Personality Traits, Job Search and the Gender Wage Gap

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Abstract

This paper investigates the determinants of gender gaps in labor market outcomes within a job search, matching and bargaining model that incorporates individual-level heterogeneity. That is, job search model parameters, pertaining to worker productivity, job offer arrival rates, job dissolution rates and the division of surplus from an employer-employee match may depend on worker personality traits, education, and other demographics. The model's estimation is based on a German panel dataset on newly-unemployed individuals between 2007 and 2008. Specification tests provide support for the heterogeneous coefficients model in comparison to more restrictive specifications and for a model in which wages are not renegotiated on the job. When the estimated model is used to decompose the sources of the gender wage gap, the results show that women and men are rewarded differently for their traits, particularly through productivity and bargaining channels. Women's lower bargaining power emerges as the key factor in explaining gender disparities. Of the Big Five personality traits considered, conscientiousness and agreeableness are the most significant determinants of job search and labor market outcomes.

1 Introduction

Despite substantial convergence in gender wage and employment differentials over the 1970s and 80s, significant differences remain with women earning on average 25 percent less

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than men (Blau and Kahn (2006), Flabbi (2010b)). A large literature uses data from the US and from Europe to investigate the reasons for gender disparities. Individual attributes, such as years of education and work experience, explain part of gender wage and employment gaps but do not fully account for them. Studies generally attribute residual gaps to either unobserved productivity differences and/or labor market discrimination.

There is increasing recognition that non-cognitive skills, such as personality traits, could be another important factor in explaining gender disparities. The most commonly used noncognitive measurements are the so-called Big Five personality traits, which measure an individual's openness to experience, conscientiousness, extraversion, agreeableness and neuroticism (the opposite of emotional stability).[1] Empirical studies across many different countries find that there are significant differences in personality traits by genders. For example, women are on average more agreeable and less emotional stable than men and that these differences are significantly associated with gender wage gaps.(e.g. Nyhus and Pons (2005), Heineck (2011), Mueller and Plug (2006), Braakmann (2009), Cattan (2013)). However, despite substantial accumulated evidence that personality traits influence labor market outcomes, the mechanisms through which they operate have not been much investigated.

This paper explores the effect of personality traits on labor market outcomes within a job search model and we use the model to better understand the mechanisms underlying gender differences in hourly wages, employment and labor market dynamics. To this end, we develop and estimate a model in which personality traits potentially operate through a number of channels. Unemployed and employed workers stochastically receive employment opportunities from firms characterized in terms of idiosyncratic match productivity values. Firms and job searchers divide the match surplus, with the fraction going to the worker determined by a bargaining parameter. We propose a way of modeling the dependence of job search parameters on a possibly high dimensional set of observable worker characteristics. In our implementing model, workers are heterogeneous in terms of observed attributes that include gender, age, education, and personality traits.

Our model builds on traditional matching-bargaining models, such as Flinn and Heckman (1982), Diamond (1982), Flinn (2002), Cahuc et al. (2006) and Dey and Flinn (2005). It also builds on the smaller literature that uses job search models to understand 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 modeling approach differs from approaches taken in prior studies by allowing job search parameters to depend in a flexible way on worker

[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)).

characteristics and by incorporating personality traits measures. We quantify the importance of heterogeneous workers characteristics operating through four distinct channels: (i) worker productivity, (ii) job finding rates, (iii) job exit rates, and (iv) bargaining power.[2] We use the estimated model examine how gender differences in observables contribute to labor market disparities.

Model parameters are obtained by maximum likelihood using the German IZA Evaluation Dataset, a panel dataset that follows individuals who became unemployed between 2007 and 2008 for up to three years. Our analysis sample includes men and women during prime-age working years (ages 25-55). An unusual feature of these data relative to other available datasets is that they contain the Big Five personality measures, which differ by gender and are significantly associated with job search behaviors and outcomes such as numbers of job applications, length of unemployment spells and hourly wage rates. In addition, we use information on age, education, wages, hours worked, and job transitions in our model's estimation .

We estimate two model specifications that differ in the assumptions on how firms negotiate with workers who receive wage offers from other firms. One model assumes that current firms can match outside offers so that workers can get wage increases at their current job. The other specification assumes that workers only get wage increases when they change jobs. When we perform a goodness-of-fit test of these two specifications, we find that the model that assumes that firms do not renegotiate wages provides a better fit to the data.[3] Using the "without-renegotiation" framework, we estimate three different nested job search models that vary in the degree of individual heterogeneity incorporated. In the most general specification, worker productivity, job arrival rates, job exit rates, and bargaining parameters all vary with individual characteristics. Likelihood ratio tests reject more restrictive specifications in favor of the one allows for the most dimensions of heterogeneity.

The model parameter estimates show that personality traits are statistically significant determinants of job search parameters and that they affect men and women in different ways. For example, women are on average more conscientious than men, but men receive a relatively higher productivity premium in the labor market for being conscientious. Both men and women are penalized for high agreeableness, but the penalty operates through productivity

[2]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.

[3]Flinn and Mullins (2019) develop a model in which equilibria can exist in which some firms do not renegotiate while others do. Such an extension is beyond the scope of our current analysis.

for men and through bargaining for women. Personality traits such as conscientiousness increase the job arrival rate, which is consistent with the observed positive relationship between number of job applications.

We use the estimated model to decompose the sources of gender wage and employment gaps. In particular, we simulate women's labor market outcomes if their education levels and personality traits were valued in the same way as those of men. We find that men and women receive a similar productivity premium for education. However, more educated women and more agreeable women are at a big disadvantage relative to men in terms of bargaining. Gender differences in the bargaining power parameters emerge as a key factor contributing to the gender wage gap, which is consistent with a long-standing literature that argues that gender differences in wage negotiation could partially explain gender pay gaps.

Our paper relates to the literature that analyzes gender differences in job search behaviors and outcomes. Most of the prior literature differentiates 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)). As noted, we allow search parameters to depend on a more extensive index of worker characteristics that includes personality traits. There are two studies that investigate the association between personality traits and job search behavior, Caliendo et al. (2015) and McGee (2015). Both papers measure personality traits using "locus of control", which is a measure of how much individuals think success depends on "internal factors"(i.e. their own actions) verses "external factors."[4] In our data, the "locus of control" measure exhibits little difference by gender in comparison to the Big-Five personality traits. To the best of our knowledge, this is the first study to incorporate the Big-Five personality traits into a job search and matching framework.

Our paper also builds on a literature discussing the association between personality traits, wage, and employment. Many studies provide evidence that gender differences in personality traits are significantly associated with wage and employment outcomes. (Nyhus and Pons (2005), Heineck (2011), Mueller and Plug (2006), Braakmann (2009), Cattan (2013)) There are only a few studies, however, that incorporate personality traits into structural models. Todd and Zhang (2020) explore the role of personality traits within a dynamic discrete choice model of education and occupation sector choices. Heckman and Raut (2016) studies the log-term impact of pre-school investment on cognitive and non-cognitive skills in a intergenerational framework. Flinn et al. (2018) estimate a static model of husband's and wives time allocation within the household where personality traits can affect wage offers

[4] A number of studies have found that the locus of control measure correlates with schooling decisions and wages. See, e.g, Heckman et al. (2006).

and household bargaining power. This paper explores the importance of personality traits as determinants of labor market outcomes through the lens of a canonical job search and matching model.

Our empirical finding that women have lower bargaining power, in part due to their personality traits, is also contribute broadly to the workplace bargaining literature. There are several studies showing that women are less likely to ask for fair wages, both from lab experiments (e.g. Stuhlmacher and Walters (1999)) and survey data (e.g. Säve-Söderbergh (2007) and Card et al. (2015)). However, there is no consensus on the reasons for this phenomenon. Possible explanations offered include gender differences in risk preferences (e.g. Croson and Gneezy (2009)), attitudes towards competition (e.g. Lavy (2013); Manning and Saidi (2010)) and negotiation skills (e.g. Babcock et al. (2003)). Our results suggest that personality trait difference could also be a key factor. Among the Big-five personality traits, we find that agreeableness largely explains the gender gap in bargaining power. As previously noted, women have on average much higher agreeableness scores than men. However, our parameter estimates show that the gender gap arises not only because of level differences but also because women receive a greater penalty for being agreeable, particularly through the bargaining channel.

The paper proceeds as follows. The next section presents our baseline model. Section 3 describes the data. Section 4 discusses the model's econometric implementation. Section 5 presents the model coefficient estimates and decomposition results. Section 6 concludes.

2 Model

In this section, we first introduce a baseline job search, matching and bargaining model, followed by a discussion of particular modeling choices. We defer the discussion of how to incorporate individual heterogeneity into the job search model until the end of the section. Our main goal is to examine the impact of personality traits, as well as other demographic and schooling characteristics, on labor market outcomes using a partial equilibrium job search framework.

2.1 Setup and Preliminaries

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", denoted by a vector z. An unemployed worker meets firms at the rate $\lambda_U(z)$, and an employed worker meets new potential employers at the rate $\lambda_E(z)$, where both of these rates are assumed to be exogenously determined. The ability of the individual is $a(z)$. When a worker matches with a firm, the productivity of this match is determined by a linear production function

$$y(z) = a(z) \times \theta$$

where θ is the match productivity value draws from distribution of matching quality $G_z(\theta)$.[5] $G_z(\theta)$ is assumed to be continuous on its domain. The draw θ is determined at the time the worker-firm contact is made and both $a(z)$ and θ are observed by the worker and the firm. The flow value of unemployment to the individual is assume to be $a(z) \times b$, where b is has different values by genders.[6] An unemployed individual meets firms at the rate $\lambda_U(z)$, and an employed individual meets new potential employers at the rate $\lambda_E(z)$,where both of these rates are assumed to be exogenously determined. Employment matches are dissolved at a rate $\eta(z)$. The common discount rate of all agents in the model, firms and workers, is ρ, which is a independent of z.[7] The worker and the firm bargain over the wage w using a Nash bargaining protocol, with the outside option of the individual dependent upon the particular bargaining protocol assumed.[8] The worker's flow payoff is w and the firm's flow revenue is $y(z) - w$ from this match. The bargaining power of the individual is denoted as $\alpha(z)$.

In our application, the "type" z will correspond to a linear combination of observed individual characteristics that include education level, gender, birth cohort and the Big Five personality trait assessments, with the weights attached to the characteristics allowed to differ across the structural parameters. Because the model is stationary and our data are

[5]The analyses of Postel-Vinay and Robin (2002) and Cahuc et al. (2006) uses similar functional form for the flow productivity $y = a\theta$, where a and θ denotes the worker's and firm's productivity type, receptively. Although the specification looks similar, the interpretation of θ is different, which is mainly driven by the nature of the data. In the case of Postel-Vinay and Robin (2002) and Cahuc et al. (2006), matched worker-firm information is available, enabling the authors to identify distributions of worker and firm types nonparametrically. To the best of our knowledge, there are no such datasets that report worker's personality traits. Therefore, our model must rely only on supply side data, but we do allow workers with different types of z (e.g. men and women) have different matching quality distributions.

[6]The assumption that the flow value of being unemployed is proportional to ability a is a common assumption in the literature (e.g. Postel-Vinay and Robin (2002), Bartolucci (2013), Flinn and Mullins (2015)) and mainly for the tractability purpose.

[7]There exists some empirical evidence indicating that workers with different cognitive ability and non-cognitive ability have different discount rates (Dohmen et al. (2011)). However, we are not able to test for such correlations since the (ρ, b) are usually not individually identified in this type of model. See related discussion in section 4.3.1.

[8]If allowing for the renegotiation between worker and the firm, the outside option of the worker is the current employment status. However, if worker is not allowed to renegotiate the contract with the firm, her outside option would be unemployment. We will discuss the model allowing for renegotiation as our leading case. The alternative model without renegotiation would be introduced in the later section of modeling choices.

a short panel (three years), we will assume that all of the characteristics upon which we ultimately condition are time-invariant.

2.2 A Model of On-the-Job Search with Renegotiation

In this section, we first present an on-the-job search model with renegotiation as our benchmark model and then discuss alternatives. A type z worker with ability $a(z)$ receives job offers with rate $\lambda_U(z)$ when unemployed and $\lambda_E(z)$ when employed. To simplify the notation, we will for now suppress the notation that conditions the primitive parameters of the model on z.[9] We will reintroduce z later when we discuss the parametric specifications.

Following Dey and Flinn (2005) and Cahuc et al. (2006), we assume firms are able to observe the productivity of the worker at the competing firm, either directly or through the process of repeated negotiations. The firms behave as Bertrand competitors, with the result being that the worker goes to the firm where her productivity is the greatest. Because general ability a is the same at all firms, the different productivity levels of the worker in the two firms are attributable to the different match quality draws. When two firms are competing 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 poacher.[10] Let θ and θ' be two match draws at the two firms. Let $\theta' > \theta$, in which case we will refer to θ' as the *dominant* match value and θ as the *dominated* match value. When firms engage in Bertrand competition in terms of wage negotiations, the firm associated with the dominated match value will attempt to attract the worker by increasing its wage offer to the point where it earns no profit from the employment contract.[11] In the case of our example, the firm with match value θ will offer a wage of $a\theta$ to attract the worker. 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 dominant firm.

We now derive the expression for the bargained wage. First, consider an employed worker with the state variable (θ', θ), where θ' is the dominant match value, θ is the dominated match

[9]Notice the worker type z should also be a state variable. We suppress dependence of the model's value functions and parameters on z to simplify exposition. The reader can think of the following model solution as applying for fixed z.

[10]This would not be the case if, for example, there was a finite positive cost associated with changing employer.

[11]This is true under the standard assumption that the value of an unfilled job opening, or vacancy, is 0.

value. When offered a wage w, the value of employment can be written as

$$
\begin{aligned}
\rho V_E(\theta', \theta; w) = w + \eta \underbrace{\left(V_U - V_E(\theta', \theta; w)\right)}_{(1)} + \underbrace{\lambda_E \int_{\theta}^{\theta'} \left(V_E(\theta', x) - V_E(\theta', \theta; w)\right) dG(x)}_{(2)} \\
+ \underbrace{\lambda_E \int_{\theta'} \left(V_E(x, \theta') - V_E(\theta', \theta; w)\right) dG(x)}_{(3)}
\end{aligned} \tag{1}
$$

where term (1) reflects the case when the current job w dissolved due to exogenous shock with rate η. The term (2) in which a new match value x, where $\theta < x \leq \theta'$, is drawn. In this case, the employee will remain at their current firm, but the wage will be renegotiated given the increased value of the employee's outside option, which increases from θ to x. Term (3) reflects the case in which the new match productivity value x exceeds the current match value θ'. In this case, the individual moves to the new job, where their productivity is given by ax, and the new dominated match value becomes θ'. In either case (2) or (3), the (potential) wage payment at the dominated firm is equal to the individual's productivity at the firm (since in this case the firm's profit flow is 0). This is the same outcome as would occur in a special situation when their was no dominant match value, with match productivity at both firms given by θ. When $\theta' = \theta$, equation 1 is simplified as

$$\rho V_E(\theta, \theta) = a\theta + \eta \left(V_U - V_E(\theta, \theta)\right) + \lambda_E \int_{\theta} \left(V_E(x, \theta) - V_E(\theta, \theta)\right) dG(x) \tag{2}$$

On the other hand, the value of the job to the firm is

$$\rho V_F(\theta', \theta; w) = a\theta' - w + \eta(0 - V_F(\theta', \theta; w)) + \lambda_E \int_{\theta}^{\theta'} \left(V_F(\theta', x) - V_F(\theta', \theta; w)\right) dG(x) \tag{3}$$

For completeness, the value of being unemployed V_U is given by

$$\rho V_U = ab + \lambda_U \int_{\theta_R^*} \left(V_E(x, \theta^*) - V_U\right) dG(x) \tag{4}$$

where θ_R^* is the reservation match value, the one at which individual is indifferent between employment and continued search, which is given by

$$V_U = V_E(\theta_R^*, \theta_R^*) \tag{5}$$

The notation R denotes the current assumed bargaining protocol which allows for wage renegotiation between worker and firm.

Then the wage $w(\theta', \theta; R)$ from the Nash bargaining problem is given by

$$w(\theta', \theta; R) = \arg\max_{w} (V_E(\theta', \theta; w) - V_E(\theta, \theta))^{\alpha} V_F(\theta', \theta; w)^{1-\alpha} \tag{6}$$

where the worker's outside option is $V_E(\theta, \theta)$ determined in equation 2, the maximum value when working a job with match value θ, the firm's outside option is 0 and the labor share of the surplus is α. The analytic solution of $w(\theta', \theta)$ and the reservation match value θ^* are provided in the appendix A.1.1.

2.3 Alternative Modeling Assumptions

2.3.1 The Renegotiation Assumption

Although assuming Bertrand competition between firms may be theoretically appealing as it avoids the Shimer critique,[12] it is not clear how realistic this assumption is. It can be shown that introducing a positive cost of negotiation would discourage Bertrand competition and make it not profitable for firms to poach workers from other firms with better match values. Mortensen (2003) argues that counteroffers are empirically uncommon.[13] Moscarini (2008) claims moral hazard concerns explain why firms do not match outside offers and why labor markets remain relatively non-competitive. Rather than making counter offers, firms may credibly prefer to commit to ignoring outside offers that their employees receive and suffer the loss to reduce the other employees' incentives to search on the job.

Due to the empirical skepticism that Bertrand competition characterizes bargaining protocols in real data, we next consider how to relax this assumption. In an environment where workers are not able to recall rejected job offers, a firm has an incentive to renege on its offered wage once the potential competitor's offer has been withdrawn. As a result, the only outside option for the worker is unemployed search with value V_U.[14] In such case, all

[12]Shimer (2006) argues that in a simple search-matching model with on-the-job search, the standard axiomatic Nash bargaining solution is inapplicable, because the set of feasible payoffs is not convex. This non-convexity arises because an increase in the wage has a direct negative effect on the firms rents but an indirect positive effect raising the duration of the job. However, such indirect effect due to wage-dependent turnover can be assumed away by allowing firm to make counteroffers to workers who receive an offer from another firm, eg. Dey and Flinn (2005) and Cahuc et al. (2006)

[13]Mortensen (2003, p. 99):"Unlike in the market for academic economists in the United States, making counteroffers is not the norm in many labor markets. More typically, a worker who informs his employer of a more lucrative outside option is first congratulated and then asked to clear out immediately."

[14]It might be argued that the worker, being fully aware of the fact that the firm will renege on its wage offer once the other offer is withdrawn, would insist on a lump sum payment, or "signing bonus," to accept the employment contract. In such case, we might see a one time payment to the worker at any moment in

on-the-job wage bargaining uses the value of unemployment as the outside option, which is an option that is always available whether or not the wage contract is enforced.[15]

We now discuss the alternative bargaining protocol not allowing for renegotiation. In this set-up, the "dominated" match value does not affect the bargained wage at the current match productivity value. The value of employment $V_E(\theta)$ is a function of the current match value θ:

$$\rho V_E(\theta; w) = w + \eta \left(V_U - V_E(\theta; w)\right) + \lambda_E \int_\theta \left(V_E(x) - V_E(\theta; w)\right) dG(x) \tag{7}$$

and the value to the firm of a filled job becomes

$$V_F(\theta; w) = \frac{a\theta - w}{\left(\rho + \eta + \lambda_E \bar{G}(\theta)\right)} \tag{8}$$

The value of being unemployed V_U is given by

$$\rho V_U = ab + \lambda_U \int_{\theta_N^*} \left(V_E(x) - V_U\right) dG(x) \tag{9}$$

where θ_N^* is the reservation match value, the one at which individual is indifferent between employment and continued search

$$V_U = V_E(\theta_N^*) \tag{10}$$

where the notation N denotes the current bargaining protocol does not allow wage regeneration.

In this case the bargaining wage is determined by the following equation

$$w(\theta; N) = \arg\max_w (V_E(\theta; w) - V_U)^\alpha V_F(\theta; w)^{1-\alpha} \tag{11}$$

which leads to the equation determining wages

$$w(\theta; N) = \alpha a\theta + (1-\alpha)\left(\rho V_U - \lambda_E \int_\theta \left(V_E(x) - V_U\right) dG(x)\right)$$

which two firms are engaged in a competition for her labor services. However, the flow wage payment would be that specified in equation 11.

[15](Gottfries, 2018) extends Shimer's model by allowing the renegotiation to occur scholastically at a Poisson rate γ and show Nash bargaining solution is justified in such as a model. Our two alternatives are nested as two limit cases in which wages are always renegotiated ($\gamma \to +\infty$) and wages are never be renegotiated ($\gamma \to 0$).

where we incorporate the strategy that worker accepts alternative job offers if and only if the alternative match quality $x > \theta$. The solution of the reservation value θ_N^* is given in the appendix A.1.2.

Clearly, the model with renegotiation and without renegotiation can yield different wage payments for identical values of the primitive parameters and match quantity distribution. We use our data to estimate both models and choose the preferred one based on Vuong's (Vuong (1989)) likelihood ratio test for non-nested models. It is worth mentioning that both models generate efficient mobility from job-to-job. That is, the worker will work at the firm for which the match productivity is greatest.[16]

2.3.2 Household Search

In Flinn et al. (2018), we make the point that in a household bargaining situation, it is crucial to model household interactions when examining gender differences in wages. Because men and women often inhabit households together, their labor supply decisions can be thought of as being simultaneously determined. The measured gender differences in wages partially reflect patterns of assortative mating in the marriage market and the manner in which household decisions are made. Ignoring the interrelatedness between men's and women's labor market decisions could yield a distorted view of the factors underlie gender differentials.

We are able to sidestep this issue in this paper because of the linear flow utility assumption.[17] Both men and women have flow utility functions given by their respective wages w when employed and by the constants ab when they are not. The linear utility assumption allows the the household's maximization problem to be decentralized as the sum of two individual maximization problems. The implication is that the choices made by a woman in the household will not be impacted by the characteristics or decision in the household and vice versa. Differently from Flinn et al. (2018), under this common assumption we do not have to be concerned with assortative mating in the marriage market or interdependence in household decision-making.

[16]Because total productivity at a firm where the match productivity is θ is simply $a\theta$, total productivity will be greater at a firm with match value θ' then it will at a firm with match value θ whenever $\theta' > \theta$.

[17]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.

2.4 Incorporating individual heterogeneity

So far we have completed the description of the job search and bargaining model given the set of labor market parameters $\Omega = \{\lambda_U, \lambda_E, \eta, \alpha, a, b, \sigma_\theta\}$. We now reintroduce individual types z and describe how we allow search parameters to depend on worker characteristics that includes education, personality traits, birth cohort and gender. For an individual i, we specify "link" functions between z_i and Ω_i as follows:

$$\begin{array}{ccc} \lambda_U(i) & : & \exp(z_i^{'}\gamma_{\lambda_U}) \\ \lambda_E(i) & : & \exp(z_i^{'}\gamma_{\lambda_E}) \\ \alpha(i) & : & \frac{\exp(z_i^{'}\gamma_\alpha)}{1+\exp(z_i^{'}\gamma_\alpha)} \\ \eta(i) & : & \exp(z_i^{'}\gamma_\eta) \\ a(i) & : & \exp(z_i^{'}\gamma_a) \\ b(i), \sigma_\theta(i) & : & \text{different by gender} \end{array} \tag{12}$$

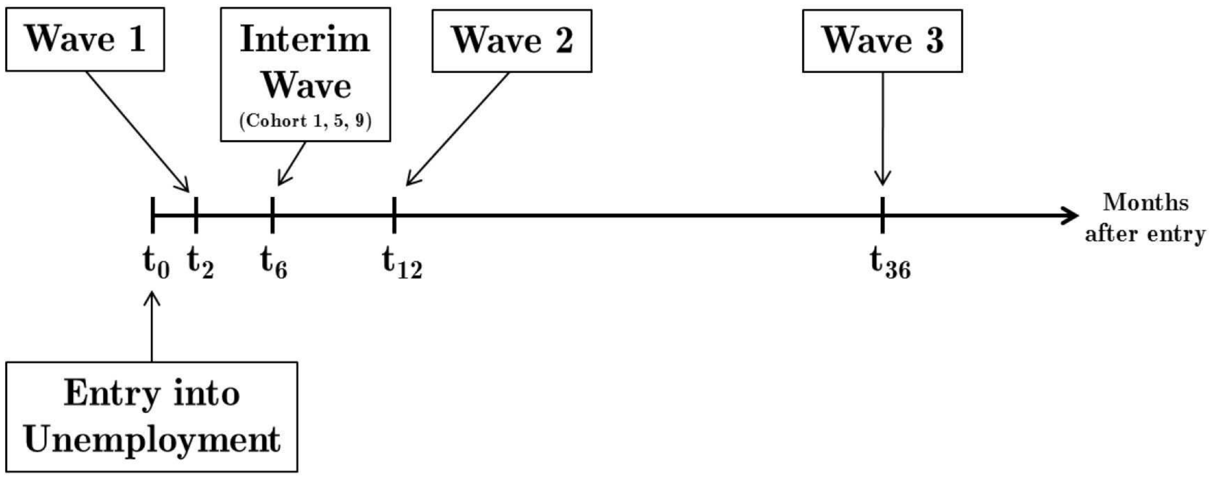
The parametric specifications are chosen deliberately to vary over the feasible sets of model parameters. For example, the logistic transformation guarantees that bargaining power value, α, is restricted to the interval $(0, 1)$.

3 The IZA Evaluation Data Set

The IZA Evaluation Dataset Survey (IZA ED) is a panel survey of 17,396 Germans who registered as newly unemployed with the Federal Employment Agency between mid-May 2007 and mid-May 2008. In each of 12 months, approximately 1,450 individuals are randomly selected to be interviewed based on their birthdays. They account for approximately 9 percent of the newly registered unemployed in the administrative records. The survey contains extensive information on factors related to job search, including the number of job applications and search channels utilized. It also contains rich information on individual characteristics, such as education, Big Five personality traits, and, for a subset of individuals, tests of cognitive abilities.

The IZA ED is a monthly cohort-specific panel. Upon entry into unemployment, each cohort was interviewed at least three times. Most cohorts did their first interviews within 55 to 84 days after entering unemployment. The second and third interviews are scheduled one year and three years later. In addition, three cohorts (corresponding to months June and October 2007 and February 2008) are interviewed at an interim time, six months after their

Figure 1: Panel Structure



Source: The dataset is constructed as a panel. Each individual was interviewed at least three times, i.e. at entry into unemployment, as well as one and three years later, while three selected cohorts received an additional interview after six months. On average, the first wave was conducted about two months after entry into unemployment.

first interview. A graph of panel structure can be found in figure 1.[18] In constructing our analysis sample, we drop individuals with missing information on age, gender, and education as well as missing personality traits information. We also exclude self-employed individuals, because our model pertains to firm-worker matches. These restrictions leave us with a final sample of 4,319 individuals.[19]

The "Big Five" information in the IZA ED is based on a 15-item personality description. Respondents were asked to pick a number between 1 to 7 to indicate how well each description applies to them. The lowest number '1' denotes a completely opposite description and the highest number '7' denotes a perfect description. Each personality trait is constructed by the average scores of three items pertaining to that trait.[20]

[18] One particular concern for the data period is the violation of the stationary environment assumed by the model. We examine this assumption in appendix A.3.1. Although the stationarity assumption may not be ideal for this period of time in Germany, it is less problematic than it would be if we were using data from the US.

[19] A detailed discussion of the sample restrictions appears in Appendix A.2.1. As a dataset focused on the unemployed, IZA ED also records very detailed information on participation in any active labor market programs (ALMP) in Germany. There are three main programs: short-term training (9.4%), long-term training(10.3%) and wage subsidies(10.6). Caliendo et al. (2017b) finds that personality traits play a significant role for selection into ALMP, but do not make a significant difference in estimating treatment effects on wages and employment prospects. We do not explicitly include information on ALMP in our analysis.

[20] In the beginning of the first wave interview, there were 10 personality items, but an additional 5 items become available beginning with the February (ninth) cohort. A detailed description of which items are used to construct each personality trait is provided in Appendix A.1.

The personality trait information is collected at each wave, including the interim wave. The completed Big Five personality traits are available for 5,601 respondents in wave 1, for 1,680 respondents for the interim wave, and for 5,747 and 5,732 respondents in waves 2 and 3, respectively. We include in our analysis individuals for whom personality traits were measured at least once. When there are multiple measures, we use the average value across the different waves, because differences observed within a 3-year time frame are likely due to measurement errors rather than fundamental changes in personality characteristics.[21] Cognitive skills are only measured for three cohorts that were selected to participate during the interim wave (June and October 2007, February 2008).

Table 1 presents summary statistics by gender. As seen in the last column, all of the gender differences are statistically significant at conventional levels. Males spend fewer months in unemployment, 2.41 on average in comparison to 2.67 for females, and more months in employment. The difference in labor market experience of men and women in our sample is not that large: 18 years for men in comparison of 16 years for women. The dataset contains information on actual wages, expected wages, and reported reservation wages. Men have on average an expected hourly wage equal to €9.51 in comparison to €8.26 for women. Their actual wage is also higher, €8.79 on average for men in comparison to €7.66 on average for women. Men also report on average a higher reservation wage than women; €8.26 for men compared to €7.24 for women. The data also shows the gender-specific job distributions by industry sectors. Men are most likely to accept their jobs in the manufacturing sector (42.8%) and the service sector (51.8%); the majority of women's jobs come from the service sector (80.1%).

As seen in the lower panel of the table 1, the statistically significant gender wage gap occurs despite the fact that women in our sample have on average higher education levels than men, with 33 percent of women having an A-level secondary degree in comparison with 26 percent of men. Women also have higher scores on cognitive ability tests. In terms of demographic characteristics, women are slightly older on average than men, though the difference is small (38.7 in comparison to 37.9). Women are more likely to be married than are men (50 percent versus 44.0 percent) and to have a dependent child under the age of 18 (40.0 percent versus 32 percent).

Comparing the average wage for men and women, there is a 14.7 percent gender wage gap. At first glance, the wage gap may seem smaller than the large wage gaps reported for Germany in other studies. For example, Blau and Kahn (2000) found a gender hourly

[21]The personality measurements available in the IZA-ED data set are the same as those used in the GSOEP.

Table 1: Summary Statistics by Gender

	Male			Female			Difference	
	Mean	Std. Dev.	Obs.	Mean	Std. Dev.	Obs.	Diff in mean	P-value
Labor market records								
Unemployment (Months)	2.417	2.596	2490	2.675	3.054	2261	-0.258	0.002
Employment (Months)	12.597	12.683	1664	11.495	12.467	1462	1.102	0.015
Actual wage (€/h)	8.787	4.425	1405	7.663	3.457	1161	1.124	0.000
Wage during last employment(€/h)	8.744	6.581	3632	7.594	4.736	3108	1.150	0.000
Industry sectors								
Agriculture and forestry, fishing	0.054	0.226	1109	0.045	0.207	1008	0.009	0.317
Manufacturing, production	0.428	0.495	1109	0.155	0.362	1008	0.274	0.000
Services, trade/banking/insurance	0.518	0.500	1109	0.801	0.400	1008	-0.283	0.000
Previous accu. experience (years)	18.276	9.982	3808	15.792	9.585	3293	2.485	0.000
Expected wage (€/h)	9.511	3.618	1915	8.259	3.332	2003	1.252	0.000
Reservation wage (€/h)	8.264	3.014	1428	7.243	2.734	1524	1.020	0.000
Number of applications	13.146	18.402	1615	12.757	17.073	1512	0.389	0.541
Individual's characteristics								
Age: mean	37.935	8.654	2084	38.699	8.677	1965	-0.764	0.005
Birth cohorts								
1952-1962	0.381	0.486	2084	0.353	0.478	1965	0.029	0.062
1963-1972	0.354	0.478	2084	0.348	0.476	1965	0.006	0.686
1973-1982	0.265	0.441	2084	0.299	0.458	1965	-0.035	0.015
Education levels								
Lower secondary school	0.368	0.482	2084	0.236	0.425	1965	0.132	0.000
(Adv.) middle sec. school	0.369	0.483	2084	0.436	0.496	1965	-0.066	0.000
Upper sec. school (A-level)	0.263	0.440	2084	0.328	0.470	1965	-0.066	0.000
Marriage	0.440	0.497	2077	0.518	0.500	1960	-0.078	0.000
Dependent child (under age 18)	0.315	0.465	2080	0.402	0.490	1964	-0.086	0.000
Cognitive Ability	1.773	0.571	530	1.888	0.523	550	-0.115	0.001
Emotional Stability	3.805	1.097	2084	3.397	1.154	1965	0.408	0.000
Openness to experience	4.755	1.110	2084	4.892	1.190	1965	-0.138	0.000
Conscientiousness	5.707	0.824	2084	5.860	0.784	1965	-0.153	0.000
Agreeableness	5.190	0.942	2084	5.509	0.909	1965	-0.319	0.000
Extraversion	4.681	1.038	2084	4.824	1.055	1965	-0.143	0.000
Locus of control	4.363	0.746	1895	4.309	0.723	1826	0.054	0.024

Source: IZA Evaluation Data Set, individuals between age 25 to 55. The p-value is for a two-sided t-test of equality of means.

gap in West Germany of 32 percent, placing West Germany in position 6 in a ranking of 22 industrialized countries. There are two potential reasons to explain the discrepancy. First, our sample of newly unemployed individuals tends to include more individuals from the lower part of the wage distribution. Second, the wages reported in IZA-ED are net earnings, which quite different from the conventional gross earning measures that most other datasets report.

To better understand the reason why our wage gap is lower, we tabulated mean wages by gender using the German Socio-Economic Panel (GSOEP) data (a random representative sample) in table 2, in which both net wages and gross wages are available.[22] Although the average wage in the newly unemployed sample is lower than the average wage in a representative sample (€8.87 vs. €11.55 for men and €7.72 vs. €9.11 for women), the smaller gender wage gap is mainly caused by the measured differences between net wages and gross wages. Due to the progressive nature of the German tax system, the gap in net wages should be smaller than the gap in gross wages. In the GSOEP data for 2007 and for newly unemployed workers similar to the individuals in our sample, the net wage gap is 22.4 percent but the gross wage gap is 30.5 percent (the average wages are €13.52 for men and €10.36 for women).

A comparison of personality trait scores shows that men have higher emotional stability scores on average. But for all other traits, women have higher scores on average. The greatest gender differences for personality traits occur for emotional stability (3.81 for males versus 3.40 for women) and agreeableness (5.19 for males versus 5.51 for females).[23] As previously noted, some studies focus on locus of control as a measure of an individual's noncognitive skills. As seen in the last row of the table, our sample shows very little gender difference in average locus of control (4.36 for men and 4.31 for women). Therefore, we focus on the Big Five personality measures as a potential source of labor market outcome disparities between men and women.[24]

Table 3 reports estimated coefficients from a linear regression of log hourly wages (at the last time of employment) on education, personality traits, cognitive ability, and reported labor market experience (before being unemployed) and its square. As seen in Table 3, the coefficient associated with education is similar for men and women (0.230 for women and

[22]The gross wage is defined as net wage plus taxes and social security, and payments for unemployment and health insurance.

[23]A more detailed comparison of personality trait distributions between genders can be found in Table A.2.

[24]Additional information on the correlation between Big-five and locus of control can be found in Table A.3 and Table A.4.

Table 2: Mean comparisons for IZA ED and GSOEP

	IZA ED		GSOEP wave 2007		GSOEP newly unemployed	
	Male	Female	Male	Female	Male	Female
Gross hourly wage (€/h)			17.77	14.24	13.52	10.36
			(8.762)	(7.385)	(26.67)	(6.563)
Net hourly wage (€/h)	8.869	7.726	11.55	9.105	7.991	6.529
	(4.523)	(3.546)	(5.338)	(4.344)	(10.79)	(3.169)
Previous accu. experience (years)	18.12	15.70	18.32	16.49	15.67	13.19
	(9.929)	(9.650)	(8.913)	(8.739)	(9.997)	(8.688)
Age	37.79	38.73	41.32	41.53	39.40	39.28
	(8.608)	(8.682)	(8.193)	(8.345)	(9.199)	(9.407)
Birth cohorts						
1952-1962	0.380	0.353	0.228	0.228	0.344	0.337
	(0.485)	(0.478)	(0.419)	(0.420)	(0.476)	(0.474)
1963-1972	0.368	0.337	0.390	0.362	0.317	0.343
	(0.482)	(0.473)	(0.488)	(0.481)	(0.467)	(0.476)
1973-1982	0.252	0.310	0.382	0.410	0.339	0.320
	(0.434)	(0.463)	(0.486)	(0.492)	(0.475)	(0.468)
Education levels						
Lower secondary school	0.379	0.224	0.290	0.207	0.421	0.244
	(0.485)	(0.417)	(0.454)	(0.405)	(0.495)	(0.431)
(Adv.) middle sec. school	0.400	0.432	0.356	0.448	0.432	0.517
	(0.490)	(0.496)	(0.479)	(0.497)	(0.497)	(0.501)
Upper sec. school (A-level)	0.222	0.344	0.355	0.345	0.148	0.238
	(0.415)	(0.475)	(0.478)	(0.475)	(0.356)	(0.427)
Marriage status	0.448	0.469	0.620	0.614	0.443	0.436
	(0.497)	(0.499)	(0.485)	(0.487)	(0.498)	(0.497)
Dependent child (under age 18)	0.338	0.363	0.454	0.445	0.399	0.500
	(0.473)	(0.481)	(0.498)	(0.497)	(0.491)	(0.501)
Emotional Stability	3.763	3.431	3.762	3.279	3.571	3.045
	(1.069)	(1.114)	(1.060)	(1.102)	(1.074)	(1.139)
Openness to experience	4.774	4.919	4.412	4.593	4.452	4.646
	(1.041)	(1.047)	(1.014)	(1.103)	(1.037)	(1.114)
Conscientiousness	5.682	5.842	5.539	5.654	5.55	5.497
	(0.778)	(0.751)	(0.809)	(0.778)	(0.851)	(0.868)
Agreeableness	5.172	5.515	4.853	5.164	4.896	5.081
	(0.906)	(0.874)	(0.888)	(0.831)	(0.811)	(0.912)
Extraversion	4.671	4.857	4.401	4.689	4.462	4.691
	(1.011)	(0.979)	(1.047)	(1.035)	(1.129)	(1.095)
Obs.	2,084	1,965	4,380	4,284	183	172

Source: IZA Evaluation Dataset (IZA ED) and German Socio-Economic Panel (GSOEP). We use a specific wave of GSOEP (Wave 24 in year 2007), which is close to the time when IZA ED is firstly conducted. We restricted both samples to persons in the labor force, age 25-55. “Big five” personality measures in IZA-ED are average scores in all waves, while “Big five” personality measures in GSOEP are average values in year 2005 and year 2009.

0.241 for men). Higher scores on emotional stability are associated with higher hourly wages for both men and women. Moreover, a higher conscientiousness score is associated with higher wages for men but lower wages for women. As is typically found in the literature, agreeableness is associated with lower wages, although this regression shows the effect is only significant only for men.

In our structural model, personality traits are allowed to affect the gender wage gap through the job search, productivity and wage bargaining channels. However, some other channels omitted from the model include occupation, marriage and fertility choices, which are also found by some studies partially explain the gender wage gaps (e.g. Blau and Kahn (2017); Adda et al. (2017);Xiao (2020)) To test how these other choices may correlate with personality trait effects on wages,

we establish a wage regression controlling for additional variables, including cognitive ability, a marriage indicator, number of children and industry sector indicators (agriculture/manufacturing/service). Our regression results in table 3 show that both marriage status and occupation sector choices are significantly associated with hourly wage rates. However, including these additional control variables does not significantly alter the association between personality traits and hourly wages.[25]

Table 4 displays estimates of the hazard rate from unemployment to employment under a Cox proportional hazard function specification. The estimation takes into account censoring, namely that all individuals start out unemployed and some are never observed to become employed during the sample window. As seen in the table, for both men and women, a higher score on emotional stability significantly increases the likelihood of finding a job. For women, education also increases the hazard out of unemployment, but education is not a significant determinant for men. Being more extraverted tends to decrease the hazard rate from unemployment for men.[26] Cognitive ability increases the hazard rate out of unemployment, but the effect is statistically significant only for men. Including the cognitive ability measure in the specification does not significantly affect magnitudes of the other estimated coefficients.

In Figure 2, we show estimates of Kaplan-Meier survival functions associated with duration in the unemployment state, where the estimation is performed separately by gender.

[25] As a robustness check, we further perform additional regressions including the interactions between personality traits and industry sectors. The hypothesis that the interaction terms are equal to 0 can not be statistically rejected at conventional levels ($p - value > 0.6$) and the coefficients associated with personality traits remain similar.

[26] Marini and Todd (2018) show that being more extraverted is associated with higher rates of alcohol consumption. Also, Todd and Zhang (2020) show that extraversion significantly increases the likelihood to work in the blue-collar sector.

Table 3: The effects of personality traits on hourly wages of first jobs out of unemployment (by gender)

Outcome variable:	Male			Female		
(log) hourly wage	(1)	(2)	(3)	(4)	(5)	(6)
Higher level sec. degree	0.241***	0.226***	0.215***	0.230***	0.230***	0.218***
(Baseline: sec. school or lower)	(0.032)	(0.032)	(6.79)	(0.034)	(0.034)	(0.034)
Emotional Stability	0.014	0.018	0.018	0.027*	0.024	0.026*
	(0.012)	(0.012)	(1.52)	(0.013)	(0.013)	(0.013)
Openness to experience	0.006	0.006	0.008	0.018	0.016	0.017
	(0.013)	(0.012)	(0.67)	(0.015)	(0.015)	(0.014)
Conscientiousness	0.063***	0.050**	0.048**	-0.071**	-0.071**	-0.065**
	(0.018)	(0.017)	(2.80)	(0.022)	(0.022)	(0.022)
Agreeableness	-0.052***	-0.051***	-0.043**	-0.013	-0.010	-0.011
	(0.015)	(0.014)	(-3.07)	(0.018)	(0.019)	(0.018)
Extraversion	-0.014	-0.015	-0.018	-0.008	-0.008	-0.006
	(0.014)	(0.014)	(-1.33)	(0.016)	(0.016)	(0.016)
Cognitive Ability		0.057	0.063		0.017	0.002
		(0.055)	(1.16)		(0.062)	(0.061)
Marriage dummy		0.145***	0.133***		-0.098**	-0.103***
		(0.031)	(4.37)		(0.031)	(0.031)
Dependent child (any)		0.053	0.054		0.041	0.030
		(0.032)	(1.73)		(0.033)	(0.033)
Industry sector (Baseline: agriculture)						
Manufacturing			0.080			0.255*
			(0.065)			(0.103)
Services			-0.025			0.262**
			(0.065)			(0.097)
Number of Obs	932	932	932	697	697	697
R^2	0.074	0.118	0.155	0.117	0.130	0.167
Experience	X	X	X	X	X	X
Experience^2	X	X	X	X	X	X
Missing cognitive indicator		X	X		X	X
Missing industry indicator			X			X

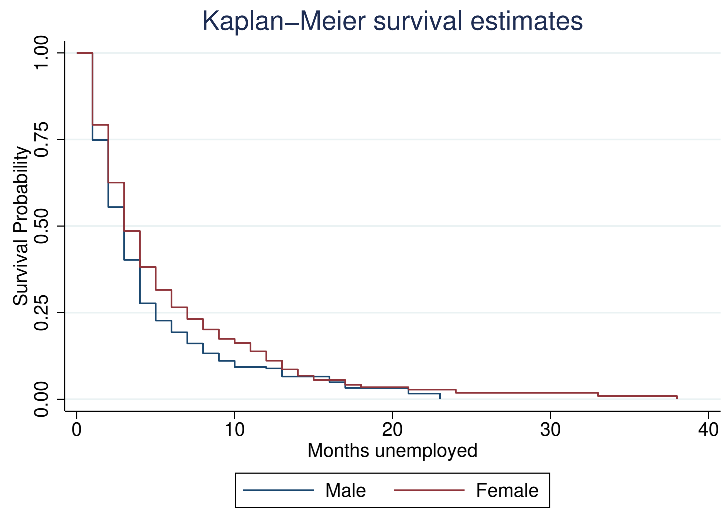
Notes: all columns display OLS regression results. The Source: IZA Evaluation Data Set, individuals age 25 to 55. Standard Errors in parentheses. $p < 0.1^{*}$, $p < 0.05^{**}$, $p < 0.01^{***}$.

Table 4: Cox proportional hazard model for exiting unemployment (by gender)

Outcome variable:	Male		Female	
Unemployment duration	(1)	(2)	(3)	(4)
Higher level secondary degree	-0.081	-0.099	0.215***	0.204**
(Baseline: secondary school or lower)	(0.059)	(0.060)	(0.061)	(0.062)
Emotional Stability	0.028	0.030	0.056*	0.051*
	(0.024)	(0.024)	(0.024)	(0.024)
Openness to experience	0.019	0.029	0.009	0.003
	(0.023)	(0.024)	(0.025)	(0.025)
Conscientiousness	-0.048	-0.062	-0.032	-0.051
	(0.032)	(0.032)	(0.039)	(0.039)
Agreeableness	-0.028	-0.030	-0.036	-0.018
	(0.027)	(0.027)	(0.034)	(0.035)
Extraversion	0.018	0.005	0.009	0.009
	(0.027)	(0.027)	(0.030)	(0.030)
Cognitive Ability		0.219*		0.115
		(0.099)		(0.115)
Marriage dummy		0.051		-0.136*
		(0.063)		(0.059)
Dependent child (any)		0.076		-0.221***
		(0.063)		(0.063)
Number of Obs	2,083	2,075	1,965	1,959
Age	X	X	X	X
Age^2	X	X	X	X
Missing cognitive indicator		X		X

Source: IZA Evaluation Data Set. Estimation based on individuals age 25 to 55. Standard Errors in parentheses. p<0.1*, p<0.05**, p<0.01***.

Figure 2: Unemployment duration: Kaplan-Meier survival estimates by gender



Note: Source: IZA Evaluation Data Set. The sample includes individuals age 25 to 55. Log-rank test for equality of survival functions yields p-values: $p = 0.000$.

As seen in Figure 2, women exit unemployment more slowly than men. However, men are more likely to experience unemployment spells in excess of 12 months. About 50 percent of the sample experiences initial unemployment spells lasting less than six months.

To summarize, we find significant gender differences in job search behaviors and wage outcomes, which are associated with differences in their observed characteristics. This descriptive evidence motives us to develop and estimate a job search and matching model that incorporates heterogeneity in worker's traits.

4 Estimation and Identification

4.1 Measurement Errors in Wages

We assume observed wages are measured with errors. The measurement errors play three roles in the estimation. First, we wish to allow for reporting errors in wages, which is common in survey data. Second, individuals only report one wage observation in each job spells. The measurement error can rationalize potential wage fluctuation within job spells. Third, the measurement error is needed to explain why some job changes are not associated with wage increases. In our model, an individual only changes employers to move to a job with a superior match value, implying that all job mobility is efficient in the sense of increasing the worker's productivity. In the model in which there is no renegotiation and the wage is determined under Nash bargaining with the worker's outside option equal to the value of search while unemployed, any job-to-job moves should be associated with a wage increase. Although the majority of job-to-job transitions in the data are associated with wage increases, a significant proportion are not.[27] There are some theoretical models in the literature that can accommodate job-to-job moves with wage declines.[28] This is also true for our specification allowing for wage renegotiation in which firms act as Bertrand competitors in attempting to hire or retain a currently employed worker.

The introduction of measurement error into nonlinear models, such as ours, is not without some cost, because we have to make assumptions regarding the measurement error process and misspecification could lead to inconsistent estimates of other model parameters. We adopt a standard classical measurement error assumption, and write observed wages $\tilde{w}$ as

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

where $\tilde{w}$ is the reported wage and w is the "true" wage received by the worker. We follow the common assumption that the measurement error in wages, ε, is independently and identically distributed (i.i.d.) as a log-normal random variable (Wolpin (1987); Flinn (2002)). The density of ε is

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

where ϕ denotes the standard normal density, and where μ_ε and σ_ε are the mean and standard deviation of $\ln\varepsilon$. We impose the restriction that $\mu_\varepsilon = -0.5\sigma_\varepsilon^2$, so that $E\left(\varepsilon|w\right) = 1$.[29] Therefore, the expectation of the observed wage is equal to the true wage.

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

[27] It is necessary for us to introduce measurement error because we use a maximum likelihood estimator, and under the model specification a wage decrease between jobs is a zero-probability event. If we were to use instead a moment-based estimator, it would not be necessary to introduce measurement error for the estimator to remain well-defined, although it still may be desirable to do so.

[28] Two such examples are Postel-Vinay and Robin (2002) and Dey and Flinn (2005). In Postel-Vinay and Robin, workers may take a wage reduction to move to a "better" firm because of the increased future bargaining advantage being at that firm conveys. In Dey and Flinn, in addition to wages, firms and workers profit from the worker having health insurance. When a worker moves from a firm in which she does not have health insurance to one in which she does, then her bargained wage may decrease. Wage decreases in this case can only be observed when the worker moves from a job without health insurance to one with health insurance, and in no other cases.

[29] Given ϵ follows a lognormal distribution, $E(\epsilon) = \exp\left(\mu_\epsilon + 0.5\sigma_\epsilon^2\right) = 1$ if $\mu_\epsilon = -0.5\sigma_\epsilon^2$.

4.2 Constructing the individual likelihood contribution

We estimate the model parameters using a maximum likelihood estimator. In this subsection, we first discuss how we construct each individual likelihood contribution $L_i, i = 1, 2, .., N$ conditional on the individual's specific parameter values Ω_i. In the next subsection, we will describe the mapping between individual characteristics z_i and the individual-specific model parameters Ω_i. To avoid notational clutter, we suppress the individual subscript i, but the reader should bear in mind that the underlying econometric model allows 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 as an employment cycle. An employment cycle begins with an unemployment spell that is then followed by one or more jobs in the employment spell that follows. For computational simplicity, we limit attention to the first two jobs in the employment spell. Each individual contributes information on one "employment spell" to the likelihood function. In describing the likelihood contribution of each individual, it will be useful to distinguish between three types of individual contributions: (1) those with information only on the (incomplete) unemployment spell; (2) those with information on the (completed) unemployment spell and one job spell; and (3) those with information on the (completed) unemployment spell and with information on the first two job spells. The data used to define the likelihood contribution of an individual can be represented as

$$\text{Employment cycle} = \underbrace{\{t_U, r_U\}}_{\text{Unemployment spell}}, \underbrace{\{t_k, \tilde{w}_k, q_k, r_k\}_{k=1}^{2}}_{\text{Up to two consecutive jobs}}$$

For the unemployment state, t_U is the length of the unemployment spell and r_U is an indicator variable that takes the value 1 if the unemployment spell is right-censored. In the following employment spell, which consists of up to 2 jobs, for each job spell $k \in 1, 2$, t_k is the length of job k in the employment spell, $\tilde{w}_k$ is the observed wage in job k, and $r_k = 1$ indicates that the duration of job k is right-censored. As described in data section, every individual observation in our sample begins with an unemployment spell. Therefore, we avoid the common difficulty of having to take into account incomplete spells at the beginning of a sample period, otherwise known as the left-censoring problem.[30] In addition, we focus on up to the first two job spells in the following employment spell. This is done to ease the

[30] For a given worker, unemployment is essentially a "reset" of her job history. Therefore, the employment experience before the first observed unemployment spell has no impact on the labor market outcomes that we observe (see Flinn (2002); Dey and Flinn (2005); Liu (2016) for a discussion of this point).

computational burden. Then the individual likelihood function covers the following three categories (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 ($r_1 = 0, q_1 = 0$)
3. One completed unemployment spell + first 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 ($r_2 = 0, q_2 = 0$)
   (c) + second completed job spell ending with third job ($r_2 = 0, q_2 = 1$)

The final specification of the individual likelihood function also depends on the bargaining protocol. Under the assumption that firms and workers renegotiate contracts, the overall likelihood contribution is

(13)

$$\begin{aligned} l\left(t_U, r_U, \tilde{w}_1, t_1, r_1, q_1, \tilde{w}_2, t_2, r_2, q_2; \Omega, R\right) &= \int_{\theta_R^*} \int_{\theta_1} \lambda_U \exp\left(-h_{U,R} t_U\right) \\ &\times \left\{\exp\left(-h_E(\theta_1) t_1\right) \left(\lambda_E^{1-q_1} \eta^{q_1}\right)^{1-r_1} m\left(\tilde{w}_1 | w\left(\theta_1, \theta_R^*; R\right)\right)\right\}^{1-r_U} \\ \times \left\{\exp\left(-h_E(\theta_2) t_2\right) \left(\left(\lambda_E \tilde{G}(\theta_2)\right)^{1-q_2} \eta^{q_2}\right)^{1-r_2} m\left(\tilde{w}_2 | w\left(\theta_2, \theta_1; R\right)\right)\right\}^{1-(r_1+q_1)} &\frac{g(\theta_2)}{\tilde{G}(\theta_1)^{r_1}} \frac{g(\theta_1)}{\tilde{G}(\theta_R^*)^{r_U}} d\theta_2 d\theta_1 \end{aligned}$$

where $w\left(\theta', \theta; R\right)$ and θ_R^* are determined by equation 6 and equation 5. Additionally,

$$\begin{aligned} h_{U,j} &= \lambda_U \tilde{G}(\theta_j^*), j = R, N \\ h_E(\theta) &= \eta + \lambda_E \tilde{G}(\theta), \end{aligned}$$

where $\tilde{G} = 1 - G$ is the complementary cumulative distribution function.When not allowing for regeneration, the overall likelihood contribution of an individual is given by

(14)

$$\begin{aligned} l\left(t_U, r_U, \tilde{w}_1, t_1, r_1, q_1, \tilde{w}_2, t_2, r_2, q_2; \Omega, N\right) &= \int_{\theta_N^*} \int_{\theta_1} \lambda_U \exp\left(-h_{U,N} t_U\right) \\ &\times \left\{\exp\left(-h_E(\theta_1) t_1\right) \left(\lambda_E^{1-q_1} \eta^{q_1}\right)^{1-r_1} m\left(\tilde{w}_1 | w\left(\theta_1; N\right)\right)\right\}^{1-r_u} \\ \times \left\{\exp\left(-h_E(\theta_2) t_2\right) \left(\left(\lambda_E \tilde{G}(\theta_2)\right)^{1-q_2} \eta^{q_2}\right)^{1-r_2} m\left(\tilde{w}_2 | w\left(\theta_2; N\right)\right)\right\}^{1-(r_1+q_1)} &\frac{g(\theta_2)}{\tilde{G}(\theta_1)^{r_1}} \frac{g(\theta_1)}{\tilde{G}(\theta_N^*)^{r_U}} d\theta_2 d\theta_1. \end{aligned}$$

where $w(\theta; N)$ and θ_N^* are determined by equation 11 and equation 10 . We compute the likelihood function by Monte Carlo integration using importance sampling.[31]

We then construct the overall log likelihood function L for the whole sample (with sample size N). Our model assumes that an individual i has their individual-specific set of labor market parameters $\Omega_i = \{\lambda_U(i), \lambda_E(i), \alpha(i), \eta(i), a(i), b(i), \sigma_\theta(i)\}$. As discussed below, these parameters are functions of observable heterogeneity represented by a row vector of characteristics z_i, which includes education, birth cohort, gender, and personality traits. The log likelihood function $\ln L$ defined for the entire sample of size N is

$$\ln L = \sum_{i=1}^{N} \ln l_i(\text{Employment cycle}_i|\Omega_i)$$

where $l_i(\text{Employment cycle}_i|\Omega_i)$ is the individual likelihood function defined by equation 13 and 14. Note that because individual heterogeneity is (essentially) continuously distributed, computing individual i's log likelihood contribution at each iteration of the estimation algorithm requires us to solve for their own unique reservation wage strategy.

4.3 Identification

We begin by considering the simplest case of estimation of bargaining model with on-the-job search when the population is homogeneous, that is, all individuals share the same labor market parameters. We then extend this analysis to cover the situation in which (potentially) each individual has their own labor market parameters. We will mainly consider the case relevant for the data we analyze, which is one in which a short labor market history is available for each individual (large N, relatively small observation period). In the estimation, we use information from one unemployment spell per individual and information from a subsequent employment spell, including wage information and information on job-to-job movements and wage changes for up to two consecutive jobs.

4.3.1 Identification of parameters in a homogeneous search model

In terms of the homogeneous case in which there is no on-the-job search and the bargaining power parameter, α, is constrained to be equal to 1, which is the case in which the worker receives the full surplus of the match, identification of the model has been consid-

[31] In practice, we generate 2500 repetitions of the (θ_1, θ_2) draws (50 draws of θ_1 and 50 draws of θ_2) for use in the importance sampling algorithm.

ered in detail in Flinn and Heckman (1982).[32] For the case without measurement error in wages, Flinn and Heckman (1982) demonstrate that the accepted wage offer distribution is nonparametrically identified; however, in the absence of information on rejected wage offers, a parametric assumption is required to identify the full wage offer distribution.[33] Flinn and Heckman (1982) show that most parametric distributions can be identified even with systematically missing data on job offers.[34]

For the case without measurement error, they show that the minimum observed accepted wage, $\hat{w}_{(1)}$, is a superconsistent estimator of the reservation wage, that is $plim_{N\to\infty}\hat{w}_{(1)} = \rho V_U \equiv w^*$, with the rate of convergence being N instead of $\sqrt{N}$. Given this estimator, they demonstrate that maximization of the concentrated log likelihood function yields $\sqrt{N}$ consistent estimators of λ_U, η, and the parameters characterizing the recoverable distribution, G. They also show that the discount rate ρ and the flow utility in unemployment b are not separately identified. Fixing one of the parameters, typically ρ, allows identification of b.

When introducing the classical measurement error ε, the observed accepted wage, $\tilde{w}$, is given by $\tilde{w} = w\varepsilon$. So that $\ln\tilde{w} = \ln w + \ln\varepsilon$, where $\ln\varepsilon$ follows a normal distribution with mean $-\frac{\sigma_\varepsilon^2}{2}$ and variance σ_ε^2, and where $\ln w$ has a truncated normal distribution, that is, $\ln w \sim N(\mu, \sigma^2 | \ln w \geq \ln w^*)$. In the case in which there is no truncation, the convolution $\ln\tilde{w}$ would have a normal distribution with mean μ and variance $\sigma^2 + \sigma_\varepsilon^2$, and separate identification of σ^2 and σ_ε^2 would not be possible. However, our accepted wage is truncated by the reservation wage w^*, $w \sim G(w|w \geq w^*)$. Therefore, the parameters μ, σ^2, σ_ε^2, and w^* are identified given access to a sufficiently large random sample of accepted wages.

Adding on-the-job search to the above framework only adds one additional parameter, λ_E, the rate of arrival of alternative employment possibilities to individuals currently working. It is straightforward to estimate this parameter if job-to-job moves are observed in the data. Ignoring measurement error in wages, the hazard rate of moving to a new job is $h_E(w) = \lambda_E\tilde{G}(w)$, where $\tilde{G} \equiv 1 - G$ is the survival function. The hazard rate of exogenous termination of the job spell is η. Thus the (joint) hazard of the job spell ending is $\eta + \lambda_E\tilde{G}(w)$, and the probability that a job spell ended due to an exit to a better job is $h_E(w)/(h_E(w) + \eta)$. Because we observe a number of first job spells (after unemployment) that end in a move to another employer, it is straightforward to identify λ_E under the assumption that all wage

[32] When the bargaining power $\alpha = 1$, the wage offer distribution is identical to the productivity distribution. In this case, the wage offer distribution is considered to be exogenous.

[33] This is true unless one is willing to make an assumption that all wage offers are accepted.

[34] They further show that not all parametric distributions are identifiable in this situation. They term those that are as "recoverable," and give examples of unrecoverable parametric distributions with support on R_+. Two leading examples of unrecoverable parametric distributions are the Pareto and the exponential.

draws are i.i.d draws from G, independent of the labor market state currently occupied.

4.3.2 Identification of the bargaining power α

We now extend our argument to consider the estimation of the bargaining power parameter α under the Nash bargaining protocol. In this case, the wage distribution is not considered to be exogenous, although the productivity distribution $G(\theta)$ is. The bargaining parameter is difficult to identify given that we only observe the portion of the surplus received by workers in the form of wages, and not the profits earned by the firm. A given wage distribution may be consistent with a "small" surplus that is mainly captured by the worker (high α) or a "large" surplus, with the worker obtaining a small share (low α). As noted in Flinn (2006), the mapping from the worker's productivity at the firm, θ, is linear, and is given by

$$w = \alpha\theta + (1-\alpha)\theta^*, \tag{15}$$

where θ^* is the reservation match value, which depends on the individual's current employment state and the bargaining protocol that is assumed.[35] Because θ^* is a constant, the function $w(\theta)$ is linear, and the wage distribution is given by $F(w) = G(\frac{w-(1-\alpha)\theta^*}{\alpha})$. Then if G is a location-scale distribution, so that $G(\theta) = G_0(\frac{\theta-c}{d})$, with G_0 a known function, c the location parameter, and d the scale parameter, the parameter α is not identified.[36] A necessary condition for α to be identified is that G not be a location-scale distribution. In this paper and in Flinn (2006), G is assumed to be lognormal, which is a log location-scale distribution.

[35] Strictly speaking, the wage determination equation in our case is $w = a(\alpha\theta+(1-\alpha)\theta^*)$. The identification of a becomes more clear when introducing individual heterogeneity. In this subsection, we fix $a = 1$ and focus our attention on the identification of α.

[36] It is straightforward to see this, because the distribution of wages becomes

$$\begin{aligned} F(w) &= G_0\left(\frac{\frac{w-(1-\alpha)\theta^*}{\alpha} - c}{d}\right) \\ &= G_0\left(\frac{w-c'}{d'}\right), \end{aligned}$$

where

$$\begin{aligned} c' &= (1-\alpha)\theta^* - c\alpha \\ d' &= \alpha d. \end{aligned}$$

Even if θ^* is known, or a consistent estimator of it is available, this leaves two equations in three unknowns, c, d, and α, and these parameters are not identified without further restrictions.

While the nonlinearity of the logarithmic function is enough to ensure the identification, our argument could be stronger by incoporating the reported reservation wage w^* in our estimation. The restriction that G distribution has to be a location-scale distribution can be removed. When both w and w^*(which is also θ^* given $a = 1$) are both observed, α can be recovered from how sensitive wages are in response to the change of reservation wages. Although the theoretical argument is appealing in the ideal case, there are two empirical challenges to incorporate the reservation wage directly in our estimation. First, job seekers may have reference-dependent behaviors and anchor their reservation wages on their past wages.(Koenig et al. (2016); DellaVigna et al. (2017)) Second, job seekers may have biased beliefs about their employment prospects due to their difference in risk and overconfidence.(Spinnewijn (2015))[37] Despite of such concerns, various studies (e.g. Le Barbanchon et al. (2019);Caliendo et al. (2017a);) found the reservation wage is meaningfully correlated with worker's characteristics. For example, women tend to have lower reservation wage. Therefore, we follow the conventional procedure and check whether the correlations between personality traits and reservation wages are consistent between model and data as the additional source of external validation.

4.3.3 Introducing observed heterogeneity

In terms of the model described above, if we had access to an indefinitely long labor market history for each individual i, we could estimate the identified model parameters separately for each i. In our case, we have access to only a very short period of observation for each of a large number of individuals, so allowing for heterogeneity requires positing restrictions on how parameters vary across individuals. In particular, we assume that each individual is characterized by the linear index function

$$z_i \gamma_j,$$

where j is specific to a given parameter of the model. The least restrictive version of the model we take to the data characterizes an individual i in terms of the full vector of characteristics z_i and specifies how the characteristics map into parameter values. The rate of arrival of job offers in the unemployment and employment states are given by

[37] Our preliminary test on the data confirm the existence of such concern: among 490 individuals who report both reservation wage during unemployment and their wages in the first jobs, only 240 of them find jobs with realized hourly wage higher than their previous reported reservation wages.

$$\begin{aligned} \lambda_U(i) &= \exp(z_i \gamma_{\lambda_U}) \\ \lambda_E(i) &= \exp(z_i \gamma_{\lambda_E}), \end{aligned}$$

and the rate of exogenous job dissolution is

$$\eta(i) = \exp(z_i \gamma_\eta).$$

In terms of the productivity distribution, recall that the productivity of an individual with time-invariant ability a and job-match ability θ is given by

$$y = a \times \theta.$$

We have assumed that θ has a lognormal distribution and that the mean of θ is one for all individuals.[38] In this case

$$E(y|a) = a,$$

and

$$\begin{aligned} Var(y|a) &= a^2(E\theta^2 - 1) \\ &= a^2(\exp(\sigma_\theta^2) - 1). \end{aligned}$$

For individual match-invariant heterogeneity a, which is restricted to be positive, we set

$$a(i) = \exp(z_i \gamma_a), \tag{16}$$

and we parameterize the variance of the match distribution for individual i as

$$\sigma_\theta^2(i) = \exp(z_i \gamma_{\sigma_\theta^2}).$$

Then $a(i)$ measures the mean productivity of individual i across matches, and $\sigma_\theta^2(i)$ is a

[38] Typically the lognormal is parameterized in terms of μ and σ^2, where $\ln\theta$ is distributed as a normal with mean μ and variance σ^2. In this case, $E\theta = \exp(\mu + 0.5\sigma^2)$, which under our normalization means that $\mu = -0.5\sigma^2$. Because the variance of the lognormal is $Var(\theta) = [\exp(\sigma^2) - 1]\exp(2\mu + \sigma^2)$, upon substitution we have that

$$Var(\theta) = \exp(\sigma^2) - 1.$$

measure of the dispersion in the productivity values. Because bad matches can be rejected, it is well known that the welfare of individuals and firms is increasing in $\sigma_\theta^2(i)$.

In some sense, we are most interested in the impact of personality characteristics on the Nash-bargaining weight α. Because $\alpha \in (0,1)$, we assume

$$\alpha(i) = \frac{\exp(z_i \gamma_\alpha)}{1 + \exp(z_i \gamma_\alpha)}.$$

Note that we have written all heterogeneous parameters in terms of the same vector z_i. We do not require any exclusion restrictions to identify the respective γ_j vectors due to the nonlinearity of the likelihood function in terms of the various components. In terms of the log likelihood function $\ln L$, note that the FOCs for each parameter can be written in a simple manner. For example, consider the parameter $a(i)$. The partial of the $\ln L$ with respect to the parameter vector γ_a for individual i is given by

$$\begin{aligned}\frac{\partial \ln L_i}{\partial \gamma_a} &= \frac{\partial \ln L_i}{\partial a(i)} \frac{\partial a(i)}{\partial \gamma_a} \\ &= \frac{\partial \ln L_i}{\partial a(i)} \times \exp(z_i \gamma_a) \times z_i'.\end{aligned}$$

As mentioned above, it is typically most difficult to obtain precise estimates of α in a homogeneous stationary search setting. In this case, the partial of $\ln L_i$ with respect to γ_α is

$$\begin{aligned}\frac{\partial \ln L_i}{\partial \gamma_\alpha} &= \frac{\partial \ln L_i}{\partial \alpha(i)} \frac{\partial \alpha(i)}{\partial \gamma_\alpha} \\ &= \frac{\partial \ln L_i}{\partial \alpha(i)} \times \exp(z_i \gamma_\alpha)[1 - \exp(z_i \gamma_\alpha)] \times z_i'.\end{aligned}$$

In terms of the first order conditions associated with γ_a and γ_α, we have

$$\frac{\partial \ln L}{\partial \hat{\gamma}_a} = 0 = \sum_{i=1}^{N} \frac{\partial \ln L_i}{\partial a(i)} \times \exp(z_i \hat{\gamma}_a) \times z_i'$$

and

$$\frac{\partial \ln L}{\partial \hat{\gamma}_\alpha} = 0 = \sum_{i=1}^{N} \frac{\partial \ln L_i}{\partial \alpha(i)} \times \exp(z_i \hat{\gamma}_\alpha)[1 - \exp(z_i \hat{\gamma}_\alpha)] \times z_i'.$$

We can see that the lack of linear dependence between $\frac{\partial \ln L}{\partial \hat{\gamma}_a}$ and $\frac{\partial \ln L}{\partial \hat{\gamma}_\alpha}$ arises both due to the difference in the mapping from the structural parameter into the log likelihood, $\frac{\partial \ln L_i}{\partial a(i)}$ and $\frac{\partial \ln L_i}{\partial \alpha(i)}$, and due to the differences in the mapping from z_i into each structural parameter, here represented by the difference in $\exp(z_i\hat{\gamma}_a) \times z_i'$ and $\exp(z_i\hat{\gamma}_\alpha)[1 - \exp(z_i\hat{\gamma}_\alpha)] \times z_i'$.

Some of the first order conditions have the same mappings from z_i into the structural parameter, such as $a(i) = \exp(z_i\gamma_a)$ and $\lambda_U(i) = \exp(z_i\gamma_{\lambda_U})$, but in these cases there remain the differences in $\frac{\partial \ln L_i}{\partial a(i)}$ and $\frac{\partial \ln L_i}{\partial \lambda_U(i)}$. All of the first order conditions are linearly independent as long as cross-products matrix $N^{-1}\sum_{i=1}^{I} z_i' z_i$ is of full-rank. Identification is achieved through functional form assumptions imposed by the search and bargaining framework and our auxiliary assumptions regarding the mappings from the observed heterogeneity z_i into each of the structural parameters.

5 Model Estimates

5.1 Comparing alternative bargaining assumptions

As previously noted, we estimate a job search model that allows for on-the-job offers. We consider two different modeling assumptions on how firms bargain with workers to set wages. In the first model, when a worker receives a wage offer from an outside firm, the current firm can bargain with the worker and increase the wage to retain the worker. In the second model, firms cannot confirm the existence of outside offers and the only way a worker can increase the wage is by switching jobs. In this section, we compare estimates obtained from both the renegotiation and the no-renegotiation specifications. These are the specifications with individual heterogeneity, so the parameters are individual-specific. The table reports means across individuals by gender.

The results are presented in Table 5. Comparing the two sets of estimates, there are substantial differences in the estimated job arrival rates λ_U and λ_E and in the bargaining parameter α. Specifically, when allowing for renegotiation, the arrival rates of unemployed workers is 1.298 for men and 1.261 for women, and the arrival rates for employed men and women are 0.060 and 0.100. These estimates are substantially larger than their corresponding values for the model without renegotiation. On the other hand, the estimated values of α are only 0.18 for men and 0.15 for women in the model with renegotiation, which are much lower than the estimated α for the model without renegotiation (0.48 for men and 0.37 for women).

The low estimated value of the surplus division parameter α in the model that allows for renegotiation is a common finding reported in the literature (Cahuc et al. (2006); Bartolucci (2013); Flinn and Mullins (2015)). Under the renegotiable contract framework, the worker's share of surplus is determined by both the surplus division parameter α and the on-the-job contact rate λ_E. A worker gets all the surplus from the match $w = a\theta$ in two extreme cases, when either $\alpha = 1$ or $\lambda_E \to +\infty$. Therefore, although the surplus division parameter is smaller in the specification with renegotiation, the share of the surplus could increase over the job spell as firms compete with other potential employers.

Lastly, our estimates indicate lower estimates of ability parameters in the specification with renegotiation than for the specification without renegotiation. The parameter values are a are 8.252 for men and 6.497 for women in the former case and 12.073 and 11.173 in the latter case. This is to be expected. In the renegotiation case, the workers' outside option is the full surplus of first job when bargaining for the initial wage at the second job. This outside option is larger than the value of unemployment, which corresponds to the outside option in the no renegotiation framework. Therefore, smaller values of ability a are needed in the model with renegotiation to generate a second job wage distribution that is similar to that generated under the no renegotiation framework.

We now start to compare the goodness-of-fit between the no-renegotiation specification and the renegotiation specification. As these two specifications are non-nested, we would apply the likelihood ratio tests for model selection proposed by Vuong (1989). Given the (log) likelihood value is -38,872 for the renegotiation specification and -36,298 for the no-renegotiation specification, the Vuong test is in favor of the no-renegotiation specification as the model closer to the true data generating process. Therefore, we can conclude the no-renegotiation specification exhibits a better fit than the renegotiation specification.

We find the better performance of the no-renegotiation specification is mainly due to its better prediction on wage distribution rather than the distributions of unemployment/employment spells. As both specifications generate efficient mobility from job-to-job, it is not surprise that both model specifications replicates the distributions of unemployment/employment spells reasonably well.[39] However, the no-renegotiation specification has much better prediction on wage distribution compared with the renegotiation specification. Figure 3 compares the model fits for both specifications of the bargaining process in terms of wage distributions of the first and second jobs. The top and bottom left panels show the fit of the model without renegotiation to the wage data for the first and second jobs. The top and bottom right panels shows the fit of the model with renegotiation to the same data. It is clear that the model without renegotiation fits the data better, particularly with regard to the first job wage distribution.

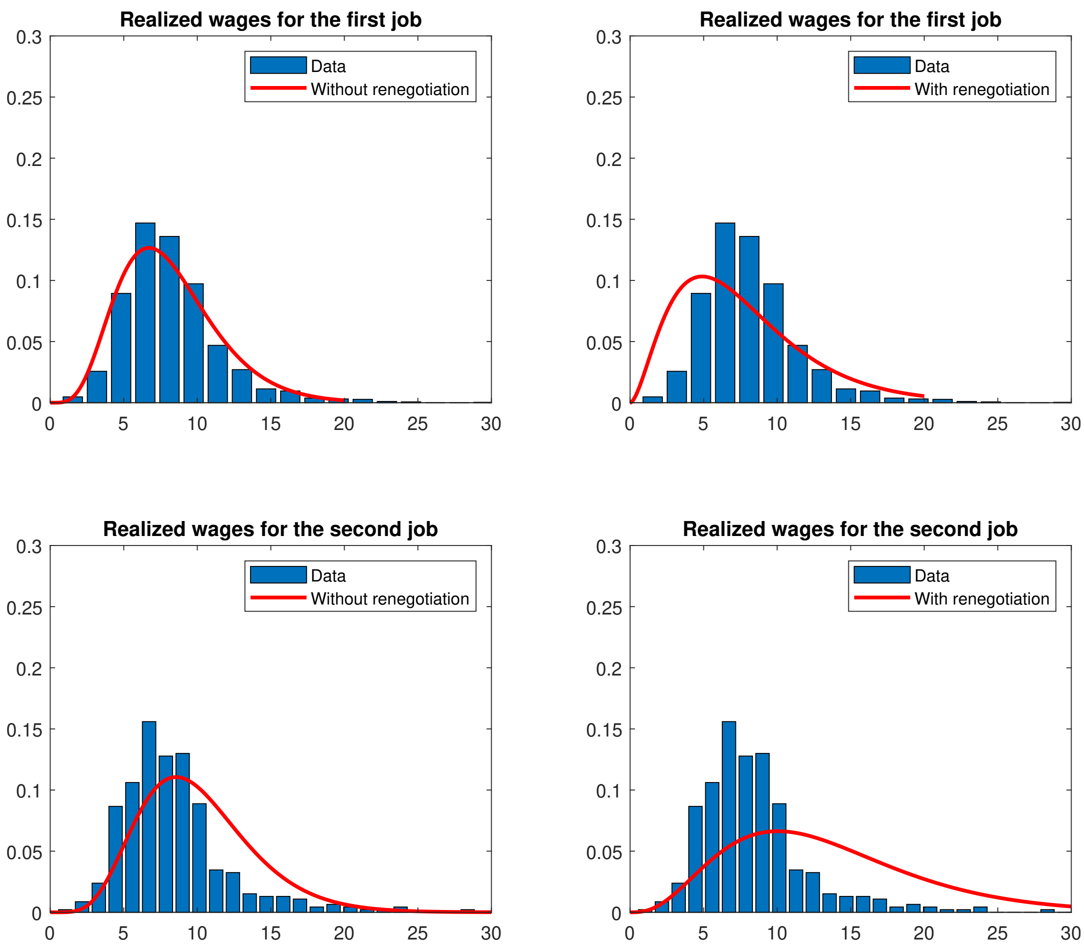
[39] See A.4.1 for a detailed comparison on distributions of unemployment spells/job spells.

Table 5: Parameter estimates under alternative bargaining assumptions

Parameter	Description	With renegotiation		Without renegotiation	
		Male	Female	Male	Female
a	time-invariant ability	8.252	6.497	12.073	11.173
		(1.208)	(0.752)	(1.076)	(1.185)
λ_u	offer arrival rate, in unemployment	1.298	1.261	0.256	0.213
		(0.207)	(0.545)	(0.025)	(0.048)
λ_e	offer arrival rate, in employment	0.060	0.100	0.044	0.070
		(0.008)	(0.029)	(0.007)	(0.015)
η	separation rate	0.031	0.026	0.027	0.027
		(0.004)	(0.010)	(0.005)	(0.007)
α	surplus division	0.177	0.150	0.484	0.370
		(0.049)	(0.055)	(0.045)	(0.052)
b	flow utility when unemployed	0.967	1.088	-1.186	-0.390
		(0.120)	(0.058)	(0.171)	(0.099)
σ_θ	$\theta \sim \log N\left(-\frac{\sigma_\theta^2}{2}, \sigma_\theta\right)$	0.413	0.408	0.324	0.349
		(0.013)	(0.012)	(0.016)	(0.019)
σ_ϵ	$\epsilon \sim \log N\left(-\frac{\sigma_\epsilon^2}{2}, \sigma_\epsilon\right)$	0.444	0.438	0.298	0.321
		(0.028)	(0.028)	(0.032)	(0.035)
N		4,049		4,049	
$\log L$		-38,872		-36,298	
Vuong test (p-value)				2.169e-60	

NOTES: Asymptotic standard errors in parentheses. Data: IZA Evaluation Dataset. The location parameter of match quality distribution μ_θ is predetermined to be $-0.5\sigma_\theta^2$. The comparion between the model with renegotiation and the model without renegotiation is based on the Vuong statistics (Vuong (1989)).

Figure 3: Observed and simulated wage distributions



The simulation from the model with renegotiation predicts lower initial wages compared with the data. The wage growth from first job to second job (€7.19/h to €12.45/h) predicted from the renegotiation model is much larger the wage growth observed in the data (€8.27/h to €8.49/h). The wage growth predicted from the no-renegotiation model (€8.14/h to €10.04/h) provides a better fit. This result is consistent with similar findings concerning these two types of specifications reported in Flinn and Mullins (2015).[40] Given that the model without renegotiation provides a substantially better fit, the remainder of our quantitative analysis will be based on that specification.

5.2 Estimated model parameters under alternative specifications

Given many previous papers differentiates search parameters by gender (e.g. Bowlus (1997), Bowlus and Grogan (2008), Flabbi (2010a), Liu (2016), Morchio and Moser (2020), Amano-Patino et al. (2020)), we would estimate three nested models varying degrees of heterogeneity to explore whether the incorporation of the heterogeneity beyond gender does statistically improve the model performance or not. The estimates are reported in Table 6. In specification (1), all parameters are assumed to be homogeneous for men and women. In specification (2) we allow the parameters to differ for men and women but assume homogeneity within gender. In specification (3), we allow the parameters to be heterogeneous across individuals in a way that may depend on individual characteristics (e.g. education, personality) as well as gender.

The results under column (3) in Table 6 indicate that men and women have different labor market parameters. The unemployment job arrival rate (λ_U) is estimated to be lower for women, which implies lower job finding rate and longer unemployment spells. On the other hand, the on-the-job arrival rate λ_E is higher for women. The job separation rates η are estimated to be similar for men and women.

Any productivity gap is captured by the ability parameters a.[41] Our results show the female productivity is 11.17 in comparison to 12.07 for men, which contributes to the gender wage gap. The productivity gap is 8%, which is smaller than the gap found in other studies (using other datasets). For example, Bowlus (1997) finds the productivity of females is 17% lower using NLSY79 data. Flabbi (2010a) finds a 21% differential in average productivity

[40] In that paper, which uses SIPP data, the wage for low-schooling workers increases from \$13.06/h to \$14.47/h from time 0 to time 1. The predicted increase from a no renegotiation model is from \$14.12/h to \$15.45/h but it is from \$12.26/h to \$18.18/h using a renegotiation model.

[41] Total productivity is $y = a \times \theta$. We have set the location parameter of the match value distribution to be $\mu = -0.5\sigma_\theta^2$ so that $E[\theta] = 1$. Therefore, $E[y] = E[a\theta] = E[a]$.

using CPS data.[42]

In terms of the surplus division parameter α, we find the value for men is 0.484 and the value for women is 0.370. The estimated values are fairly consistent with papers using similar models in the literature. 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 0.421 across genders. Flinn and Mabli (2009) use US employee-level data and find the overall bargaining power is around 0.45.

The two bottom lines of table 6 report p-values for likelihood ratio (LR) tests where we test specification (2) against specification (1) and also test specification (3) against specification (2). The heterogeneous model nests the two homogeneous specifications. The tests reject the homogeneous specifications in favor of the heterogeneous model (3).

6 Understanding the role of personality traits in a job search model

6.1 Understanding the role of personality traits in determining model parameters

In this section, we examine how education and personality traits affect job search parameters $\{\lambda_U, \lambda_E, \eta, \alpha, a\}$. In Table 7, we present the estimates for the model that allows for individual heterogeneity and for different model coefficients for men and women. This model allows us to explore the channels through which education, birth cohort and personality traits influence wage and employment outcomes. For men and women, education increases the unemployment job offer arrival rate. Education decreases the on-the-job offer arrival rate for women. It lowers the job separation rate for both men and women, with a much larger effect for women. As would be expected, education increases ability for both genders. With regard to the bargaining parameter, education increases the bargaining parameter for men but lowers it for women.

As seen in Table 7, many of the personality traits are statistically significant determinants of job search parameters. However, they sometimes affect men and women in different ways. For women, emotional stability increases job offer arrival rates, lowers the job separation rate, and enhances productivity. For men, emotional stability increases job offer arrival

[42]As was noted in the data section, the wages reported in our sample are net wages (wages net of income tax, social security tax and health insurance).

Table 6: Parameter estimates under alternative heterogeneity specifications

Parameter	Description	(1) homogeneous	(2) homogeneous within gender		(3) All heterogeneity included	
		Combined	Male	Female	Male	Female
a	time-invariant ability	10.799	12.644	10.609	12.073	11.173
		(1.176)	(2.714)	(2.071)	(1.076)	(1.185)
λ_U	offer arrival rate, in unemployment	0.231	0.251	0.201	0.256	0.213
		(0.005)	(0.006)	(0.005)	(0.025)	(0.048)
λ_E	offer arrival rate, in employment	0.053	0.043	0.068	0.044	0.070
		(0.002)	(0.002)	(0.002)	(0.007)	(0.015)
η	separation rate	0.027	0.027	0.026	0.027	0.027
		(0.000)	(0.001)	(0.001)	(0.005)	(0.007)
α	surplus division	0.456	0.425	0.424	0.484	0.370
		(0.114)	(0.154)	(0.155)	(0.045)	(0.052)
b	flow utility when unemployed	-0.316	-0.912	-0.445	-1.186	-0.390
		(0.038)	(0.363)	(0.206)	(0.171)	(0.099)
σ_θ	$\theta \sim \log N\left(-\frac{\sigma_\theta^2}{2}, \sigma_\theta\right)$	0.339	0.322	0.321	0.324	0.349
		(0.034)	(0.027)	(0.027)	(0.016)	(0.019)
σ_ϵ	$\epsilon \sim \log N\left(-\frac{\sigma_\epsilon^2}{2}, \sigma_\epsilon\right)$	0.339	0.322	0.321	0.298	0.321
		(0.067)	(0.054)	(0.055)	(0.032)	(0.035)
N		4,049	4,049		4,049	
$\log L$		-36,597	-36,492		-36,298	
LR tests			(1)&(2)		(2)&(3)	
P-value			0.000		0.000	

NOTES: Asymptotic standard errors are reported in parentheses. Data: IZA Evaluation Dataset. The first likelihood ratio (LR) test tests the current specification test against the previous specification (e.g. (2) against (1)). The monthly discount rate is set at 0.005. We impose an assumption on the location parameter of the match value distribution $\mu_\theta = -0.5\sigma_\theta^2$.

rates while employed, lowers the job separation rate, and increases productivity. Openness to experience has no statistically significant effect on any of the parameters for either men or women.

Conscientiousness increases the unemployment job offer rate and lowers the job separation rate for both men and women. It also increases the employed job offer arrival rate for women. In terms of productivity, conscientiousness augments productivity for men but lowers it for women.

Agreeableness is another trait that affects men and women in different ways. For both men and women, agreeableness lowers the unemployment job offer arrival rate. It enhances productivity for women but lowers productivity for men. Lastly, agreeableness has a big negative effect on the bargaining parameter for women. Extraversion generally increases job offer arrival rates and job separation rates for both men and women, with no significant effect on productivity or bargaining.

The job search model we estimate is stationary and we therefore do not condition on initial time-varying state space elements (such as labor market experience). However, we do include birth cohort indicator variables as a potential source of heterogeneous labor market parameters to capture possible differences in the labor markets for older and younger workers. As seen in the bottom rows of Table 7, older workers experience lower job offer arrival rates, with the age penalty being larger for women. Workers who are age 35-44 (birth cohort 63-72 in 2007) have the lowest job destruction rate relative to younger or older workers. Age does not have a statistically significant effect on productivity or bargaining.

6.2 Wage gap decomposition

In Table 8, we examine which channels of the model contribute most to explaining the gender wage gap. To generate the table, we simulate outcomes under the heterogeneous specification (specification (3) in Table 5) and then perform additional simulations where we set a subset of the coefficients for women equal to those estimated for men. For example, we ask what the outcomes would look like for women if they had the same labor force transition parameters $(\lambda_U, \lambda_E, \eta)$, surplus parameters (α), and productivity parameters (a, σ_θ) as men. We also perform a simulation where we give women all of the estimated parameter values for men. In these simulations, women retain their characteristics (e.g. education, personality traits, birth cohort), but we change the way these characteristics are valued in the labor market.

As can be seen in Table 8, giving females all of the male parameters ("All parameters,

Table 7: Other parameters in specification (3): Individual heterogeneity with gender-specific model coefficients

	$\log \lambda_U$		$\log \lambda_E$		$\log \eta$		$\log a$		$\log\left(\frac{\alpha}{1-\alpha}\right)$	
	Male	Female	Male	Female	Male	Female	Male	Female	Male	Female
Cons.	-1.548	-1.821	-3.318	-3.519	-3.076	-3.200	2.274	2.190	0.621	0.940
	(0.112)	(0.092)	(0.234)	(0.117)	(0.213)	(0.132)	(0.099)	(0.100)	(0.375)	(0.260)
Edu	0.062	0.335	0.021	-0.386	-0.039	-0.418	0.142	0.162	0.098	-0.199
	(0.037)	(0.040)	(0.067)	(0.071)	(0.057)	(0.065)	(0.043)	(0.081)	(0.207)	(0.235)
Stb	-0.012	0.027	0.129	0.079	-0.118	-0.066	0.032	0.026	-0.116	-0.053
	(0.014)	(0.012)	(0.029)	(0.024)	(0.024)	(0.022)	(0.019)	(0.014)	(0.094)	(0.042)
Opn	0.007	0.016	0.024	0.019	-0.034	0.004	0.006	0.016	0.045	0.011
	(0.015)	(0.011)	(0.031)	(0.021)	(0.026)	(0.026)	(0.021)	(0.011)	(0.100)	(0.033)
Cos	0.046	0.020	-0.022	0.073	-0.071	-0.022	0.043	-0.041	0.032	-0.016
	(0.019)	(0.015)	(0.037)	(0.022)	(0.030)	(0.030)	(0.016)	(0.015)	(0.093)	(0.042)
Agr	-0.057	-0.050	-0.036	-0.003	-0.020	-0.023	-0.036	0.045	-0.059	-0.168
	(0.014)	(0.014)	(0.033)	(0.024)	(0.028)	(0.031)	(0.022)	(0.014)	(0.103)	(0.035)
Ext	0.054	0.049	-0.015	0.047	0.124	0.043	-0.008	-0.002	-0.068	-0.055
	(0.019)	(0.013)	(0.032)	(0.026)	(0.027)	(0.028)	(0.023)	(0.015)	(0.103)	(0.042)
Cohort (Omitted cat: 73-82)										
63-72	-0.045	-0.156	-0.052	-0.050	-0.133	-0.279	0.038	0.022	-0.080	-0.025
	(0.036)	(0.035)	(0.064)	(0.060)	(0.060)	(0.071)	(0.043)	(0.027)	(0.182)	(0.079)
52-62	-0.096	-0.163	-0.071	-0.062	0.117	0.108	-0.012	-0.024	-0.066	0.048
	(0.036)	(0.037)	(0.075)	(0.059)	(0.063)	(0.067)	(0.046)	(0.039)	(0.197)	(0.142)

NOTE: This table reports gender-specific estimated coefficients of education and personality traits in specification (3). Asymptotic standard errors using numerical scoring function are reported in parentheses. Data: IZA Evaluation Dataset.

Total") fully explains the gap in offered and accepted wages. Looking at the rows "All parameters, Education" and "All parameters, Personality," we see that giving women the male coefficients associated with education has almost no effect on the wage gap relative to the baseline. The main area in which women are being rewarded less is for their personality traits. Giving females the estimated male coefficients associated with personality traits would completely eliminate the wage gap.

The bottom three panels of the Table 8 examine which of the separate components of the model contributes most to wage gaps. With regard to productivity, as seen in Table 6, women were rewarded differently for their personality traits than men, but the overall net effect of gender differences in education coefficients or in personality coefficients in explaining the wage gap is minor. Overall, gender differences in the estimated productivity parameters are not an important channel.

On the other hand, differences in the surplus division parameters account for a significant portion of the wage gap. If women's personality traits were valued in the same way as men's, then they would have higher bargaining power and the wage gap would be eliminated. Women with higher education are also at a slight disadvantage relative to men in terms of bargaining.

Lastly, with regard to labor market transition parameters, giving women the same job offer arrival rate and job dissolution rate parameters as men also helps to some extent to explain the wage gap. However, this channel is not nearly empirically as important as is the surplus division channel.

These decompositions show that the area in which women appear to be at a significant disadvantage is with regard to bargaining. More educated women and more agreeable women, in particular, have substantially lower bargaining parameters.

To further examine which personality trait matters most for each model channel, we perform the same decompositions as in Table 8 except now setting the female parameters associated with different personality traits equal to the male estimated parameters (across all model channels and separately by channel). Table 9 reports the difference between the resulting simulated gender wage ratio and the wage ratio in the baseline model (0.863). A positive value means men are being rewarded more (or penalized less) for that trait. As seen in the column (1), differences in the estimated parameters associated with conscientiousness and agreeableness emerge as two most important traits in explaining the gender wage gap, but they affect the gender wage gap in opposite ways. Men are more highly rewarded for conscientiousness than are women (primarily through the productivity channel), which widens the wage gap. With regard to agreeableness, both men and women receive a

Table 8: How the gender wage gap changes when women's coefficients are set equal to those of men

Women/Men Ratio Generated by	Offered wage	Accepted wage
Baseline	0.859	0.863
All parameters		
-Constant	0.878	0.871
-Personality	1.096	1.084
-Education	0.853	0.856
-Total	1.001	0.993
Productivity (a, σ)		
-Constant	0.946	0.945
-Personality	0.846	0.852
-Education	0.853	0.857
-Total	0.933	0.933
Surplus division (α)		
-Constant	0.790	0.788
-Personality	1.032	1.046
-Education	0.894	0.900
-Total	0.985	0.996
Transitions $(\lambda_U, \lambda_E, \eta)$		
-Constant	0.879	0.881
-Personality	0.906	0.890
-Education	0.840	0.841
-Total	0.868	0.853

Notes: We calculate the counterfactual women/men wage ratio when setting the female parameters associated with a subset of the coefficients equal to the male estimated parameters. Meanwhile, other parameter values remain as female values.

Table 9: Wage differential decomposition by each trait and channel

	All channels	Surplus division	Transitions	Productivity
“Big-five”’ in total	0.236	0.181	0.045	-0.015
Emotional stability	-0.021	-0.051	0.010	0.019
Openness to experience	0.010	0.044	0.015	-0.042
Conscientiousness	0.795	0.073	0.066	0.551
Agreeableness	-0.219	0.148	-0.003	-0.307
Extraversion	-0.071	-0.013	-0.035	-0.021

Notes: We calculate the counterfactual women/men accepted wage ratio setting the the female parameters associated with different personality traits equal to the male estimated parameters (across all channels of the model and separately). The table reports the deviation of counterfactual wage ratios from the baseline model ratio (0.863).

Table 10: How agreeableness affects surplus parameters α by gender

	Male		Female	
Agreeableness	α	Proportion	α	Proportion
(0,3]	0.471	0.044	0.405	0.056
[3,4)	0.476	0.175	0.381	0.141
[4,5)	0.484	0.318	0.373	0.273
[5,6)	0.487	0.294	0.365	0.311
[6,7)	0.493	0.146	0.364	0.180

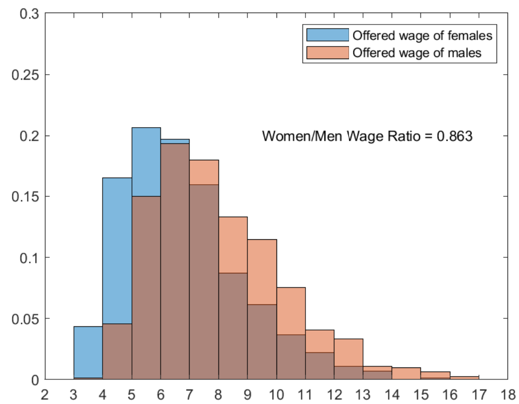
bargaining penalty for being agreeable (see column (2)). However, the penalty is greater for women. Concomitantly, men receive a productivity penalty for agreeableness that women do not experience. On net, combining both the surplus division and the productivity channels, differences in the estimated agreeableness parameters reduce the gender wage gap.

Table 10 examines how the bargaining surplus parameters vary with agreeableness, separately by gender. Recall from Table 1 that the mean value of agreeableness is 5.19 for the male sample and 5.51 for the female sample. As can be seen in Table 10, the male bargaining parameter is relatively insensitive to changes in agreeableness and is on average 0.5. In contrast, the female bargaining parameter estimates are much lower and vary over a wider range (0.36-0.41). Thus, agreeableness affects bargaining for women but not much for men.

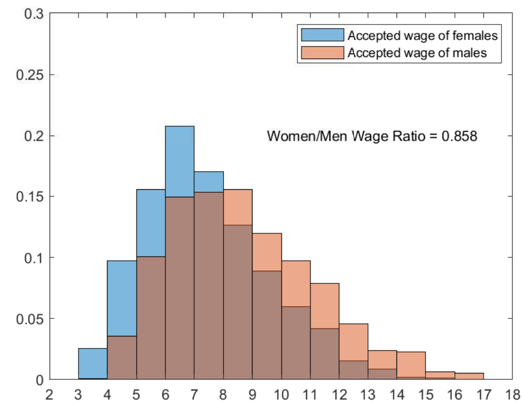
Figure 4 shows the offered wage and accepted wage distributions for both the baseline and the counterfactual “equal pay experiment” in which women were paid according to the male labor marker parameters. In the baseline model (upper panel), the female wage distribution is more left-skewed than male wage distribution. Offered wages and accepted wages are lower for women than for men. However, the wage gap is totally eliminated under the simulation that gives women the estimated model parameters for men. (bottom panel).

Figure 4: Distributions of accepted wages and offered wages

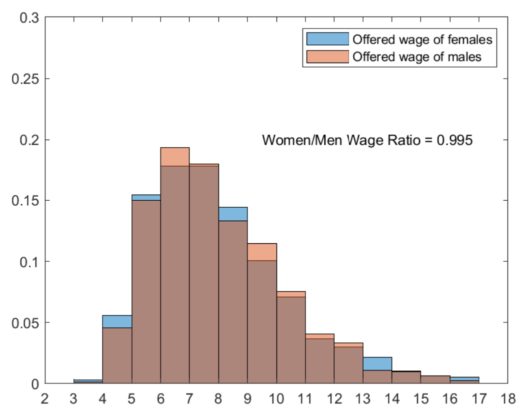
(a) Offered wages in baseline model



(b) Accepted wages in baseline model



(c) Offered wages under equal parameters



(d) Accepted wages under equal parameters

Table 11: The effects of personality traits on search efforts (by gender)

Outcome variable:	Male		Female	
Arrival rates/Num. of Application	(1)log λ_U	(2)Num	(3)log λ_U	(4)Num
Higher level secondary degree	0.062	2.980	0.335	0.363
	(0.037)	(1.277)	(0.040)	(0.937)
Emotional Stability	-0.012	0.167	0.027	0.283
	(0.014)	(0.538)	(0.012)	(0.378)
Openness to experience	0.007	0.442	0.016	0.702
	(0.015)	(0.545)	(0.011)	(0.387)
Conscientiousness	0.046	2.168	0.020	2.305
	(0.019)	(0.745)	(0.015)	(0.604)
Agreeableness	-0.057	-0.394	-0.050	-1.097
	(0.014)	(0.629)	(0.014)	(0.509)
Extraversion	0.054	1.052	0.049	0.498
	(0.019)	(0.613)	(0.013)	(0.448)

Notes: The sample includes unemployed workers age 25 to 55. Standard errors in parentheses.

6.3 External validations

In Table 11, we explore how education and personality traits affect job search effort, as measured by the number of job applications. The information on numbers of job applications was not used in estimating the model. However, numbers of applications is likely to be a key factor underlying individual heterogeneity in job offer arrival rates.

As seen in Table 11, having a higher education level is associated with a greater number of applications, but only for males. Conscientiousness appears to be the most important personality trait that increases numbers of applications for both men and women. Agreeableness is associated with fewer job applications for both men and women. For comparison purposes, columns (1) and (3) show the estimates that were previously reported in Table 6 for the unemployment job offer arrival rate. They are largely consistent with the regression results shown in columns (2) and (4) in terms of signs and statistical significance, which suggests that heterogeneous job arrival rates may in part reflect differing numbers of job applications.

7 Conclusions

We have developed and estimated a job search model to investigate how individual heterogeneity in education, personality and other dimensions affect labor market outcomes for men and women. We considered two modeling frameworks that differed in terms of whether firms renegotiate wage offers from competing firms. We also considered three alternative model specifications that varied in the degree to which they accommodated individual parameter heterogeneity.

When considering the two modeling frameworks that differ in assumptions on whether firms renegotiate wages, we find that the model that does not allow for renegotiation provides a better fit to the data (even though the models are not formally nested). With regard to parameter heterogeneity, specification tests reject the more restrictive models in favor of the most general model that allows job search parameters to be heterogeneous across individuals and by gender. There is strong evidence that heterogeneity is an important feature of the data.

The estimates for the heterogeneous model show that there are statistically significant differences in the labor market parameters for men and women. Education and personality traits are important determinants of productivity, bargaining and job offer arrival rates for both genders, but the attributes are valued in different ways for men and women.

Our decomposition results showed that women are not less productive than men. Women and men receive a similar productivity premium for their education. Personality traits, on the other hand, are valued differently in terms of productivity. Men receive a high return for conscientiousness that women do not receive and also a slightly higher return for emotional stability. However, they receive a large productivity penalty for agreeableness that women do not receive. Despite there being differences in the estimated coefficients associated with personality traits by gender, the overall net effect of coefficient differences operating through the productivity channel turns out to be minimal.

Our accounting of how different channels of the model contribute to gender wage gaps showed that differences in the estimated bargaining surplus parameters is the single-most important channel. Women who have higher education levels and/or high levels of agreeableness experience large penalties in terms of bargaining. Gender differences in labor market transitions due to different job offer arrival and job destruction rates contributes to the wage gap to a much lesser extent.

When we assess the contribution of different personality traits one by one to explaining the gender wage gap, as they operate simultaneously through all model channels, we find that differences in the estimated coefficients associated with conscientiousness and agreeableness emerge as the most important determinants of gender wage gaps. The fact that men receive a significant productivity premium for conscientiousness serves to widen the gender wage gap. With regard to agreeableness, we found that agreeableness is associated with a lower bargaining surplus for both men and women, with a much greater penalty for women. At the same time, though, men experience a productivity penalty for being agreeable that women do not experience. The combined effects of gender differences in estimated agreeableness parameters reduces the gender wage gap.

Our findings suggest that it may be profitable to further explore the origins of these gender differences. For example, Flinn and Mullins (2019) estimate an equilibrium search model in which some firms post wages while other firms bargain with employees over compensation. Their framework assumes individuals meet firms at random; but, if individuals could direct their search to firms or occupations associated with wage posting or bargaining, then women may choose to work in sectors in which wage posting predominates to minimize their bargaining disadvantage. This may be one explanation for the large degree of occupational gender segregation still observed in the labor market, in addition to gender differences in preferences or more direct forms of firm discrimination. Developing and estimating a sectoral model of search may allow us to learn more about the mechanisms behind gender and personality-based labor market segregation that produce persistent differences in observed outcomes.

A Appendices

A.1 Model Solutions

A.1.1 Solving the reservation match quality θ^* with renegotiation

In this appendix, we provide further detail on how to solve for the bargained wage $w(\theta', \theta)$ as well as the reservation match value θ^*.

$$\left(\rho + \eta + \lambda_E \bar{G}(\theta)\right) V_E(\theta', \theta; w) = w + \eta V_U + \lambda_E \int_{\theta}^{\theta'} V_E(\theta', x) dG(x) + \lambda_E \int_{\theta'} V_E(x, \theta') dG(x)$$

We use the bargaining protocol

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

which yields the equivalent expression

(17)

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

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

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

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

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

and the bargained wage has the following expression

$$w(\theta', \theta) = \alpha a \theta'^2 \lambda_E \int_{\theta}^{\theta'} \frac{a \bar{G}(x)}{\rho + \eta + \lambda_E \alpha \bar{G}(x)} dx$$

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

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

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

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

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

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

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

A.1.2 Solving the reservation match value θ^* without renegotiation

We next describe the method for solving the model. First, we need to discretize the continuous θ interval into L grids $\{\theta_1, ..., \theta_L\}$ with probability $\{p_1, ..., p_L\}$. To initialize the algorithm, we set a initial value of unemployment V_U to be equal to ab:

1. Solve the value of employment with match quality $V_E(\theta_L)$ and $w(\theta_L)$.

The state θ_L is an absorbing state, because no further job mobility can take place from that state during the current employment spell. The only way such a spell can end is through exogenous termination, which occurs at the constant rate η.

$$V_E(\theta_L) = \frac{w(\theta_L) + \eta V_U}{\rho+\eta}$$

with the wage

$$w(\theta_L) = a\left(\alpha\theta_L + (1-\alpha)\rho V_U\right)$$

and the implied value of being unemployed (if reservation match value $\theta^* = \theta_L$) is given by

$$\bar{V}_U(\theta^* = \theta_L) = \frac{ab + \lambda_U p_L V_E(\theta_L)}{\rho + \lambda_U p_L}$$

2. Sequentially solve the value of employment with match $V_E(\theta_l)$ and $w(\theta_l)$ as well as $\bar{V}_U(\theta^* = \theta_l)$

Given $(V_E(\theta_{l+1}), ..., V_E(\theta_L))$, solve wage associated with state $w(\theta_l)$ as

$$w(\theta_l) = a\left(\alpha\theta_l + (1-\alpha)\left(\left(\rho + \lambda_E p^+_{l+1}\right)V_U - \lambda_E \sum_{i\geq l+1}^{L} p_i V_E(\theta_i)\right)\right)$$

and the value of employment at an acceptable match value θ_l is given by

$$V_E(\theta_l) = \frac{w(\theta_l) + \eta V_U + \lambda_E \sum_{i\geq l}^{L} p_i V_E(\theta_i)}{\rho + \eta + \lambda_E p^+_l}$$

where the notation $p^+_l = \sum_{i\geq l}^{L} p_i$. And the implied value of being unemployed (if reservation match value $\theta^* = \theta_l$) is given by

$$\bar{V}_U(\theta^* = \theta_l) = \frac{ab + \lambda_U \sum_{i\geq l}^{L} p_i V_E(\theta_i)}{\rho + \lambda_U p^+_l}$$

3. Determine the optimal acceptable match quality θ^*

For all match quality $\{\theta_1, ..., \theta_L\}$, each "potential" acceptable match θ_l implies a unique value of being unemployed given by $\bar{V}_U(\theta^* = \theta_l)$. The optimal acceptance match is the one that produces that highest value of unemployment state, i.e.,

$$j = \arg\max_l \left\{\bar{V}_U(\theta^* = \theta_l)\right\}_{l=1}^{L}$$
$$V_U^{new} = \bar{V}_U(\theta^* = \theta_j), \theta^* = \theta_j$$

4. Stop if $V_U^{new} = V_U$. Otherwise update V_U with the new value V_U^{new}

A.1.3 The likelihood function

Individuals only observed to be unemployed $l^{(1)}$

In this case, $r_U = 1$, and the initial unemployment is incomplete at the time the observation period ends, in which case we say that the unemployment spell is right-censored. The hazard rate out of unemployment is

$$h_{U,j} = \lambda_U \tilde{G}(\theta^*_j), j = \{N, R\}$$

where $\tilde{G} = 1 - G$ is the complementary cumulative distribution function, θ^*_R and θ^*_N are the reservation match value with and without renegotiation, respectively.The density of the complete length of the unemployment spell is

$$f_U(t_U; j) = h_{U,j} \exp(-h_{U,j} t_U)$$

When the unemployment spell is ongoing at the end of the sample period, then we know that the complete spell length is no less than t_U, and the probability of this event is $P(\tilde{t}_U > t_U; j) = \tilde{F}_U(t_U; j) = \exp(-h_{U,j} t_U)$, where $\tilde{F}_U \equiv 1 - F_U$ is the survival function. The likelihood contribution in this case is

$$l^{(1)}(t_U, r_U = 1) = \exp(-h_{U,j} t_U)$$

Individuals with one job spell $l^{(2)}$

Let the match productivity value at the first job be given by θ_1. We estimate the model under two different assumptions regarding the renegotiation of wages between workers and firms, in the case in which the worker has the possibility of working at either of two firms at a particular moment in time. While the wage $w(\theta_1; N)$ is strictly increasing in θ in the case without renegotiation, the bargaining wage $w(\theta_1, \theta_R^*; R)$ created by Bertrand competition may not be monotonic in θ in general. As the function $w(\theta_1, \theta_R^*; R)$ is not 1-1, we define the marginal distribution using the joint density of $\tilde{w}_1$ and θ_1 rather than the joint density of $\tilde{w}_1$ and w_1.[43]

In the first job in an employment spell, the marginal density of θ_1 is simply $g(\theta_1 | \theta_1 \geq \theta_j^*) = \frac{g(\theta_1)}{\tilde{G}(\theta_j^*)}$, $\theta \geq \theta_j^*$, $j = R, N$. Given the value of θ_1 and given the bargaining protocol j, the conditional c.d.f. of $\tilde{w}|w$ is

$$M(\tilde{w}|w) = \Phi\left(\frac{\ln \frac{\tilde{w}}{w} - \mu_\varepsilon}{\sigma_\varepsilon}\right)$$

because $\varepsilon = \frac{\tilde{w}}{w}$ Then, the conditional density of $\tilde{w}$ given w is

$$m(\tilde{w}|w) = \phi\left(\frac{\ln \frac{\tilde{w}}{w} - \mu_\varepsilon}{\sigma_\varepsilon}\right) / (\tilde{w}\sigma_\varepsilon).$$

Because w is a deterministic function, we have

$$f(\tilde{w}_1, \theta_1; j) = m(\tilde{w}_1 | w(\theta_1, \theta_j^*; j)) \times g(\theta_1) / \tilde{G}(\theta_j^*).$$

[43]To simplify the expression, we will write $w(\theta_1; N)$ as $w(\theta_1, \theta_N^*; N)$ in this section.

The marginal density of $\tilde{w}_1$ under bargaining rule j is

$$f(\tilde{w}_1; j) = \int_{\theta_j^*} m(\tilde{w}_1 | w(\theta_1, \theta_j^*; j)) \times g(\theta_1)/\tilde{G}(\theta_j^*) d\theta_1.$$

The likelihood contribution of an individual with a first job that is on-going at the end of the sample period is

$$\begin{aligned}
&l^{(2)}(t_U, \tilde{w}_1, t_1, r_1 = 1; j) \\
&= h_{U,j} \exp(-h_{U,j} t_U) \int_{\theta_j^*} \exp(-h_E(\theta_1) t_1) \times m(\tilde{w}_1 | w(\theta_1, \theta_j^*; j)) \times g(\theta_1)/\tilde{G}(\theta_j^*) d\theta_1,
\end{aligned}$$

where

$$\begin{aligned}
h_{U,j} &= \lambda_U \tilde{G}(\theta_j^*), j = R, N \\
h_E(\theta_1) &= \eta + \lambda_E \tilde{G}(\theta_1),
\end{aligned}$$

The term $h_{U,j}$ is the hazard rate out of unemployment under bargaining protocol j, and $h_E(\theta_1)$ is the "total" hazard rate associated with the first job spell as a function of the match value θ_1. This hazard rate is independent of the bargaining protocol, because both protocols imply efficient mobility. Thus, the likelihood of finding a better job is only a function of the current productivity value θ_1. This expression simplifies to

$$\begin{aligned}
&l^{(2)}(t_U, \tilde{w}_1, t_1, r_1 = 1; j) \\
&= \lambda_U \exp(-h_{U,j} t_U) \int_{\theta_j^*} \exp(-h_E(\theta_1) t_1) m(\tilde{w}_1 | w(\theta_1, \theta_j^*; j)) g(\theta_1) d\theta_1.
\end{aligned}$$

For an individual with a complete first-job spell who enters the unemployment state directly after the first job, the likelihood contribution is

$$\begin{aligned}
&l^{(2)}(t_U, \tilde{w}_1, t_1, r_1 = 0, q_1 = 0; j) \\
&= \lambda_U \exp(-h_{U,j} t_U) \int_{\theta_j^*} \eta \exp(-h_E(\theta_1) t_1) m(\tilde{w}_1 | w(\theta_1, \theta_j^*; j)) g(\theta_1) d\theta_1.
\end{aligned}$$

In this case we do not use information on the second unemployment spell, because this begins a different "employment cycle."

Individuals with two or more job spells $l^{(3)}$

When there exist two or more jobs in the employment spell, we only use information on the first two job spells to reduce the computational burden. Under renegotiation, the wage function in the second job spell also includes the first job match value as an argument, so the bargaining wage is $w(\theta_2, \theta_1; R)$, where θ_2 is the productivity match value for the second job and we have the order $\theta_2 \geq \theta_1 \geq \theta_R^*$ because job-to-job transition is efficient. Under no renegotiation, the first job spell match value has no impact on the bargained wage at the second job, so the bargaining wage is $w(\theta_2; R)$, $\theta_2 \geq \theta_1 \geq \theta_N^*$.

We first consider the case in which the second job spell is right-censored. Because there is efficient mobility, under either bargaining scenario, it must be the case that $\theta_2 \geq \theta_1 \geq \theta_j^*$, $j = R, N$. Without renegotiation, the likelihood is

$$\begin{aligned}
&l^{(3)}(t_U, \tilde{w}_1, t_1, r_1 = 0, q_1 = 1, \tilde{w}_2, t_2, r_2 = 1; N) \\
&= h_{U,N} \exp(-h_{U,N} t_U) \int_{\theta_N^*} \int_{\theta_1} \lambda_E \tilde{G}(\theta_1) \exp(-h_E(\theta_1) t_1) \exp(-h_E(\theta_2) t_2) \\
&\times m(\tilde{w}_1 | w(\theta_1; N)) m(\tilde{w}_2 | w(\theta_2; N)) \frac{g(\theta_2)}{\tilde{G}(\theta_1)} \frac{g(\theta_1)}{\tilde{G}(\theta_N^*)} d\theta_2 d\theta_1,
\end{aligned}$$

which can be simplified as

$$\begin{aligned}
&l^{(3)}(t_U, \tilde{w}_1, t_1, r_1 = 0, q_1 = 1, \tilde{w}_2, t_2, r_2 = 1; N) \\
&= \lambda_U \exp(-h_{U,N} t_U) \lambda_E \int_{\theta_N^*} \int_{\theta_1} \exp(-h_E(\theta_1) t_1) \exp(-h_E(\theta_2) t_2) \\
&\times m(\tilde{w}_1 | w(\theta_1; N)) m(\tilde{w}_2 | w(\theta_2; N)) g(\theta_2) g(\theta_1) d\theta_2 d\theta_1.
\end{aligned}$$

With renegotiation, we have

$$\begin{aligned}
&l^{(3)}(t_U, \tilde{w}_1, t_1, r_1 = 0, q_1 = 1, \tilde{w}_2, t_2, r_2 = 1; R) \\
&= \lambda_U \exp(-h_{U,R} t_U) \lambda_E \int_{\theta_R^*} \int_{\theta_1} \exp(-h_E(\theta_1) t_1) \exp(-h_E(\theta_2) t_2) \\
&\times m(\tilde{w}_1 | w(\theta_2, \theta_1; R)) m(\tilde{w}_2 | w(\theta_2, \theta_1; R)) g(\theta_2) g(\theta_1) d\theta_2 d\theta_1.
\end{aligned}$$

If the second job ends with a transition into unemployment, under no renegotiation the likelihood contribution is

$$\begin{aligned}
&l^{(3)}(t_U, \tilde{w}_1, t_1, r_1 = 0, q_1 = 1, \tilde{w}_2, t_2, r_2 = 0, q_2 = 0; N) \\
&= \lambda_U \exp(-h_{U,N} t_U) \lambda_E \eta \int_{\theta_N^*} \int_{\theta_1} \exp(-h_E(\theta_1) t_1) \exp(-h_E(\theta_2) t_2) \\
&\times m(\tilde{w}_1 | w(\theta_1; N)) m(\tilde{w}_2 | w(\theta_2; N)) g(\theta_2) g(\theta_1) d\theta_2 d\theta_1.
\end{aligned}$$

Under renegotiation, it is

$$
\begin{aligned}
& l^{(3)}(t_U, \tilde{w}_1, t_1, r_1 = 0, q_1 = 1, \tilde{w}_2, t_2, r_2 = 0, q_2 = 0; R) \\
& = \lambda_U \exp(-h_{U,R} t_U) \lambda_E \eta \int_{\theta_R^*} \int_{\theta_1} \exp(-h_E(\theta_1) t_1) \exp(-h_E(\theta_2) t_2) \\
& \times m(\tilde{w}_1 | w(\theta_2, \theta_1; R)) m(\tilde{w}_2 | w(\theta_2, \theta_1; R)) g(\theta_2) g(\theta_1) d\theta_2 d\theta_1.
\end{aligned}
$$

If the second job ends with a transition into another (third) job, under no renegotiation we have

$$
\begin{aligned}
& l^{(3)}(t_U, \tilde{w}_1, t_1, r_1 = 0, q_1 = 1, \tilde{w}_2, t_2, r_2 = 0, q_2 = 0; N) \\
& = \lambda_U \exp(-h_{U,R} t_U) \lambda_E^2 \int_{\theta_N^*} \int_{\theta_1} \exp(-h_E(\theta_1) t_1) \tilde{G}(\theta_2) \exp(-h_E(\theta_2) t_2) \\
& \times m(\tilde{w}_1 | w(\theta_1; N)) m(\tilde{w}_2 | w(\theta_2; N)) g(\theta_2) g(\theta_1) d\theta_2 d\theta_1.
\end{aligned}
$$

Under renegotiation, the likelihood contribution becomes

$$
\begin{aligned}
& l^{(3)}(t_U, \tilde{w}_1, t_1, r_1 = 0, q_1 = 1, \tilde{w}_2, t_2, r_2 = 0, q_2 = 0; R) \\
& = \lambda_U \exp(-h_{U,N} t_U) \lambda_E^2 \int_{\theta_R^*} \int_{\theta_1} \exp(-h_E(\theta_1) t_1) \tilde{G}(\theta_2) \exp(-h_E(\theta_2) t_2) \\
& \times m(\tilde{w}_1 | w(\theta_2, \theta_1; R)) m(\tilde{w}_2 | w(\theta_2, \theta_1; R)) g(\theta_2) g(\theta_1) d\theta_2 d\theta_1.
\end{aligned}
$$

A.2 Sample construction

A.2.1 Obtaining the dataset used in our analysis

In this appendix, we describe the sample restrictions we imposed to obtain the dataset used for our analysis. First, we calculated the exact duration spells of each labor market activities, including unemployment spells and job spells. The monthly unemployment/employment activities are recorded and updated retrospectively during each interview, starting at the last interview or at unemployment entry in case of the first interview. Therefore, we are able to calculate the duration of each of the spells based on the starting dates and ending dates of each activities. Unfortunately, IZA ED only records the months rather than the exact date of each activities. Therefore, we calculate the days of duration based on a randomly assigned the dates within that month. Thus, the spell durations are calculated based on “statistical months rather than calendar months. For example, we calculate the month spell is equal to 1 when the duration is less or equal to 30 days. After we calculate the duration spells of each activities, we convert the data into a panel structure where working information (monthly salary, working hours) as well as personal characteristics are collected for different employment/unemployment spells and different individuals. The raw sample has 62,439 observations. During the sample selection process, we drop individuals for the following reasons:

- We drop the duplicated spells number counted in different waves, reducing the number of observations to 51,334.
- We drop any spells after the fourth spell, which leaves 43,229 observations. (17,395 for the first spells, 13,269 for the second spells, 7,532 for the third spells and 5043 for the fourth spells)
- We drop observations with incorrect/missing starting or ending dates of spells, reducing the observations 37,188. We assume the start year should no early than 2007 and the end year should be no late than 2011.
- We drop the individuals whose activities are out of labor force (e.g. attending school or other activities unrelated to the activities incorporated in our model) or whose unemployment benefit information is missing. These restrictions leave us with 20,012.
- We drop the individuals who ever reported self-employment, which reduces the sample size to 31,111.
- We combine any consecutive unemployment spells across waves into one longer spell, which reduces the observation to 18,367.
- We further drop any individuals missing information on characteristics included in our model: age and gender, educational attainment and personality traits. We further restrict the age of individuals to be between 25 to 55. Our final estimation sample has 4,049 individuals with 7,872 observations, consisting of 4,049 first unemployment spells, 2,267 first job spells, 1,053 second job spells and 503 third job spells.

A.2.2 Personality trait questionnaire

Table A.1: Questions used to measure Big Five personality traits in the IZA ED

The following statements describe different characteristics that a person can possess. Please tell me how much each statement applies to you. 1 means "it does not apply at all" and 7 means "it applies fully". You can gauge your evaluations with in-between values. I am someone who...
1) ... works thoroughly *2) ... is communicative, talkative* *3) ... is sometimes rough to others (starting cohort 9)* *4) ... is inventive, brings new ideas* *5) ... worries often* *6) ... can forgive easily (starting cohort 9)* *7) ... is rather lazy (starting cohort 9)* *8) ... can be an extrovert, sociable* *9) ... places value on artistic experiences (starting cohort 9)* *10) ... becomes nervous easily* *11) ... carries out tasks effectively and efficiently* *12) ... is cautious* *13) ... deals with others in a considerate and friendly way (starting cohort 9)* *14) ... has a vivid fantasy, imagination* *15) ... is relaxed, can work well under stress*
1: does not apply at all ... 7: applies fully, 97: refused, 98: do not know *Note: 5 additional items were added starting with No. 9 (February) cohort)* Each of the personality traits are calculated as the average scores of three items. (The scores of 3, 5, 7, 10, 12 are reversed before calculating the average)
Openness to experience: 4, 9, 14 **Conscientiousness**: 1, 7, 11 **Extraversion**: 2, 8, 12 **Agreeableness**: 3, 6, 13 **Emotional stability (opposite to Neuroticism)**: 5, 10, 15

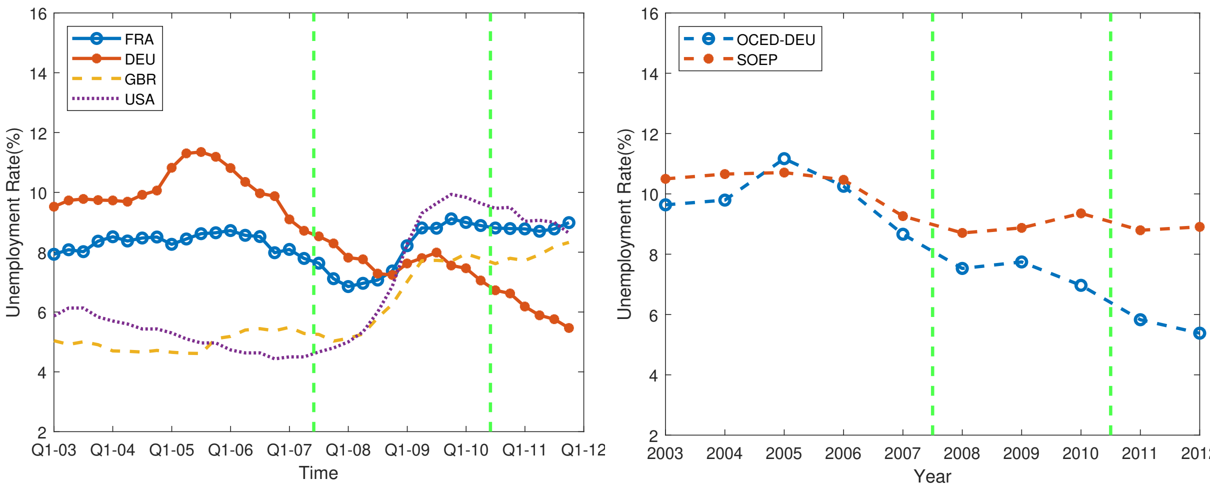
A.3 Additional data results

A.3.1 Testing for the stationarity assumption

We examine the labor market conditions in Germany during the years 2007-2010 when our sample was collected to see if the stationarity assumption is at all plausible. One concern in particular is how the German labor market was affected by the financial crisis of 2007-2008. Figure A.1 shows the unemployment rates for Germany, France, the UK, and the US. The unemployment rate in the US experienced a dramatic increase between 2007-2010 (purple

Figure A.1: The evolution of unemployment rates between year 2002-2013 in Germany, France, UK and US

(a) The evolution of unemployment rate overt time (b) The unemployment rate by different sources



Source: OECD statistics (left panel). OECD statistics and GSOEP (right panel)

dashed line), but the unemployment rates in Germany (DEU) remained much more stable during the same period (solid dotted line). In the right panel, we compare the unemployment rates obtained using two data sources (OECD and GSOEP). The trends are consistent with trends reported in Carrillo-Tudela et al. (2018). Our conclusion is that the stationarity assumption may not be ideal for this period of time in Germany, but that it is much less problematic than it would be if we were using data from the US during this period.

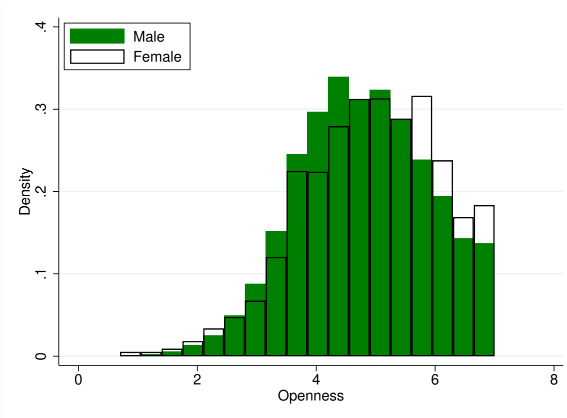
A.3.2 The comparison for personality trait distributions between genders

In Figure A.2, we compare the personality trait distributions for men and women. Although all trait measures defined on a scale of 1 to 7, there are clearly differences in the shape of the distributions across traits and between men and women. The traits conscientiousness and agreeableness exhibit a high degree of skewness. Women are much more likely to rate themselves in the highest categories on openness, conscientiousness, and agreeableness and in the lowest categories on emotional stability.

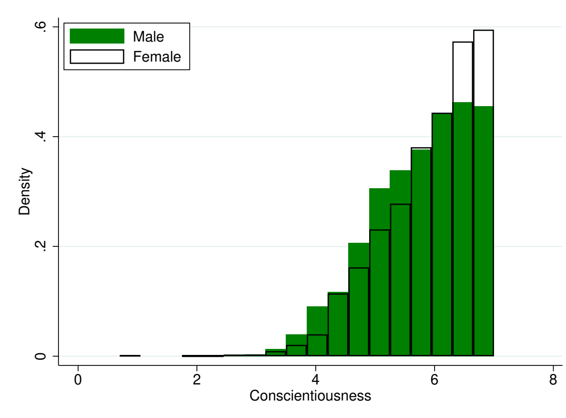
A.3.3 Do measured personality traits vary with labor force status?

Figure A.2: The distributions of “big five” personality traits by genders

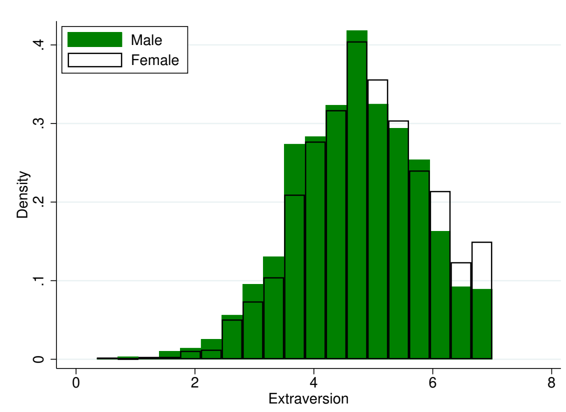
(a) Openness to experience



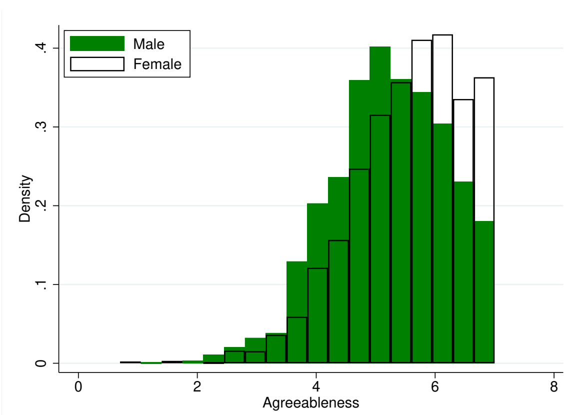
(b) Conscientiousness



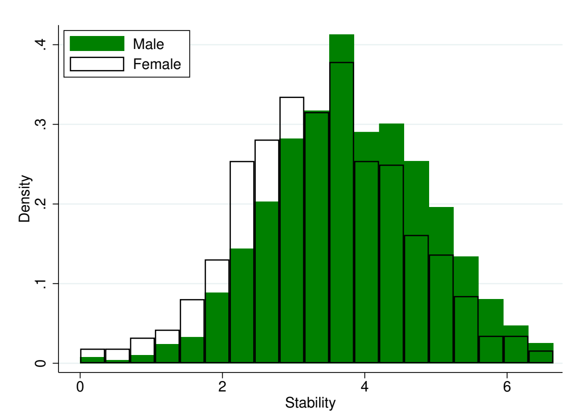
(c) Extraversion



(d) Agreeableness



(e) Emotional Stability



Notes: This figure shows the comparison of of “big five” personality traits by genders. The measures are based on the average scores of individuals between age 25 to 55 who reports their personality traits in all waves, IZA ED.

Table A.2: The effect of employment/unemployment experience on personality traits

Changes between waves	(1) Opn	(2) Cos	(3) Agr	(4) Stb	(5) Ext
Employment experience	0.004	-0.007	0.000	-0.001	-0.006
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Unemployment experience	0.001	-0.001	0.004	0.004	0.008
	(0.007)	(0.007)	(0.006)	(0.007)	(0.006)
Age	0.008	-0.009	0.000	-0.008	0.044
	(0.035)	(0.035)	(0.031)	(0.035)	(0.030)
$Age^2/100$	-0.011	0.012	-0.008	0.010	-0.059
	(0.045)	(0.045)	(0.040)	(0.045)	(0.039)
Constant	-0.268	0.303	0.117	0.138	-0.729
	(0.658)	(0.659)	(0.579)	(0.652)	(0.569)
Observations	1003	1003	1003	1003	1003
R^2	0.001	0.004	0.004	0.001	0.010

NOTE: the sample for this regression consists of individuals whose personality traits are measured both in wave 2 and wave 3. This table reports estimates from regressions of the changes of "big five" personality traits on the indicated variables. Standard errors are reported in parentheses.

A.3.4 Relationship between Big Five personality traits and internal locus of control

As noted in the text, some studies in the literature focus on internal locus of control as a determinant of job search behaviors and outcomes. We therefore examine the correlation between the Big Five measures that we use and the internal locus of control measure (the IZA-Ed database contains all these measures). As seen in Table A2, the internal locus of control measure is positively correlated with all of the Big Five measures except for openness to experience. The strongest correlations are with emotional stability, agreeableness and conscientiousness. Table A3 shows the mean personality trait scores for individuals who are classified by whether their internal locus of control score is above or below the median. Individuals who have a higher than median internal locus of control score have on average higher Big Five scores on all traits.

Table A.3: The correlation between "Big 5" traits and locus of control

	Emot. Stability	Openness to experience	Conscientiousness	Extrav.	Agreeableness	Locus of control
Emotional Stability	1.000					
Openness to experience	0.056	1.000				
Conscientiousness	0.090	0.177	1.000			
Extraversion	0.098	0.154	0.347	1.000		
Agreeableness	0.205	0.353	0.286	0.155	1.000	
Locus of control	0.391	0.096	0.203	0.132	0.271	1.000

Source: IZA Evaluation Data Set, own calculations. Notes: individuals were asked, "The following statements characterize different attitudes towards life and the future. To what extent do you personally agree with these statements? Please answer on the basis of a scale of 1 to 7." The answers include ten items: Q1, Q6 and Q9 measure the internal locus of control index while the rest seven items measure the external index. The final index of LOC is constructed by equation [Q1 + Q6 + Q9 + R(Q2 + Q3 + Q5 + Q7 + Q8 + Q10)]/9, where the notation R represents all external items are reversely coded.

Table A.4: The value of "Big 5" personality traits by locus of control

	LOC indicator			
	External	Internal	Diff	p-value
"Big 5" traits	$N = 2,009$	$N = 1,943$		
Emotional Stability	3.260	4.003	-0.743	0.000
Openness to experience	4.747	4.952	-0.205	0.000
Conscientiousness	5.645	5.900	-0.255	0.000
Agreeableness	5.242	5.454	-0.211	0.000
Extraversion	4.516	5.013	-0.497	0.000

Notes: individuals are classified as being internal if their LOC scores are higher than the median and external otherwise. See notes in table A.3 for the definition of the LOC scores.

A.4 Additional model results

A.4.1 Observed and simulated unemployment spells/job spells

Figure A.3 reports the goodness-of-fit for the observed and simulated unemployment and job spell lengths (on the first and second jobs). The left panels show the histogram for the observed data spells. The top panel shows the length of unemployment spells, the middle panel shows the length of the first job spell, and the bottom panel shows the length of second job spell. The three middle panels show the histograms generated by simulating the model without renegotiation for the same time periods. The right three panels show the histograms for the model with renegotiation.

The first thing to note is the high frequency of short unemployment and employment spells (1 or 2 months). These short spells are mainly censored spells coming from respondents who only participate in the first survey wave. The time lag between unemployment entry and the first interview ranges from 55 to 84 days (around two months). To maintain comparability between the data and the simulations, we impose the same censoring on the simulated observations as in the data.

A.4.2 Parameter estimates for the heterogeneous model with renegotiation

Figure A.3: Observed and simulated unemployment spells/job spells

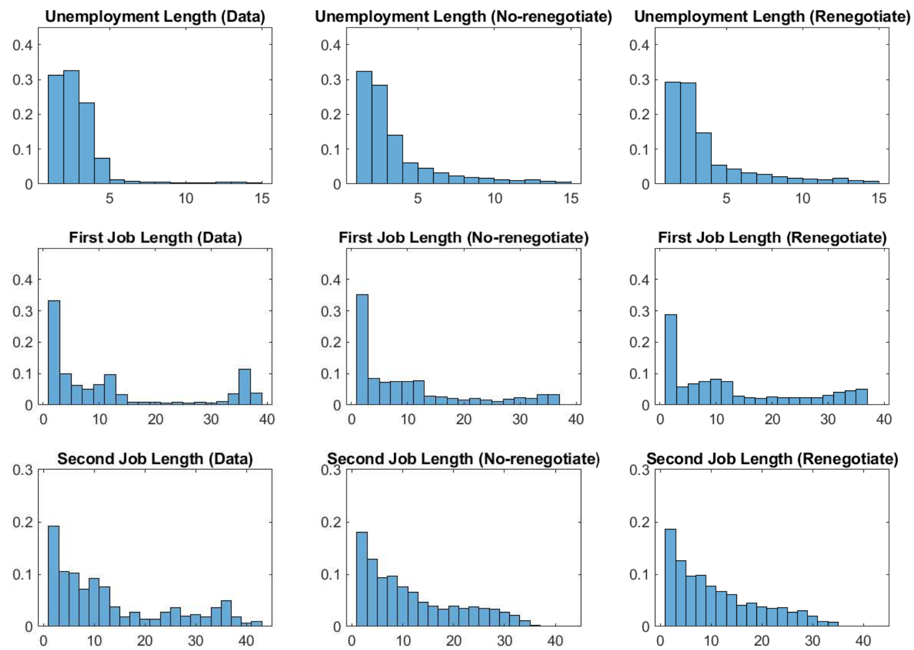


Table A.5: Other parameters in specification (3) under the renegotiation model: individual heterogeneity with gender-specific model coefficients

Cons.	-0.248	-0.036	-2.871	-3.967	-3.346	-3.208	2.114	2.107	0.136	-0.472
	(0.302)	(0.242)	(0.383)	(0.296)	(0.187)	(0.240)	(0.122)	(0.102)	(0.553)	(0.442)
Edu	0.245	-0.297	-0.206	-0.280	-0.117	0.006	0.113	0.163	0.499	0.558
	(0.131)	(0.079)	(0.095)	(0.059)	(0.044)	(0.052)	(0.051)	(0.044)	(0.189)	(0.156)
Stb	0.000	-0.026	-0.008	0.125	-0.027	-0.074	0.083	-0.008	-0.031	-0.041
	(0.044)	(0.037)	(0.044)	(0.028)	(0.020)	(0.021)	(0.022)	(0.017)	(0.064)	(0.050)
Opn	0.074	-0.002	0.100	0.103	0.038	0.083	-0.028	0.018	-0.097	0.025
	(0.049)	(0.037)	(0.052)	(0.032)	(0.022)	(0.027)	(0.019)	(0.017)	(0.056)	(0.054)
Cos	0.059	-0.045	-0.029	0.048	0.020	-0.006	-0.088	-0.069	-0.018	-0.010
	(0.063)	(0.054)	(0.056)	(0.041)	(0.030)	(0.038)	(0.024)	(0.022)	(0.079)	(0.077)
Agr	-0.052	0.098	-0.029	0.089	-0.034	-0.306	0.054	0.031	-0.183	-0.329
	(0.046)	(0.047)	(0.050)	(0.038)	(0.024)	(0.025)	(0.023)	(0.019)	(0.057)	(0.049)
Ext	-0.003	-0.087	-0.011	0.031	-0.006	0.185	0.008	-0.019	-0.023	0.104
	(0.047)	(0.038)	(0.046)	(0.033)	(0.024)	(0.029)	(0.021)	(0.020)	(0.065)	(0.067)
Cohort (Omitted cat: 73-82)										
63-72	0.073	0.659	0.019	-0.148	-0.214	0.262	-0.072	-0.008	-0.124	0.128
	(0.106)	(0.102)	(0.090)	(0.060)	(0.045)	(0.065)	(0.038)	(0.045)	(0.116)	(0.184)
52-62	0.004	0.925	0.090	-0.268	-0.091	0.202	-0.055	-0.089	-0.192	0.133
	(0.102)	(0.114)	(0.116)	(0.061)	(0.048)	(0.069)	(0.045)	(0.042)	(0.139)	(0.191)

NOTE: this table reports the gender-specific coefficients of education and personality traits in specification (3) under renegotiation model assumption. Asymptotic standard errors using numerical scoring function are reported in parentheses. Data: IZA Evaluation Dataset.

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