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 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 decompose the sources of the gender wage gap. The results show that the gap arises largely because women's personality traits are valued differently than men's. Of the Big Five traits, conscientiousness and agreeableness 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 differences remain with women earning on average 25 percent less

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

There is increasing recognition that 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] For example, Heckman et al. (2006), Heckman and Raut (2016) and Todd and Zhang (2018) estimate dynamic education and occupation choice models and find that personality traits have both direct effects on worker productivity and indirect effects on preferences for schooling, working and/or occupations. Cubel et al. (2016) examine whether personality traits affect productivity in a laboratory setting and find that individuals with high levels of conscientiousness and emotional stability exert more effort on a task. Fletcher (2013) uses sibling samples and family fixed effect estimators and finds a robust relationship between personality traits and wages. Although the accumulated evidence shows that personality traits are related to labor market outcomes, the mechanisms through which they operate have not been fully explored.[2]

Reviews of gender differences in preferences and in personality traits can be found in Croson and Gneezy (2009) and Bertrand (2011). Empirical 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 what extent these traits contribute to 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 than men, but men receive a higher wage premium for being conscientious. The static household time allocation model that they develop assumes that nonemployment

[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 neuroticism (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 e.g. Nyhus and Pons (2005), Heineck (2011), Mueller and Plug (2006), Braakmann (2009), Cattan (2013)

is voluntary and does not incorprate labor market search frictions.

This paper explores the effect of personality traits on labor market outcomes through job search channels. We develop and estimate a partial equilibrium job search model in which personality traits potentially operate through a number of 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. We propose a way of modeling the dependence of job search parameters on a possibly high dimensional set of observable characteristics. 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) bargaining power. 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. Using data from National Longitudinal Survey of Youth 1979 (NLSY79), Bowlus (1997) 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 nonparticipation 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 incorporating 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. A positive proportion of prejudiced firms lowers women's outside options, generating spillover effects even at nondiscriminatory firms. Using Census Population Survey (CPS) data, Flabbi (2010a) finds that average female productivity is 6.5 percent lower than male productivity and that about half of the employers discriminate. A recent study by Liu (2016) also estimates a job search model for the purpose of studying sources of gender wage gaps. Using data from the Survey of Income and Program Participation (SIPP), he finds that the key explanatory factors are differences in mean offered wages (conditional on observed characteristics), job search parameters, the wage penalty for part-time work, and demographic factors. None of the above papers consider personality characteristics as potential determinants of gender labor market disparities.

To the best of our knowledge, only two 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 some of the model's implications using the IZA Evaluation Dataset but do not estimate the model's primitive parameters. 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 NLSY97. 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 equilibrium search model. The search and matching model that we estimated allows workers to receive wage offers both while unemployed and on-the-job. Model parameters are obtained by maximum likelihood using the German IZA Evaluation Dataset, a panel dataset that follows individuals who became unemployed between 2007 and 2008 for up to three years. An unusual feature of these data relative to other available datasets is that they contain the Big Five personality measures. Previous studies typically focus on a single noncognitive measure, such as locus of control (e.g. Caliendo et al. (2015), McGee (2015)). We consider the Big Five personality traits because (i) there is a significant gender difference in the five measures but little gender difference in the locus of control measure and (ii) we aim to explore which personality traits matter most for the various job search channels in the model. In addition, we use information on age, gender, education, wages, hours worked, and job transitions, and incorporate these observables in our estimation procedure.[4] Our analysis sample includes men and women during prime-age working years (ages 25-55).

We estimate two different model specifications that make different assumptions on how

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

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

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 at their current job, while another specification (without renegotiation) assumes that firms cannot confirm outside offers and workers only get 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.[5]

Using the"without-renegotiation" framework, we estimate three different nested job search models that vary in the degree of individual heterogeneity incorporated. In the most general specification, worker productivity, job arrival rates, job exit rates, and bargaining parameters 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.

The estimates indicate that personality traits are statistically significant determinants of job search parameters for both men and women, but that they sometimes affect men and women in different ways. For example, women are on average more conscientious than men, but men receive a higher wage premium in the labor market for being conscientious. Both men and women are penalized for being agreeable, but the penalty operates through the productivity parameter for men and through the bargaining parameter for women. The model parameter estimates also show personality trait effects on the job arrival rate, which is consistent with the observed positive relationship between number of job applications and conscientiousness.

Lastly, we use the estimated model to decompose 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 similar for men and women. However, more educated women and more agreeable women are at a large disadvantage relative to men in terms of bargaining. Gender differences in bargaining parameters emerge as a key factor contributing to the wage gap.[6]

[5]Flinn and Mullins (2018) develop a model in which equilibria can exist in which some forms do not renegotiate while others do. Such an extension is beyond the scope of our current analysis.

[6]Our finding is consistent with the long-standing literature that argues that gender differences in wage negotation could be a major factor in explaining gender pay gaps (see e.g. Robinson (1969)). Stuhlmacher and Walters (1999) present a meta-analysis of the results from lab-based studies and concludes that women on average obtain a smaller share of the bargaining surplus than men. Säve-Söderbergh (2007) found that female college graduates tended to ask for a lower salary at the start of their first job and ended up receiving lower salaries than men. Card et al. (2015) used longitudinal data for Portuguese workers and found that within firms women received 90% of the pay earned by men.

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

2 Model

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 standard partial equilibrium job search framework. Let an individual "type" be denoted by the vector 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 $G_z(\theta)$. The θ draw is determined at the time the searcher-firm contact is made and is perfectly observed by both agents. 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 assumed.[7] 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 common scalar independent of z. 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, the scalar value z will be written as a linear combination of observed individual characteristics that include education level, gender, birth cohort and the Big Five personality assessments, with the weights attached to the characteristics allowed to differ across structural parameters. Because our model is stationary 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 labor market diffferences through the lens of the canonical search, matching, and bargaining model.

[7]If allowing for the renegotiation 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 unemployment. We will discuss these two cases separately later.

2.1 Baseline Model with No On-the-Job(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.[8] 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.[9] In the environment with no OTJ search, the only way that an employment spell can end is exogenously, occurring at rate η. Then the value of employment at a job with 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. [10]

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 $\alpha \in [0,1]$ represents the bargaining power of the worker and we have used the assumption that the firm's outside option, keeping the vacancy open, has value zero due to a

[8] When we will later 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 can postpone this more technical discussion.

[9] 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.

[10] 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.

free entry condition (FEC). 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

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

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

The value of unemployed search is defined as

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

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 for an individual of type a is $y^*(a) = a \times \theta^*$. We can write the wage function in the Nash bargaining case with no OTJ search as

$$w(\theta, a) = aw^*(\theta, \theta^*),$$

where

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

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 in labor market outcomes. 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 $w^*(a) = y^*(a) = a\theta^*$. Then the c.d.f. of wages for workers with ability a is

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

where $\bar{G} \equiv 1 - G$. 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 an individual's type 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 in principal depend on all heterogeneity, 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 reservation match value 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 $E_\theta[y(z,\theta)] = a(z)E_\theta[\theta] = a(z)$.[11] In such a 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.[12]

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

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

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 necessary to account for job-to-job transitions in the data. We assume the job arrival rate from other potential employers is $\lambda_E(z)$. When meeting another firm, 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 make 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 will then describe the case in which firms do not respond to offers from competing firms. This may occur either because the potential outside options are not verifiable or firms have an incentive to renege on their offered wage once the potential competitor's offer has been withdrawn.[13] 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. However, in each of these cases efficient mobility will result, that is, the worker will work at the firm for which their match productivity is greatest.[14] We will estimate the model under both bargaining protocols.

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

[13]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.

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

the incumbent has no advantage or disadvantage in retaining the worker with respect to the poacher.[15] Let θ and θ' be the two match draws at the two firms. Let $\theta' > \theta$, in which case we will refer to θ' as the *dominant* match value and θ as the *dominated* match value. When firms engage in Bertrand competition in terms of wage negotiations, the firm associated with the dominated match value will attempt to attract the worker by increasing its wage offer to the point where it earns no profit from the employment contract.[16] In the case of our example, the firm with match value θ will offer a wage of $a\theta$ to attract the worker. The value of working in the dominated firm with wage $a\theta$ (equal to worker's productivity) then serves as the worker's outside option when engaging in Nash bargaining with the dominant firm.

We now derive the expression for the bargained wage. First, consider an employed worker with the state variable (θ', θ, a), where θ' is the dominant match value, θ is the dominated match value, 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 θ^*. 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 term (1) reflects the case in which a new dominated match value x, where $\theta < x \leq \theta'$, is drawn. In this case, the employee will remain at their current firm, but the wage will be renegotiated given the increased value of the employee's outside option, which increases from θ to x. Term (2) reflects the case in which the new match productivity value x exceeds the (current) dominant match value θ'. In this case, the individual moves to the new job, where their productivity is given by ax, and the new dominated match value becomes θ'. In either case, the (potential) wage payment at the dominated firm is equal to the individual's productivity at the firm (since in this case the firm's profit flow is 0). This is the same outcome as would occur in the bargaining situation when their was no dominant match value, with match productivity at both firms given by θ. Then

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

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

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

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 the surplus 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.

As was the case for when there was no OTJ search, the wage function can be written as

$$w(\theta',\theta,a;R)=aw^*_R(\theta',\theta)$$

since the reservation match value is independent of a. When the individual is unemployed, their reservation match value is given by θ^*_R in the case of negotiation. Then for a currently unemployed searcher, who locates a match value $\theta'\geq\theta^*_R$, their wage is

$$w(\theta',\theta^*_R,a;R)=aw^*_R(\theta',\theta^*_R).$$

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.[17] In such case, all on-the-job wage bargaining uses the value of unemployment

[17]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

as the value of outside option, which is an option always available whether or not the wage contract is enforced.

In this bargaining protocol, the "dominated" match value does not affect the bargained wage at the dominant match productivity value. 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 a filled job becomes

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

In this case the bargaining problem is

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

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 unemployment to a searcher of ability a in this case is $a\bar{V}_U$, where

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

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

As in the case of the renegotiation, when the worker is unemployed there will be a critical match value θ_N^* (which is not equal to θ_R^*, in general), and the wage received by a currently unemployed searcher who locates a job match θ is given by

$$w(\theta,\theta_N^*,a;N)=aw_N^*(\theta,\theta_N^*).$$

For an individual who is currently employed at a job with match productivity $\theta\geq\theta_N^*$, if they meet a new employer where the match value is $\theta'>\theta$, their wage at the new employer

be that specified in equation 4.

will be

$$w(\theta', \theta^*_N, a; N) = a w^*_N(\theta', \theta^*_N).$$

Since w^* is strictly increasing in its first argument whenever $\alpha > 0$, so that

$$w^*_N(\theta', \theta^*_N) > w^*_N(\theta, \theta^*_N),$$

it follows that all firm-to-firm mobility will be efficient, that is, if $\theta' > \theta$, the individual will work at the firm at which the match value is θ'.[18] Firm-to-firm mobility will be efficient whether the bargaining protocol is when of renegoation or non-renegotiation.

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 households together, their labor supply decisions should be thought of as being simultaneously determined. The measured gender differences in wages partially reflect patterns of assortative mating in the marriage market and the manner in which household decisions are made. Ignoring the interrelatedness between men's and women's labor market decisions would yield a distorted view of the factors behind gender wage differentials.

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.[19] Let the current "earnings" 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

[18] In the case of renegotiation, the value of a match is not only reflected in its wage, and $w^*_R(\theta', \theta)$ is not, in general, monotonically increasing in θ' for $\theta' > \theta$. This nonmonotonicity is due to the future bargaining advantage θ' gives. With no renegotiation, the value of a match is solely reflected in the wage paid, so that $w^*_N(\theta', \theta^*_N)$ is monotonically increasing in θ'.

[19] 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.

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), under this common assumption we do not have to be concerned with assortative mating in the marriage market or interdependence in decision-making within the household.[20]

3 The IZA Evaluation Data Set

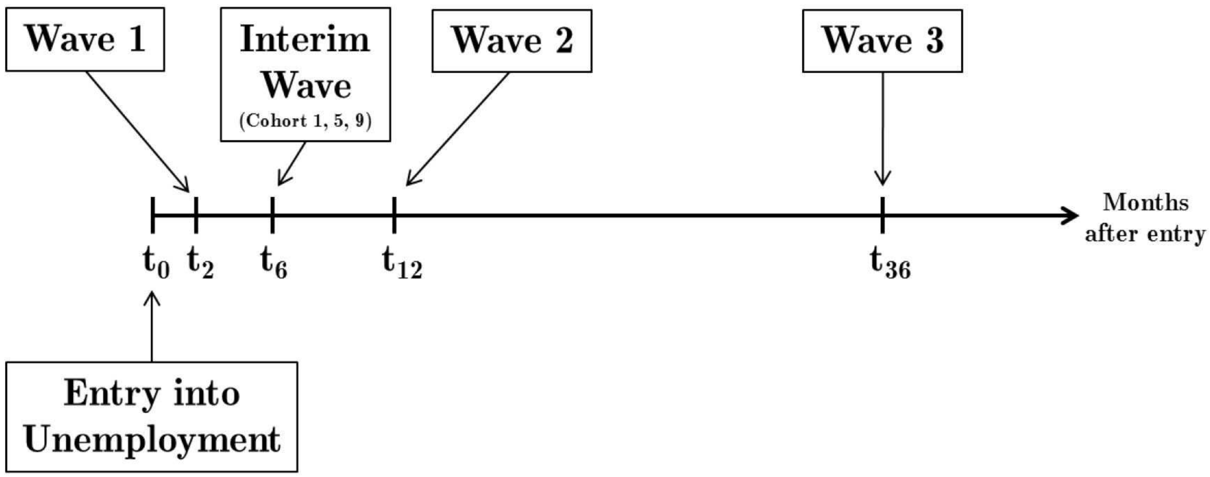
The IZA Evaluation Dataset Survey (IZA ED) is a panel survey of 17,396 Germans who registered as newly unemployed with the Federal Employment Agency between mid-May 2007 and mid-May 2008. In each of 12 months, approximately 1,450 individuals are randomly selected to be interviewed based on their birthdays.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

The IZA ED is a monthly cohort-specific panel. Upon entry into unemployment, each cohort was interviewed at least three times. Most cohorts did their first interviews within 55 to 84 days after entering unemployment. The second and third interviews are scheduled one year and three years later. In addition, three cohorts (corresponding to months June and October 2007 and February 2008) are interviewed at an interim time, six months after their first interview. A graph of panel structure can be found in figure 1. In constructing our analysis sample, we drop individuals with missing information, such as age, gender, and education, as well as missing information on their personality traits. We also exclude self-employed individuals, because our model pertains to firm-worker matches. These restrictions leave us with a final sample of 4,319 individuals.[21]

[20]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.

[21]A detailed discussion of the sample restrictions appears in Appendix A.2.1. As a dataset focused on

Figure 1: Panel Structure



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

The "Big Five" information in the IZA ED is based on a 15-item personality description. Respondents were asked to pick a number between 1 to 7 to indicate how well each description applies to them. The lowest number '1' denotes a completely opposite description and the highest number '7' denotes a perfect description. Each personality trait is constructed by the average scores of three items pertaining to that trait.[22]

The personality trait information is collected at each wave, including the interim wave. The completed Big Five personality traits are available for 5,601 respondents in wave 1, for 1,680 respondents for the interim wave, and for 5,747 and 5,732 respondents in waves 2 and 3, respectively. We include in our analysis individuals for whom personality traits were measured at least once. For individuals with multiple measures, we use the average value across the different waves, because differences observed within a 3-year time frame are likely due to measurement errors rather than fundamental changes in personality characteristics.[23]

the unemployed, IZA ED also records very detailed information on participation in any active labor market programs (ALMP) in Germany. There are three main programs: short-term training (9.4%), long-term training(10.3%) and wage subsidies(10.6). Caliendo et al. (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. We do not explicitly include information on ALMP in our analysis.

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

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

Cognitive skills are only measured for three cohorts that were selected to participate during the interim wave (June and October 2007, February 2008).

Table 1 presents summary statistics by gender. As seen in the last column, all of the gender differences are statistically significant at conventional levels. Males spend fewer months in unemployment, 2.41 on average in comparison to 2.67 for females. 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 €9.51 in comparison to €8.26 for women. Their actual wage is also higher, €8.79 on average for men in comparison to €7.66 on average for women. Men also report on average a higher reservation wage than women; €8.26 for men compared to €7.24 for women.

Comparing the average wage for men and women, we find a 14.7 percent gender wage gap. At first glance, the wage gap we find seems substantially smaller than the large wage gaps reported for Germany in other studies. For example, Blau and Kahn (2000) found a gender hourly gap in West Germany of 32 percent, placing West Germany in position 6 in a ranking of 22 industrialized countries. In order to better understand the reason why our wage gap is lower, we also tabulated mean wages by gender using the German Socio-Economic Panel (GSOEP) data (a random representative sample). We determined that the difference in wage gaps across the datasets arises primarily because the wages reported in IZA-ED are net wages, whereas the wages used in most studies are gross wages, which are net wages plus taxes and social security, and payments for unemployment and health insurance. Due to the progressive nature of the German tax system, the gap in net wages should be smaller than the gap in gross wages. In the GSOEP data for 2007 and for newly unemployed workers similar to the individuals in our sample, the net wage gap is 22.4 percent but the gross wage gap is 30.5 percent (the average wages are €13.52 for men and €10.36 for women).[24]

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

[24]For a detailed comparison between IZA-ED and GSOEP, please refer to Table 4.

A comparison of personality trait scores shows that men have higher emotional stability scores on average. But for all other traits, women have higher scores on average. The greatest gender differences for personality traits occur for emotional stability (3.81 for males versus 3.40 for women) and agreeableness (5.19 for males versus 5.51 for females). As previously noted, some studies focus on locus of control as a measure of an individual's noncognitive skills. As seen in the last row of the table, our sample shows very little gender difference in average locus of control (4.36 for men and 4.31 for women). Because of this small difference, we focus on the Big Five personality measures as a potential source of labor market outcome disparities between men and women.[25]

The theoretical model we estimate is set in a stationary environment, and this assumption may be problematic given the period of time when the data were collected. We examine the labor market conditions in Germany during the years 2007-2010 when our sample was collected to see if the stationarity assumption is at all plausible. One concern in particular is how the German labor market was affected by the financial crisis of 2007-2008. Figure 2 shows the unemployment rates for Germany, France, the UK, and the US. The unemployment rate in the US experienced a dramatic increase between 2007-2010 (purple dashed line), but the unemployment rates in Germany (DEU) remained much more stable during the same period (solid dotted line). In the right panel, we compare the unemployment rates obtained using two data sources (OECD and GSOEP). The trends are consistent with trends reported in Carrillo-Tudela et al. (2018). Our conclusion is that the stationarity assumption may not be ideal for this period of time in Germany, but that it is much less problematic than it would be if we were using data from the US during this period.

Table 2 reports estimated coefficients from a linear regression of log hourly wages (at the last time of employment) on the covariates education, personality traits, cognitive ability, and reported labor market experience before being unemployed and its square. As seen in Table 2, the coefficient associated with education is similar for men and women (0.230 for women compared to 0.241 for men). For both men and women, higher scores on emotional stability are associated with higher hourly wages. A higher conscientiousness score is associated with higher wages for men but lower wages for women. As is typically found in the literature, agreeableness is associated with lower wages, although our regression shows an effect only for men. Conditional on the other included variables, the cognitive ability score is associated with higher wages but the associated coefficient is not statistically significant at conventional levels.

[25] Additional information on the correlation between Big-five and locus of control can be found in Table 2 and Table 3.

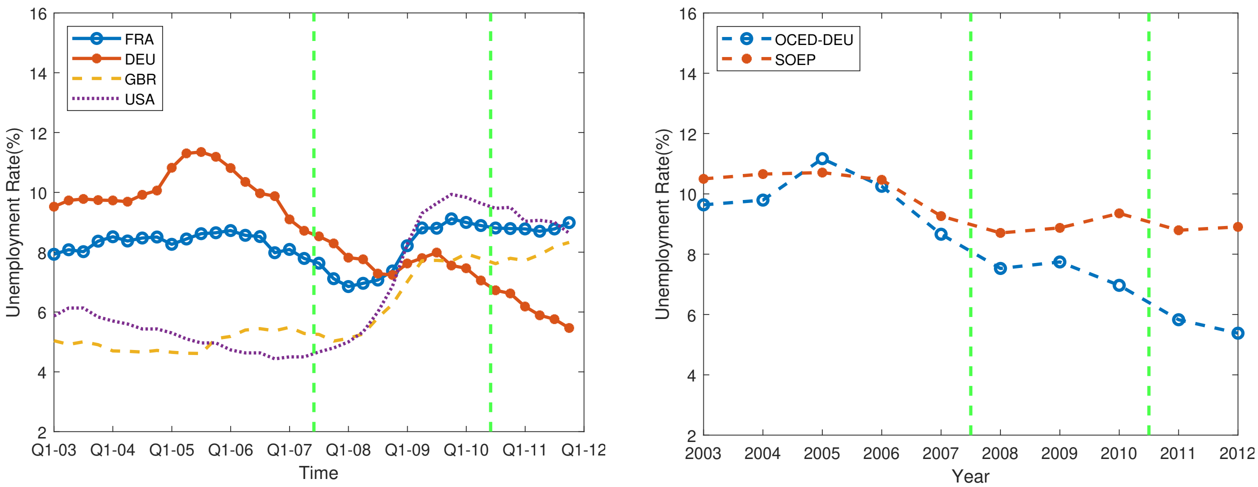
Table 1: Summary Statistics by Gender

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

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

Figure 2: The evolution of unemployment rates between year 2002-2013 in Germany, France, UK and US

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



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

In light of our theoretical model, wage differences can occur because of differences in reservation wages, productivity, job finding rates, job destruction rates, and/or bargaining. The structural model we estimate below allows us to explore these different mechanisms.

Table 3 displays estimates of the hazard rate from unemployment to employment under a Cox proportional hazard function specification. The estimation takes into account censoring, namely that all individuals start out unemployed and some are never observed to become employed during the sample window. As seen in the Table, for both men and women, a higher score on emotional stability significantly increases the likelihood of finding a job. For women, education also increases the hazard out of unemployment, but education is not a significant determinant for men. Being more extraverted tends to decrease the hazard rate from unemployment for men.[26] Cognitive ability increases the hazard rate out of unemployment, but the effect is statistically significant only for men. Including the cognitive ability measure in the specification does not significantly affect the magnitude of the other estimated coefficients.

In Figure 3, we show estimates of Kaplan-Meier survival functions associated with duration in the unemployment state, where the estimation is performed separately by gender. As seen in Figure 3, women exit unemployment more slowly than men. However, men are more

[26] 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.

Table 2: The effects of personality traits on hourly wages of first jobs out of unemployment (by gender)

Outcome variable:	Male		Female	
(log) hourly wage	(1)	(2)	(3)	(4)
Higher level sec. degree	0.241***	0.226***	0.230***	0.230***
(Baseline: sec. school or lower)	(0.032)	(0.032)	(0.034)	(0.034)
Emotional Stability	0.014	0.018	0.027*	0.024
	(0.012)	(0.012)	(0.013)	(0.013)
Openness to experience	0.006	0.006	0.018	0.016
	(0.013)	(0.012)	(0.015)	(0.015)
Conscientiousness	0.063***	0.050**	-0.071**	-0.071**
	(0.018)	(0.017)	(0.022)	(0.022)
Agreeableness	-0.052***	-0.051***	-0.013	-0.010
	(0.015)	(0.014)	(0.018)	(0.019)
Extraversion	-0.014	-0.015	-0.008	-0.008
	(0.014)	(0.014)	(0.016)	(0.016)
Cognitive Ability		0.057		0.017
		(0.055)		(0.062)
Marriage dummy		0.145***		-0.098**
		(0.031)		(0.031)
Dependent child (any)		0.053		0.041
		(0.032)		(0.033)
Number of Obs	932	932	697	697
R^2	0.074	0.118	0.117	0.130
Experience	X	X	X	X
$Experience^2$	X	X	X	X
Missing cognitive indicator		X		X

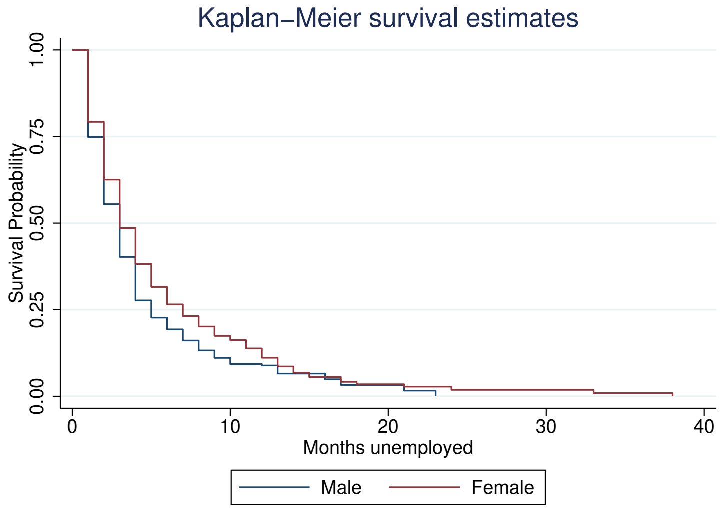
Notes: all columns display OLS regression results. The column "diff" shows the difference between female coefficients and male coefficients. The Source: IZA Evaluation Data Set, individuals age 25 to 55. Standard Errors in parentheses. $p<0.1^{*}$, $p<0.05^{**}$, $p<0.01^{***}$.

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

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

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

Figure 3: Unemployment duration: Kaplan-Meier survival estimates by gender



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

likely to experience longer spells in excess of 12 months. About 50 percent of the sample experiences initial unemployment spells lasting less than six months.

In Figure 4, we compare the personality trait distributions for men and women. Although all trait measures defined on a scale of 1 to 7, there are clearly differences in the shape of the distributions across traits and between men and women. The traits conscientiousness and agreeableness exhibit a high degree of skewness. Women are much more likely to rate themselves in the highest categories on openness, conscientiousness, and agreeableness and in the lowest categories on emotional stability.

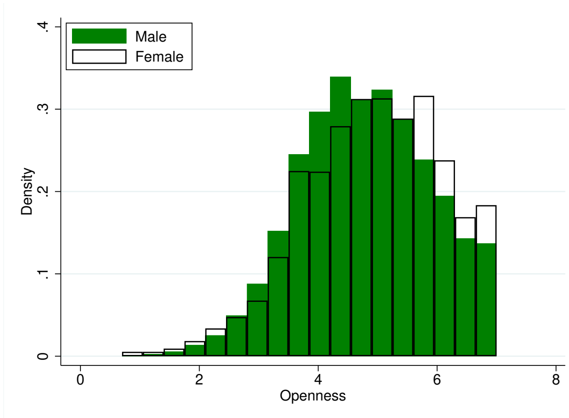
4 Econometric implementation

4.1 Wage specifications

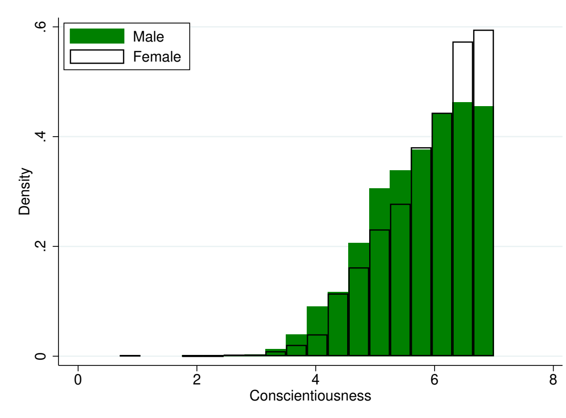
In our model, an individual only changes employers to move to a job with a superior match value, implying that all job mobility is efficient in the sense of increasing the worker's productivity. In the model in which there is no renegotiation and the wage is determined under Nash bargaining with the worker's outside option equal to the value of search while unemployed, any job-to-job move will be associated with a wage increase. Although the majority of job-to-job transitions in the data are associated with wage increases, a substantial proportion are not. There are some theoretical models in the literature that can accom-

Figure 4: The distributions of “big five” personality traits by genders

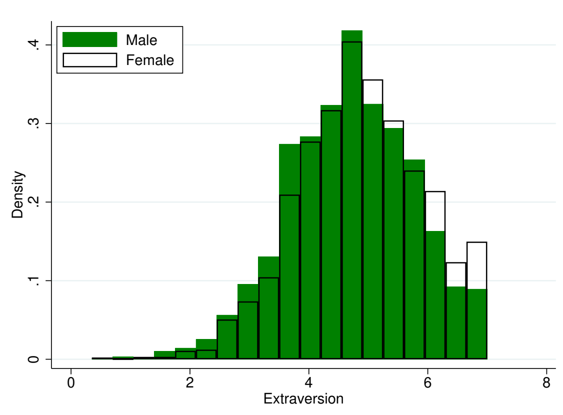
(a) Openness to experience



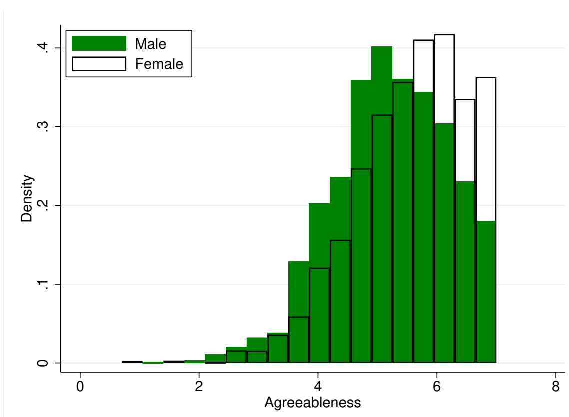
(b) Conscientiousness



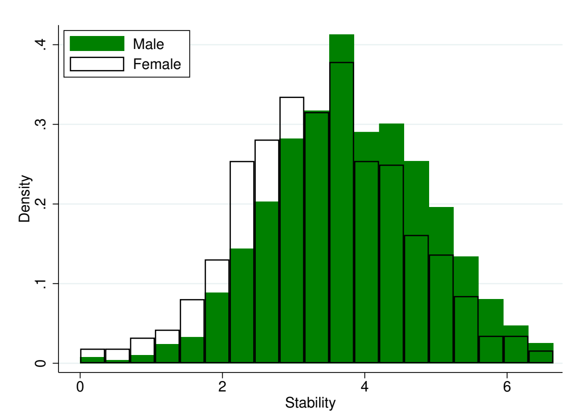
(c) Extraversion



(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.

modate job-to-job moves with wage declines.[27] This is also true of our Nash bargaining specification in which firms act as Bertrand competitors in attempting to hire or retain a currently employed worker. However, even in this case, the pattern of wage decreases that are observed in the data are not consistent with those generated by the model. For this reason, the addition of measurement error to the model is necessary.[28]

It is obviously the case that virtually all of the data we utilize are contaminated with reporting errors of various types. Nevertheless, the introduction of measurement error into nonlinear models, such as ours, is not costless. We are forced to make assumptions regarding the nature of the measurement error process, and misspecification of this process generally will lead to inconsistent estimates of other model parameters. In the absence of validating information, any assumptions we make regarding the form of the measurement error process are untestable. Recognizing these issues, we adapt a standard classical measurement error assumption, and write observed wages $\tilde{w}$ as

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

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

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

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

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

[27] 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.

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

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

4.2 Constructing the individual likelihood contribution

We estimate the model using a maximum likelihood estimator. In this subsection, we first discuss how we construct each individual likelihood contribution conditional on the individual's specific parameter values Ω_i, with the individual likelihood contribution of individual i denoted L_i. In the next subsection, we will describe the mapping between individual characteristics z_i and the individual-specific model parameters Ω_i. In order to avoid notational clutter in this subsection, we will suppress the individual subscript i, but the reader should bear in mind that the underlying econometric model allows for rich heterogeneity in parameters across individuals.

As in Flinn (2002) and Dey and Flinn (2005), for example, the information used to construct the likelihood function is defined as an employment cycle. An employment cycle begins with an unemployment spell that is then followed by one or more jobs in the employment spell that follows. For computational simplicity, we limit attention to the first two jobs in the employment spell. Each individual contributes information on one "employment spell" to the likelihood function. In describing the likelihood contribution of each individual, it will be useful to distinguish between three types of individual contributions: (1) those with information only on the (incomplete) unemployment spell; (2) those with information on the (completed) unemployment spell and one job spell; and (3) those with information on the (completed) unemployment spell and with information on the first two job spells. The data used to define the likelihood contribution of an individual can be represented as

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

For the unemployment state, t_U is the length of the unemployment spell and r_U is an indicator variable that takes the value 1 if the unemployment spell is right-censored. In the following employment spell, which consists of up to 2 jobs, for each job spell $k \in 1, 2$, t_k is the length of job k in the employment spell, $\tilde{w}_k$ is the observed wage in job k, and $r_k = 1$ indicates that the duration of job k is right-censored. When $r_1 = 0$, so that the end of the first job spell is observed, we set $q_1 = 1$ if job 1 ends with a move immediately into another job (which would be the second job in the employment spell). If the individual enters unemployment after the first job in the employment spell then $q_1 = 0$. Similarly, when there is a second job spell, $r_2 = 1$ when the second job is still in progress at the end of the observation period. When $r_2 = 0$, $q_2 = 1$ indicates that the second job spell ended with a move directly into a third job, while $q_2 = 0$ indicates that the individual became unemployed following the second job spell.

As described in Section 3, every individual observation in our sample begins with an unemployment spell. Therefore, we avoid the common difficulty of having to take into account incomplete spells at the beginning of a sample period, otherwise known as the left-censoring problem.[30] In addition, we focus on up to the first two job spells in the following employment spell. This is done to ease the computational burden.

Individuals only observed to be unemployed

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

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

where $\tilde{G} = 1 - G$ is the complementary cumulative distribution function and the density of the complete length of the unemployment spell 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, then we know that the complete spell length is no less than t_U, and the probability of this even is $P(\tilde{t}_U > t_U) = \tilde{F}_U(t_U) = \exp(-h_U t_U)$, where $\tilde{F}_U \equiv 1 - F_U$ is the survivor function. The likelihood contribution in this case is

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

Individuals with one job spell

Let the match productivity value at the first job be given by θ_1 (and recall that the individual's general ability is a). We estimate the model under two different assumptions regarding the renegotiation of wages between workers and firms in the case in which the worker has the possibility of working at either of two firms at a particular moment in time. In the case of Bertrand competition, there will be a wage function for a worker of type a who enters employment from an unemployment spell given by

$$w(\theta, a; R) = a w_R^*(\theta, \theta_R^*), \;\; \theta \geq \theta_R^*$$

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

where θ_R^* is the reservation match value for an unemployed individual in the model with renegotiation. From Postel-Vinay and Robin (2002), Dey and Flinn (2005), and Cahuc et al. (2006), we know that the function $w^*(\theta, \theta_R^*)$ is not monotone in θ, in general. For the case in which there is no renegotiation, and where the worker's outside option in every instance of worker-firm bargaining is the value of unemployed search, the wage is given by

$$w(\theta, a; N) = aw_N^*(\theta, \theta_N^*), \ \theta \geq \theta_N^*.$$

In this case, the function $w_N^*(\theta, \theta_N^*)$ is strictly increasing in θ.

Since the function $w_R(\theta, \theta_R^*)$ is not 1-1, we define the marginal distribution of $\tilde{w}_1$ by utilizing the joint density of $\tilde{w}_1$ and θ_1. In the first job in an employment spell, the marginal density of θ_1 is simply $g(\theta_1|\theta_1 \geq \theta_j^*) = g(\theta_1)/\tilde{G}(\theta_j^*)$, $\theta \geq \theta_j^*, \ j = R, N$. Given the value of θ_1 and given the bargaining protocol j, the conditional c.d.f. of $\tilde{w}|w$ is

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

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

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

Since w is a deterministic function, we have

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

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

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

In terms of the likelihood contribution of an individual with a first job that is on-going at the end of the sample period, we have

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

where

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

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

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

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

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

Recall that in this case we do not use information on the second unemployment spell, since this begins a different "employment cycle."

Individuals with two or more job spells

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. The cases in which bargaining involves renegotiation and when it does not generate somewhat different likelihood contributions. This is the case because under renegotiation, the wage function in the second job spell also includes the first job match value as an argument, so that

$$w_2(\theta_2, \theta_1, a; R) = a w_R^*(\theta_2, \theta_1), \ \theta_2 \geq \theta_1 \geq \theta_R^*.$$

Under no renegotiation, the first job spell match value has no impact on the bargained wage at the second job, so that

$$w_2(\theta_2, a; N) = a w_N^*(\theta_2; \theta_N^*), \ \theta_2 \geq \theta_1 \geq \theta_N^*.$$

We first consider the case in which the second job spell is right-censored. Since there is efficient mobility no matter which bargaining scenario is assumed, it must be the case that $\theta_2 \geq \theta_1 \geq \theta_j^*$, $j = R, N$. If there is no renegotiation, then

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

which simplifies to

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

If there is renegotiation, then we have

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

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

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

Under renegotiation, this is

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

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

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

Under renegotiation, the likelihood contribution becomes

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

This completes the specification of all of the cases that we can encounter in our data.

4.3 Incorporating individual heterogeneity

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

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

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 (large N, relatively small observation period). In the estimation, we use information from one unemployment spell per individual and information from a subsequent employment spell, including wage information and information on job-to-job movements and wage changes for up to two consecutive jobs.

In terms of the homogeneous case in which there is no on-the-job search and the bargaining power parameter, α, is constrained to be equal to 1, which is the case in which the worker receives the full surplus of the match, identification of the model has been considered in detail in Flinn and Heckman (1982).[31] For the case without measurement error in wages, Flinn and Heckman demonstrate that the accepted wage offer distribution is nonparametrically identified; however, in the absence of information on rejected wage offers, a parametric assumption is required to identify the full wage offer distribution.[32] Flinn and Heckman (1982) show that most parametric distributions can be identified even with systematically missing data on job offers.[33]

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 underlying 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 $G(w|w \geq w^*)$.

[31] 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.

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

[33] 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.

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.

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 $h_E(w)/(h_E(w) + \eta)$.[34] Because we observe a number of first job spells (after unemployment) that end in a move to another employer, it is straightforward to identify λ_E under the assumption that all wage draws are i.i.d draws from G, independent of the labor market state currently occupied.

We now extend our argument to consider the estimation of the bargaining power parameter α under the Nash bargaining protocol. In this case, the wage distribution is not considered to be exogenous, although the productivity distribution $G(\theta)$ is. The bargaining parameter is difficult to identify given that we only observe the portion of the surplus received by workers in the form of wages, and not the profits earned by the firm. A given wage distribution may be consistent with a "small" surplus that is mainly captured by the

[34] 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.

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, the function $w(\theta)$ is linear, and the wage distribution is given by $F(w) = G(\frac{w-(1-\alpha)\theta^*}{\alpha})$. Then if G is a location-scale distribution, so that $G(\theta) = G_0(\frac{\theta-c}{d})$, with G_0 a known function, c the location parameter, and d the scale parameter, the parameter α is not identified.[35] 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, although the parameter will not be estimated with precision unless the sample size is large. The fact that we assume that the wage observations are measured with error makes estimating α precisely even more challenging.

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 individual i, we could estimate the identified model parameters separately for each i. In our case, we have access to only a very short period of observation for each of a large number of individuals, so allowing for heterogeneity requires positing restrictions on how parameters vary across individuals. In particular, we assume that each

[35] 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.

individual is characterized by the linear index function

$$z_i \gamma_j,$$

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

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

and the rate of exogenous job dissolutions is

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

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

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

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.[36] In this case

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

[36] 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

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

and

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

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

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

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, it is well known that the welfare of individuals and firms is increasing in $\sigma_\theta^2(i)$.

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

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

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

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

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

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

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

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

and

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

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

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

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 1.21 for men and 1.49 for women, and the arrival rates for employed men and women are 0.09 and 0.11. These estimates are substantially larger than their corresponding values for the model without renegotiation. On the other hand, the estimated values of α are only 0.18 for men and 0.17 for women in the model with renegotiation, which are much lower than the estimated α for the model without renegotiation (0.48 for men and 0.37 for women).

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

Lastly, our estimates indicate lower estimates of ability parameters in the specification with renegotiation than for the specification without renegotiation. The parameter values are a are 7.61 for men and 5.86 for women in the former case and 12.07 and 11.17 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.

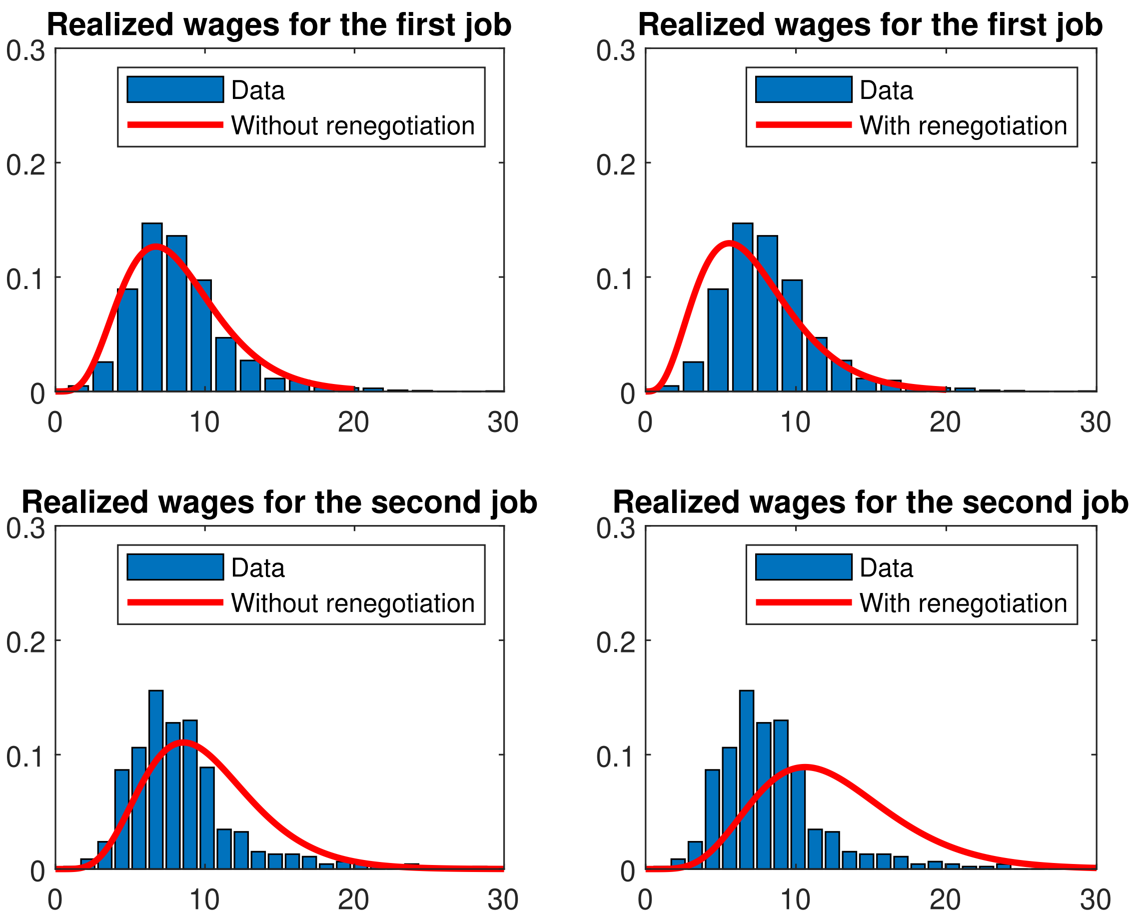
Figure 5 compares the model fits for both specifications of the bargaining process in terms of wage distributions of the first and second jobs. The top and bottom left panels show the fit of the model without renegotiation to the wage data for the first and second jobs. The top and bottom right panels 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.

Table 4: Parameter estimates under alternative bargaining assumptions

Parameter	Description	With renegotiation		Without renegotiation	
		Male	Female	Male	Female
a	time-invariant ability	7.608	5.859	12.073	11.173
		(1.175)	(0.477)	(1.076)	(1.185)
λ_u	offer arrival rate, in unemployment	1.214	1.490	0.256	0.213
		(0.146)	(0.636)	(0.025)	(0.048)
λ_e	offer arrival rate, in employment	0.091	0.109	0.044	0.070
		(0.008)	(0.033)	(0.007)	(0.015)
η	separation rate	0.033	0.020	0.027	0.027
		(0.006)	(0.009)	(0.005)	(0.007)
α	surplus division	0.184	0.169	0.484	0.370
		(0.034)	(0.049)	(0.045)	(0.052)
b	flow utility when unemployed	1.033	1.126	-1.186	-0.390
		(0.057)	(0.048)	(0.171)	(0.099)
σ_θ	$\theta \sim \log N\left(-\frac{\sigma_\theta^2}{2}, \sigma_\theta\right)$	0.291	0.281	0.324	0.349
		(0.005)	(0.006)	(0.016)	(0.019)
N		4,049		4,049	
$\log L$		-39,499		-36,298	

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 5: Observed and simulated wage distributions



The simulation from the model with renegotiation predicts lower initial wages compared with the data. The wage growth from first job to second job (€7.19/h to €12.45/h) predicted from the renegotiation model is much larger the wage growth observed in the data (€8.27/h to €8.49/h). The wage growth predicted from the no-renegotiation model (€8.14/h to €10.04/h) provides a better fit. This result is consistent with similar findings concerning these two types of specifications reported in Flinn and Mullins (2015).[37]

Figure 6 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.

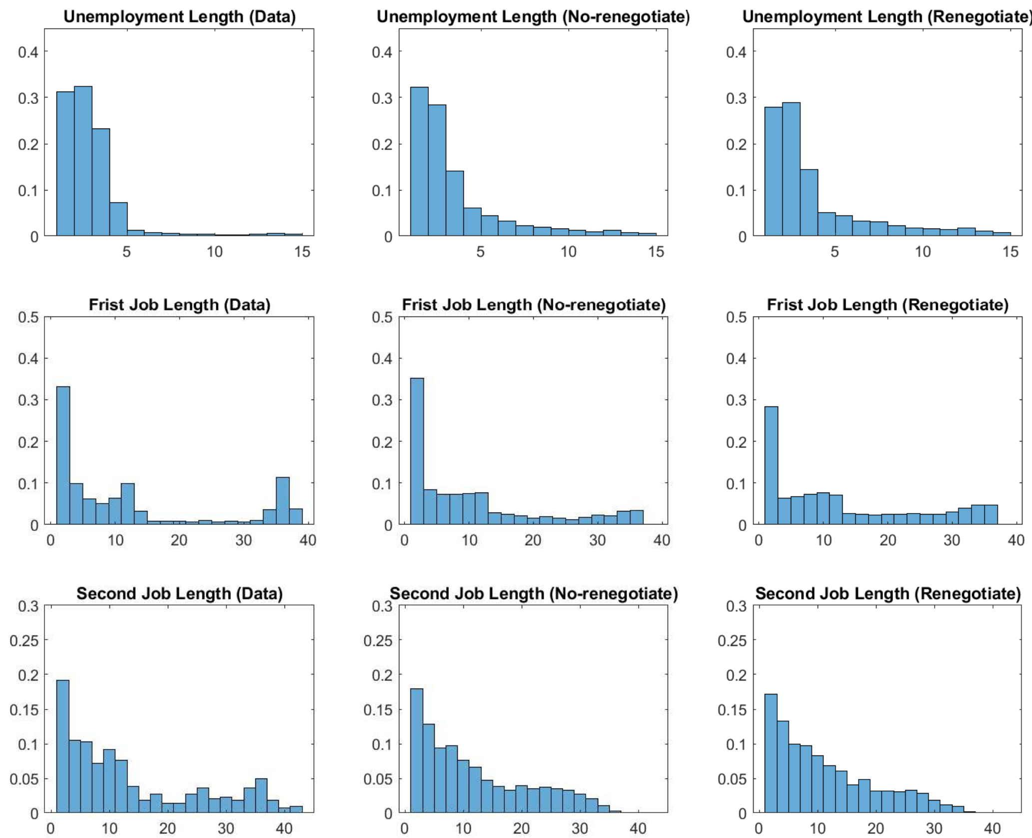
The simulations from both model specifications replicate the distributions of unemployment/employment spells reasonably well. In general, the no-renegotiation specification exhibits a better fit than the renegotiation specification, with the (log) likelihood value of -39,499 and -36,298, respectively. 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

[37] 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 6: Observed and simulated unemployment spells/job spells



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 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.[38] Our results show the female productivity is 11.17 in comparison to 12.07 for men, which contributes to the gender wage gap. The productivity gap is 8%, which is smaller than the gap found in other studies (using other datasets). For example, Bowlus (1997) finds the productivity of females is 17% lower using NLSY79 data. Flabbi (2010a) finds a 21% differential in average productivity using CPS data.[39]

In terms of the surplus division parameter α, we find the value for men is 0.484 and the value for women is 0.370. The estimated values are fairly consistent with papers using similar models in the literature. For example, Bartolucci (2013) uses German matched employer-employee data and finds female workers have on average slightly lower bargaining power than their male counterparts, with an average α of 0.421 across genders. Flinn and Mabli (2009) use US employee-level data and find the overall bargaining power is around 0.45.

The two bottom lines of table 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

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

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

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

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

influence wage and employment outcomes. For men and women, education increases the unemployment job offer arrival rate. Education decreases the on-the-job offer arrival rate for women. It lowers the job separation rate for both men and women, with a much larger effect for women. As would be expected, education increases ability for both genders. With regard to the bargaining parameter, education increases the bargaining parameter for men but lowers it for women.

As seen in Table 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 women, emotional stability increases job offer arrival rates, lowers the job separation rate, and enhances productivity. For men, emotional stability increases job offer arrival rates while employed, lowers the job separation rate, and increases productivity. Openness to experience has no statistically significant effect on any of the parameters for either men or women.

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

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

The job search model we estimate is stationary and we therefore do not condition on initial time-varying state space elements (such as labor market experience). However, we do include birth cohort indicator variables as a potential source of heterogeneous labor market parameters to capture possible differences in the labor markets for older and younger workers. As seen in the bottom rows of Table 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 or bargaining.

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

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

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
Higher level secondary degree	0.062	2.980	0.335	0.363
	(0.037)	(1.277)	(0.040)	(0.937)
Emotional Stability	-0.012	0.167	0.027	0.283
	(0.014)	(0.538)	(0.012)	(0.378)
Openness to experience	0.007	0.442	0.016	0.702
	(0.015)	(0.545)	(0.011)	(0.387)
Conscientiousness	0.046	2.168	0.020	2.305
	(0.019)	(0.745)	(0.015)	(0.604)
Agreeableness	-0.057	-0.394	-0.050	-1.097
	(0.014)	(0.629)	(0.014)	(0.509)
Extraversion	0.054	1.052	0.049	0.498
	(0.019)	(0.613)	(0.013)	(0.448)
Cohort (base: 73-82)				
1963-72	-0.045	-0.379	-0.129	-0.796
	(0.036)	(1.332)	(0.037)	(1.020)
1952-62	-0.096	-0.346	-0.189	-1.795
	(0.036)	(1.441)	(0.039)	(1.079)

Notes: The sample includes unemployed workers 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. However, 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 both men and women. For comparison purposes, columns (1) and (3) show the estimates that were previously reported in Table 6 for the unemployment job offer arrival rate. They are largely consistent with the regression results shown in columns (2) and (4) in terms of signs and statistical significance, which suggests that heterogeneous job arrival rates may in part reflect differing numbers of job applications.

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

As can be seen in Table 8, giving females all of the male parameters ("All parameters, Total") fully explains the gap in offered and accepted wages. Looking at the rows "All parameters, Education" and "All parameters, Personality," we see that giving women the male coefficients associated with education has almost no effect on the wage gap relative to the baseline. The main area in which women are being rewarded less is for their personality traits. Giving females the estimated male coefficients associated with personality traits would completely eliminate the wage gap.

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

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

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

These decompositions show that the area in which women appear to be at a significant

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

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

Notes: We calculate the counterfactual women/men wage ratio when setting the female parameters associated with a subset of the coefficients equal to the male estimated parameters. Meanwhile, other parameter values remain as female values, reporting in table 6.

disadvantage is with regard to bargaining. More educated women and more agreeable women, in particular, have substantially lower bargaining parameters.

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

Table 9: Wage differential decomposition by each trait and channel

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

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

Table 10: How agreeableness affects surplus parameters α by gender

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

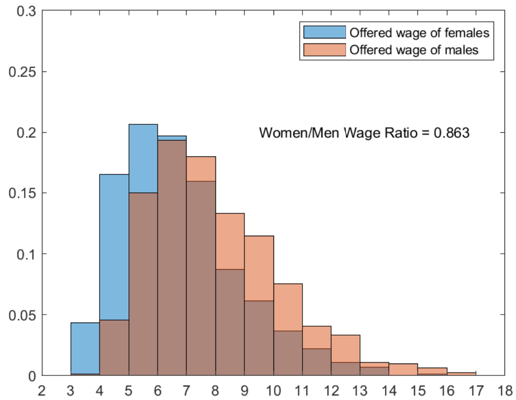
warded for conscientiousness than are women (primarily through the productivity channel), which widens the wage gap. With regard to agreeableness, both men and women receive a bargaining penalty for being agreeable (see column (2)). However, the penalty is greater for women. Concomitantly, men receive a productivity penalty for agreeableness that women do not experience. On net, combining both the surplus division and the productivity channels, differences in the estimated agreeableness parameters reduce the gender wage gap.

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

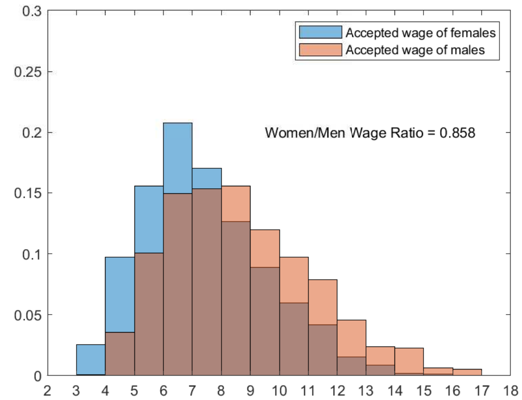
Figure 7 shows the offered wage and accepted wage distributions for both the baseline and the counterfactual "equal pay experiment" in which women were paid according to the male labor marker parameters. In the baseline model (upper panel), the female wage distribution is more left-skewed than male wage distribution. Offered wages and accepted wages are lower

Figure 7: Distributions of accepted wages and offered wages

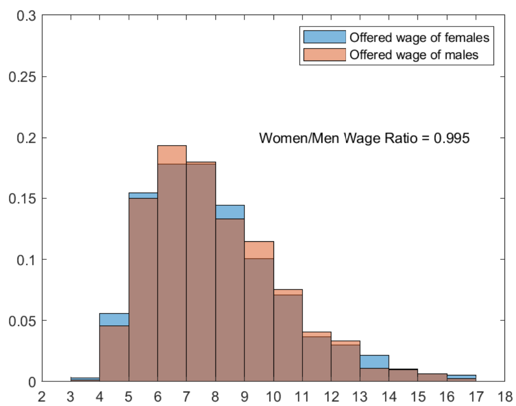
(a) Offered wages in baseline model



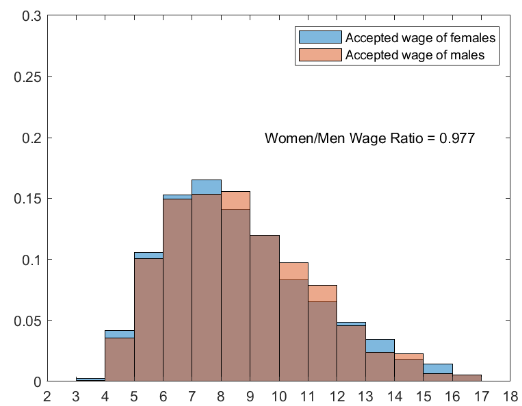
(b) Accepted wages in baseline model



(c) Offered wages under equal parameters



(d) Accepted wages under equal parameters



for women than for men. However, the wage gap is totally eliminated under the simulation that gives women the estimated model parameters for men. (bottom panel).

7 Conclusions

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

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

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

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

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

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

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

A Appendices

A.1 Model Solutions

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

In this appendix, we provide further detail on how to solve for 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 bargaining protocol

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

which yields the equivalent expression

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

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

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

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

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

and the bargained wage has the following expression

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

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

To calculate the reservation match value $\theta^*(a)$, 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 definition 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 to solve $\theta^*(a)$ as a fixed point problem

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

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

We next describe the method for solving the model. First, we need to discretize the continuous θ interval into L grids $\{\theta_1, ..., \theta_L\}$ with probability $\{p_1, ..., p_L\}$. To initialize the algorithm, we set a initial value of unemployment $V_U(a)$ 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, because no further job mobility can take place from that state during the current employment spell. The only way such a spell can end is through exogenous termination, which occurs at the constant rate η.

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

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

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

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

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

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

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

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

Here, the goal is to calculate the equilibrium wage distribution $q(w)$ when there is no renegotiation between firms and workers. Assume $l(a, \theta)$ is the equilibrium distribution for workers' with ability a and matching quality θ. On the outflow side, 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 $\theta' \geq \theta$ and 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 lower 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:

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

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 that $w = a(\alpha\theta + (1-\alpha)\theta^*(a))$, the equilibrium wage distribution $q(w|a)$ is

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

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

A.2 Sample construction

A.2.1 Obtaining the dataset used in our analysis

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

- We drop the duplicated spells number counted in different waves, reducing the number of observations to 51,334.

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

A.3 Additional results

A.3.1 Do measured personality traits vary with labor force status?

Table 1: The effect of employment/unemployment experience on personality traits

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

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

A.3.2 Relationship between Big Five personality traits and internal locus of control

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

Table 2: The correlation between "Big 5" traits and locus of control

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

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

Table 3: 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 2 for the definition of the LOC scores.

A.3.3 Comparison between IZA ED and GSOEP

Table 4: Mean comparisons for IZA ED and GSOEP

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

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

A.3.4 Personality trait questionnaire

Table 5: Questions used to measure Big Five personality traits in the IZA ED

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

A.3.5 Parameter estimates for the heterogeneous model with renegotiation

Table 6: Other parameters in specification (3) under the renegotiation model: individual heterogeneity with gender-specific model coefficients

Cons.	-0.283	0.045	-2.755	-3.913	-3.521	-3.177	2.109	2.096	0.032	-0.766
	(0.212)	(0.217)	(0.319)	(0.254)	(0.172)	(0.248)	(0.057)	(0.050)	(0.247)	(0.319)
Edu	0.145	-0.311	-0.052	-0.193	0.151	-0.249	0.135	0.074	0.090	0.421
	(0.078)	(0.074)	(0.081)	(0.054)	(0.047)	(0.051)	(0.025)	(0.027)	(0.097)	(0.116)
Stb	-0.005	-0.042	-0.013	0.122	0.054	-0.043	0.085	-0.022	-0.009	-0.053
	(0.030)	(0.033)	(0.036)	(0.025)	(0.021)	(0.025)	(0.012)	(0.010)	(0.042)	(0.036)
Opn	0.073	0.010	0.064	0.063	-0.022	0.046	-0.019	0.015	-0.093	0.052
	(0.033)	(0.031)	(0.040)	(0.028)	(0.020)	(0.025)	(0.009)	(0.010)	(0.033)	(0.041)
Cos	0.035	-0.045	-0.001	-0.019	-0.008	0.020	-0.089	-0.060	-0.013	0.015
	(0.039)	(0.046)	(0.044)	(0.032)	(0.027)	(0.040)	(0.012)	(0.012)	(0.050)	(0.054)
Agr	-0.027	0.090	-0.006	0.096	-0.038	-0.356	0.056	0.014	-0.155	-0.278
	(0.034)	(0.042)	(0.042)	(0.035)	(0.023)	(0.026)	(0.012)	(0.010)	(0.039)	(0.032)
Ext	0.004	-0.057	0.026	0.142	0.067	0.183	-0.022	-0.008	-0.019	0.059
	(0.034)	(0.033)	(0.037)	(0.031)	(0.024)	(0.031)	(0.011)	(0.012)	(0.047)	(0.051)
Cohort (Omitted cat: 73-82)										
63-72	0.078	0.631	0.025	-0.133	-0.272	0.330	-0.081	-0.019	-0.224	0.139
	(0.080)	(0.095)	(0.075)	(0.055)	(0.042)	(0.069)	(0.021)	(0.027)	(0.079)	(0.119)
52-62	0.020	0.922	0.081	-0.202	-0.013	0.175	-0.045	-0.086	-0.125	0.112
	(0.077)	(0.100)	(0.098)	(0.057)	(0.049)	(0.072)	(0.029)	(0.025)	(0.104)	(0.129)

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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