bar{G}(\theta)}{1+\kappa_1 \bar{G}(\theta')}\right)^2, \theta^* \leq \theta' < \theta, \kappa_1 = \frac{\lambda_E}{\eta}.$$

A.2 The likelihood function

Our model is estimated using maximum likelihood. In this section, we describe in detail how we construct the likelihood function of an employment cycle. For notational simplicity, we suppress the dependence of all of the search-environment parameters on type z_i, but the reader should bear in mind that the underlying econometric model allows the parameters to vary across individuals due to their characteristics. 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 data elements relevant to constructing the employment cycle are

$$\text{Employment cycle} = \underbrace{\{T_U, r_U\}}_{\text{Unemployment spell}}, \underbrace{\left\{\{T_k, q_k, r_k\}, \{\tilde{w}_k^{t_{kj}}\}_{j=1}^{n_k}\right\}_{k=1}^{K}}_{\text{Consecutive K jobs}}$$

If the individual begins the sample employed, then the relevant data elements are

$$\text{Employment cycle} = \underbrace{\left\{\{T_k, q_k, r_k\}, \{\tilde{w}_k^{t_{kj}}\}_{j=1}^{n_k}\right\}_{k=1}^{K}}_{\text{Consecutive K jobs}}.$$

In the above equations, t_U represents the unemployment spell duration and r_U is an indicator variable denoting whether the unemployment spell is right-censored. If we observe subsequent employment spell(s) (up to two), then T_k denotes the duration of job k. Within each job spell, wages are sequentially reported n_k times, at the corresponding periods $\{t_{k1}, t_{k2}, ..., t_{kn_k}\}$. We use notation $\tilde{w}_k^{t_{kj}}$ to denote the wage reported at period t_{kj} within the job spell k. The indicator variable r_k denotes whether the kth employment spell duration is right-censored. The indicator variable $q_k = 1$ if the job k is dissolved at the end of the job spell with the individual exiting into unemployment, whereas $q_k = 0$ if the individual transitions from one job immediately to another job with no intervening unemployment spell. There are up to K job spells in total within one employment cycle.

In the subsequent discussion, we initially explain the likelihood function corresponding to a single unemployment spell. Then, we describe the likelihood contribution for a single job spell, including the probability of observing a series of wages throughout the job spell. Lastly, we describe the likelihood contribution for a completed employment cycle, consisting of a combination of unemployment spells and up to two job spells, along with a wage series.

The likelihood contribution of an unemployment spell. Suppose we observe an individual with an unemployment spell of length t_U. The hazard rate is

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

and the density of the unemployment spell duration is

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

The likelihood contribution from this unemployment spell will depend on whether the unemployment spell is censored. If censored, then

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

if the unemployment spell is completed, the likelihood contribution is

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

The likelihood contribution from a job spell k. We next describe the contribution of a job spell k to the likelihood function. Given match productivity θ_{k-1} from the last job spell or match productivity θ^* if the person was hired from unemployment, the distribution of the match offer at the current job spell is drawn from a truncated log normal distribution with the lower boundary equal to θ_{k-1}, that is, $\theta_k \sim \frac{f(\theta)}{\bar{F}(\theta_{k-1})}, \theta_k > \theta_{k-1}$. Given the current job offer θ_k, the worker will only leave the current job spell for one of two reasons: (i) the current job exogenously dissolves with rate η and the worker becomes unemployed. ($q_k = 1$) (ii) the worker moves to an alternate job with a better match productivity $\theta_{k+1} > \theta_k$.($q_m = 0$) Therefore, the 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 likelihood contribution from the sequential wage observations across job spell k, conditional on the match productivity from the last job θ_{k-1} (it is also the best dominated offer at the beginning of the current job spell) and current job offer θ_k, is denoted by $f_{w_k}(\tilde{w}_k^{t_{k1}}, ..., \tilde{w}_k^{t_{kn_k}}, T_k|\theta_k, \theta_{k-1})$. Unlike the hazard rate, which solely depends on the current job match productivity θ_k (which remains constant throughout job spell k), the observed wage also depends on the best dominated offer sequences $\{\theta_k^{'}(t)\}_{t=1}^{T_k}$, which can evolve during the job spell due to receiving external offers. The joint probability of a series of wage observations across job spell k can be expressed as:

$$f_{w_k}(\tilde{w}_k^{t_{k1}}, ..., \tilde{w}_k^{t_{kn_k}}, T_k|\theta_k, \theta_{k-1}) = \int_{\theta_{k-1}} \int_{\theta_{k-1}} ... \int_{\theta_{k-1}} \Pi_{j=1}^{n_k} m\left(\frac{\tilde{w}_k^{t_{kj}}}{w(\theta_k, \theta_k^{'}(t_{kj}))}\right) dF_{(t_{kn_k})}(\theta_k^{'})...dF_{(t_{k2})}(\theta_k^{'})dF_{(t_{k1})}(\theta_k^{'})$$

Here, $w(\theta_k, \theta_k^{'}(t_{ki}))$ represents the "true" wage (as defined in equation 6), which depends on the current job offer θ_k and the best dominated offer $\theta_k^{'}(t_{ki})$ as of the surveyed period t_{kj}. The term $\Pi_{j=1}^{n_k} m\left(\frac{\tilde{w}_k^{t_{kj}}}{w(\theta_k, \theta_k^{'}(t_{kj}))}\right)$ captures the product of observing a wage sequence $\{\tilde{w}_k^{t_{kj}}\}_{j=1}^{n_k}$ given the "true" wage sequence is $\{w(\theta_k, \theta_k^{'}(t_{kj}))\}_{j=1}^{n_k}$ at surveyed periods $\{t_{k1}, t_{k2}, ..., t_{kn_k}\}$, where function $m(.)$ is the density function of wage measurement error as outlined in equation 11. Lastly, $\{F_{(t_{kj})}(\theta_k^{'})\}_{j=1}^{n_j}$ signifies a series of cumulative density functions for the best dominated offer at period t_{kj}, with its exact functional form being quite intricate due to its largest order statistic feature. The best dominated offer at period t_{kj} is the best outside offer ever arrived up to period t_{kj}. However, the precise number of external offers is ambiguous as they arrive stochastically. A Monte Carlo simulation method is therefore employed to compute the empirical value of $f_{w_k}(\tilde{w}_k^{t_{k1}}, ..., \tilde{w}_k^{t_{kn_k}}, T_k|\theta_k, \theta_{k-1})$, with further details provided in Appendix A.3.

The likelihood contribution from a job spell depends on how the job spell terminates and there are three possible scenarios. First, the first job can be right censored at period T_k ($r_k = 1$). The likelihood corresponding to this scenario is $\exp(-h_E(\theta_k)T_k)$, where $h_E(\theta_k) = \eta + \lambda_E \bar{G}(\theta_k)$. Second, the individual may transit to another job due to a more favorable outside offer ($r_k = 0, q_k = 0$). The probability associated with this case is $\lambda_E \bar{G}(\theta_k)\exp(-h_E(\theta_k)T_k)$. Third, the current job may be terminated due to an exogenous shock($r_k = 0, q_k = 1$). The likelihood contribution under this scenario is $\eta \exp(-h_E(\theta_k)T_k)$.

Thus, the individual likelihood, conditional on the match quality θ_{k-1} from the previous job, is formulated as:

$$l_E(T_k, r_k, q_k, \{\tilde{w}_k^{t_{kj}}\}_{j=1}^{n_k}|\theta_{k-1}) = \int_{\theta_{k-1}} \exp\left(-h_E(\theta_k)T_k\right)$$
$$\left[\left(\lambda_E \bar{G}(\theta_k)\right)^{1-q_k} \eta^{q_k}\right]^{1-r_k} f_{w_k}(\tilde{w}_k^{t_{k1}}, ..., \tilde{w}_k^{t_{kn_k}}, T_k|\theta_k, \theta_{k-1})d\theta_k$$

Note that our likelihood function needs to integrate out θ_k as we do not observe the true match quality θ_k at the current job.

The complete likelihood function over one employment cycle. We now describe the likelihood contribution of a complete employment cycle. We incorporate at most two job spells ($K \leq 2$) in each employment cycle to reduce the computational burden. For the case where the employment cycle begins with an unemployment spell, we have

$$l(t_U, r_U, \{\tilde{w}_1^{t_{1k}}\}_{k=1}^{n_1}, T_1, r_1, q_1, \{\tilde{w}_2^{t_{2k}}\}_{k=1}^{n_2}, T_2, r_2, q_2) = \int_{\theta^*} \int_{\theta_1} h_U^{(1-r_U)} \exp(-h_U t_U)$$
$$\times \left\{\exp\left(-h_E(\theta_1)T_1\right) \left[\left(\lambda_E \bar{G}(\theta_1)\right)^{1-q_1} \eta^{q_1}\right]^{1-r_1} f_{w_1}(\tilde{w}_1^{t_{11}}, \tilde{w}_1^{t_{12}}, \tilde{w}_1^{t_{13}}, ..., \tilde{w}_1^{t_{1n_1}}, T_1|\theta_1; \theta^*)\right\}^{1-r_U}$$
$$\times \left\{\exp\left(-h_E(\theta_2)T_2\right) \left[\left(\lambda_E \bar{G}(\theta_2)\right)^{1-q_2} \eta^{q_2}\right]^{1-r_2} f_{w_2}(\tilde{w}_2^{t_{21}}, \tilde{w}_2^{t_{22}}, \tilde{w}_2^{t_{23}}, ..., \tilde{w}_2^{t_{2n_2}}, T_2|\theta_1, \theta_2)\right\}^{1-r_1} \frac{dG(\theta_2)}{\bar{G}(\theta_1)} \frac{dG(\theta_1)}{\bar{G}(\theta^*)}.$$

For the case where the employment cycle starts with an employment spell, we have

$$l(\{\tilde{w}_1^{t_{1k}}\}_{k=1}^{n_1}, T_1, r_1, q_1, \{\tilde{w}_2^{t_{2k}}\}_{k=1}^{n_2}, T_2, r_2, q_2|\theta_1^{'}, \theta_1) =$$
$$\int_{\theta_1} \exp\left(-h_E(\theta_1)t_1\right) \left[\left(\lambda_E \bar{G}(\theta_1)\right)^{1-q_1} \eta^{q_1}\right]^{1-r_1} f_{w_1}(\tilde{w}_1^{t_{11}}, \tilde{w}_1^{t_{12}}, \tilde{w}_1^{t_{13}}, ..., \tilde{w}_1^{t_{1n_1}}, T_1|\theta_1^{'}, \theta_1)$$
$$\times \left\{\exp(-h_E(\theta_2)t_2) \left[\left(\lambda_E \bar{G}(\theta_2)\right)^{1-q_2} \eta^{q_2}\right]^{1-r_2} f_{w_2}(\tilde{w}_2^{t_{21}}, \tilde{w}_2^{t_{22}}, \tilde{w}_2^{t_{23}}, ..., \tilde{w}_2^{t_{2n_2}}, T_2|\theta_1, \theta_2)\right\}^{1-r_1} \frac{dG(\theta_2)}{\bar{G}(\theta_1)}.$$

Note that we do not observe the true match quality of the first job θ_1 or the best dominated offer $\theta_1^{'}$ at the beginning of the initial employment spell. We therefore assume the initial θ_1 and best dominated job $\theta_1^{'}$ are drawn from the steady-state distributions, which we derive in Appendix A.1.2.

Therefore, the likelihood contribution for an employment cycle beginning with an employment spell is:

$$l(\{\tilde{w}_1^{t_{1k}}\}_{k=1}^{n_1}, T_1, r_1, q_1, \{\tilde{w}_2^{t_{2k}}\}_{k=1}^{n_2}, T_2, r_2, q_2) =$$
$$\int_{\theta^*}\int_{\theta^*}^{\theta_1}\int_{\theta_1} \exp\left(-h_E(\theta_1)t_1\right)\left[\left(\lambda_E\bar{G}(\theta_1)\right)^{1-q_1}\eta^{q_1}\right]^{1-r_1} f_{w_1}(\tilde{w}_1^{t_{11}}, \tilde{w}_1^{t_{12}}, \tilde{w}_1^{t_{13}}, ..., \tilde{w}_1^{t_{1n_1}}, T_1|\theta_1^{'}, \theta_1)$$
$$\left\{\exp(-h_E(\theta_2)t_2)\left[\left(\lambda_E\bar{G}(\theta_2)\right)^{1-q_2}\eta^{q_2}\right]^{1-r_2} f_{w_2}(\tilde{w}_2^{t_{21}}, \tilde{w}_2^{t_{22}}, \tilde{w}_2^{t_{23}}, ..., \tilde{w}_2^{t_{2n_2}}, T_2|\theta_1, \theta_2)\right\}^{1-r_1} \frac{dG(\theta_2)}{\bar{G}(\theta_1)} dS(\theta_1^{'}|\theta_1)dL(\theta_1).$$

$S(\theta_1^{'}|\theta_1)$ denotes the cdf of $\theta_1^{'}$ conditional on θ_1, and $L(\theta_1)$ denotes the unconditional cdf of θ_1 in the steady-state. (See Appendix A.1.2 for their derivations)

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

Lastly, as outlined in section 4.3, we need to further address the left-censoring issue if the employment cycle is the first one over the observation period. This issue emerges because individuals are already engaged in unemployment or employment spells at the start of our observation period. For individuals initially unemployed, the unconditional likelihood function is the joint likelihood of the duration of left-censored unemployment spells and the probability of being sampled in unemployment. Conversely, for those initially employed, the unconditional likelihood function is the joint likelihood of the duration of left-censored employment spells and the probability of being sampled in employment. The exact expression for these calculations is detailed in equation 16.

A.3 Simulating the likelihood function

In this section, we describe how we calculate the likelihood function value specified in equations 14 and 15 and, specifically, where we use Monte Carlo simulation in calculating some likelihood components. In the following discussion, one period refers to one month as the data are observed monthly. The procedure for calculating the likelihood can be described by eight steps:

1. *The likelihood contribution of an unemployment spell.* When the employment cycle starts from unemployment, there is an analytical expression for the likelihood. Therefore, this calculation does not require simulation. There are two possible scenarios under which the unemployment spell terminates at time T_U

   (a) Transition to the first job at period T_U. The associated probability is $h_U \exp(-h_U T_U)$, where $h_U = \lambda_U \bar{G}(\theta^*)$. Following such transition, we advance to Step 2.

   (b) The unemployment spell is right censored at period T_U. The likelihood associated with this scenario is $\exp(-h_U T_U)$. The employment cycle finishes under this case.

In calculating the likelihood associated with any job spells, Monte Carlo simulation methods are required to simulate the current match productivity best dominated match productivity values. As described in the text, for each employment cycle, we construct r=1..R paths, and calculate the individual likelihood contribution by averaging over them. Steps 2 through 7 describe one single sample path r for an employment cycle.

2. *Simulation of for the first job match productivity.* For the first job spell and for each sample path r, we simulate the best dominated match productivity ($\theta_1^{'}(r)$) and dominant match productivity ($\theta_1(r)$).

   (a) When the employment cycle follows unemployment (as shown in equation 14), we assign $\theta_1^{'}(r) = \theta^*$, and the current job offer job offer is generated from a truncated lognormal distribution, truncated at θ^*, which we write as $\theta_1(r) \sim \log G(\theta^*)$

   (b) If the employment cycle was preceeded by another employment spell (as shown in equation 15), then we draw a dominated and current match productivity pair $(\theta_1^{'}(r), \theta_1(r))$ from the steady-state distribution, denoted as $\theta_1(r) \sim L(\theta), \theta_1^{'}(r) \sim S(\theta_1^{'}|\theta_1)$.(See Appendix A.1.2 for the derivations of these distributions)

3. *Simulating density of wages observed within the first job spell.* In this step, we simulate the probability of n_1 joint wage observations $\{\tilde{w}_1^{t_{11}}, \tilde{w}_1^{t_{12}}, \tilde{w}_1^{t_{13}}, ..., \tilde{w}_1^{t_{1n_1}}\}$ measured over time periods $\{t_{11}, t_{12}, t_{13}, ..., t_{1n_1}\}$ within the first job spell, provided that the first spell endures for T_1 periods.

   (a) To calculate the likelihood contribution for the joint wage observations, we simulate I trajectories for the best dominated offer up to period T_1. Here, $\theta_1^{'}(t, r, i)$ denotes the best dominated offer at period t of the $i - th$ simulated trajectory.

   (b) The initial value of the best dominated offer is derived from Step 1, $\theta_1^{'}(1, r, i) = \theta_1^{'}(r)$.

   (c) At each period t, we draw a potential outside offer $\tilde{\theta}_1^t$ from a truncated lognormal distribution with upper truncation value equal to $\theta_1(r)$, represented by $\tilde{\theta}_1^t \sim \log \bar{G}(\theta_1(r))$, occurring at a probability $1 - \exp(-\lambda_E \bar{G}(\theta_1(r)))$. (Note $\exp(-\lambda_E \bar{G}(\theta_1(r)))$ is the probability no offer arrives within one period)

   (d) The current best dominated offer is updated to the drawn outside offer if it holds a higher value than the preceding best dominated offer, that is, $\theta_1^{'}(t, r, i) = \tilde{\theta}_1^t$ if $\tilde{\theta}_1^t > \theta_1^{'}(t-1, r, i)$. Otherwise, the best dominated offer remains unchanged, i.e. $\theta_1^{'}(t, r, i) = \theta_1^{'}(t-1, r, i)$, either due to the outside offer being inferior or due to no outside offer being drawn at the current period.

   (e) We iterate on steps (c) and (d) to simulate the optimal dominated offer trajectory from period 1 to T_1, denoted by $\{\theta_1^{'}(t, r, j)\}_{t=1}^{T_1}$. Following this, wages at specified observation periods $\{t_{11}, t_{12}, t_{13}, \ldots, t_{1n_1}\}$ are computed based on the wage determination equation (defined in equation 6), where

$$w_1^t(r,i) = w(\theta_1(r), \theta_1^{'}(t,r,i), z, a)$$

and where $w_1^t(r,i)$ denotes the simulated "true" wage observed at period t in the $i-th$ simulated trajectory, given the current job offer is valued at $\theta_1(r)$. The likelihood contribution for the vector of n_1 wage observations $\{\tilde{w}_1^{t_{11}}, \tilde{w}_1^{t_{12}}, \tilde{w}_1^{t_{13}}, ..., \tilde{w}_1^{t_{1n_1}}\}$, conditional on this trajectory, is a product

$$\Pi_{k=1}^{n_1} m\left(\tilde{w}_1^{t_{1k}}/w_1^{t_{1k}}(r,i)\right),$$

where $m(.)$ denotes the density function for the measurement error, defined in equation 11.

(f) The unconditional likelihood contribution of the wage series is obtained by averaging over the simulated trajectories:

$$f_{w_1}^{(r)}(\tilde{w}_1^{t_{11}}, \tilde{w}_1^{t_{12}}, \tilde{w}_1^{t_{13}}, ..., \tilde{w}_1^{t_{1n_1}}, T_1|\theta_1^{'}(r), \theta_1(r)) = I^{-1}\sum_{i=1}^{I} \Pi_{k=1}^{n_1} m\left(\tilde{w}_1^{t_{1k}}/w_1^{t_{1k}}(r,i)\right) \tag{24}$$

4. *First job spell termination at duration T_1.* There are three possible ways in which the first job spell can terminate.

   (a) Job transition: the individual may transition to another firm in response to a more favorable outside offer. The probability of an individual, with a current offer $\theta_1(r)$, finding a better outside offer at duration T_1 of the first job spell is

   $$\lambda_E \bar{G}(\theta_1(r)) \exp(-h_E(\theta_1(r))T_1), \text{ where } h_E(\theta_1(r)) = \eta + \lambda_E \bar{G}(\theta_1(r)).$$

   Upon such transition, the procedure for forming the likelihood advances to Step 5.

   (b) Forced termination: there can be an exogenous termination of the job at duration T_1 with likelihood

   $$\eta \exp(-h_E(\theta_1(r))T_1), h_E(\theta_1(r)) = \eta + \lambda_E \bar{G}(\theta_1(r))$$

   (c) Right censoring at T_1: the first job can be right censored at period T_1 with likelihood

   $$\exp(-h_E(\theta_1(r))T_1).$$

5. *Second job initial offer.* When a second job spell exists, we simulate a match value for the second job, denoted as $\theta_2(r)$, which is drawn from a truncated lognormal distribution with a lower truncation value $\theta_1(r)$ ($\theta_2(r) \sim \log G(\theta_1(r))$). At the beginning of second job, the

best dominated offer is updated to $\theta_2^{'}(r) = \theta_1(r)$, whereas the current job offer has match productivity $\theta_2(r)$.

6. *Simulating density of wages observed within the second job spell.* In this step, akin to Step 3, we simulate the likelihood for a vector of n_2 wage observations $\{\tilde{w}_2^{t_{21}}, \tilde{w}_2^{t_{22}}, \tilde{w}_2^{t_{23}}, ..., \tilde{w}_2^{t_{2n_2}}\}$ observed in time periods $\{t_{21}, t_{22}, t_{23}, ..., t_{1n_1}\}$ within the second job spell, which lasts for T_2 periods total.

   (a) To calculate the likelihood, we first simulate J trajectories for the best dominated match values up to period T_2. Let $\theta_2^{'}(t, r, j)$ denote the best dominated offer at period t of the $j - th$ simulated trajectory during the second job spell.

   (b) The initial value of the best dominated offer is derived from Step 4: $\theta_2^{'}(1, r, j) = \theta_2^{'}(r) = \theta_1(r)$.

   (c) In each period t, with probability $1 - \exp(-\lambda_E \bar{G}(\theta_2(r)))$, we draw a potential outside match productivity value $\tilde{\theta}_2^t$ from a truncated lognormal distribution with upper truncation value equal to $\theta_2(r)$ ($\tilde{\theta}_2^t \sim \log \bar{G}(\theta_2(r))$.) Note that $\exp(-\lambda_E \bar{G}(\theta_2(r)))$ is the probability no outside offer arrives within the period.

   (d) The current best dominated match value is updated to the drawn outside offer if it exceeds the preceding best dominated offer, that is, if $\theta_2^{'}(t, r, j) = \tilde{\theta}_2^t$ if $\tilde{\theta}_2^t > \theta_2^{'}(t-1, r, j)$. Otherwise, the best dominated offer remains unchanged, i.e. $\theta_2^{'}(t, r, j) = \theta_2^{'}(t-1, r, j)$, either due to the outside offer being inferior or no outside offer being drawn.

   (e) Steps (c) and (d) are repeated to simulate the dominated match value trajectory from period 1 to T_2, denoted by $\{\theta_2^{'}(t, r, j)\}_{t=1}^{T_2}$. Following this, the wages at specified observation periods $\{t_{21}, t_{22}, t_{23}, \ldots, t_{2n_2}\}$ are calculated based on the wage determination equation (defined in equation 6), where

$$w_2^t(r, j) = w(\theta_2(r), \theta_2^{'}(t, r, j), z, a)$$

   $w_2^t(r, j)$ represents the simulated "true" wage observed at period t in the $j - th$ simulated trajectory, given the current job offer valued at $\theta_2(r)$. The likelihood contribution for the vector of wages based on this trajectory is a product of n_2 observations, formulated as

$$\prod_{k=1}^{n_2} m\left(\tilde{w}_2^{t_{2k}} / w_2^{t_{2k}}(r, j)\right)$$

   where $m(.)$ denotes the density function for measurement error (as defined in equation 11).

   (f) The unconditional likelihood contribution for the joint wage observations is computed by averaging across trajectories as follows:

$$(25)\quad f_{w_2}^{(r)}(\tilde{w}_2^{t_{21}}, \tilde{w}_2^{t_{22}}, \tilde{w}_2^{t_{23}}, ..., \tilde{w}_2^{t_{2n_2}}, T_2|\theta_2^{'}(r), \theta_2(r)) = J^{-1}\sum_{j=1}^{J}\Pi_{k=1}^{n_2} m\left(\tilde{w}_2^{t_{2k}}/w_2^{t_{2k}}(r,j)\right)$$

7. *Second job spell termination simulation.* There are three possible scenarios under which the second job spell can terminate after T_2 time periods.

   (a) Transition to a new firm in response to a more favorable offer: The probability of an individual, with a current offer $\theta_2(r)$, finding a better outside offer at duration T_2 in the second job spell is

   $$\lambda_E\bar{G}(\theta_2(r))\exp(-h_E(\theta_2(r))T_2),\ \text{where } h_E(\theta_2(r)) = \eta + \lambda_E\bar{G}(\theta_2(r)).$$

   (b) Forced termination: the second job may exogenously terminate at duration T_2 with the likelihood:

   $$\eta\exp(-h_E(\theta_2(r))T_2), h_E(\theta_2(r)) = \eta + \lambda_E\bar{G}(\theta_2(r)).$$

   (c) Right censoring at T_2: the second job can be right censored after T_2 periods with likelihood:

   $$\exp(-h_E(\theta_2(r))T_2)$$

8. *Likelihood calculation for the entire employment cycle.* By following steps (2) - (7), we calculate the likelihood contribution for an employment cycle starting from unemployment for a simulated path with match value of $\theta_1(r)$ at the first job and $\theta_2(r)$ at the second job

$$l^{(r)}(t_U, r_U, \{\tilde{w}_1^{t_{1k}}\}_{k=1}^{n_1}, T_1, r_1, q_1, \{\tilde{w}_2^{t_{2k}}\}_{k=1}^{n_2}, T_2, r_2, q_2|\theta_1(r), \theta_2(r)) = h_U^{(1-r_U)}\exp(-h_U t_U)$$
$$\times\left\{\exp\left(-h_E(\theta_1(r))T_1\right)\left[\left(\lambda_E\bar{G}(\theta_1(r))\right)^{1-q_1}\eta^{q_1}\right]^{1-r_1} f_{w_1}^{(r)}(\tilde{w}_1^{t_{11}}, \tilde{w}_1^{t_{12}}, \tilde{w}_1^{t_{13}}, ..., \tilde{w}_1^{t_{1n_1}}, T_1|\theta^*, \theta_1(r))\right\}^{1-r_U}$$
$$\times\left\{\exp\left(-h_E(\theta_2(r))T_2\right)\left[\left(\lambda_E\bar{G}(\theta_2(r))\right)^{1-q_2}\eta^{q_2}\right]^{1-r_2} f_{w_2}^{(r)}(\tilde{w}_2^{t_{21}}, \tilde{w}_2^{t_{22}}, \tilde{w}_2^{t_{23}}, ..., \tilde{w}_2^{t_{2n_2}}, T_2|\theta_1(r), \theta_2(r))\right\}^{1-r_1}$$

   The simulation method used to obtain $f_{w_1}^{(r)}(.)$ and $f_{w_2}^{(r)}(.)$ was described in steps 3 and 6, respectively.

   The empirical likelihood function for the entire employment cycle is then calculated by averaging over the R simulated paths

$$l(t_U, r_U, \{\tilde{w}_1^{t_{1k}}\}_{k=1}^{n_1}, T_1, r_1, q_1, \{\tilde{w}_2^{t_{2k}}\}_{k=1}^{n_2}, T_2, r_2, q_2)$$
$$= R^{-1}\sum_{r=1}^{R} l^{(r)}\left(t_U, r_U, \{\tilde{w}_1^{t_{1k}}\}_{k=1}^{n_1}, T_1, r_1, q_1, \{\tilde{w}_2^{t_{2k}}\}_{k=1}^{n_2}, T_2, r_2, q_2|\theta_1(r), \theta_2(r)\right)$$

   We can analogously construct the likelihood contribution for an employment cycle that starts from employment, with the initial best dominated match value and current match value ,

$\theta_1^{'}(r)$ and $\theta_1(r)$ (drawn from the steady state distribution) and the job match value $\theta_2(r)$

$$l(\{\tilde{w}_1^{t_{1k}}\}_{k=1}^{n_1}, T_1, r_1, q_1, \{\tilde{w}_2^{t_{2k}}\}_{k=1}^{n_2}, T_2, r_2, q_2 | \theta_1^{'}(r), \theta_1(r), \theta_2(r)) =$$
$$\exp\left(-h_E(\theta_1(r))T_1\right)\left[\left(\lambda_E \bar{G}(\theta_1(r))\right)^{1-q_1}\eta^{q_1}\right]^{1-r_1} f_{w_1}^{(r)}(\tilde{w}_1^{t_{11}}, \tilde{w}_1^{t_{12}}, \tilde{w}_1^{t_{13}}, ..., \tilde{w}_1^{t_{1n_1}}, T_1 | \theta_1^{'}(r), \theta_1(r))$$
$$\left\{\exp\left(-h_E(\theta_2(r))T_2\right)\left[\left(\lambda_E \bar{G}(\theta_2(r))\right)^{1-q_2}\eta^{q_2}\right]^{1-r_2} f_{w_2}^{(r)}(\tilde{w}_2^{t_{21}}, \tilde{w}_2^{t_{22}}, \tilde{w}_2^{t_{23}}, ..., \tilde{w}_2^{t_{2n_2}}, T_2 | \theta_1(r), \theta_2(r))\right\}^{1-r_1}$$

The empirical likelihood function for the entire employment cycle is then calculated by averaging over the R simulated paths

$$l(\{\tilde{w}_1^{t_{1k}}\}_{k=1}^{n_1}, T_1, r_1, q_1, \{\tilde{w}_2^{t_{2k}}\}_{k=1}^{n_2}, T_2, r_2, q_2)$$
$$= R^{-1}\sum_{r=1}^{R} l^{(r)}\left(\{\tilde{w}_1^{t_{2k}}\}_{k=1}^{n_1}, T_1, r_1, q_1, \{\tilde{w}_2^{t_{2k}}\}_{k=1}^{n_2}, T_2, r_2, q_2 | \theta_1^{'}(r), \theta_1(r), \theta_2(r)\right)$$

A.4 Sample construction

A.4.1 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.

4. Individuals whose are out of labor force (olf) during the entire observation period (the one we never see 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 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.

A.4.2 Treatment of out of labor force observation periods

In our model, decisions to exit the labor force are not explicitly modeled. We focus on the dynamics of employment cycles in our estimation process. These cycles are considered concluded when individuals transition from being employed or unemployed to out of the labor force (OLF). We incorporate data on their labor force participation up to the point they transition to OLF. Should an individual re-enter the labor force, this re-entry is modeled as the start of a new employment cycle. This approach essentially ignores out of labor force time periods, implicitly assuming no change in human capital during these intervals.

Additionally, our model does not differentiate between part-time and full-time employment, primarily focusing on hourly wages. However, we do make use of actual data on reported lifetime labor market experience in calculating the initial conditions used in estimating the model. For this purpose, we count part-time past work as half a year experience. As a result, women with a history of part-time work prior to the study period are likely to exhibit lower initial work experience in our analysis.

A.4.3 Personality trait questionnaire

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

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]
Extroversion	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.

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 (-)
Extroversion:	.. 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.5 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.[50] 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.[51] 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

$$w(\theta) = \alpha\theta + (1-\alpha)\theta^*, \tag{26}$$

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

[51]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 (26) 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 given functional form, such as the standard normal c.d.f., $\Phi(\cdot)$. 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 defined over the observed wages in 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 *A necessary condition for identification of the parameter α is that G does not belong to a location-scale family 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

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

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 above.

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. When we allow for on-the-job search and assume Bertrand competition, as in our paper, repeated wage measurements at the same job 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 at its onset and there is no possible wage wage growth on that job that can occur from renegotiation of the worker’s share of the surplus. 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.

Another source of identifying information regarding α in our modeling is through the introduction of heterogeneous parameters across individuals that are functions of a vector of observable individual characteristics and common parameter vectors. In the text we give an example in which a small amount of observable heterogeneity enables identification of α and the parameters describing the match productivity distribution $G(\theta)$. In fact, in that example it is assumed that the match distribution belongs to a location-scale family. In a homogeneous labor market with no parameter heterogeneity, we know that α is not identified, as stated in Proposition 1. Observable heterogeneity generally leads to over-identification of model parameters in large samples and with sufficient variation in observed characteristics. We now consider the introduction of heterogeneity to the model in more detail.

A.5.1 Adding Heterogeneity to the Model

In many cases, researchers estimating 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 cases, 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 deriving the sampling distributions of the estimators.

In this paper, we have taken a different tact, in part because we have a large number of observable characteristics and there is no obvious way to assign individuals to predetermined classes. 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.[52] 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 2 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

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

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.

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

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

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 due to the invariance property of maximum likelihood estimators.

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.[53]

The standard rank condition that we derive to establish identification of the coefficient vectors γ assumes that the homogeneous model is identified. Our example in the text shows that hetero-

[53]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.

geneity actually allows for identification of the primitive parameters even when the homogeneous model is not identified. Therefore the identification of the homogeneous model condition should be viewed as sufficient but not necessary.

A.5.2 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 study compensated its workers.[54] However, the results nonetheless suggest that measurement error is a significant component of the total wage variance.[55]

The presence of measurement error is required for us to define a maximum likelihood estimator for at least two cases, both of which involve counterfactual sample observations given the data generating process (DGP) associated with the model. These are:

1. The observation of a wage w_i that is less than $w^*(z_i, \gamma)$. For any value of z_i and the parameter vectors γ the model implies a reservation wage that can be written as

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

   where γ_{-a} includes all γ vectors except for the one associated with initial ability. Any observed wage for individual i that is less than this is probability 0 under the model.

2. The observation of decreasing wages at the same job for any individual i. Under the model, wage growth at a job is always positive and comes from two sources. The first is the continuous acquisition of human capital through the learning-by-doing and continuous renegotiation process, the impact of which is captured by the parameter $\psi > 0$. The second is due to the assumption of Bertrand competition. In this case the arrival of job matches that dominate

[54] 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.

[55] 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.

the current outside option but not the productivity at the current employer result in wage increases after renegotiation. Thus an observed (real) wage decrease at an employer is a probability 0 event under the model.

In addition, allowing for measurement error in wages allows the model to better fit the data regarding wage changes when an employee moves between firms with no intervening unemployment spell. Although the DGP of our model with Bertrand competition does not imply that such events are probability 0,[56] the proportion of such moves involving a wage decrease typically exceeds the proportion implied under the assumption of no measurement error.

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

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

with ϕ denoting 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

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

With these assumptions on the measurement error distribution, we have added only one additional parameter to the likelihood function, σ_ε. The parameter is identified from the fact that without $\sigma_\varepsilon > 0$ the log likelihood function is not well-defined due to sample observations being inconsistent with the DGP of the model. As noted in the Section 4.1, asymmetry in the distribution of observed wages is a major component of the for the identification of σ_ε. For example, for any individual i with a wage observed after moving from unemployment to employment, the distribution of the observed wage is the product of a lognormally distributed measurement error with full support on R_+ and a truncated lognormal distribution of θ with support $[a(z_i)\theta^*(z_i), \infty)$. The departure of the observed wage distribution from a truncated lognormal distribution is key to the identification of σ_ε.

[56]The models of Postel-Vinay and Robin (2002), Dey and Flinn (2005), and Cahuc et al. (2006) are all capable of producing the possibility of wage decreases when moving between firms.