Personality Traits, Job Search and the Gender Wage Gap

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Abstract

This paper introduces the Big Five personality traits along with other covariates in a job search, matching and bargaining model and investigates how education and personality traits affect primitive model parameters that discipline job search behavior and labor market outcomes. It develops and estimates a partial equilibrium search model in which personality traits can influence worker productivity, job offer arrival rates, job dissolution rates and the division of surplus from an employer-employee match. The estimation is based on the IZA Evaluation Dataset, a panel dataset on newly-unemployed individuals in Germany between 2007 and 2008. Model specification tests provide support for a model that allows job search parameters to be heterogeneous across individuals, varying with levels of education, birth cohort, personality traits and gender. We use the estimated model to perform a decomposition of the sources of the gender wage gap. The results show that gender wage gaps arise mainly because of gender differences in bargaining power rather than differences in productivity. They also show that women's personality traits are valued differently in the labor market than men's traits. Of the Big Five traits, conscientiousness and emotional stability emerge as the most important in explaining the gender wage gap.

1 Introduction

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

In the recent economics literature, there is increasing recognition that traditional measures of worker productivity such as education and work experience do not fully characterize the attributes that are relevant for labor market success. In particular, recent research considers non-cognitive traits as potential productivity determinants along with cognitive skills.[1] Heckman et al. (2006), Heckman and Raut (2016) and Todd and Zhang (2018) estimate dynamic choice models using longitudinal data and note that personality traits have both direct effects on worker productivity and indirect effects by affecting preferences for schooling, working and/or occupations. Cubel et al. (2016) examine whether personality traits affect productivity in a laboratory setting that directly measures effort on a task. They find that individuals with high levels of conscientiousness and emotional stability perform better on the task. A study by Fletcher (2013) uses sibling samples and family fixed effect estimators and finds a robust relationship between personality traits and wages. There is substantial evidence that personality traits are related to labor market outcomes.[2] However, the precise mechanisms through which personality traits affect labor market outcomes have not been much explored.

Recent reviews of gender differences in preferences and in personality traits can be found in Croson and Gneezy (2009) and Bertrand (2011). Studies across many different countries find that women are on average more agreeable and less emotionally stable than men. The fact that women and men exhibit, on average, different personality traits raises the question as to whether these traits could be important in explaining gender labor market disparities. Flinn et al. (2018) estimate a static neoclassical household labor supply model for households using the Household, Income and Labour Dynamics in Australia (HILDA) dataset and find personality traits to be important determinants of gender wage and employment differentials. They find that the key factor explaining the gender wage gap is that women are paid differently for their traits than men. For example, women are on average more conscientious

[1]The most commonly used measures of noncognitive traits are the so-called Big Five personality traits. They measure an individual's openness to experience, conscientiousness, extraversion, agreeable and neurotism (the opposite of emotional stability). 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)).

[2]See Nyhus and Pons (2005),Heineck (2011),Mueller and Plug (2006),Braakmann (2009),Cattan (2013)

than men, but men receive a higher wage return for being conscientious. However, the labor market search frictions are not considered in their framework.

This paper contributes to the literature by explicitly exploring the effect of personality traits through the job search channels. We develop and estimate a partial equilibrium job search model in which personality traits can operate through distinct channels. In the model, unemployed and employed workers stochastically receive employment opportunities from firms characterized in terms of idiosyncratic match productivity values. Workers are heterogeneous in terms of observed attributes that include gender, age, education, and personality traits. Firms are heterogeneous in terms of match productivities. Firms and job searchers divide the match surplus, with the fraction going to the worker determined by a bargaining parameter. Within the model, personality traits are introduced as potential determinants of (i) worker productivity, (ii) job search effort, (iii) job exit rates, and (iv) the bargaining parameter. The model also allows for potential labor market discrimination as reflected in gender differences in hourly wage offer functions. We use the estimated model to better understand the mechanisms underlying gender disparities in hourly wages, employment and labor market dynamics.

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). More specifically, it builds on a smaller literature that uses job search models to understand the sources of gender wage gaps using datasets from various countries. Bowlus (1997), using data from National Longitudinal Survey of Youth 1979 (NLSY79), is the first paper to develop and estimate a job search model to explain gender wage gaps. She finds that gender differences in job exit rates explain 20-30% of the gender wage differential. Bowlus and Grogan (2008) extends the previous framework by incorporating a part-time work option; they find that women's greater tendency to work part-time and to exit the labor market into the non-participation state lowers their reservation wages, shortens job spells and prevents women from climbing the wage distribution as fast as men via on-the-job search. More recently, Flabbi (2010a) develops a search and matching model emphasizing employer's taste-based discrimination. In his model, there are male and female workers and discriminatory or nondiscriminatory firms. When workers and firms meet, they observe a match productivity value and bargain over wages. The existence of a positive proportion of prejudiced firms lowers women's outside options, generating spillover effects even for jobs at nondiscriminatory firms. Using Census Population Survey (CPS) data, Flabbi (2010a) finds that average female productivity is 6.5% lower than male productivity and that about half of the employers discriminate. Liu (2016) also estimates a job search model for the purpose of studying the sources of gender wage gaps. Using the Survey of Income and Program Participation (SIPP) data, he finds that the key factors explaining the gender wage gap are differences in mean offered wages (conditional on observed characteristics), job search parameters, the wage cost of part-time work, and demographic factors affecting preferences for part-time work. None of the above papers explore the personality characteristics as potential factors to explain gender gaps.

To the best of our knowledge, only two previous studies have investigated how personality characteristics affect job search behaviors. Caliendo et al. (2015) exposit a job search model where individuals have subjective beliefs about the impact of their search efforts on the job offer arrival rate that are assumed to depend on their perceived "locus of control" - a measure of how much they think their success depends on "internal factors" (i.e. their own actions) verses "external factors".[3] They test implications from the model using the IZA Evaluation Dataset, but they do not structurally estimate the model. They find that individuals with internal locus of control search for jobs more intensively and have higher reservation wages. McGee (2015) also analyzes the relationship between locus of control and job search behavior using data from the NLSY. He similarly finds that young men with internal locus of control search more and have higher reservation wages.

This paper also explores how personality traits affect job search behavior, but we do so within a structural modeling framework. The search and matching model that we estimate allows workers to receive wage offers both while unemployed and on-the-job. Model parameters are estimated by maximum likelihood using the IZA Evaluation Dataset, a panel dataset that follows individuals in Germany who were newly unemployed between 2007 and 2008. An unusual feature of these data relative to other available datasets is that they contain the Big Five personality measures. Previous studies that typically focus on a one-dimensional measure, such as locus of control (e.g. Caliendo et al. (2015),McGee (2015)), but considering five personality meausures make it possible to explore which traits are most important for different job search channels. In addition, we use information on age, gender, education, wages, hours worked, and job transitions. Our analysis sample includes men and women during prime-age working years (age 25-54).

We estimate two different model specifications that make different assumptions on how firms negotiate with workers who receive wage offers from other firms. One model (with renegotiation) assumes that current firms can match outside offers so that workers can get wage increases while at the same job, while another specification (without renegotiation) as-

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

sumes that firms cannot verify outside offers and that workers only experience wage increases when they change jobs. When we perform goodness-of-fit of these two model specifications, we find that the model that assumes that firms do not renegotiate wages provides a better fit to the wage and job spell data. 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 variant, worker productivity, job arrival rates, job exit rates, and bargaining parameters may vary with individual characteristics and differ for men and women. Likelihood ratio tests reject the more restrictive specifications in favor of the most flexible one.

Our estimates indicate that the personality traits are statistically significant determinants on job search parameters for both men and women, but they sometimes affect men and women in different ways. For example, women are on average more conscientious than men, but men receive a higher premium in the labor market for being conscientious. Both men and women receive a penalty for being agreeable, but the penalty operates through the productivity parameter for men and through the bargaining parameter for women. We observe a positive empirical association between the number of job applications and conscientiousness, which is consistent with the estimates obtained under the model for the effect of personality traits on the job arrival rate.

Lastly, we use the estimated model parameters to perform a decomposition of the sources of gender wage 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 the productivity premium for education is actually higher for women than for men. However, more educated women and more agreeable women are at a big disadvantage relative to men in terms of bargaining. Gender differences in bargaining parameters emerges as a primary factor in explaining the wage gap.

The rest of the paper is structured as follows. In the next section we present our baseline model. Section 3 describes the dataset. Section 4 discusses the econometric implementation of the model. Section 5 presents the model estimates and empirical results. Section 6 concludes.

2 Model

Our main interest is in determining the impact of personality traits, as well as other demographic and schooling characteristics, on labor market success using a simple partial equilibrium job search framework. Let an individual "type" be denoted by z. 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. The time-invariant productivity of the individual is $a(z)$, and their productivity at a particular firm is $a(z) \times \theta$, where θ is a draw from the distribution $G_z(\theta)$ and is realized at the time that the individual meets a prospective employer. The worker and the firm bargain over the wage using a Nash bargaining protocol, with the outside option of the individual dependent upon the particular bargaining protocol they use. [4] The bargaining power of the individual is $\alpha(z)$. The flow value of unemployment to the individual is $b \times a(z)$, where b is a scalar. Employment matches dissolve exogenously at rate $\eta(z)$. The common discount rate of all agents in the model, firms and workers, is ρ, which is a constant independent of z.

In our application, components of the vector z include education level, gender, birth cohort and the Big Five personality assessment. Because our model is a stationary model and our data are a short panel (three years), we will assume that all of the characteristics upon which we ultimately condition are time-invariant. Our main interest is to investigate sources of gender discrimination in the labor market through the lens of the canonical search, matching, and bargaining model.

2.1 Baseline Model with No OTJ Search

For simplicity, we first describe a model in which employed individuals do not receive job offers. We will later extend the model to allow for on-the-job search.[5] To simplify the notation, we will not explicitly condition the primitive parameters of the model on z. We will reintroduce z when we discuss the model's estimation.

We denote the value of unemployed search to an individual of ability a by $V_U(a)$. We assume that the only utility-yielding characteristic of a job to the worker is the hourly wage paid, w, and we adopt the usual assumption that flow utility is linear in wages when employed.[6] In the environment with no OTJ search, the only way that an employment spell can end is exogenously, happening at rate η. Then the value of employment at a job with

[4] If allowing for the regurgitation between worker and the firm, the outside option of the worker is the current employment status. However, if the worker is not allow to renegotiate the contract with the firm, her outside option would be the unemployment status. We would discuss these two cases separately later.

[5] When we do allow for on-the-job (OTJ) search, some additional issues will arise with respect to the nature of worker-firm bargaining. By ignoring OTJ search, we postpone these more subtle discussions.

[6] The linearity assumption will be particularly important when considering the trade-off between adopting an individual or a household search model, as discussed in section 2.4.

wage w is given by

$$(\rho+\eta)V_E(\theta,a;w) = w + \eta V_U(a),$$

or

$$V_E(\theta,a;w) = \frac{w+\eta V_U(a)}{\rho+\eta}.$$

The value to a firm of match productivity $a\theta$ with wage w is

$$(\rho+\eta)V_F(a,\theta;w) = a\theta - w.$$

When a employment match ends, the firm's value reverts to 0. [7]

The Nash-bargained wage is then given by

$$w^*(\theta,a) = \arg\max_w \left(V_E(\theta,a;w) - V_U(a)\right)^\alpha V_F(a,\theta;w)^{1-\alpha},$$

where we have used that the firm's outside option, keeping the vacancy open, has value zero. Because

$$\begin{aligned} V_E(\theta,a;w) - V_U(a) &= \frac{w+\eta V_U(a)}{\rho+\eta} - V_U(a) \\ &= \frac{w-\rho V_U(a)}{\rho+\eta}, \end{aligned}$$

we have

$$\begin{aligned} w(\theta,a) &= \arg\max\nolimits_w (w-\rho V_U(a))^\alpha (a\theta - w)^{1-\alpha} \\ &= \alpha a\theta + (1-\alpha)\rho V_U(a) \qquad (1) \\ &= \alpha a\theta + (1-\alpha)a\theta^*(a) \end{aligned}$$

given the definition that $\rho V_U(a) \equiv y(\theta^*(a),a) = a\theta^*(a)$.

The value of unemployed search is defined as

$$\begin{gathered} \rho V_U(a) = ba + \lambda_U \int_{\theta^*(a)} (V_E(\theta;a) - V_U(a))dG(\theta) \\ \Rightarrow a\theta^*(a) = ba + \tfrac{\lambda_U \alpha a}{\rho+\eta} \int_{\theta^*(a)} (\theta - \theta^*(a))dG(\theta) \\ \Rightarrow \theta^*(a) = b + \tfrac{\lambda_U \alpha}{\rho+\eta} \int_{\theta^*(a)} (\theta - \theta^*(a))dG(\theta) \end{gathered}$$

[7] Although we only consider partial equilibrium models of the labor market, we do assume that the value of an unfilled vacancy is 0, which is an implication of the Free Entry Condition in general equilibrium characterizations of the labor market.

There is one solution to the last equation, which does not depend on a, so we have

$$\theta^*(a) = \theta^* \ \forall a.$$

This means that to see whether a match is acceptable, it is enough to compare the value of θ with θ^*, which is independent of a. The actual reservation productivity value, $a \times \theta$, is $a \times \theta^*$.

2.2 Implications for the Wage Distribution

As noted above, our aim is to investigate how personality characteristics and other individual traits impact wage distributions and potentially contribute to gender gaps. We assume that the support of the matching distribution G is nonnegative and that G is differentiable with density g. The wage distribution is truncated from below at $a\theta^*$ for a type a individual. From equation 1, we establish a one-to-one mapping between matching quality θ and wage w as:

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

the lower limit of the wage distribution for an individual of ability a is $w^*(a) = a\theta^*$. Then the c.d.f. of wages for workers with ability a is

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

where $\bar{G}(\theta^*) \equiv 1 - G(\theta^*)$. The corresponding p.d.f. is given by

$$f(w|a) = \frac{1}{a\alpha} \times \frac{g\left(\alpha^{-1}\left(\frac{w}{a} - (1-\alpha)\theta^*\right)\right)}{\bar{G}(\theta^*)}, \ w \geq a\theta^*, \tag{2}$$

where $\frac{1}{a\alpha}$ is the Jacobian of the transformation.

We can see from equation 2 that z can potentially impact the wage distribution through a number of channels. A key parameter is α, the bargaining power of the worker. Individual characteristics, including personality type and gender may impact this parameter, which determines how much of the surplus from the job the worker is able to obtain. Although the match value distribution $G_z(\theta)$ could depend on all heterogeneity in theory, we allow it only to differ by gender in the empirical work reported below. That is, we allow men and women to have potentially different match value distributions. However, we do allow individual productivity, a, to be a function of all characteristics in the vector z. The remaining parameters of the model all impact $f(w|a)$ only through the decision rule θ^*.

When we estimate the model we will be making the (common) assumption that θ is lognormally distributed, with $\ln\theta$ distributed as a normal random variable with mean μ_θ and variance σ_θ^2. That is, $\log\theta \sim N(\mu_\theta(z), \sigma_\theta^2(z))$. We further restrict $\mu_\theta(z) = -0.5\sigma_\theta^2(z)$ so that $E_\theta[y(z,\theta)] = a(z)E_\theta[\theta] = a(z)$.[8] In such case, $a(z)$ captures the heterogeneity in the mean value of productivity at a match and $\sigma_\theta(z)$ captures the heterogeneity in the dispersion of productivity across employers.[9]

2.3 Adding On-the-Job (OTJ) Search

In this section, we extend the model to allow workers to receive job offers from firms even when they are currently employed. This extension is useful to explain job-to-job transitions in the data. We assume the job arrival rate from other potential employers is λ_E. When meeting another employer, the match quality from this alternative pair, $\tilde{\theta}$, is immediately revealed to both the worker and the employer. Whether or not the worker leaves for the new job and what the new wage will be after the encounter depends on the particular assumptions we made about the wage negotiation environment.

There are two different types of assumptions that are typically made regarding the amount of information available to the worker and firm during the wage negotiation process. In the first case, following Postel-Vinay and Robin (2002), and, for the surplus division case, following Dey and Flinn (2005) and Cahuc et al. (2006), it is assumed that 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 wherever her productivity is the greatest. This is what we refer to as the wage renegotiation case. We then describe the case in which firms do not respond to offers from competing firms. This may happen either because the potential outside options are not verifiable or firms have an incentive to renege on its offered wage once the potential competitor's offer has been withdrawn.[10] We refer to this case as the non-renegotiation case.

Clearly, the two cases may yield different wage payments for identical values of the primitive parameters and match qualities. As a result, the impact of z on gender wage differences in the two cases may also differ. We will estimate the model under both bargaining

[8]Given θ follows a lognormal distribution, $E(\theta) = \exp\left(\mu_\theta(z) + 0.5\sigma_\theta^2(z)\right) = 1$ if $\mu_\theta(z) = -0.5\sigma_\theta^2(z)$.

[9]In practice, we assume $\sigma_\theta(z)$ only depends on gender but not other elements of z.

[10]It is typically assumed that recall is not possible in models with OTJ search, so that as soon as an offer is rejected it is no longer available.

assumptions separately below.

2.3.1 OTJ Search with Renegotiation

In the renegotiation case, we allow firms to engage in Bertrand competition for the employee. 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.[11] Let θ and θ' be the two match draws at the two firms. Let $\theta' > \theta$ and call θ' the dominant match value and θ the dominated value. When firms engage in Bertrand competition in term of wage setting, whichever firm is associated with the lowest match productivity value will attempt to attract the worker by increasing its wage offer to the point where it earns no profit from the employment contract.[12] In the above 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 where the match value is θ'.

We now derive the expression for the bargained wage. First, consider an employed worker with the state variable (θ', θ, a), where θ' is the match value of the dominant firm, θ is the matching value of the dominated firm and a is time-invariant ability. In the case in which the worker came from the state of unemployment, the dominated offer θ is equal to the offer from a firm with reservation matching quality $\theta^*(a)$. When offering a wage w, the value of employment can be written as

$$\left(\rho + \eta + \lambda_E \bar{G}(\theta)\right) V_E(\theta', \theta, a; w) = w + \eta V_U(a) + \underbrace{\lambda_E \int_{\theta}^{\theta'} V_E(\theta', x, a) dG(x)}_{(1)} + \underbrace{\lambda_E \int_{\theta'} V_E(x, \theta', a) dG(x)}_{(2)}$$

where the term (1) captures the expected value when the "dominated" outside match value x triggers the current firm to increases the wage to ax to retain the individual, where $\theta < x \leq \theta'$. The term (2) captures the value gain when the individual switches to a new firm at which her match value is $\tilde{\theta} > \theta'$, in which case the "dominated" match value is θ'. In both cases, the value of the worker's outside option is the value of employment at the firm with

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

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

the dominated match value when the worker is paid her productivity, so that $w = a\theta$. This is the same outcome as would be obtained if the worker had two firms competing for her services when the match value θ was identical at each firm (or $\theta' = \theta$). Then

$$\left(\rho + \eta + \lambda_E \bar{G}(\theta)\right) V_E(\theta, \theta, a) = a\theta + \eta V_U(a) + \lambda_E \int_{\theta} V_E(x, \theta, a) dG(x).$$

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

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

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

$$w(\theta', \theta, a) = \arg\max_{w} (V_E(\theta', \theta, a; w) - V_E(\theta, \theta, a))^{\alpha} V_F(\theta', \theta, a; w)^{1-\alpha} \tag{3}$$

where the firm's outside option is 0 and the labor share of surplus division is α. The analytic solution of $w(\theta', \theta, a)$ and the reservation match value $\theta^*(a)$ are provided in the appendix A.1.1

2.3.2 OTJ Search without Renegotiation

In the non-renegotiation case, firms do not respond to competing firms for a given individual's productive services. There are at least two possible justifications for this assumption. The first reason is that it may not be possible for the firm to verify the existence of a potential competitor, or, if it is, it may not be possible to determine the value of the individual's productivity there. A second rationale is that the firm has an incentive to renege on its offered wage once the potential competitor's offer has been withdrawn. Given that time is continuous, this means that the resolution of the bargaining problem occurs instantaneously and the rejected offer is also lost instantaneously. Once the alternative offer is withdrawn, the only outside option of the worker is unemployed search, with value aV_U to a type a individual.[13] In such case, all on-the-job wage bargaining uses the value of unemployment as the value of outside option, which is an option always available whether or not the wage contract is enforced.

[13] 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 which two firms are engaged in a competition for her labor services. However, the flow wage payment would be that specified in equation 4.

In this bargaining protocol, the historical "dominated" match value does not affect the current wage bargaining any more. The value of employment at a match value θ is only a function of θ and a. Then

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

and the value of the job (vacancy) becomes

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

In this case the bargaining problem becomes

$$w(\theta, a) = \arg\max_w (V_E(\theta, a; w) - V_U(a))^\alpha V_F(\theta, a; w)^{1-\alpha}. \tag{4}$$

which leads to the wage equation

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

where we incorporate the reservation strategy that worker accepts the alternative job offers if and only if the alternative match quality $x > \theta$. Redefine that $V_E(\theta, a) = a\bar{V}_E(\theta), V_F(\theta, a) = a\bar{V}_F(\theta)$ and $V_U(a) = a\bar{V}_U$. Then the value of unemployed searcher in this case is:

$$\bar{V}_U = \frac{b + \lambda_U \int_{\theta^*} \bar{V}_E(\theta) dG(\theta)}{\rho + \lambda_U \bar{G}(\theta)}$$

The solution of reservation value θ^* is given in the appendix A.1.2.

Whether we assume renegotiation or non-renegotiation, all inter-firm moves will be efficient in that the employee will always accept employment at the firm at which she is most productive. As long as the outside option used to determine the wage is equal to $V_U(a)$ and $w(\theta, a)$ is strictly increasing in θ (for all $a > 0$), then a worker will leave one employer at which her match value is θ for another employer at which her match value is θ' if and only if $\theta' > \theta$.

2.4 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 the same household, their labor supply decisions are 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 in labor market decisions could yield a distorted view of gender wage differences.

We are able to sidestep this issue in this paper solely because we adopt the assumption that both men and women have flow utility functions given by their respective wages when employed and by the constants $b \times a$ when they are not. The linear flow utility assumption is made in virtually all analyses conducted within the search framework, and we follow it here.[14] Now let the current "earning" of individual i in the household be given by e_i, $i = 1, 2$, where $e_i = w_i$ if the individual is employed at wage i and is equal to b_i if individual i is not employed. If all "consumption" in the household is public, then each individual's flow utility is

$$U = e_1 + e_2.$$

As discussed in Dey and Flinn (2008), in this case the total value of the household's problem at any point in time, $V(e_1, e_2) = V_1(e_1) + V_2(e_2)$. In other words, the value of the household's maximization problem is the sum of the values of the individuals' problems. Household welfare is optimized by allowing each individual to make choices as if they were unattached. The implication is that the choices made by a woman will not be impacted by the characteristics or decisions of the man in the household and vice versa. Differently from Flinn et al. (2018), we do not have to be concerned with assortative mating in the marriage market or interdependence in decision-making within the household.[15]

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-

[14]One 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.

[15]In Dey and Flinn (2008), when the household only cares about consumption, they specify the household flow utility as $(w_1 + w_2 + y)^\delta/\delta$, where y is the nonlabor income flow of the household, and where the wage w_i is equal to 0 when individual i is unemployed. When $\delta = 1$, we have the linear case of risk neutrality. Dey and Flinn estimate a value of δ which is significantly less than 1, indicating risk aversion. In this case, the assumption of no capital markets, precluding borrowing and saving, is substantively significant. The decisions of the household regarding when an offer to individual i is to be accepted will depend on the characteristics of the spouse and their current labor market state.

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 around 9% of the newly registered unemployed in the administrative records.

In contrast to general population surveys such as the German Socio-Economic Panel Study (GSOEP), the IZA ED survey focuses on individuals who recently became unemployed. The survey contains extensive information on factors related to job search, including, for example, reservation wages, the number of job applications and search channels. It also contains rich information on individual characteristics, such as education, personality traits and 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 with a time lag with ranges from 55 to 84 days after entry into unemployment. Then the second interview and third interview are scheduled one year and three years later. In addition, three cohorts, i.e. June and October 2007 and February 2008, are interviewed at an interim time, six months after their first interview. In constructing our analysis sample, we drop individuals with missing personal information, such as age, gender, education as well as personality traits. These restrictions leave us with a final sample of 4,319 individuals.[16]

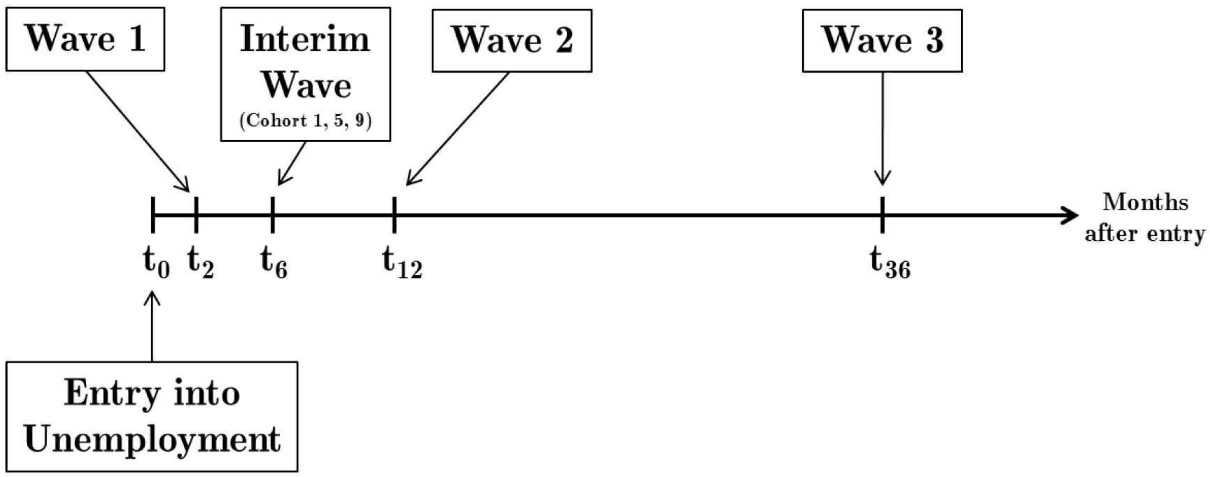
The "Big Five" information in the IZA ED is based on a 15-item personality descriptions. Respondents were asked to pick a number between 1 to 7 to assess how well each description applies to them. The lowest number 1 denotes a total opposite description and the highest number 7 denotes a perfect description. Each personality trait is constructed by the average scores of three items pertaining to that trait.[17]

The personality trait information is collected repeatedly at all waves including the interim wave. The completed Big Five personality traits are available for 5,601 respondents in wave 1, for 1,680 respondents for interim wave and for 5,747 and 5,732 respondents in waves 2 and 3. We include in our analysis individuals for whom personality traits were measured at least one time. For individuals with multiple measures, we use the average value across the

[16]A detailed discussion of the restrictions used to select the sample is provided in Appendix A.2.1. As a dataset specifically focuses on the unemployed workers, IZA ED also records very detailed information of active labor market policies (ALMP) in Germany. There are three main programs in our raw data: short-term training (9.4%), long-term training(10.3%) and wage subsidies(10.6). Caliendo et al. (2017) 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. This finding suggests that the effect of personality traits on labor market outcomes through the ALMP participation is rather small. Therefore, we don't explicitly include the ALMP variables in our following analysis.

[17]In the beginning of the first wave interview, there were 10 personality items, but an additional 5 items become available later starting from the February (No. 9) cohort. A detailed description of which items are used to construct each personality trait is discussed in Appendix A5.

Figure 1: Panel Structure



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.

different waves, because differences observed within a 3-year time frame are likely due to measurement errors rather than to fundamental changes.[18] Meanwhile, the cognitive skills are only measured in three cohorts which are selected to participate 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 2.66 for females. Correspondingly, they spend on average more months in employment. The dataset contains information on actual wages, expected wages, and reported reservation wages. Men have on average an expected hourly wage equal to 9.24 € in comparison to 8.15 € for women. Their actual wage is also higher, 8.26 € on average for men in comparison to 7.54 € on average for women. Men also report on average a higher reservation wage than women; 8.02 € for men compared to 7.09 € for women. As seen in the lower panel of the table, a significant gender gap occurs despite the fact that women in our sample have on average higher education levels than men. 34% of women have an A-level secondary degree in comparison with 28% of men. They also score on average higher on cognitive ability tests. With regard to demographic characteristics, the average for women is 38.7 in comparison to 37.9 for men, so the gap is less than one year. Women are more likely to be married (51.4% in comparison to 44.1%) and to have a

[18]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)	2.411	2.547	2674	2.659	3.048	2385	-0.248	0.002
Employment (Months)	12.375	12.499	1918	11.216	12.208	1633	1.159	0.005
Actual wage (€/h)	8.264	2.512	1355	7.544	2.449	1125	0.719	0.000
Wage during last employment(€/h)	8.571	3.760	3981	7.553	3.147	3352	1.018	0.000
Previous accu. experience (years)	18.102	9.945	4226	15.749	9.548	3569	2.353	0.000
Expected wage (€/h)	9.237	2.482	1981	8.147	2.421	1980	1.090	0.000
Reservation wage (€/h)	8.023	2.169	1474	7.088	2.051	1528	0.934	0.000
Number of applications	13.200	18.046	1752	12.548	16.722	1608	0.652	0.279
Individual's characteristics								
Age: mean	37.890	8.602	2244	38.683	8.648	2075	-0.793	0.003
Birth cohorts								
1952-1962	0.386	0.487	2244	0.355	0.479	2075	0.031	0.034
1963-1972	0.353	0.478	2244	0.347	0.476	2075	0.006	0.659
1973-1982	0.260	0.439	2244	0.298	0.457	2075	-0.037	0.006
Education levels								
Lower secondary school	0.355	0.479	2244	0.229	0.421	2075	0.126	0.000
(Adv.) middle sec. school	0.363	0.481	2244	0.429	0.495	2075	-0.066	0.000
Upper sec. school (A-level)	0.282	0.450	2244	0.341	0.474	2075	-0.059	0.000
Marriage	0.441	0.497	2236	0.514	0.500	2070	-0.072	0.000
Dependent child (under age 18)	0.320	0.466	2240	0.398	0.490	2074	-0.079	0.000
Cognitive Ability	1.788	0.571	569	1.892	0.525	572	-0.104	0.002
Emotional Stability	3.820	1.097	2244	3.411	1.162	2075	0.409	0.000
Openness to experience	4.769	1.121	2244	4.923	1.188	2075	-0.154	0.000
Conscientiousness	5.696	0.823	2244	5.858	0.792	2075	-0.162	0.000
Agreeableness	5.181	0.945	2244	5.512	0.906	2075	-0.331	0.000
Extraversion	4.696	1.047	2244	4.840	1.064	2075	-0.145	0.000
Locus of control	4.385	0.746	2036	4.322	0.725	1916	0.064	0.006

Source: IZA Evaluation Data Set, individuals between age 25 to 55. P-value refers to a two-sided t-test of quality of means.

dependent child under the age of 18 (39.8% vs. 32.0%).

A comparison of personality trait scores shows that men have on average a higher emotional stability score. But for all other traits, women have on average higher scores. The greatest gender differences for personality traits occur for emotional stability (3.82 for males and 3.41 for women) and agreeableness (5.18 for males and 5.51 for females).

Table 2 reports estimated coefficients from a regression of log hourly wages (at last time of employment) on education, personality traits, cognitive ability and reported lifetime labor market experience and its square. As seen in Table 2, women receive a higher return to their education than men (23% wage premium for women compared to 17% for men). For both men and women, higher scores on emotional stability are associated with higher hourly

Table 2: The effects of personality traits on hourly wages at last employment (by gender)

Outcome variable:	Male		Female	
(log) hourly wage	(1)	(2)	(3)	(4)
Experience	0.030***	0.024***	0.015***	0.014***
	(0.004)	(0.004)	(0.004)	(0.004)
$Experience^2/100$	-0.064***	-0.055***	-0.030**	-0.026*
	(0.009)	(0.009)	(0.010)	(0.010)
Higher level sec. degree	0.174***	0.159***	0.227***	0.230***
(Baseline: sec. school or lower)	(0.021)	(0.021)	(0.021)	(0.022)
Emotional Stability	0.016	0.016*	0.023**	0.021*
	(0.008)	(0.008)	(0.008)	(0.008)
Openness to experience	0.000	0.004	0.014	0.013
	(0.008)	(0.008)	(0.008)	(0.008)
Conscientiousness	0.020	0.013	-0.025	-0.025
	(0.012)	(0.012)	(0.013)	(0.013)
Agreeableness	-0.010	-0.009	-0.002	-0.001
	(0.010)	(0.010)	(0.011)	(0.011)
Extraversion	-0.018	-0.021*	0.004	0.003
	(0.009)	(0.009)	(0.010)	(0.010)
Cognitive Ability		0.110***		-0.067***
		(0.021)		(0.019)
Marriage dummy		0.067**		0.052**
		(0.022)		(0.020)
Dependent child (any)		0.060		0.020
		(0.031)		(0.034)
Number of Obs	1,930	1,930	1,702	1,702
Missing cognitive indicator		X		X

Notes: all columns display OLS regression results. The column "diff" shows the difference between female coefficients and male coefficients. Source: IZA Evaluation Data Set, individuals age 25 to 55. Standard Errors in parentheses. $p<0.1^*$, $p<0.05^{**}$, $p<0.01^{***}$.

wages. For men, a higher extraversion score is associated with lower wages. Conditional on the other included variables, the cognitive ability score is associated with higher wages for men but not for women. In light of the theoretical model, wage differences can occur because of differences in reservation wages, productivity, job finding rates and/or bargaining. The structural model for which we report estimates below explores these different mechanisms.

Table 3 shows estimates from a Cox proportional hazard model of the hazard rate out of unemployment. The estimation takes into account censoring, namely that all individuals start out unemployed and some are never observed to get employed. 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 increases the hazard out of unemployment,

Table 3: Cox proportional hazard model for exiting unemployment (by gender)

Outcome variable:	Male		Female	
Unemployment duration	(1)	(2)	(3)	(4)
Higher level secondary degree	0.044	0.017	0.279***	0.274***
(Baseline: secondary school or lower)	(0.057)	(0.058)	(0.062)	(0.063)
Emotional Stability	0.041	0.039	0.056*	0.053*
	(0.023)	(0.022)	(0.024)	(0.024)
Openness to experience	0.022	0.031	0.018	0.018
	(0.023)	(0.023)	(0.025)	(0.025)
Conscientiousness	-0.049	-0.057	-0.06	-0.075
	(0.031)	(0.031)	(0.039)	(0.039)
Agreeableness	-0.032	-0.035	-0.027	-0.015
	(0.026)	(0.026)	(0.034)	(0.035)
Extraversion	0.008	-0.002	0.046	0.042
	(0.025)	(0.025)	(0.030)	(0.029)
Cognitive Ability		0.238*		0.134
		(0.099)		(0.116)
Marriage dummy		0.062		-0.156**
		(0.060)		(0.057)
Dependent child (any)		0.083		-0.167**
		(0.058)		(0.059)
Joint test $p-value$	0.145	0.085	0.013	0.018
Number of Obs	2,060	2,055	1,830	1,824
Working experience	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. $p<0.1^{*}$, $p<0.05^{**}$, $p<0.01^{***}$.

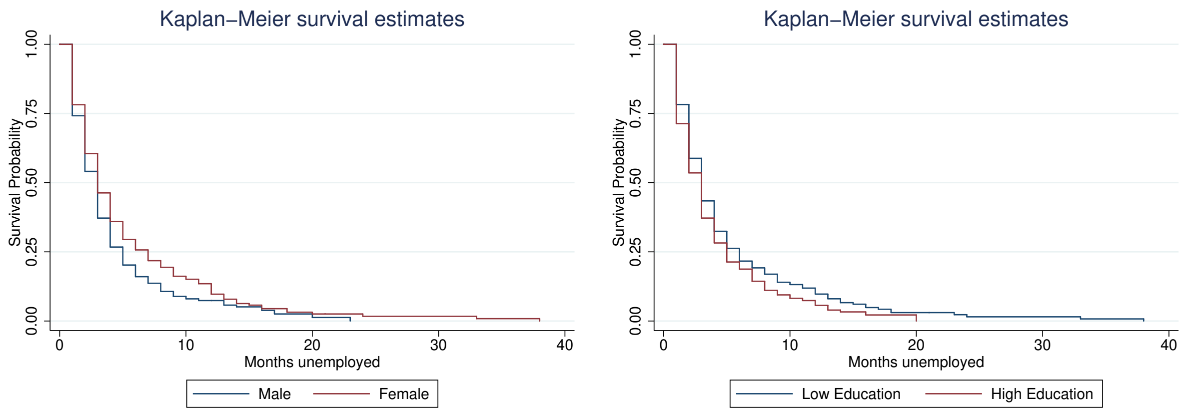
but education is not a significant determinant for men. Being more extraverted tends to decrease the hazard for men.[19] Cognitive ability increases the hazard out of unemployment, but the effect is statistically significant only for men. Including the cognitive ability measure in the specification does not have much effect on the magnitude of the other estimated coefficients.

In Figure 2, we estimate Kaplan-Meier Survival Functions for "surviving" unemployment, where the sample is divided by gender and by education level. As seen in Figure 2(a), women exit unemployment more slowly than men. However, men are more likely to experience longer spells in excess of 12 months. About 50% of the sample experiences initial unemployment spells than last less than six months. Figure 2(b) shows that workers with more education

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

Figure 2: Unemployment duration: Kaplan-Meier Survival Estimates

(a) Survival Probabilities by Gender (b) Survival Probabilities by Education Levels



Note: Source: IZA Evaluation Data Set. The sample includes individuals age 25 to 55. Log-rank test for equality of survivor functions yields p-values: $p = 0.000$ (left panel) and $p = 0.000$ (right panel).

(in the highest category shown in Table 3) exit unemployment more quickly than those with less education.

In Figure 3, we compare the personality trait distributions for men and women. Although all trait measures are on the scale of 1 to 7, there are clearly some differences in the shape of the distributions. 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.

4 Econometric implementation

4.1 Wage specifications

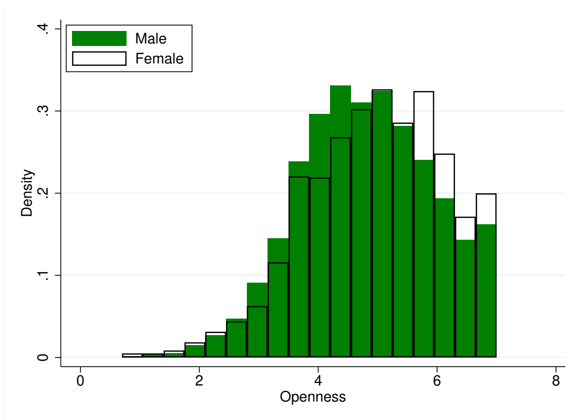
In our model, an individual only changes jobs to move to a job with a better match value and higher wages. Although most job-to-job transitions in the data are accompanied by wage increases, we need to allow for the possibility that sometimes people may switch to jobs with lower wages. For this reason, we allow for a measurement error ϵ in observed wages:

$$\tilde{w} = w\epsilon$$

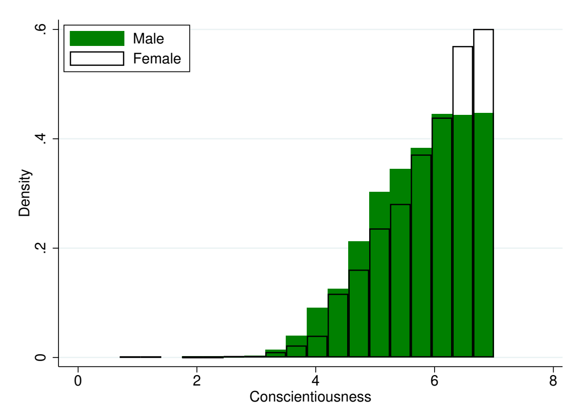
where $\tilde{w}$ is the reported wage and w is the true wage received by the worker.

Figure 3: The distributions of “big five” personality traits by genders

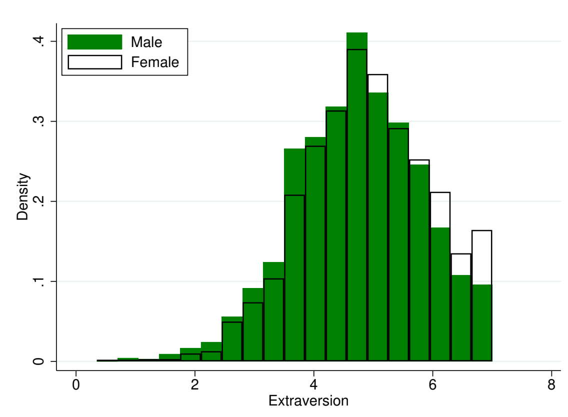
(a) Openness to experience



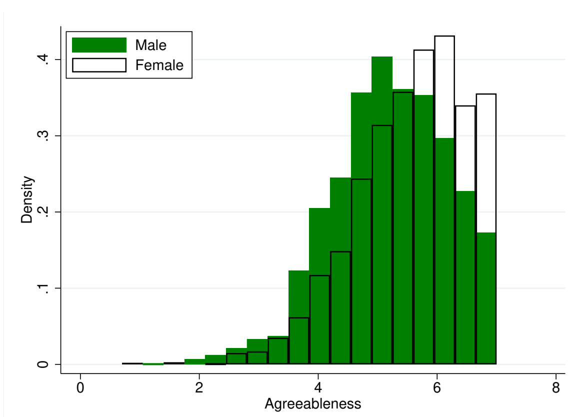
(b) Conscientiousness



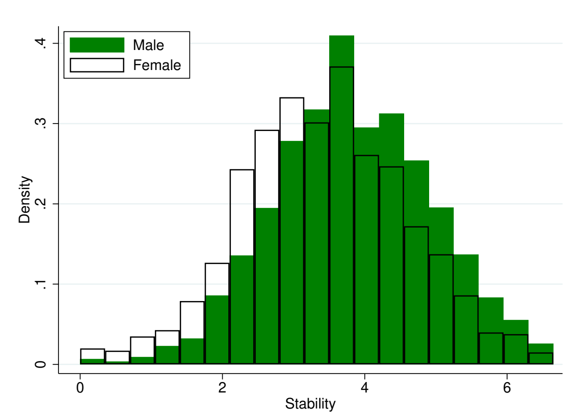
(c) Extraversion



(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.

There are some theoretical models in the literature that can accommodate job-to-job moves with wage declines, but these models typically are not able to not fully explain the pattern of wage changes observed in the data.[20] Another reason that we introduce measurement error is to address a data limitation, in that we only only wage data at the time of the survey waves. We do not fully observe all the wages that a person may experience during a particular job spell. Of course, reporting error can provide another rationale for including a measurement error process.

We follow the common assumption that the measurement error in wages ϵ is distributed i.i.d. log-normal.(Wolpin (1987); Flinn (2002)) The density of ϵ is

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

where μ_ϵ and σ_ϵ are the mean and standard error of the normal distribution. We further restrict the correlation between μ_ϵ and σ_ϵ to be $\mu_{\epsilon_1} = -0.5\sigma^2_{\epsilon_1}$so that $E\left(\epsilon|w\right) = 1$.[21] Therefore, the expectation of observed wages and the expectation of received wages are assumed to be the same.

$$E(\tilde{w}) = E(\epsilon|w)E(w) = E(w)$$

4.2 Constructing the individual likelihood function

Our model will be estimated using maximum likelihood. In this section, we first discuss how we construct each individual likelihood function conditional on her specific labor market search parameters $L(\text{employment}_i|\Omega_i)$. In the next section, we will further describe how individual labor market parameters Ω_i depend on individual heterogeneity z_i.

In line with Flinn (2002) and Dey and Flinn (2005), the information used in estimation is defined as an employment cycle. An employment cycle starts with an unemployment spell followed by one or more jobs in the employment spell. It is defined in terms of the following

[20] 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.

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

random variables:

$$\text{Employment cycle} = \underbrace{\{t_u, r_u\}}_{\text{Unemployment spell}}, \underbrace{\{t_m, \tilde{w}_m, q_m, r_m\}_{m=1}^{M}}_{\text{Consecutive M jobs}}$$

For the unemployment spell, t_u is the length of the unemployment spell, and r_u is whether the unemployment spell is right censored. For any employment spell $m \in M$, t_m is the length of the mth consecutive job, $\tilde{w}_m$ is the observed wage corresponding to the $m-th$ job. $r_m = 1$ means the $m-th$ job spell is right censored. When $r_m = 0$, we further set $q_m = 0$ if the $m-th$ job ends with a transit to another job, and $q_m = 1$ if the $m-th$ job is terminates with unemployment.

As described in section three, every individual in our sample starts with an unemployment spell. Therefore, we avoid the common difficulty of having to take into account incomplete spells at the start of the sample period.[22] Furthermore, we focus on at most the first two job spells to reduce the computational burden.

Individuals only observed to be unemployed:

We first describe the likelihood function for the case when the only spell we observe is the unemployment spell. The hazard rate is assumed to be

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

and the density of the unemployment spell duration is

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

When the unemployment spell is ongoing at the end of the sample period (which means the unemployment spell is right-censored $r_u = 1$), we have a likelihood function with only one spell of unemployment.

$$L^{(1)}(t_u, r_u = 1) = \exp(-h_U t_u)$$

Individuals with one job spell ($M = 1$):

To evaluate the likelihood for employment spells, we use simulation methods. Each individual in the sample starts with an unemployment spell and we simulate R paths. The

[22] For a given worker, unemployment is essentially a "reset" of her job history. Therefore, the employment experience before the initial unemployment spell is irreverent to future job offers. (See also See Flinn (2002); Dey and Flinn (2005); Liu (2016).)

likelihood of completing unemployment with a duration t_u is:

$$h_U \exp(-h_U t_u)$$

An individual leaves unemployment for any job offer with match quality higher than θ^*. We simulate this match value at the first firm by drawing a random number ε_1 from a uniform distribution defined in an interval $U(0,1)$. We then simulate a match draw of $\theta(\varepsilon_1)$ from a truncated log-normal distribution with lower truncation point given by reservation value θ^*.

$$\theta(\varepsilon_1) = \exp\left(\mu_\theta + \sigma_\theta \Phi^{-1}\left(1 - \Phi\left(\frac{\log\theta^* - \mu_\theta}{\sigma_\theta}\right)\right)(1-\varepsilon_1)\right)$$

After the workers find their first job with match quality $\theta(\varepsilon_1)$, they can leave the job for one of two reasons. First, the current job may exogenously dissolve with rate η and the worker becomes unemployed. Second, the worker may move to an alternate firm with a better wage offer $\theta > \theta(\varepsilon_1)$. The "total hazard" associated with the employment spell is simply the sum of these two cases:

$$h_E(\varepsilon_1) = \lambda_E \bar{G}(\theta(\varepsilon_1)) + \eta$$

If the first employment spell is still ongoing at the end of the sample, then the job spell is right-censored with the following probability:

$$L_r^{(2)}(t_u, r_u = 0, \tilde{w}_1, t_1, r_1 = 1|\varepsilon_1) = h_U \exp(-h_U t_u) \int_{w^*} \exp\left(-h_E(\varepsilon_1)t_1\right) \frac{1}{w_1} m\left(\frac{\tilde{w}_1}{w_1}\right) \frac{f(w_1)}{\tilde{F}(w^*)} dw_1$$

where $r_1 = 1$ denotes that the first job spell is right-censored and the worker is still employed at the end of sample period. Therefore, the value of q_1 is not revealed within the sample period. The part $\frac{1}{w_1} m\left(\frac{\tilde{w}_1}{w_1}\right)$ is the density function of observed wage $\tilde{w}_1$ in the first job with measurement error. The term $\frac{1}{w_1}$ is the Jacobian of the transformation. The term $\exp\left(-h_E(\varepsilon_1)t_1\right)$ is the probability that the first job is still ongoing after a duration of t_1. $w^* = a\theta^*$ represents the reservation wage for workers with ability a and the reservation match value θ^*.

If the first job is dissolved and worker goes back into unemployment, then we have $q_1 = 0$ and the probability function is

$$L_r^{(2)}(t_u, r_u = 0, \tilde{w}_1, t_1, r_1 = 1, q_1 = 0|\varepsilon_1) = h_U \exp(-h_U t_u) \int_{w^*} \eta \exp\left(-h_E(\varepsilon_1)t_1\right) \frac{1}{w_1} m\left(\frac{\tilde{w}_1}{w_1}\right) \frac{f(w_1)}{\tilde{F}(w^*)} dw_1$$

where $\eta \exp\left(-h_e(\varepsilon_1)t_1\right)$ captures the probability that first job lasts for duration t_1 and ends exogenously at time t_1.

Individuals with two or more job spells ($M \geq 2$):

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. If the match quality in the first job is $\theta(\varepsilon_1)$, the worker accepts to switch to a second job if and only if $\theta > \theta(\varepsilon_1)$. We simulate the match quality $\theta(\varepsilon_1, \varepsilon_2)$ in the second job as:

$$\theta(\varepsilon_1, \varepsilon_2) = \theta\left(\varepsilon_2 | \theta(\varepsilon_2) > \theta(\varepsilon_1)\right) = \exp\left(\mu_\theta + \sigma_\theta \Phi^{-1}\left(1 - \Phi\left(\frac{\log\theta(\varepsilon_1) - \mu_\theta}{\sigma_\theta}\right)\right)(1 - \varepsilon_2)\right)$$

where ε_2 is a random draw from a uniform distribution $U(0,1)$. After entering the second job spell, there are three possibilities at the end of the observation period. First, the current job may still be ongoing. Second, the worker may move into a third job with a better match quality. Third, she may exit the spell due to a forced separation, which occurs at rate η. The "total hazard" associated with the second job in the employment spell is the sum of latter two cases:

$$h_E(\varepsilon_1, \varepsilon_2) = \lambda_E \bar{G}(\theta(\varepsilon_1, \varepsilon_2)) + \eta$$

The likelihood of the first case (the second job is right censored $r_2 = 1$) is:

$$\begin{gathered} L_r^{(3)}(t_u, r_u = 0, \tilde{w}_1, t_1, r_1 = 0, q_1 = 0, \tilde{w}_2, t_2, r_2 = 1 | \varepsilon_1, \varepsilon_2) = \\ h_U \exp(-h_U t_u) \int_{w^*} \lambda_E \bar{G}(\theta(\varepsilon_1)) \exp(-h_E(\varepsilon_1) t_1) \tfrac{1}{w_1} m\left(\tfrac{\tilde{w_1}}{w_1}\right) \tfrac{f(w_1)}{\tilde{F}(w^*)} \\ \int_{w_1} \exp(-h_E(\varepsilon_1, \varepsilon_2) t_2) \tfrac{1}{w_2} m\left(\tfrac{\tilde{w_2}}{w_2}\right) \tfrac{f(w_2)}{\tilde{F}(w_1)} dw_2 dw_1 \end{gathered}$$

where $r_2 = 1$ represent the first job spell is right-censored and the worker is still employed at the end of sample period. Similarly, we construct an analogous term for the case in which the second job spell ends with unemployment ($r_2 = 0, q_2 = 1$)

$$\begin{gathered} L_r^{(3)}(t_u, r_u = 0, \tilde{w}_1, t_1, r_1 = 0, q_1 = 0, \tilde{w}_2, t_2, r_2 = 0, q_2 = 1 | \varepsilon_1, \varepsilon_2) = \\ h_U \exp(-h_U t_u) \int_{w^*} \lambda_E \bar{G}(\theta(\varepsilon_1)) \exp(-h_E(\varepsilon_1) t_1) \tfrac{1}{w_1} m\left(\tfrac{\tilde{w_1}}{w_1}\right) \tfrac{f(w_1)}{\tilde{F}(w^*)} \\ \int_{w_1} \eta \exp(-h_E(\varepsilon_1, \varepsilon_2) t_2) \tfrac{1}{w_2} m\left(\tfrac{\tilde{w_2}}{w_2}\right) \tfrac{f(w_2)}{\tilde{F}(w_1)} dw_2 dw_1 \end{gathered}$$

And lastly, the case in which the second employment spell ends by entering into a third employment spell ($r_2 = 0, q_2 = 0$) gives the likelihood

$$\begin{gathered} L_r^{(3)}(t_u, r_u = 0, \tilde{w}_1, t_1, r_1 = 0, q_1 = 0, \tilde{w}_2, t_2, r_2 = 0, q_2 = 0|\varepsilon_1, \varepsilon_2) = \\ h_U \exp(-h_U t_u) \int_{w^*} \lambda_E \bar{G}(\theta(\varepsilon_1)) \exp(-h_E(\varepsilon_1) t_1) \frac{1}{w_1} m\left(\frac{\tilde{w}_1}{w_1}\right) \frac{f(w_1)}{\tilde{F}(w^*)} \\ \int_{w_1} \lambda_E \bar{G}(\theta(\varepsilon_1, \varepsilon_2)) \exp(-h_E(\varepsilon_1, \varepsilon_2) t_2) \frac{1}{w_2} m\left(\frac{\tilde{w}_2}{w_2}\right) \frac{f(w_2)}{\tilde{F}(w_1)} dw_2 dw_1 \end{gathered}$$

To summarize, the overall likelihood contribution for the particular random draw $(\varepsilon_1, \varepsilon_2)$, combining the three cases, is

$$\begin{gathered} L_r(t_u, r_u, \tilde{w}_1, t_1, r_1, q_1, \tilde{w}_2, t_2, r_2, q_2|\varepsilon_1, \varepsilon_2) = \int_{w^*} \int_{w_1} (h_U)^{1-r_u} \exp(-h_U t_u) \\ \times \left\{ \exp(-h_E(\varepsilon_1) t_1) \left[\left(\lambda_E \bar{G}(\theta(\varepsilon_1)) \right)^{1-q_1} \eta^{q_1} \right]^{1-r_1} \frac{1}{w_1} m\left(\frac{\tilde{w}_1}{w_1}\right) \right\}^{1-r_u} \\ \times \left\{ \exp(-h_E(\varepsilon_1, \varepsilon_2) t_2) \left[\left(\lambda_E \bar{G}(\theta(\varepsilon_1, \varepsilon_2)) \right)^{1-q_2} \eta^{q_2} \right]^{1-r_2} \frac{1}{w_2} m\left(\frac{\tilde{w}_2}{w_2}\right) \right\}^{1-(r_1+q_1)} \\ \times \frac{f(w_1)}{\tilde{F}(w^*)} \frac{f(w_2)}{\tilde{F}(w_1)} dw_2 dw_1 \end{gathered}$$

To form the likelihood contribution conditional only on the observed labor market history, we need to take the average over the R random draws of $(\varepsilon_1(r), \varepsilon_2(r))$

$$\begin{aligned} L(Employment|\Omega) &= L(t_u, r_u, \tilde{w}_1, t_1, r_1, q_1, \tilde{w}_2, t_2, r_2, q_2|\Omega) \\ &= R^{-1} \sum_{r=1}^{R} L_r(t_u, \tilde{w}_e, r_u, \tilde{w}_1, t_1, r_1, q_1, \tilde{w}_2, t_2, r_2, q_2|\varepsilon_1(r), \varepsilon_2(r), \Omega) \end{aligned}$$

where, as previously noted, $\varepsilon_1(r), \varepsilon_2(r)$ are draws from the uniform distribution $U(0, 1)$.[23]

4.3 Incorporating individual heterogeneity

Our model assumes that an individual i has her individual specific set of labor market parameters $\Omega_i = \{\lambda_U(i), \lambda_e(i), \alpha(i), \eta(i), a(i), b(i), \sigma_\theta(i)\}$ which is uniquely determined by characteristics z_i, representing education, birth cohort, gender, and personality traits. We next describe the mapping of the set of characteristics z_i into the parameter set Ω_i. For a

[23]We set $R = 2,500$.

specific individual i with the characteristics z_i, the set of "link" functions $M : z_i \to \Omega_i$ is

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

We construct the overall log likelihood function LL for the whole sample (with sample size N)

$$\log LL = \sum_{i=1}^{N} L(Employment_i|z_i) = \sum_{i=1}^{N} L\left(Employment_i|\Omega_i\right)$$

where $L(Employment_i|\Omega_i)$ is the likelihood function of each individual with observed individual characteristics Ω_i.

5 Identification

5.1 Identification of parameters in a homogeneous search model

We begin this discussion 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 our analysis to cover the situation in which (potentially) each individual operates within their own labor market, that is, 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. In the estimation, we use 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.

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,identification of the model has been considered in detail in Flinn and Heckman (1982).[24] For the case without measurement error in wages, they demonstrate that the accepted wage offer distribution is nonparametrically

[24]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.

identified; however, in the absence of information on rejected wage offers, a parametric assumption is required to identify the full wage offer distribution.[25] Flinn and Heckman (1982) show that most parametric distributions can be identified even with systematically missing data on job offers.[26]

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.

Wolpin (1987) considers the estimation of a "one-shot" search model, that is, he estimates a search model defined only for the first spell of unemployment experienced by sample members after (or before, in some cases) exiting formal schooling. His model is cast in discrete time, (the time period is a week) and he allows the probability of receiving an offer to vary over time. As opposed to Flinn and Heckman, who considered the stationary search case in continuous time with no measurement error in wages, Wolpin allows for measurement error that follows a parametric distribution. He assumes that the wage offer distribution is log normal, as is the measurement error distribution.

In terms of the stationary, continuous-time case we are considering, there exists a reservation wage w^*, and all accepted wages are draws from the truncated distribution $G(w|w \geq w^*)$. We assume that 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 0 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. Under the parametric assumptions on the distributions and with truncation, however, the parameters μ, σ^2, σ_ε^2, and w^* are identified given access to a sufficiently large random sample of accepted wages.

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

[26] 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.

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 survivor 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 $h_E(w)/(h_E(w) + \eta)$.[27] Because we observe a number of first job spells (after unemployment) end in a move to another employer, it is straightforward to identify λ_E under the assumption that all wage draws are i.i.d draws from G, independent of the labor market state currently occupied.

We now consider the estimation of the bargaining power parameter α. Thus, 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

$$w = \alpha\theta + (1-\alpha)\theta^*,$$

where θ^* is the reservation match value, which depends on the individual's current employment state and the bargaining protocol that is assumed. Because θ^* is a constant, $w(\theta)$ 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 loca-

[27] In the case of measurement error of the form discussed above, we have $\tilde{w}/w = \varepsilon$, so that the conditional density of w given $\tilde{w}$ is given by

$$\frac{m(\frac{\tilde{w}}{w})\frac{\tilde{w}}{w^2}}{\Gamma(\tilde{w})},\ w \geq w^*,$$

where m is the lognormal density of ε, $\tilde{w}/w^2$ is the Jacobian of the transformation, and $\Gamma(\tilde{w})$ is a normalizing constant that ensures that the density integrates to 1 (see Flinn (2002), equation 17). Then if only the measured wage is available, we have

$$h_E(\tilde{w}) = \lambda_E \int_{w^*} \tilde{G}(w)\frac{m(\frac{\tilde{w}}{w})\frac{\tilde{w}}{w^2}}{\Gamma(\tilde{w})}dw.$$

In this case, $h_E(\tilde{w})$ is strictly increasing in $\tilde{w}$ just as $h_E(w)$ is strictly increasing in the actual wage w.

tion parameter, and d the scale parameter, then α is not identified.[28] 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. The nonlinearity of the logarithmic function is enough to ensure identification.

5.2 Introducing observed heterogeneity

In terms of the model described above, if we had access to an indefinitely long labor market history for each I individual, we could estimate the identified model parameters separately for each individual. In our case, we have access to only a very short period of observation on each of a large number of individuals, so allowing for heterogeneity requires positing restrictions on how parameters vary across individuals. In particular, the most unrestricted version of the model we take to the data characterizes individuals i in terms of the vector of characteristics z_i and specifies how the characteristics map into parameter values. For example, the rate of arrival of job offers in the unemployment and employment states are given by

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

and the rate of exogenous job dissolutions is

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

[28]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.

The flow utility of unemployment, b, can take any value on R in principle, so that

$$b(i) = z_i'\gamma_b.$$

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.[29] In this case

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

and

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

In terms of a, which is restricted to be positive, we set

$$a(i) = \exp(z_i'\gamma_a), \tag{5}$$

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 measure of the dispersion in the productivity values. Because bad matches can be rejected, 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

[29]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

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

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

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

As long as the the cross-products matrix $I^{-1} \sum_{i=1}^{I} z_i z_i'$ is of full-rank, the coefficients associated with each of the z_i vector in each of the parameterizations are identified.

6 Model Estimates

6.1 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 4. 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 1.410 for men and 1.125 for women, and the arrival rates for employed men and women are 0.070 and 0.127. 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 0.228 for men and 0.161 for women in the model with renegotiation, which are much lower than the estimated α for the model without renegotiation (0.50 for men and 0.33 for women).

The low estimated value of the surplus division parameter α in the model that allows for renegotiation is a common finding 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 7.54 for men and 6.69 for women in the former case and 10.703and 10.37 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.

Figure 4 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.

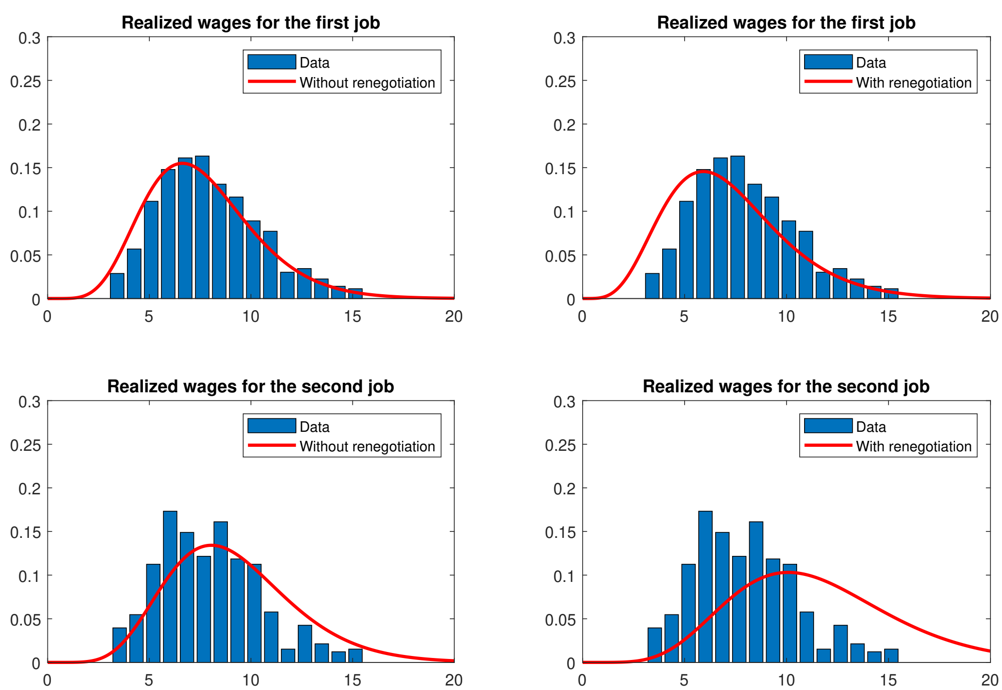
The simulation from the model with renegotiation predicts lower initial wages compared with the data. The wage growth from first job to second job (€5.59/h to €9.46/h) predicted from the renegotiation model is much larger the wage growth observed in the data (€7.66/h to €7.76/h). The wage growth predicted from the no-renegotiation model (€7.54/h to €8.69/h) provides a better fit. This result is consistent with similar findings concerning

Table 4: Parameter estimates under alternative bargaining assumptions

Parameter	Description	With renegotiation		Without renegotiation	
		Male	Female	Male	Female
a	time-invariant ability	7.539	6.686	10.703	10.366
		(1.403)	(1.215)	(0.844)	(1.026)
λ_u	offer arrival rate, in unemployment	1.410	1.254	0.274	0.216
		(0.360)	(0.587)	(0.025)	(0.048)
λ_e	offer arrival rate, in employment	0.070	0.127	0.052	0.078
		(0.014)	(0.035)	(0.008)	(0.015)
η	separation rate	0.026	0.029	0.025	0.028
		(0.006)	(0.010)	(0.005)	(0.008)
α	surplus division	0.228	0.161	0.503	0.325
		(0.076)	(0.038)	(0.038)	(0.050)
b	flow utility when unemployed	0.773	1.091	-1.190	-0.197
		(0.188)	(0.062)	(0.420)	(0.123)
σ_θ	$\theta \sim \log N\left(-\frac{\sigma_\theta^2}{2}, \sigma_\theta\right)$	0.284	0.232	0.326	0.354
		(0.020)	(0.015)	(0.040)	(0.042)
N		4,319		4,319	
$\log L$		-20,537		-18,954	

NOTES: Asymptotic standard errors in parentheses. Data: IZA Evaluation Dataset. The location parameter of match quality distribution μ_θ is predetermined to be $-0.5\sigma_\theta^2$. We fix the values of the ratio $\frac{\sigma_\theta}{\sigma_\epsilon}$ in the specification without renegotiation the same as the values in the specification with renegotiation.

Figure 4: Observed and simulated wage distributions



these two types of specifications reported in Flinn and Mullins (2015).[30]

Figure 5 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.

The simulations from both model specifications replicate the distributions of unemployment/employment spells reasonably well. In general, the no-renegotiation specification exhibits a better fit than the renegotiation specification, with the (log) likelihood value of -21,629 and -18,931, respectively. This finding is consistent with other studies estimating similar types of specifications of the bargaining process (Flinn and Mabli (2009); Flinn and Mullins (2015)). Given that the model without renegotiation provides a substantially better fit, the remainder of our quantitative analysis will be based on that specification.

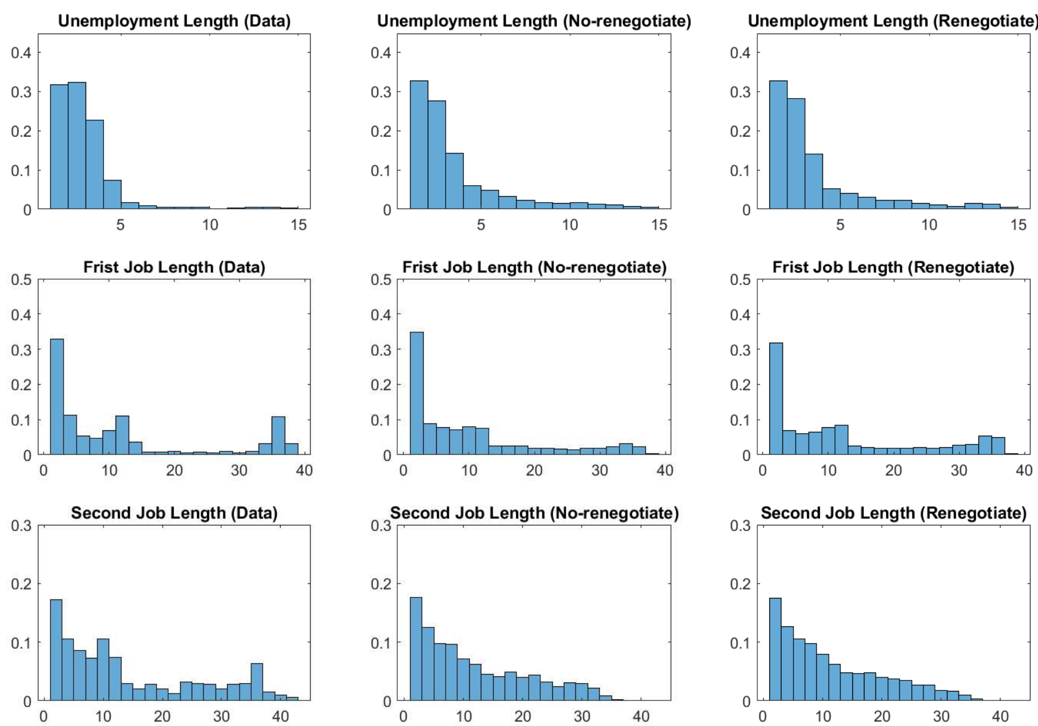
6.2 Estimated model parameters under alternative specifications

Using the no-renegotiation modeling framework, we estimate three different models that incorporate varying degrees of individual parameter heterogeneity. The estimates are reported in Table 5. 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 5 indicate that men and women have different labor market parameters. The unemployment job arrival rate (λ_U) is estimated to be lower

[30] 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.

Figure 5: Observed and simulated unemployment spells/job spells



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.[31] Our results show the female productivity is 10.366 in comparison to 10.703 for men, which contributes to the gender wage gap. Compared with previous studies, we find a smaller gap in productivity. For example, Bowlus (1997) finds the productivity of females is 17% lower using NLSY79 data. Flabbi (2010a) finds a 21% differential in average productivity using CPS data.

The smaller hourly wage gap in our sample in comparison to other survey samples could partly be due to the fact that the sample consists of newly unemployed workers. The gender wage gap in Germany is generally considered to be fairly large. According to Blau and Kahn (2000), the gender hourly gap in West Germany is 32 percent, placing West Germany in position 6 in a ranking of 22 industrialized countries. However, for these newly unemployed workers, the wages in the initial jobs out of unemployment show a smaller wage gap of 7.2% (see Table 1).

In terms of the surplus division parameter α, we find the value for men is 0.503 and the value for women is 0.325. The estimated values are fairly consistent with Bartolucci (2013). He 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.

The two bottom lines of table 5 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).

6.3 Understanding the role of personality traits in determining model parameters

In this section, we examine how education and personality traits affect job search parameters $\{\lambda_U, \lambda_E, \eta, \alpha, \beta\}$. In Table 6, 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

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

Table 5: 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	10.458	10.232	9.514	10.703	10.366
		(0.276)	(1.320)	(0.683)	(0.844)	(1.026)
λ_U	offer arrival rate, in unemployment	0.235	0.272	0.212	0.274	0.216
		(0.007)	(0.012)	(0.011)	(0.025)	(0.048)
λ_E	offer arrival rate, in employment	0.050	0.051	0.066	0.052	0.078
		(0.002)	(0.003)	(0.004)	(0.008)	(0.015)
η	separation rate	0.026	0.026	0.026	0.025	0.028
		(0.001)	(0.001)	(0.001)	(0.005)	(0.008)
α	surplus division	0.439	0.534	0.513	0.503	0.325
		(0.022)	(0.163)	(0.075)	(0.038)	(0.050)
b	flow utility when unemployed	-5.997	-2.513	-3.621	-1.190	-0.197
		(0.015)	(0.015)	(0.054)	(0.420)	(0.123)
σ_θ	$\theta \sim \log N\left(-\frac{\sigma_\theta^2}{2}, \sigma_\theta\right)$	0.301	0.289	0.308	0.326	0.354
		(0.020)	(0.030)	(0.024)	(0.040)	(0.042)
σ_ϵ	$\epsilon \sim \log N\left(-\frac{\sigma_\epsilon^2}{2}, \sigma_\epsilon\right)$	0.253	0.235	0.250	0.232	0.252
		(0.040)	(0.049)	(0.045)	(0.050)	(0.052)
N		4,319	4,319		4,319	
$\log L$		-19,056	-19,005		-18,954	
LR tests			(1)&(2)		(2)&(3)	
P value			0.000		0.000	

NOTES: Asymptotic standard errors using numerical scoring function are reported in parentheses. Data: IZA Evaluation Dataset. The first likelihood ratio (LR) test is the current specification test against the previous specification. The monthly discount rate is set ex ante to be 0.005. The location parameter of match value distribution μ is predetermined to be $\mu_\theta = -0.5\sigma_\theta^2$.

increases the unemployment job offer arrival rate and decreases the on-the-job offer arrival rate. It lowers the job destruction rate for both men and women, with a larger effect for women. As would be expected, it also increases ability for both genders. With regard to the bargaining surplus parameter, education increases the bargaining surplus parameter for men but lowers it for women.

As seen in Table 6, many of the personality traits are statistically significant determinants of job search parameters. However, they sometimes affect men and women in different ways. For both men and women, emotional stability increases job offer arrival rates (for women, only when employed), lowers the job destruction rate, enhances productivity, and decreases the bargaining parameter.

For men, openness to experience increases the on-the-job arrival rate and lowers productivity but does not affect any other model parameters. For women, openness to experience has no statistically significant effect on any of the parameters.

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 increases productivity for men but lowers it for women. It also decreases the bargaining parameter for women only.

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. For women only, it decreases the job separation rate. It enhances productivity for women but lowers productivity for men. Lastly, agreeableness has a big negative effect on the bargaining parameter for women.

Lastly, extraversion generally increases job offer arrival rates and job separation rates for both men and women. Extraversion also has a statistically significant effect on lowering the bargaining parameter for women.

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 6, 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, but being in the age 35-44 category is associated with a lower bargaining parameter for both men.

Table 6: 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.	-1.589	-1.822	-3.343	-3.533	-3.077	-3.200	2.203	2.151	0.637	0.966
	(0.246)	(0.205)	(0.458)	(0.282)	(0.422)	(0.246)	(0.192)	(0.161)	(0.649)	(0.401)
Edu	0.082	0.329	-0.141	-0.284	-0.028	-0.409	0.114	0.160	0.072	-0.169
	(0.008)	(0.023)	(0.015)	(0.031)	(0.039)	(0.048)	(0.009)	(0.017)	(0.060)	(0.059)
Stb	-0.008	0.024	0.128	0.083	-0.117	-0.047	0.036	0.020	-0.084	-0.051
	(0.027)	(0.011)	(0.007)	(0.004)	(0.005)	(0.009)	(0.009)	(0.011)	(0.023)	(0.015)
Opn	0.008	0.011	0.034	0.018	-0.032	0.008	0.004	0.011	0.026	-0.001
	(0.026)	(0.013)	(0.015)	(0.022)	(0.015)	(0.028)	(0.027)	(0.012)	(0.061)	(0.026)
Cos	0.046	0.022	-0.014	0.074	-0.070	-0.028	0.034	-0.036	0.036	-0.031
	(0.008)	(0.014)	(0.050)	(0.004)	(0.009)	(0.017)	(0.011)	(0.006)	(0.065)	(0.013)
Agr	-0.041	-0.045	-0.027	0.009	-0.028	-0.040	-0.035	0.040	-0.057	-0.176
	(0.008)	(0.006)	(0.022)	(0.026)	(0.020)	(0.010)	(0.009)	(0.006)	(0.036)	(0.011)
Ext	0.052	0.049	0.006	0.049	0.116	0.045	-0.011	-0.001	-0.063	-0.057
	(0.006)	(0.005)	(0.051)	(0.008)	(0.007)	(0.010)	(0.031)	(0.020)	(0.032)	(0.010)
Cohort (Omitted cat: 73-82)										
63-72	-0.045	-0.151	-0.058	-0.060	-0.182	-0.238	0.031	0.021	-0.126	-0.024
	(0.015)	(0.009)	(0.020)	(0.018)	(0.020)	(0.031)	(0.026)	(0.022)	(0.055)	(0.065)
52-62	-0.065	-0.171	-0.086	-0.048	0.109	0.264	0.001	-0.023	-0.072	-0.098
	(0.012)	(0.012)	(0.017)	(0.027)	(0.015)	(0.035)	(0.084)	(0.034)	(0.073)	(0.029)

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

Table 7: 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
Emotional Stability	-0.008	-0.038	0.024	0.274
	(0.027)	(0.511)	(0.011)	(0.366)
Openness to experience	0.008	0.375	0.011	0.682
	(0.026)	(0.514)	(0.013)	(0.378)
Conscientiousness	0.046	2.159**	0.022	2.436***
	(0.008)	(0.709)	(0.014)	(0.589)
Agreeableness	-0.041	-0.231	-0.045	-1.181*
	(0.008)	(0.599)	(0.006)	(0.497)
Extraversion	0.052	1.055	0.049	0.499
	(0.006)	(0.581)	(0.005)	(0.434)
Higher level secondary degree	0.082	2.822*	0.329	0.398
	(0.008)	(1.224)	(0.023)	(0.903)
Cohort (base: 73-82)				
1963-72	-0.045	-0.207	-0.151	-0.905
	(0.015)	(1.265)	(0.009)	(0.990)
1952-62	-0.065	-0.179	-0.171	-1.894
	(0.012)	(1.370)	(0.012)	(1.045)

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

6.4 Evidence on determinants of job search effort

In Table 7, 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, but examining this relationship can provide some insight into the mechanisms being captured by the estimated model parameters. Numbers of applications is likely to be a key factor underlying individual heterogeneity in job offer arrival rates.

As seen in Table 7, 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 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 arrivals may in part be a results of differing numbers of job applications.

6.5 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)) 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, Total") fully explains the gap in offered and accepted wages. Looking at the rows "All parameters, Education" and "All parameters, Personality," we see that women receive a premium for their education relative to men and that giving them the male coefficients associated with education would increase the wage gap relative to the baseline. The main area in which they are being rewarded less is for their personality traits. Giving females the estimated male coefficients associated with personality traits would reverse 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, women receive a higher valuation for their education than men. As seen in Table 6, women were rewarded differently for their personality traits than men, but the net effect of gender differences in the personality coefficients in explaining the wage gap is minor. Overall, gender differences in the estimated productivity parameters are not an important channel in explaining the wage gap.

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 empirically as important a determinant of wage gaps as is the surplus division channel.

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	Value of unemployment
Baseline	0.839	0.861	0.909
All parameters			
-Constant	0.828	0.840	0.905
-Personality	1.162	1.171	1.151
-Education	0.815	0.831	0.872
-Total	0.979	0.992	0.965
Productivity (a, σ)			
-Constant	0.897	0.914	0.968
-Personality	0.818	0.840	0.886
-Education	0.825	0.844	0.893
-Total	0.868	0.883	0.937
Surplus division (α)			
-Constant	0.768	0.781	0.831
-Personality	1.068	1.113	1.148
-Education	0.867	0.892	0.939
-Total	1.018	1.059	1.097
Transitions $(\lambda_U, \lambda_E, \eta)$			
-Constant	0.853	0.878	0.937
-Personality	0.912	0.913	0.922
-Education	0.813	0.827	0.870
-Total	0.898	0.893	0.916

Notes: The simulation results are based on specification (3), Table 6. Except for the indicated parameter subset, other parameter values are set at female values.

These decompositions show that women generally have an education premium vis-a-vis labor market productivity. 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 much lower bargaining parameters. Gender differences in the parameters that determine the bargaining surplus can fully account for observed gender wage gaps and these differences are the most important determinant of gender wage gaps.

In Table 9 we further examine how the agreeableness parameter varies by gender. Recall from Table 1 that the mean value of agreeableness is 5.181 for the male sample and 5.512 for the female sample. As can be seen in the table, the male bargaining parameter is relatively insensitive to changes in agreeableness and is on average 0.5. The female bargaining parameter estimates are much lower and vary over the range 0.32-0.37.

Table 10 performs the same decompositions as Table 8 except that now we set the female

Table 9: How agreeableness affects surplus parameters α by gender

	Male		Female	
Agreeableness	α	Proportion	α	Proportion
(0,3]	0.501	0.044	0.368	0.054
[3,4)	0.501	0.172	0.339	0.137
[4,5)	0.504	0.316	0.329	0.266
[5,6)	0.504	0.292	0.319	0.316
[6,7)	0.505	0.150	0.315	0.187

Table 10: Wage differential decomposition by each trait and channel

	All channels	Surplus division	Transitions	Productivity
"Big-five"' in total	1.162	1.068	0.912	0.818
Emotional stability	0.893	0.832	0.871	0.911
Openness to experience	0.880	0.895	0.877	0.830
Conscientiousness	1.566	0.960	0.922	1.297
Agreeableness	0.679	1.026	0.856	0.574
Extraversion	0.784	0.854	0.828	0.820

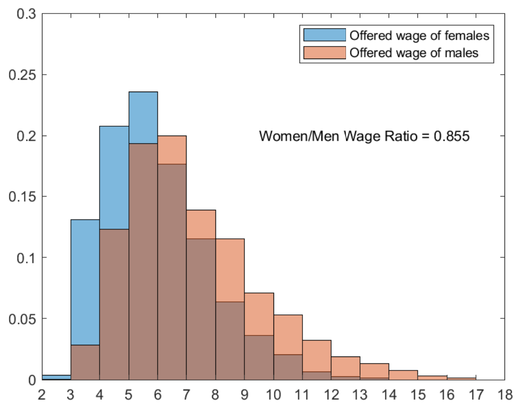
Notes: Women/men average wage ratio in steady-state is reported in each columns.

parameters associated with different personality traits equal to the male estimated parameters (across all channels of the model and separately). This decomposition examines which personality traits are the most important determinants of gender wage gaps. Of the five traits, differences in the estimated parameters associated with conscientiousness emerge as most important overall in explaining the gender wage gap. We see a ratio above 1 for conscientiousness (particularly with regard to productivity), which means that men are being more highly rewarded for this trait. Both men and women receive a penalty for agreeableness, but in different ways. Agreeableness lowers productivity for men and lowers bargaining surplus for women. Men also receive a productivity penalty for extraversion. The surplus division channel is the most important to explaining the wage gap.

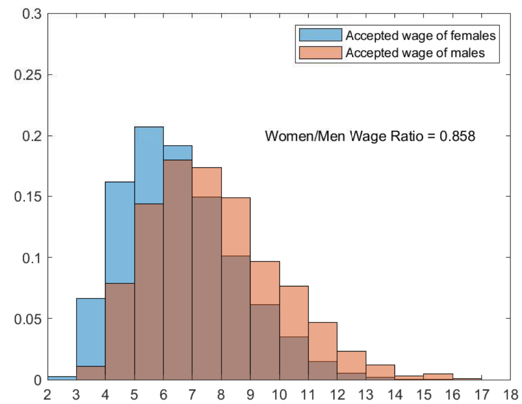
Figure 6 displays the distributions of offered wages and accepted wages in both the baseline and the counterfactual "equal pay experiment" in which women were paid according to the male labor marker parameters. In the baseline model (upper panel), the female's wage distribution is more left-skewed than male's wage distribution, indicating that the offered wages and accepted wages are lower for women than for men. However, this gap is totally eliminated under the simulation that gives women the estimated model parameters for men. (bottom panel).

Figure 6: Distributions of accepted wages and offered wages

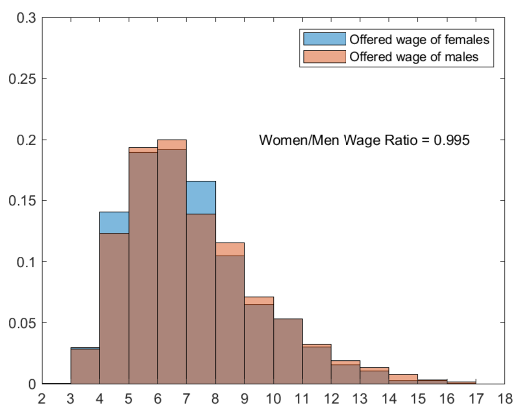
(a) Offered wages in baseline model



(b) Accepted wages in baseline model



(c) Offered wages under equal parameters



(d) Accepted wages in equal parameters

7 Conclusions

In this paper, we develop and estimate a job search framework to investigate how individual heterogeneity in 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 we consider the two specifications 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. 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 individual 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. If anything, women receive an education premium in terms of productivity. Women are mainly disadvantaged in terms of the labor market valuation of their personality traits. Giving women the same labor market returns to personality-traits that men have would eliminate observed and accepted wage gaps.

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 most important channel, followed by differences in labor market transitions due to different job offer arrival and job destruction rates.

When we examine the different personality traits in isolation, we find that men are much more highly rewarded in the labor market than women for conscientiousness and emotional stability. Both men and women are penalized for being aggreeable - men in terms of productivity and women in terms of bargaining surplus. Of the five traits, differences in the valuation of conscientiousness and emotional stability emerge as overall the most important traits in explaining gender wage gaps.

A Appendices

A.1 Model Solutions

A.1.1 Solving the reservation match quality $\theta^*(a)$ with renegotiation

In this section we provide further details for solving the bargained wage $w(\theta, \theta, a)$ as well as the reservation match value $\theta^*(a)$.

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

We use the rent splitting rules

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

yields the equivalent expression

$$\begin{aligned} (6) \quad \left(\rho + \eta + \lambda_E \bar{G}(\theta)\right) V_E(\theta', \theta, a; w) &= w + V_U(a) + \lambda_E \int_{\theta}^{\theta'} \left[(1-\alpha) V_E(x, x, a) + \alpha V_E(\theta', \theta', a)\right] dG(x) \\ &+ \lambda_E \int_{\theta'} \left[(1-\alpha) V_E(\theta', \theta', a) + \alpha V_E(x, x, a)\right] dG(x) \end{aligned}$$

Consider the case $\theta' = \theta$ and $w = a\theta'$, take the derivative, one gets

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

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

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

and the bargained wage has the following expression

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

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

In order to calculate the reservation match value $\theta^*(a)$, we first use the definition of $V_U(a)$

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

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

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

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

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

A.1.2 Solving the reservation match value $\theta^*(a)$ without renegotiation

In this section we describe the method of solution of 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 $V_U(a)$ to be equal to ab:

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

The state θ_L is an absorbing state, since 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.

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

with the wage

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

and the implied value (if acceptable match quality is θ_L) is given by

$$V_U(a;\theta_L) = \frac{ab + \lambda_U p_L V_E(\theta_L, a)}{\rho + \lambda_U p_L}$$

2. Sequentially solve the value of employment with match $V_E(\theta_l, a)$ and $w(\theta_l, a)$ as well as $\bar{V}_U(a;\theta_l)$

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

$$w(\theta_l,a)=a\left(\alpha\theta_l+(1-\alpha)\left(\left(\rho+\lambda_E p_{l+1}^+\right)V_U(a)-\lambda_E\sum_{i\geq l+1}^{L}p_iV_E(\theta_i,a)\right)\right)$$

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

$$V_E(\theta_l,a)=\frac{w(\theta_l,a)+\eta V_U(a)+\lambda_E\sum_{i\geq l}^{L}p_iV_E(\theta_i,a)}{\rho+\eta+\lambda_E p_l^+}$$

where the notation $p_l^+=\sum_{i\geq l}^{L}p_i$. And the implied value (if acceptable match quality is θ_l) is given by

$$V_U(a;\theta_l)=\frac{ab+\lambda_U\sum_{i\geq l}^{L}p_iV_E(\theta_i,a)}{\rho+\lambda_U p_l^+}$$

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 a value of unemployed search value given by $V_U(a;\theta_l)$. The optimal acceptance match is the one that produces that highest value of unemployment state, i.e.,

$$j=\arg\max_i\{V_U(a;\theta_l)\}_{l=1}^{L}$$
$$V_U^{new}(a)=V_U(a;\theta_j),\theta^*(a)=\theta_j$$

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

A.1.3 Solving the equilibrium wage distribution without renegotiation

In this section we want to calculate the equilibrium wage distribution $q(w)$ when there is no renegotiation between firms and workers. Assuming $l(a,\theta)$ is the equilibrium distribution for workers' with ability a and matching quality θ. On the outflow side, the workers leave jobs with matching quality θ either because they are laid off (rate η) or because they receive an offer from another firm with better matching quality $\theta'\geq\theta$ therefore join that firm. On the inflow side, workers enter into jobs with matching quality θ from two sources. Either they are hired away from a job with less matching quality $\theta'\leq\theta$ or they come from unemployment. The steady-state equality between flows into and out of the stocks determines $l(a,\theta)$ as:

$$\left(\eta+\lambda_E\bar{G}(\theta)\right)l(a,\theta)(1-U)=\left[\lambda_U Uh(a)+\lambda_E(1-U)\int_{\theta^*}^{\theta}l(a,x)dx\right]g(\theta)$$

where $\lambda_U U = \eta(1-U)$ and $h(a)$ is the distribution of worker with time-invariant ability a in the unemployment pool. Then we get

$$\left(\eta + \lambda_E \bar{G}(\theta)\right) l(a,\theta)(1-U) = \left[\eta h(a) + \lambda_E (1-U) \int_{\theta^*}^{\theta} l(a,x)dx\right] g(\theta)$$

which solves

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

where $\kappa_1 = \frac{\lambda_E}{\eta}$. Then given the connection that $w = a(\alpha\theta + (1-\alpha)\theta^*(a))$, the equilibrium wage distribution $q(w|a)$ follows

$$q(w|a) = \frac{1}{a\alpha} \frac{l\left(\alpha^{-1}\left(\frac{w}{a} - (1-\alpha)\rho V_U\right)|a\right)}{\bar{L}(\theta^*(a)|a)}, w \geq a\theta^*(a)$$

where $\bar{L}(\theta^*|a) = \int_{\theta^*(a)} l(\theta|a)d\theta$. Then the unconditional distribution would be $q(w) = q(w|a)h(a)$.

A.2 Sample construction

A.2.1 Obtaining the final dataset used in our analysis

As a general rule, we focused our effort on avoiding dropping relevant observations to maintain the maximum possible coverage. Our data cleaning proceeded as follows. First, we need to calculate 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 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. And the month durations of spells are calculated based on the “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 following the below steps:

- We drop the duplicated spells number counted in different waves, reducing the number of observation to 51,334.
- We drop any spells after the fourth spell, which leave the total observations 43,229. (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 the 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 irrelevant activities) or whose unemployment benefit information is missing. These restrictions leave us with 20,012.
- We combine any consecutive unemployment spells into one spell, which reduces the observation to 19,138.
- We further drop any individuals without key personal characteristics: 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 4,319 individuals with 5,874 observations, consisting of 4,319 first unemployment spells, 2,526 first job spells and 540 second job spells.

A.3 The stability of personality traits and the correlation between personality traits and locus of control

A.4 The comparison between IZA ED and GSOEP

A.5 Additional figures and tables

Table A1: 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: sample for this regressions is restricted to all 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. Significance levels: $*p < 0.05$, $**p < 0.01$, $***p < 0.001$.

Table A2: The correlation between "Big 5" traits and locus of control

	Emotional Stability	Openness to experience	Conscientiousness	Extraversion	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 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 all external items are reversely coded.

Table A3: 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 as being internal if their LOC scores are higher than the median and external otherwise. See notes in table A2 for the definition of the LOC scores.

Table A4: The comparison between IZA ED and GSOEP

	IZA ED		GSOEP	
	Male	Female	Male	Female
Current hourly wage (€/h)	8.282	7.577	16.26	13.33
	(2.506)	(2.449)	(7.574)	(6.701)
Previous accu. experience (years)	18.05	15.64	18.59	17.14
	(9.986)	(9.632)	(8.755)	(8.620)
Age	37.64	38.72	41.23	41.60
	(8.660)	(8.685)	(8.059)	(8.298)
Birth cohorts				
1952-1962	0.389	0.358	0.372	0.413
	(0.488)	(0.480)	(0.483)	(0.492)
1963-1972	0.362	0.330	0.399	0.359
	(0.481)	(0.470)	(0.490)	(0.480)
1973-1982	0.249	0.313	0.228	0.228
	(0.433)	(0.464)	(0.420)	(0.420)
Education levels				
Lower secondary school	0.383	0.223	0.286	0.197
	(0.486)	(0.416)	(0.452)	(0.397)
(Adv.) middle sec. school	0.404	0.429	0.370	0.452
	(0.491)	(0.495)	(0.483)	(0.498)
Upper sec. school (A-level)	0.212	0.349	0.343	0.351
	(0.409)	(0.477)	(0.475)	(0.477)
Marriage status	0.436	0.472	0.633	0.628
	(0.496)	(0.499)	(0.482)	(0.484)
Dependent child (under age 18)	0.333	0.363	0.457	0.431
	(0.471)	(0.481)	(0.498)	(0.495)
Emotional Stability	3.757	3.432	3.768	3.308
	(1.071)	(1.132)	(1.056)	(1.102)
Openness to experience	4.744	4.932	4.409	4.601
	(1.049)	(1.048)	(1.003)	(1.093)
Conscientiousness	5.668	5.841	5.550	5.670
	(0.787)	(0.749)	(0.798)	(0.766)
Agreeableness	5.169	5.507	4.853	5.164
	(0.907)	(0.873)	(0.892)	(0.827)
Extraversion	4.664	4.853	4.397	4.702
	(1.022)	(0.992)	(1.042)	(1.032)
Obs.	2,244	2,075	4,380	4,284

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.

Table A5: Questionnaire about personality traits in the IZA ED

Big Five 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 the in between values. I am someone who...
5 more items added (starting cohort February, No. 9)
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 considerately and friendly (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
Each of the personality traits are calculated as the average scores of three items. (The scores of 3, 5, 7, 10, 12 needs to be reverted before calculating the average values)
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

Table A6: Other parameters in specification (3) under the renegotiation model: individual heterogeneity with gender-specific model coefficients

Cons.	-0.538	-0.525	-3.076	-3.399	-3.427	-2.479	2.625	2.400	-0.090	-0.424
	(0.638)	(0.474)	(0.621)	(0.460)	(0.386)	(0.451)	(0.199)	(0.139)	(0.715)	(0.760)
Edu	-0.500	-0.394	0.280	0.343	-0.436	-0.405	0.297	0.233	-0.975	-0.082
	(0.155)	(0.131)	(0.147)	(0.089)	(0.103)	(0.109)	(0.057)	(0.037)	(0.215)	(0.202)
Stb	0.046	-0.042	0.075	0.054	0.088	-0.194	0.010	0.005	-0.053	-0.026
	(0.075)	(0.053)	(0.069)	(0.042)	(0.040)	(0.044)	(0.024)	(0.014)	(0.077)	(0.079)
Opn	-0.045	0.052	0.029	0.045	-0.042	0.016	-0.021	0.074	-0.038	-0.069
	(0.072)	(0.051)	(0.071)	(0.047)	(0.043)	(0.046)	(0.024)	(0.014)	(0.074)	(0.077)
Cos	0.043	0.041	-0.057	0.056	-0.050	-0.088	-0.075	-0.095	0.038	-0.099
	(0.091)	(0.049)	(0.086)	(0.056)	(0.061)	(0.061)	(0.029)	(0.019)	(0.095)	(0.098)
Agr	0.086	-0.077	0.069	-0.041	-0.022	0.014	0.011	-0.033	-0.127	-0.056
	(0.089)	(0.067)	(0.081)	(0.045)	(0.048)	(0.058)	(0.029)	(0.020)	(0.092)	(0.105)
Ext	0.062	0.095	-0.026	0.138	0.056	-0.014	-0.052	-0.050	0.026	0.083
	(0.077)	(0.062)	(0.068)	(0.049)	(0.046)	(0.050)	(0.025)	(0.016)	(0.078)	(0.074)
Cohort (Omitted cat: 73-82)										
63-72	0.073	0.360	-0.092	0.051	-0.185	0.322	-0.004	-0.006	-0.410	-0.477
	(0.143)	(0.142)	(0.154)	(0.103)	(0.098)	(0.113)	(0.043)	(0.040)	(0.164)	(0.246)
52-62	0.063	0.904	0.080	-0.027	-0.212	-0.096	-0.087	0.023	-0.258	-0.469
	(0.173)	(0.167)	(0.169)	(0.104)	(0.105)	(0.129)	(0.059)	(0.043)	(0.188)	(0.245)

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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