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 and matching model and investigates how education and personality traits affect parameters and job search behavior. We build on prior research by Flinn et al. (2018) that estimated a neoclassical labor supply model for households using the HILDA dataset for Australia and found personality traits to be important determinants of gender wage and employment differentials. This paper develops and estimates a partial equilibrium search model in which personality traits can influence productivity, job offer arrival rates, job dissolution rates and the division of surplus from the employer-employee match. The estimation is based on the IZA Evaluation Dataset, a panel dataset focusing on newly-unemployed individuals in Germany between 2007 and 2008. Model specification and goodness-of-fit tests provide support for a model that allows job search parameters to be heterogeneous across individuals, varying with levels of education, personality traits and gender. We use the model to perform a decomposition that gives women subsets of estimated male model parameters. The results show that women receive a premium in the labor market for their education relative to men, but they are disadvantaged in terms of the return that they receive for their personality traits.

1 Introduction

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

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

In the recent economics literature, there is increasing recognition that traditional measures of worker productivity such as educational attainment and work experience do not fully characterize the attributes that are relevant for labor market success. In particular, recent research considers non-cognitive traits, such as personality characteristics, as potential productivity determinants along with cognitive traits. The most commonly used measures of personality are the so-called Big Five. They measure an individual’s openness to experience, conscientiousness, extraversion, agreeable and neurotism (the opposite of emotional stability). The measures aim to capture patterns of thoughts, feelings and behavior that correspond to individual differences in how people actually think, feel and act (Borghans et al. (2008), Almlund et al. (2011)).

Heckman et al. (2006) and Heckman & Raut (2016) note that personality traits have both direct effects on worker productivity and indirect effects by affecting preferences for schooling, working and/or occupation choices. A study by Fletcher (2013) uses sibling samples and family fixed effect estimators and finds a robust relationship between personality traits and wages. Cubel et al. (2016) examine whether personality traits affect productivity using data gathered in a laboratory setting that directly measures effort on a task. They find that individuals who exhibit high levels of conscientiousness and emotional stability perform better on the task.

Recent reviews of gender differences in preferences and in personality traits can be found in Croson & Gneezy (2009) and Marianne (2011). Studies across many different countries find that women are on average more agreeable and more neurotic than men. However, the most crucial traits found to affect wages differ somewhat depending on the dataset analyzed. Using Dutch data, Nyhus & Pons (2005) find that emotional stability is positively associated with wages for both genders and agreeableness is associated with lower wages for women. Using data from the British Household Panel Study, Heineck (2011) analyzes correlations between Big Five personality traits and wages and finds a positive relationship between openness to experience and wages and a negative relationship between agreeableness and wages for men. He also finds a negative relationship between neuroticism and wages for women. Using data from the Wisconsin Longitudinal Study, Mueller & Plug (2006) find that
nonagreeableness, openness to experience and emotional stability are positively related to men’s earnings, whereas conscientiousness and openness to experience are positively related to women’s earnings. They find that the return that men receive for being nonagreeable is the most significant factor explaining the gender wage gap. Braakmann (2009), using German Socioeconomic Panel (GSOEP) data, finds that higher levels of conscientiousness increase the probability of being full-time employed for both genders, while higher levels of neuroticism and agreeableness have the opposite effect.

Flinn et al. (2018) estimate a static neoclassical labor supply model for households using the HILDA dataset for Australia and find personality traits to be important determinants of gender wage and employment differentials. Applying a decomposition to an estimated wage offer equation, they find that the key factor explaining the gender wage gap is that women are paid differently than men for their characteristics. For example, women are on average more conscientious than men, but men receive a higher wage return for being conscientious. Using data from the NLSY that include different types of personality measures, Cattan (2013) also applies a decomposition method and finds that gender differences in self-confidence largely explain the gender wage gap.

The accumulated evidence that personality traits are significantly related to labor market outcomes is fairly substantial. The fact that women and men exhibit, on average, different personality traits raises the question as to whether these traits could be important in explaining gender disparities in labor market outcomes. However, the mechanisms through which personality traits affect labor market employment and earnings outcomes have not been much explored.

To explore the mechanisms, this paper develops and estimates a partial equilibrium job search model in which personal traits can operate through distinct channels. In the model, unemployed and employed workers stochastically receive employment opportunities from firms characterized in terms of idiosyncratic match productivity values. Workers are heterogeneous in terms of observed attributes that include gender, age, education, cognitive ability and personality traits. Firms are heterogeneous in terms of match productivities. Firms and job searchers divide the match surplus, with the fraction going to the worker determined by a bargaining parameter. Within the model, personality traits are introduced as potential determinants of (i) worker productivity, (ii) job search effort, (iii) job exit rates, and (iv) the bargaining parameter that specifies how the match surplus is divided. The model also allows for potential labor market discrimination as reflected in gender differences in hourly wage offer functions. We use the estimated model to better understand the mechanisms underlying gender disparities in hourly wages, employment and labor market dynamics.
The model we develop builds on traditional matching-bargaining models, such as Flinn & Heckman (1982), Diamond (1982), Flinn (2002), Cahuc et al. (2006) and Dey & Flinn (2005). It also builds on the smaller literature that uses job search models to understand the sources of gender wage gaps. Bowlus (1997) was the first to build a job search model to explain gender wage gaps. Using data from the NLSY, she finds that gender differences in job exit rates explain 20-30% of the gender wage differential. Bowlus & Grogan (2008) use a general equilibrium search framework to examine how much of the gender wage differential can be accounted for by differences in labor market behaviors, such as transitions between labor market states and across jobs. The model takes into account that part-time workers exhibit different labor market behaviors from full-time workers. They find that women’s greater tendency to work part-time and to exit the labor market into the non-participation state lowers their reservation wages and shortens job spells. This prevents women from climbing the wage distribution as fast as men via on-the-job search. 

Flabbi (2010a) develops a search model of the labor market with matching, bargaining and employer’s taste-based discrimination. In his model, there are two types of workers, male and female, and two types of firms, prejudiced or not. When workers and firms meet, they observe a match productivity value and bargain over wages. The existence of a positive proportion of prejudiced firms lowers women’s outside options, generating spillover effects even on job matches at nondiscriminatory firms. Using CPS data, Flabbi (2010a) finds evidence of both productivity differences and of taste discrimination. Average female productivity is estimated to be 6.5% lower than male productivity and about half of the employers are found to be prejudiced.

Liu (2016) estimates a dynamic model of wage, hours and job changes using SIPP data. He uses the model to distinguish whether gender differentials are due to differences in preferences for part-time work or to differences in labor market parameters, such as, differences in job arrival rates, job destruction rates, the mean and variance of the wage offer distribution, and the full-time/part-time wage premium. He finds that the key factors explaining the gender wage gap are the mean offered wage (conditional on observed characteristics), job search parameters, the wage cost of part-time work, and demographic factors affecting preferences for part-time work.

There is a small literature examining the relationship between job search behaviors and

\footnote{Flabbi & Moro (2012) develop and estimate a job search and bargaining model to study the effects of job flexibility on female labor market outcomes. Their framework assumes that job flexibility is a job characteristic that is valued by workers but is costly for firms to provide. They find that preferences for flexibility have a substantial impact on the wage distribution but not on unemployment.}
personality characteristics. Caliendo et al. (2015) propose 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 their own actions (“internal factors” versus “external” factors). They derive implications from the model, which they test using the IZA Evaluation Dataset, but they do not structurally estimate the model. They find that individuals with internal locus of control believe that their actions influence the probability of getting a job and, as a result, search for jobs more intensively and have higher reservation wages. McGee (2015) also analyzes the relationship between locus of control and job search behavior using data from the NLSY. He similarly finds that young men with internal locus of control tend to search more and have higher reservation wages.

We estimate our job search model using the IZA Evaluation Dataset, a panel dataset that follows individuals in Germany who were newly unemployed between 2007 and 2008. An unusual feature of these data relative to other available datasets is that they contain the Big Five personality measures. In addition to personality trait measures, we also use information on age, gender, educational attainment, wages, hours worked, and job transitions. Our analysis focuses on men and women during prime-age working years (up to age 55). Model parameters are estimated by Maximum likelihood.

We estimate two different model specifications that make different assumptions on how firms negotiate with workers when they receive an outside wage offer from another firm. When we evaluate goodness-of-fit, we find support for the model specification that assumes no-renegotiation, that is, that firms do not renegotiate wages upon receipt of on-the-job competing wage offers. Using the no-renegotiation framework, we estimate four different job search models that vary in the degree of individual heterogeneity incorporated. Likelihood ratio tests reject the more restrictive specifications in favor of the most flexible one that allows job search parameters to vary with individual characteristics (education and personality traits) and to differ for males and females.

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

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2A number of studies have found that the locus of control measure correlates with schooling decisions and with wages. See, e.g, Heckman et al. (2006).

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2 Model

Our main interest is in tracing the impact of personality traits, as well as other demographic and schooling characteristics, on labor market success using a simple partial equilibrium job search framework. Let an individual “type” be denoted by $z$. An unemployed individual will meet firms at the rate $\lambda_U(z)$, and an employed individual will meet 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 given by $a(z) \times \theta$, where $\theta$ is a draw from the distribution $G_z(\theta)$, and is realized at the time that the individual meets a prospective employer. The worker and firm bargain over the wage using a Nash bargaining protocol, with the outside option of the individual dependent upon their current employment state. The bargaining power of the individual is given by $\alpha(z)$. The flow value of unemployment to the individual is given by $b \times a(z)$, where $b$ is a scalar. Employment matches dissolve exogenously at rate $\eta(z)$. The discount rate of all agents in the model, firms and workers, is $\rho$, where $\rho > 0$ is a constant which is independent of $z$.

In our application, components of the vector $z$ potentially include (1) the individual’s birth cohort, (2) the individual’s geographic location, (3) their education level, (4) their gender, and (5) their scores on the Big Five personality assessment. Because our model is based on an assumption of stationarity, we will assume that all of the characteristics upon which we ultimately condition are time-invariant. Our main interest will be in investigating sources of gender discrimination in the labor market through the lens of the canonical search, matching, and bargaining model.

2.1 Baseline Model with No OTJ Search

For simplicity, we first describe a model in which employed individuals do not receive job offers; we will later extend the model to allow for on-the-job search.\footnote{When we do allow for on-the-job (OTJ) search, some additional issues will arise with respect to the nature of worker-firm bargaining. By ignoring OTJ search, we postpone discussion of these somewhat more subtle points.} In order to reduce notational clutter, we will not explicitly condition the primitive parameters of the model on $z$. We will reintroduce $z$ when we discuss the estimation of the model.

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 wage paid,
w, and we adopt the usual assumption that flow utility is linear in wages when employed.\footnote{This assumption will be particularly important for the analysis of gender wage differentials for reasons discussed below.}

In the environment with no OTJ search, the only way that an employment spell can end is exogenously, which happens at rate $\eta$. Then the value of being employed at a job paying a wage of $w$ 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 the firm of match productivity $a\theta$ when paying a wage of $w$ is

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

since, when a employment match ends, the firm’s value reverts to 0. \footnote{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.}

The Nash-bargained wage is then given by

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

where we have used the implication that the value of the firm’s outside option, keeping the vacancy open, has value zero. Since

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

we have

$$w(\theta, a) = \arg\max_w (w - \rho V_U(a))^\alpha (a\theta - w)^{1-\alpha}$$

(1)

$$= \alpha a\theta + (1 - \alpha)\rho V_U(a)$$

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

given the definition that $\rho V_U(a) \equiv y(\theta^*(a), a) = a\theta^*(a)$. 
Now the value of unemployed search is defined as

$$
\rho V_U(a) = ba + \lambda U \int_{\theta^*}^\theta (V_E(\theta; a) - V_U(a))dG(\theta)
$$

$$
\Rightarrow a\theta^*(a) = ba + \frac{\lambda U a}{\rho + \eta} \int_{\theta^*}^\theta (\theta - \theta^*(a))dG(\theta)
$$

$$
\Rightarrow \theta^*(a) = b + \frac{\lambda U a}{\rho + \eta} \int_{\theta^*}^\theta (\theta - \theta^*(a))dG(\theta)
$$

Since this last equation is independent of $a$, we have

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

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

### 2.2 Implications for the Wage Distribution

As mentioned above, our main concern will be to trace the impact of personality characteristics and other individual traits on (observed) wage distributions. We assume that the support of the matching distribution $G$ is nonnegative and that $G$ is differentiable on its support with corresponding 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 $\theta$ and wage $w$ as:

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

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

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

where $G(\theta^*) = 1 - G(\theta^*)$ is the complementary function of $G(\theta^*)$. The corresponding p.d.f. is given by

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

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

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

When we estimate the model we will be making the (common) assumption that \( \theta \) is lognormally distributed, with \( \ln \theta \) distributed as a Normal random variable with mean \( \mu_\theta \) and variance \( \sigma^2_\theta \). That is, \( \log \theta \sim N(\mu_\theta(z), \sigma^2_\theta(z)) \). We further restrict \( \mu_\theta(z) = -0.5\sigma^2_\theta(z) \) so that \( E[\theta(z,\theta)] = a(z)E[\theta] = a(z) \).

In this case, \( a(z) \) captures heterogeneity in mean productivity at a match and \( \sigma_\theta(z) \) captures the heterogeneity in the dispersion of productivity across employers.

### 2.3 Adding On-the-Job (OTJ) Search

In this section, we extend the model to allow workers to receive job offers from potential employers while currently employed. This extension is required to explain job-to-job transitions in the data. We assume the job arrival rate from other potential employers is \( \lambda_E \). When meeting another employer, the match quality from this alternative pair, \( \tilde{\theta} \), is immediately revealed to the worker. Whether or not this 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 & Robin (2002), and for the surplus division case, following Dey & 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 where her productivity is the greatest. This is what we refer to as the renegotiation case. We then describe the case in which firms do not respond to potential competitors’ behavior for a given individual’s productive services. This may happen either

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\footnote{Given \( \theta \) follows lognormally distribution, \( E(\theta) = \exp(\mu_\theta(z) + 0.5\sigma^2_\theta(z)) = 1 \text{ if } \mu_\theta(z) = -0.5\sigma^2_\theta(z) \).}

\footnote{In practice, we assume \( \sigma_\theta(z) \) only depends on gender but not other elements of \( z \).}
because the potential outside options are not verifiable or firms have an incentive to renege on its offered wage once the potential competitor’s offer has been withdrawn.\textsuperscript{8} This is referred to as the non-renegotiation case.

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

### 2.3.1 OTJ Search with Renegotiation

In the renegotiation case, we allow firms to engage in a Bertrand competition for the employee. Since general ability \( a \) is the same at all firms, the different productivity levels of the worker in the two firms are entirely attributable to the different draws of match quality. When two firms are competing for the same worker, their positions are symmetric. This means the incumbent has no advantage or disadvantage regarding of retaining the worker with respect to the poacher.\textsuperscript{9} Let \( \theta \) and \( \theta' \) be the two match draws at the two firms. Let \( \theta' > \theta \) and call \( \theta' \) the dominant match value and \( \theta \) the dominated value. When firms engage in Bertrand competition in term of wage setting, whichever firm is associated with the lowest value of match productivity will attempt to attract the worker by increasing its wage offer up to the point where it earns no profit from the employment contract.\textsuperscript{10} In the above example, the firm with match value \( \theta \) will offer a wage of \( a\theta \) to attract the worker. The value of working in the dominant firm with maximum possible wage \( a\theta \) (equal to worker’s productivity) then serves as the worker’s outside option when engaging in Nash bargaining with the firm at which her match value is \( \theta' \).

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

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\textsuperscript{8}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.

\textsuperscript{9}This would not be the case if, for example, there was a finite positive cost associated with changing employer.

\textsuperscript{10}This is true under the standard assumption that the value of an unfilled job opening, or vacancy, is 0.
employment can be written as

\[
(\rho + \eta + \lambda E G(\theta)) V_E(\theta', \theta, a; w) = w + \eta V_U(a) + \lambda E \int_\theta^{\theta'} V_E(\theta', x, a)dG(x) + \lambda E \int_{\theta'} V_E(x, \theta', a)dG(x)
\]

where the term (1) captures the value of the problem when the dominated match value against which the current firm responds increases from \( \theta \) to \( x \), where \( \theta < x \leq \theta' \). The term (2) captures the value gain when the individual switches to a new firm at which her match value is \( \tilde{\theta} > \theta' \), in which case the “dominated” match value is \( \theta' \). In every case, the value of the worker’s outside option is value of employment at the firm with the dominated match value when the worker is paid her productivity, so that \( w = a\theta \). This is the same outcome as would be obtained if the worker had two firms competing for her services when the match value \( \theta \) was identical at each firm (or \( \theta' = \theta \)). Then

\[
(\rho + \eta + \lambda E G(\theta)) V_E(\theta, \theta, a) = a\theta + \eta V_U(a) + \lambda E \int_\theta V_E(x, \theta, a)dG(x)
\]

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

\[
(\rho + \eta + \lambda E G(\theta)) V_F(\theta', \theta, a; w) = a\theta' - w + \lambda E \int_{\theta'} V_F(\theta', x, a)dG(x)
\]

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

\[
w(\theta', \theta, a) = \arg \max_w (V_E(\theta', \theta, a; w) - V_E(\theta, \theta, a))^\alpha V_F(\theta', \theta, a; w)^{1-\alpha}
\]

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

### 2.3.2 OTJ Search without Renegotiation

In this non-renegotiation case, firms do not respond to potential competitors 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 renegot 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.\(^{11}\) In such case, all on-the-job wage bargaining uses the value of unem-
ployment as the value of outside option, which is an option always available whether or not
the wage contract is enforced.

In such case, the historical “dominated” match value doesn’t affect the current wage
bargaining any more. The value of employment at a match value \( \theta \) is only a function of \( \theta \)
and \( a \). Then

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

and the value of the job (vacancy) becomes

\[
(\rho + \eta + \lambda_E \bar{G}(\theta)) \ V_F(\theta, a; w) = a\theta - w
\]

In this case the bargaining problem becomes

\[(3) \quad w(\theta, a) = \arg \max_w (V_E(\theta, a; w) - V_U(a))^a V_F(\theta, a; w)^{1-a}.\]

which leads to the wage equation

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

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

\[
\bar{V}_U = \frac{b + \lambda_U \int_{\theta} \bar{V}_E(\theta) dG(\theta)}{\rho + \lambda_U \bar{G}(\theta)}
\]

The solution of reservation value \( \theta^* \) is given in the appendix A.1.2.

Note that as long as the outside option used to determine the wage is equal to \( \bar{V}_U(a) \) in

\(^{11}\)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 this case, we might see a one time payment to the worker at any moment in
which two firms are engaged in a competition for her labor services. However, the flow wage payment would
be that specified in equation 3.
all cases, and since $w(\theta, a)$ is strictly increasing in $\theta$ for all $a$ as long as $\alpha > 0$, this implies that a worker will leave one employer at which her match value is $\theta$ for another employer at which her match value is $\theta'$ if and only if $\theta' > \theta$. Thus whether we assume renegotiation or non-renegotiation, all inter-firm moves will be efficient in that the employee will always accept employment at the firm at which she is most productive.

### 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. Since men and women often inhabit the same household, in general their labor supply decisions are simultaneously determined, so that 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 interconnections between the choices of men and women in the labor market is likely to yield a distorted view of gender wage differences.

We are able to sidestep this issue in this paper solely because we adopt the assumption that both men and women have flow utility functions given by their respective wages when employed and by the constants $b \times a$ when they are not. The linear flow utility assumption is made in virtually all analyses conducted within the search framework, and we follow it here.\(^{12}\) Now let the current employment state 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 & Flinn (2008), in this case the total value of the household’s problem at any point in time, $V(e_1, e_2) = V_1(e_1) + V_2(e_2)$. In other words, the value of the household’s problem is the sum of the two values of the individual problems. Household welfare is optimized by allowing each individual to make choices as if they were unattached. The implication is that the choices made by a woman will not be impacted by the characteristics or decisions of the man in the household, and vice versa. Differently from Flinn et al. (2018), we do not have to be concerned with assortative mating in the marriage market or interdependence in decision-making within the household.\(^{13}\)

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\(^{12}\)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, since there is no demand for borrowing or saving under the risk neutrality assumption.

\(^{13}\)In Dey & Flinn (2008), when the household only cared about consumption, they specified the household
3 The IZA Evaluation Data Set

The IZA Evaluation Dataset Survey (IZA ED) is a panel survey of 17,396 Germans who registered as 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 around 9% of the newly registered unemployed in the administrative records.

In contrast to general population surveys such as the German Socio-Economic Panel Study (GSOEP), the IZA ED survey focuses on individuals who recently became unemployed. The survey contains extensive information on factors related to job search, including, for example, reservation wages, search intensity and search channels. Moreover, it also contains a rich information on individual characteristics, such as education, personality traits and cognitive abilities.

The IZA ED is a monthly cohort-specific panel. Upon entry into unemployment, each cohort was interviewed at least three times. Most cohorts did their first interviews with a time lag with ranges from 55 to 84 days after entry into unemployment. Then the second interview and third interview are scheduled one year and three years later. In addition, three cohorts, i.e. June and October 2007 and February 2008, are interviewed at an interim time, six months after their first interview. An illustrative graph of panel structure can be found in figure 1. Finally, we drop individuals with missing personal information, such as age, gender, education as well as personality traits. We further trim the data to exclude individuals whose reported hourly wages and expected wages were in the lowest or highest 3 percentile of the wage distribution. There restrictions leave us with a final sample of 5,941 individuals.  

The “Big Five” information in the IZA Evaluation Dataset is based on 15 personality questions. Respondents were asked to pick a number between 1 to 7 to assess how well each personality adjective describes them. The lowest number 1 denotes a total opposite description and the highest number 7 denotes a perfect description. Each personality trait is constructed by the average scores of three items belonging to each personality component.

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

14 A detailed discussion of the restrictions used to select the sample is provided in Appendix A.2.1.

15 The 10 items are surveyed from the the beginning of the first wave interview, the other 5 items become
The personality trait information is collected repeatedly at all waves including the interim wave. The completed Big Five personality traits are available for 5,601 respondents in wave 1, for 1,680 respondents for interim wave and for 5,747 and 5,732 respondents in waves 2 and 3. We include in our analysis individuals who have at least one personality trait measure. For the individuals who have multiple measures, we use the average value from different waves, because differences observed within a 3 year time frame are more likely due to measurement errors rather than fundamental changes. The items used in our data set are the same as those used in the GSOEP.

Table 1 presents summary statistics by gender. As seen in the last column of the table, all of the gender differences are statistically significant at conventional levels. Males spend fewer months in unemployment, 2.41 on average in comparison to 2.65 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 9.23 Euros in comparison to 8.15 for women. Their actual wage is also higher, 8.26 on average for men in comparison to 7.54 on average for women. Men also report on average a higher reservation wage than women; 8.02 for men compared to 7.09 for women. As seen in the lower panel of the table, the significant gender gap occurs despite the fact that women in our sample have on average higher education levels than men. 34% of women have an A-level secondary degree in comparison with 28% of men. They also score on average higher on cognitive ability tests.

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

Table 2 reports estimated coefficients from a regression of log hourly wages on education, personality traits, cognitive ability and reported lifetime labor market experience and its square. The regression is only estimated on the sample of individuals who are employed for whom an hourly wage can be calculated. In light of the theoretical model, observed wage differences can occur because of differences in reservation wages, differences in productivity, and/or differences in bargaining. As seen in Table 2, women receive a higher return to their education than men (18% wage premium for women compared to 13% for men). For men, higher scores on emotional stability and conscientiousness are associated with higher wages whereas higher scores on agreeableness are associated with lower wages. For women, the only

available later starting from the February (No. 9) cohort. A detailed description of which items construct which personality trait is discussed in Appendix A.3.
trait that is statistically significantly associated with observed wages is conscientiousness, which has a negative sign. Conditional on the other included variables, the cognitive ability score is not a statistically significant determinant for men nor women.

Table 3 shows estimates from estimating a Cox proportional hazard model of the hazard rate out of unemployment. The estimation takes into account censoring, namely that all individuals start out unemployed and some are never observed to get employed. As seen in the table, for both men and women, a higher score on emotional stability significantly increases the likelihood of finding a job. For women, education substantially increases the hazard out of unemployment, but education is not a significant determinant for men. Being more extraverted tends to decrease job finding for men.\footnote{Marini and Todd (2018) show that being more extraverted is associated with higher rates of alcohol consumption. Also, Todd and Zhang (2019) show that extraversion significantly increases the likelihood to work in the blue-collar sector.} Cognitive ability increases the hazard out of unemployment, but the effect is statistically significant only for men. Including the cognitive ability measure in the specification does not have much effect on the magnitude of the other estimated coefficients.

Table 4 shows the estimated coefficients from a Cox proportional hazards model for the probability of experiencing a job separation that results in unemployment. This model is estimated only for the subset of individuals who are in employment spells. Education decreases the probability of a job separation for both men and women. For men, extraversion decreases the probability of entering into unemployment and for women emotional stability decreases the probability.

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

4 Econometric implementation

4.1 Wage specifications

In the model, an individual only accepts a job when the wage offer exceeds their reservation wage. Although this is true also in the data for most individuals, we need to introduce
some measurement error to allow for the possibility that the accepted wage can sometimes be lower than the reservation wage. We allow for a measurement error $\epsilon$ in observed wages:

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

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

Although it is clearly the case that all survey data to which we have access contain considerable amounts of measurement error (Bound et al. (1994)), introducing measurement error into the model requires that we take a position as to its form. Because the measurement error process must be estimated simultaneously with the other primitive parameters of the model, misspecification of the measurement error process is a potential concern. Nonetheless, adding measurement error to wage observations give us two significant benefits. First, it is virtually required when the model includes on-the-job search, since a large proportion of job-to-job moves are associated with wage declines. Even though some formal models produce the implication that wages may decline in a job-to-job move, it is typically the case that they are not able to reconcile all of the wage decreases observed in the data.\footnote{Two such examples are Postel-Vinay & Robin (2002) and Dey & 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 he does not have health insurance to one in which he does, then his 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.}

Second, measurement error helps to address a limitation in our data. Although the model with renegotiation generates potential wage increases within a job spell, our data only provide the wage measured once at a “random” time within the job spell. For this reason, wages in the data are measured with error. Of course, reporting error can also be an additional motivation for including a measurement error process.

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

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

where $\mu_\epsilon$ and $\sigma_\epsilon$ are the mean and standard error of the normal distribution. We further restrict the correlation between $\mu_\epsilon$ and $\sigma_\epsilon$ to be $\mu_{\epsilon_1} = -0.5\sigma_{\epsilon_1}^2$ so that $E(\epsilon|w) = 1$.\footnote{Given $\epsilon$ follows lognormally distribution, $E(\epsilon) = \exp{\left(\mu_\epsilon + 0.5\sigma_\epsilon^2\right)} = 1$ if $\mu_\epsilon = -0.5\sigma_\epsilon^2$.}

Therefore, the expectation of observed wages and the expectation of received wages are assumed
to be the same.

\[ E(\tilde{w}) = E(\epsilon|w)E(w) = E(w) \]

### 4.2 Constructing the individual likelihood function

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

In line with Flinn (2002) and Dey & Flinn (2005), the information used in estimation is defined as an employment cycle. An employment cycle starts with an unemployment spell followed by one or more jobs in the employment spell. As we mentioned before, our data limits us to only have one wage observation in one job spell and will change if and only if the worker switches into different jobs. An employment cycle is defined in terms of the following random variables:

\[
\text{Employment cycle} = \{t_u, r_u\} \cup \{t_m, \tilde{w}_m, q_m, r_m\}_{m=1}^{M}
\]

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

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

**Individuals only observed to be unemployed:**

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

\[ h_U = \lambda_U G(\theta^*) \]

\(^{19}\)For a given worker, unemployment is essentially a “reset” of his/her job history. Therefore, the employment experience before the initial unemployment spell is irreverent to future job offers. (See also See Flinn (2002); Dey & Flinn (2005); Liu (2016).)
and the density of the unemployment spell duration is

\[ f_U(t_u) = h_U \exp(-h_U t_u) \]

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

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

**Individuals with one job spell \((M = 1)\):**

To evaluate the likelihood for employment spells, we use simulation methods. Each individual in the sample starts with an unemployment spell and we simulate \( R \) paths. The likelihood of completing unemployment with a duration \( t_u \) is:

\[ h_U \exp(-h_U t_u) \]

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

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

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

\[ h_E(\varepsilon_1) = \lambda E \tilde{G}(\theta(\varepsilon_1)) + \eta \]

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

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

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

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

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

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

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

When there exist two or more jobs in the employment spell, we only use information on the first two job spells to reduce computational burden. If the match quality in the first job is \( \theta(\varepsilon_1) \), the worker accepts to switch to a second job if and only if \( \theta > \theta(\varepsilon_1) \). We simulate the match quality \( \theta(\varepsilon_1, \varepsilon_2) \) in the second job as:

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

where \( \varepsilon_2 \) is a random draw from a uniform distribution \( U(0, 1) \). After entering the second job spell, there are three possibilities at the end of the observation period. First, the current job may still be ongoing. Second, the worker may move into a third job with a better match quality. Third, she/he may exit the spell due to a forced separation, which occurs at rate \( \eta \). The “total hazard” associated with the second job in the employment spell is the sum of latter two cases:

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

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

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

where \( r_2 = 1 \) represent the first job spell is right-censored and the worker is still employed.
at the end of sample period. Similarly, we construct an analogous term for the case in which
the second job spell ends with unemployment \((r_2 = 0, q_2 = 1)\)
\[
L_r^{(3)}(u, r_u = 0, \bar{w}_1, t_1, r_1 = 0, q_1 = 0, \bar{w}_2, t_2, r_2 = 0, q_2 = 1|\varepsilon_1, \varepsilon_2) =
\int_{w^*} w_1 \eta \exp(-h_E(\varepsilon_1) t_1) \frac{1}{w_1} m \left( \frac{\bar{w}_1}{w_1} \right) \frac{f(w_1)}{F(w^*)} \int_{w_1} \exp(-h_E(\varepsilon_1, \varepsilon_2) t_2) \frac{1}{w_2} m \left( \frac{\bar{w}_2}{w_2} \right) \frac{f(w_2)}{F(w_1)} dw_2 dw_1
\]

And lastly, the case in which the second employment spell ends by entering into a third
employment spell \((r_2 = 0, q_2 = 0)\) gives the likelihood
\[
L_r^{(3)}(t_u, r_u = 0, \bar{w}_1, t_1, r_1 = 0, q_1 = 0, \bar{w}_2, t_2, r_2 = 0, q_2 = 0|\varepsilon_1, \varepsilon_2) =
\int_{w^*} w_1 \eta \exp(-h_E(\varepsilon_1) t_1) \frac{1}{w_1} m \left( \frac{\bar{w}_1}{w_1} \right) \frac{f(w_1)}{F(w^*)} \int_{w_1} \exp(-h_E(\varepsilon_1, \varepsilon_2) t_2) \frac{1}{w_2} m \left( \frac{\bar{w}_2}{w_2} \right) \frac{f(w_2)}{F(w_1)} dw_2 dw_1
\]

To summarize, the overall likelihood contribution for the particular random draw \((\varepsilon_1, \varepsilon_2)\),
combining the three cases, is
\[
L_r(t_u, r_u, \bar{w}_1, t_1, r_1, q_1, \bar{w}_2, t_2, r_2, q_2|\varepsilon_1, \varepsilon_2) = \int_{w^*} \int_{w_1} \left( h_u \right)^{1-r_u} \exp(-h_u t_u) \times \exp(-h_E(\varepsilon_1) t_1) \left[ \left( \lambda_E \bar{G}(\theta(\varepsilon_1)) \right)^{1-q_1} \eta^{q_1} \right]^{1-r_1} \frac{1}{w_1} m \left( \frac{\bar{w}_1}{w_1} \right) \int_{w_1} \exp(-h_E(\varepsilon_1, \varepsilon_2) t_2) \left[ \left( \lambda_E \bar{G}(\theta(\varepsilon_1, \varepsilon_2)) \right)^{1-q_2} \eta^{q_2} \right]^{1-r_2} \frac{1}{w_2} m \left( \frac{\bar{w}_2}{w_2} \right) \frac{f(w_1)}{F(w^*)} \frac{f(w_2)}{F(w_1)} dw_2 dw_1
\]

To form the likelihood contribution conditional only on the observed labor market history,
we need to take the average over the \(R\) random draws of \((\varepsilon_1(r), \varepsilon_2(r))\)
\[
L(\text{Employment}|\Omega) = R^{-1} \sum_{r=1}^{R} L_r(t_u, \bar{w}_u, \bar{w}_1, t_1, r_1, q_1, \bar{w}_2, t_2, r_2, q_2|\varepsilon_1(r), \varepsilon_2(r), \Omega)
\]

where, as previously noted, \(\varepsilon_1(r), \varepsilon_2(r)\) are draws from the uniform distribution \(U(0, 1)\).\(^{20}\)

### 4.3 Incorporating individual heterogeneity

Our model assumes that an individual \(i\) has her/his individual specific set of labor market
parameters \(\Omega_i = \{\lambda_u(i), \lambda_e(i), \alpha(i), \eta(i), a(i), b(i), \sigma(i)\}\) which is uniquely determined by
their characteristics \(z_i\), representing education, gender, and personality traits. In this section,

---

\(^{20}\)We set \(R = 1,000\).
we describe the mapping of the set of characteristics $z_i$ to the parameter set $\Omega_i$. For a specific individual $i$ with the characteristics $z_i$, the set of “link” functions $M : z_i \rightarrow \Omega_i$ is

$$
\begin{align*}
\lambda_u(i) & : \exp(z_i'\gamma_{\lambda_u}) \\
\lambda_e(i) & : \exp(z_i'\gamma_{\lambda_e}) \\
\alpha(i) & : \frac{\exp(z_i'\gamma_\alpha)}{1+\exp(z_i'\gamma_\alpha)} \\
\eta(i) & : \exp(z_i'\gamma_\eta) \\
\alpha(i) & : \exp(z_i'\gamma_\alpha) \\
b(i), \sigma_\theta(i) & : \text{different by gender}
\end{align*}
$$

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

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

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

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. In the estimation, we use one unemployment spell per individual and information from a subsequent employment spell, including wage information and information on job-to-job movements and wage changes.

In terms of the homogeneous case in which there is no on-the-job search and the bargaining power parameter, $\alpha$, is constrained to be equal to 1, identification of the model has been considered in detail in Flinn & Heckman (1982).\textsuperscript{21} For the case without measurement error

\textsuperscript{21}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.
in wages, they 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. Flinn & Heckman (1982) show that most parametric distributions can be identified even with systematically missing data on job offers. 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 \( \text{plim}_{N \to \infty} \hat{w}(1) = \rho V_U \equiv w^* \), 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 \( \lambda_U, \eta \), and the parameters characterizing the recoverable distribution, \( G \). They also show that the discount rate \( \rho \) and the flow utility in unemployment \( b \) are not separately identified. Fixing one of the parameters, typically \( \rho \), allows identification of \( b \).

Wolpin (1987) considers the estimation of a “one-shot” search model, that is, he estimates a search model defined only for the first spell of unemployment experienced by sample members after (or before, in some cases) exiting formal schooling. His model is cast in discrete time, (the time period is a week) and he allows the probability of receiving an offer to vary over time. As opposed to Flinn and Heckman, who considered the stationary search case in continuous time with no measurement error in wages, Wolpin allows for measurement error that follows a parametric distribution. He assumes that the wage offer distribution is log normal, as is the measurement error distribution. In terms of the stationary, continuous-time case we are considering, there exists a reservation wage \( w^* \), and all accepted wages are draws from the truncated distribution \( G(w|w \geq w^*) \). We assume that the observed accepted wage, \( \tilde{w} \), is given by

\[
\tilde{w} = w \varepsilon,
\]

so that \( \ln \tilde{w} = \ln w + \ln \varepsilon \), where \( \ln \varepsilon \) follows a normal distribution with mean 0 and variance \( \sigma^2 \), 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 \( \mu \) and variance \( \sigma^2 + \sigma^2 \varepsilon \), and separate identification of \( \sigma^2 \) and \( \sigma^2 \varepsilon \) would not be possible. Under the parametric assumptions on the distributions and with truncation, however, the parameters \( \mu, \sigma^2, \sigma^2 \varepsilon \), and \( w^* \) are identified given access to a sufficiently large

---

22This is true unless one is willing to make an assumption that all wage offers are accepted.

23They further show that not all parametric distributions are identifiable in this situation. They term those that are as “recoverable,” and give examples of unrecoverable parametric distributions with support on \( R_+ \). Two leading examples of unrecoverable parametric distributions are the Pareto and the exponential.
Adding on-the-job search to the above framework only adds one additional parameter, \( \lambda_E \), 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 \( \eta \). 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 \( h_E(w) / (h_E(w) + \eta) \).\(^{24}\)

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

We now consider the estimation of the bargaining power parameter \( \alpha \). Thus, the wage distribution is not considered to be exogenous, although the productivity distribution \( G(\theta) \) is. The bargaining parameter is more 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. Thus, a given wage distribution may be consistent with a “small” surplus that is mainly captured by the worker (high \( \alpha \)) or a “large” surplus, with the worker obtaining a small share (low \( \alpha \)). As noted in Flinn (2006), the mapping from the worker’s productivity at the firm, \( \theta \), is linear, and is given by

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

where \( \theta^* \) is the reservation match value, which depends on the individual’s current employment state and the bargaining protocol that is assumed. Because \( \theta^* \) is a constant, \( w(\theta) \) is linear, and the wage distribution is given by \( F(w) = G\left(\frac{w - (1 - \alpha) \theta^*}{\alpha}\right) \). Then if \( G \) is a location-scale distribution, so that \( G(\theta) = G_0\left(\frac{\theta - c}{d}\right) \), with \( G_0 \) a known function, \( c \) the loca-

\(^{24}\)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

\[
\frac{m\left(\frac{\tilde{w}}{w}\right) \tilde{w}^2}{\Gamma(\tilde{w})}, \ w \geq w^*,
\]

where \( m \) is the lognormal density of \( \varepsilon \), \( \tilde{w}/w^2 \) 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

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

In this case, \( h_E(\tilde{w}) \) is strictly increasing in \( \tilde{w} \) just as \( h_E(w) \) is strictly increasing in the actual wage \( w \).
tion parameter, and $d$ the scale parameter, then $\alpha$ is not identified. A necessary condition for $\alpha$ to be identified is that $G$ not be a location-scale distribution. In this paper and in Flinn (2006), $G$ is assumed to be lognormal, which is a log location-scale distribution. The nonlinearity of the logarithmic function is enough to ensure identification.

5.2 Introducing observed heterogeneity

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

$$
\lambda_U(i) = \exp(z_i'\gamma_{\lambda_U}) \\
\lambda_E(i) = \exp(z_i'\gamma_{\lambda_E}),
$$

and the rate of exogenous dissolutions is

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

It is straightforward to see this, since the distribution of wages becomes

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

where

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

Even if $\theta^*$ is known, or a consistent estimator of it is available, this leaves two equations in three unknowns, $c, d,$ and $\alpha$, and these parameters are not identified without further restrictions.
The flow utility of unemployment, $b$, can assume any value on $\mathbb{R}$ in principle, so that

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

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

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

We have assumed that theta has a lognormal distribution, and that the mean of $\theta$ is one for all individuals.\footnote{Typically the lognormal is parameterized in terms of $\mu$ and $\sigma^2$, where $\ln \theta$ is distributed as a normal with mean $\mu$ and variance $\sigma^2$. In this case, $E\theta = \exp(\mu + 0.5 \sigma^2)$, which under our normalization means that $\mu = -0.5 \sigma^2$. Since the variance of the lognormal is $Var(\theta) = [\exp(\sigma^2) - 1] \exp(2\mu + \sigma^2)$, upon substitution we have that

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

In this case

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

and

$$
    Var(y|a) = a^2(E\theta^2 - 1) = a^2(\exp(\sigma^2) - 1).
$$

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

$$
    a(i) = \exp(z_i' \gamma_a),
$$

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

$$
    \sigma^2_\theta(i) = \exp(z_i' \gamma_{a^2}).
$$

Then $a(i)$ measures the mean productivity of individual $i$ across matches, and $\sigma^2_\theta(i)$ is a measure of the dispersion in the productivity values. Because bad matches can be rejected, the welfare of individuals and firms is increasing in $\sigma^2_\theta(i)$.

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

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

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 $\gamma_j$ vectors due to the nonlinearity of the likelihood function in terms of the various functions. 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 $\gamma_a$ for individual $i$ is given by

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

As long as the the cross-products matrix $I^{-1} \sum_{i=1}^{T} z_i z_i'$ is of full-rank, the coefficients associated with each of the $z_i$ vector in each of the parameterizations are identified.

6 Model Estimates

6.1 Comparing alternative bargaining assumptions

As previously noted, we estimate a job search model that allows for on-the-job offers. We consider two different assumptions on how firms bargain with workers to set wages, one that allows firms to bargain against competing outside offers and one where firms cannot confirm the existence of outside offers.

In this section, we compare estimates obtained from both the renegotiation and the no-renegotiation specifications. The results are presented in Table 5. Comparing the two sets of estimates, the estimated values of $\lambda_u$ and $\lambda_e$ are relatively high but the value of $\alpha$ is relatively low. More specifically, allowing for renegotiation, the contact rates of unemployed workers is 1.011 for men and 1.127 for women, and the contact rates for employed men and women are 0.079 and 0.090. These estimates are substantially larger than their corresponding values for the model without renegotiation. On the other hand, the estimated values of $\alpha$ are only 0.221 for men and 0.051 for women in the model with renegotiation, which are significantly lower than the estimated $\alpha$ for the model without renegotiation.
The low estimated value of the surplus division parameter $\alpha$ is a common finding in the literature (Cahuc et al. (2006); Bartolucci (2013); Flinn & Mullins (2015)). Under the renegotiable contract framework, the worker's share of surplus is determined by both the surplus division parameter $\alpha$ and the on-the-job contact rate $\lambda_e$. 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 would increase over the job spell due to competition 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 7.459 for men and 6.729 for women in the former case and 9.07 and 8.73 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 3 compares the model fits for both specifications of the bargaining process in terms of unemployment/employment spells. The top and bottom left panels show the fit of the model without renegotiation to the wage data for the first and second jobs. The top and bottom right panels shows the fit of the model with renegotiation to the same data. It is clear that the model without renegotiation fits the data better, particularly with regard to the first job wage distribution.

The simulation from the model with renegotiation predicts lower initial wages compared with data. The wage growth from first job to second job (€5.59/h to €9.46/h) predicted from the renegotiation model is much larger the wage growth observed in the data (€7.66/h to €7.76/h). The wage growth predicted from the no-renegotiation model (€7.54/h to €8.69/h) provides a better fit. This result is consistent with similar findings concerning these two types of specifications reported in Flinn & Mullins (2015).27

Figure 4 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

---

27In 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.
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 wave of the survey. The median 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.

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 27,560 and 26,090, respectively. This finding is consistent with other studies estimating similar types of specifications of the bargaining process (Flinn & Mabli (2009); Flinn & 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 heterogeneity. The estimates are reported in Table 6. In specification (1), all parameters are assumed to be homogeneous for men and women. In specification (2) we allow the parameters to differ for men and women but assume homogeneity within gender. In specification (3), we allow the parameters to be heterogeneous across individuals in a way that may depend on individual characteristics (e.g. education, personality) as well as gender.

The results under column (3) in Table 6 indicate that men and women have different labor market parameters. The unemployment job arrival rate ($\lambda_u$) 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 $\lambda_e$ is higher for women. The job separation rate $\eta$ are fairly similar for men and women.

Any productivity gap is captured by the ability parameters $a$ (given the location parameter $\mu$ of matching quality is set at 2). Our results shows the female productivity is 8.71% in comparison to 9.66% for men, which contributes to the gender wage gap. In general, we
find a smaller gap in productivity compared with other studies. For example, Bowlus (1997) finds the productivity of females is 17% lower using NLSY79 data. Flabbi (2010a) finds a 21% differential in average productivity using CPS data.

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

In terms of the surplus division parameter $\alpha$, we find the value for men is 0.496 and the value for women is 0.474. The estimated values are fairly consistent with Bartolucci (2013). He uses German matched employer-employee data and finds female workers have on average slightly lower bargaining power than their male counterparts, with an average $\alpha$ of 0.421 across genders.

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

### 6.3 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 7, we present the estimates for the model that allows for individual heterogeneity and for different model coefficients for men and women. This model allows us to explore the channels through which education and personality traits influence wage and employment outcomes. For men and women, education increases the unemployment job offer arrival rate and decreases the on-the-job job offer arrival rate. It lowers the job destruction rate for both men and women, with a larger effect for women. As would be expected, it also increases ability for both genders. With regard to the bargaining surplus parameter, education increases the bargaining surplus parameter for men but lowers it for women.

As seen in the table 7, many of the personality traits are statistically significant determinants of job search parameters. However, they sometimes affect men and women in different
ways. For men, emotional stability increases job arrival rates and lowers the job destruction rate and increases ability; however, it lowers bargaining power. For women, emotional stability increases the on-the-job arrival rate and lowers the job destruction rate; it has a negligible effect on productivity and a small positive effect on bargaining.

For men, conscientiousness increases unemployment job offer arrival rates but decreases arrival rates while on-the-job. It lowers the job destruction rate and increases bargaining power but has no significant effect on productivity. For women, conscientiousness increases both unemployed and on-the-job job offer arrival rates. It decreases job destruction rates and increases the bargaining surplus parameter, with no statistically significant effect on productivity.

For men, openness to experience lowers unemployed job offer arrival rates but increases on-the-job job offer arrival rates. It lowers job destruction rates but does not affect productivity or bargaining. For women, openness to experience has a positive effect on both unemployed and on-the-job job offer arrival rates. It also increases bargaining power. However, it increases job destruction rates.

For men, agreeableness lowers the job arrival rate, lowers the job destruction rate, lowers productivity and lowers the bargaining surplus. For women agreeableness lowers the unemployed job arrival rates, lowers job destruction rates and dramatically lowers the bargaining surplus parameter. There is no statistically significant effect of agreeableness on productivity for females. Lastly, extraversion generally increases unemployment job offer arrival rates for both men and women. However, it also increases job destruction rates for both genders. Extraversion lowers productivity for men but not for women and lowers the bargaining parameter for both men and women.

6.4 Evidence in how individual characteristics affect job search effort

In Table 8, we explore how education and personality traits affect job search effort, as measured by the number of job applications. The information on numbers of job applications was not used in estimating the model, but we explore this relationship to gain insight into the mechanisms being captured by the estimated model. Numbers of applications is probably a key factor underlying individual heterogeneity in job offer arrival rates. As seen in Table 8, having a higher education level is associated with a significantly greater number of applications, but only for males. Conscientiousness appears to be the key personality trait that positively affects numbers of applications for both men and women. Extraver-
sion has a statistically significant positive influence on numbers of applications for men, and agreeableness is associated with fewer job applications for women.

6.5 Wage gap decomposition

In Table 9, we examine which channels of the model contribute most to explaining the gender wage gap. To generate the table, we simulate outcomes under the heterogeneous specification (specification (3)) and then perform additional simulations where we set a subset of the coefficients for women equal to those estimated for men. For example, we ask what the outcomes would look like for women if they had the same labor force transition parameters ($\lambda_U, \lambda_E, \eta$), surplus parameters ($\alpha$), and productivity parameters ($a, \sigma_\theta$) 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 own characteristics (education, personality traits), but we change the way these characteristics are valued in the labor market.

As can be seen in Table 9, giving females all of the male parameters (“All parameters, Total”) fully explains the gap in offered and accepted wages. Looking at the rows “All parameters, Education” and “All parameters, Personality,” we see that women receive a premium for their education relative to men and that giving them the male coefficients associated with education would increase the wage gap relative to the baseline. The main area in which they are being rewarded less is for their personality traits. Giving them the estimated male coefficients associated with personality traits fully eliminates the wage gap.

The bottom three panels of the Table 9 examine which of the separate components of the model contributes most to wage gaps. With regard to productivity, females have slightly lower productivity as implied by a lower estimated constant term, but their personality traits and education receive a higher valuation in terms of productivity than for males. Overall, gender differences in the estimated productivity parameters is not a very important channel in explaining the wage gap.

On the other hand, differences in the surplus division parameters account for a significant portion of the wage gap. If women’s personality traits were valued in the same way as men’s, then they would have higher bargaining power and the wage gap would be eliminated. 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 explain the wage gap. However, this channel is not as important a determinant of wage gaps as is the surplus division channel.

These decompositions show that women are not disadvantaged in terms of the return they receive for education. In fact, women generally have an education premium vis-a-vis labor
market productivity and bargaining surplus division. The area in which women appear to be at a disadvantage is with regard to how the labor market rewards their personality traits. Gender differences in estimated personality trait parameters affect bargaining surplus fully account for observed gender wage gaps. Gender differences in bargaining surplus parameters is the most important determinant of gender wage gaps.

Table 10 performs the same decompositions as Table 9 except that now we set the female parameters associated with different personality traits equal to the male estimated parameters. This decomposition examines which personality traits are the most important determinants of gender wage gaps. We see ratios above 1 for conscientiousness and emotional stability (particularly with regard to productivity and transition rates), which means that men are being more highly rewarded for these traits. Women experience a large penalty for agreeableness in terms of bargaining surplus relative to men. However, they do not receive the large productivity penalty that men receive for agreeableness and extraversion. Of the five traits, differences in the estimated parameters associated with conscientiousness are the most important in explaining the gender wage gap.

7 Conclusions

In this paper, we develop and estimate a job search framework to investigate how individual heterogeneity in personality and other dimensions affect labor market outcomes for men and women. We considered two modeling frameworks that differed in whether firms renegotiate wage offers from competing firms. We also considered three alternative modeling specifications that varied in the degree to which they accommodated individual parameter heterogeneity.

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

The estimates for the heterogeneous model show that there are statistically significant differences in the labor market parameters for men and women. Education and personality traits are important determinants of productivity, bargaining and job offer arrival rates for both genders, but they are valued in different ways.
The decomposition results showed that women do not appear to be at any disadvantage in terms of the return that they receive for their education. If anything, they receive an education premium. Women are mainly disadvantaged in terms of the labor market valuation of their personality traits. Giving women the same labor market returns to personality-traits that men have would eliminate observed and accepted wage gaps.

Our accounting of how different channels of the model contribute to gender wage gaps showed that gender differences in the estimated bargaining surplus parameters is the most important channel, followed by differences in the estimated parameters governing labor market transitions (job offer arrival and job destruction rates).

When we examine the different personality traits in isolation, we find that men are much more highly rewarded in the labor market than women for conscientiousness and emotional stability. However, they are also penalized relative to women for agreeableness and extraversion. Women experience a large penalty for agreeableness relative to men in terms of bargaining surplus. Of the five traits, differences in the valuation of conscientiousness and emotional stability emerge as overall the most important traits in explaining gender wage gaps.


A Appendices

A.1 Model Solutions

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

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

\[
(\rho + \eta + \lambda E \bar{G}(\theta)) V_E(\theta', \theta, a; w) = w + \eta V_U(a) + \lambda E \int_{\theta}^{\theta'} V_E(\theta', x, a)dG(x) + \lambda E \int_{\theta'}^{\theta} V_E(x, \theta', a)dG(x)
\]

We use the rent splitting rules

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

yields the equivalent expression

\[
(5) \quad (\rho + \eta + \lambda E \bar{G}(\theta)) V_E(\theta', \theta, a; w) = w + \eta V_U(a) + \lambda E \int_{\theta}^{\theta'} [(1 - \alpha)V_E(x, x, a) + \alpha V_E(\theta', \theta', a)] dG(x) + \lambda E \int_{\theta'}^{\theta} [(1 - \alpha)V_E(\theta', \theta', a) + \alpha V_E(x, x, a)] dG(x)
\]

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

\[
\frac{dV_E(\theta', \theta', a)}{d\theta'} = \frac{a}{\rho + \eta + \lambda E \bar{G}(\theta')}
\]

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

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

and the bargained wage has the following expression

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

The third term in this expression signifies the extent to which the worker is willing to sacrifice today for the promise of future appreciation in wages.
In order to calculate the reservation match value $\theta^*(a)$, we first use the definition of $V_U(a)$

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

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

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

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

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

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

In this section we describe the method of solution of the model. First, we need to discretize the continuous $\theta$ interval into $L$ grids $\{\theta_1, ..., \theta_L\}$ with probability $\{p_1, ..., p_L\}$. To initialize the algorithm, we set an 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 $\theta_L$ is an absorbing state, since no further job mobility can take place from that state during the current employment spell. The only way such a spell can end is through exogenous termination, which occurs at the constant rate $\eta$.

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

   with the wage

   $$w(\theta_L, a) = a (\alpha \theta_L + (1 - \alpha)\rho V_u(a))$$

   and the implied value (if acceptable match quality is $\theta_L$) 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 $V_E(\theta_1, a)$ and $w(\theta_1, a)$ as well as $V_U(a; \theta_1)$
Given \((V_E(\theta_1, a), ..., V_E(\theta_L, a))\), solve wage associated with state \(w(\theta_{t-1}, a)\) as

\[
   w(\theta_{t-1}, a) = a \left( \alpha \theta_{t-1} + (1 - \alpha) \left( (\rho + \lambda E \sum_{i \geq 1} p_i V_E(\theta_i, a)) \right) \right)
\]

and the value of employment at an acceptable match value \(\theta_i\) is given by

\[
   V_E(\theta_i, a) = \frac{w(\theta_{t-1}, a) + \eta V_u(a) + \lambda E \sum_{i \geq 1} p_i V_E(\theta_i, a)}{\rho + \eta + \lambda E p_i^+}
\]

where the notation \(p_i^+ = \sum_{i \geq 1} p_i\). And the implied value (if acceptable match quality is \(\theta_i\)) is given by

\[
   V_U(a; \theta_i) = \frac{ab + \lambda_U \sum_{i \geq 1} p_i V_E(\theta_i, a)}{\rho + \lambda_U p_i^+}
\]

3. Determine the optimal acceptable match quality \(\theta^*\)

For all match quality \(\{\theta_1, ..., \theta_L\}\), each “potential” acceptable match \(\theta_i\) implies a unique a value of unemployed search value given by \(V_U(a; \theta_i)\). The optimal acceptance match is the one that produces that highest value of unemployment state, i.e.,

\[
   j = \arg \max_i \{V_U(a; \theta_i)\}_{i=1}^L
   V_{U^{\text{new}}}(a) = V_U(a; \theta_j), \theta^*(a) = \theta_j
\]

4. Stop if \(V_{U^{\text{new}}}(a) = V_U(a)\). Otherwise update \(V_U(a)\) with the new value \(V_{U^{\text{new}}}(a)\).

### A.1.3 Solving the equilibrium wage distribution without renegotiation

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

\[
   (\eta + \lambda_E \tilde{G}(\theta)) l(a, \theta)(1 - U) = \left[ \lambda_U U h(a) + \lambda_E (1 - U) \int_{\theta^*}^{\theta} l(a, x) dx \right] g(\theta)
\]
where $\lambda U = \eta (1 - U)$ and $h(a)$ is the distribution of worker with time-invariant ability $a$ in the unemployment pool. Then we get

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

which solves

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

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

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

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

A.2 Sample construction

A.2.1 Obtaining the final dataset used in our analysis

As a general rule, we focused our effort on avoiding dropping relevant observations to maintain the maximum possible coverage. Our data cleaning proceeded as follows. First, we need to calculate the exact duration spells of each labor market activities, including unemployment spells and job spells. The monthly unemployment/employment activities are recorded and updated retrospectively during each interview, starting at the last interview or at unemployment entry in case of the first interview. Therefore, we are able to calculate the duration of each spells based on the starting dates and ending dates of each activities. Unfortunately, IZA ED only records the months rather than the exact date of each activities. Therefore, we calculate the days of duration based on a randomly assigned the dates within that month. And the month duration of spells is calculated based on the “statistical months rather than calendar months. For example, we calculate the month spell is equal to 1 when the duration is less or equal to 30 days. After we calculate the duration spells of each activities, we convert the data into a panel structure where working information (monthly salary, working hours) as well as personal characteristics are collected for different employment/unemployment spells and different individuals. The raw sample has 62,439 observations. During the sample selection process, we drop individuals following the below
steps:

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

- We drop any spells after the fourth spell, which leave the total observations 43,229. (17,395 for the first spells, 13,269 for the second spells, 7,532 for the third spells and 5,043 for the fourth spells)

- We drop the observations with incorrect/missing starting or ending dates of spells, reducing the observations 37,188. We assume the start year should no early than 2007 and the end year should be no late than 2011.

- We drop the observations whose activities are out of labor force. (e.g. attending school or other irrelevant activities) These restrictions leave us with 34,230.

- We drop the observations without any missing unemployment benefit information. This restriction leaves us with 26,258.

- We further drop the individuals whose spells are not consecutive. This restriction leaves us with 20,012.

- We combine two consecutive unemployment spells into one spell, which reduces the observation to 19,138.

- We further drop any individuals without key personal characteristics: age and gender, educational attainment and personality traits. We further restrict the age of individuals to be between 25 to 55. Our final estimation sample has 4,319 individuals with 5,874 observations, consisting of 4,319 first unemployment spells, 2,526 first job spells and 540 second job spells.
A.3 Additional figures and tables

Appendix Table A.1 - Questionnaire about personality traits in the IZA ED

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

Openness to experience: 4, 9, 14
Conscientiousness: 1, 7, 11
Extraversion: 2, 8, 12
Agreeableness: 3, 6, 13
Emotional stability (opposite to Neuroticism): 5, 10, 15
Appendix Table A.2 - Other parameters in specification (3) under the renegotiation model: individual heterogeneity with gender-specific model coefficients

<table>
<thead>
<tr>
<th></th>
<th>log $\lambda_U$</th>
<th></th>
<th>log $\lambda_E$</th>
<th></th>
<th>log $\eta$</th>
<th></th>
<th>log $\alpha$</th>
<th></th>
<th>log $\left(\frac{\alpha}{1-\alpha}\right)$</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Male</td>
<td>Female</td>
<td></td>
<td>Male</td>
<td>Female</td>
<td></td>
<td>Male</td>
<td>Female</td>
<td></td>
</tr>
<tr>
<td>Cons</td>
<td>-0.060</td>
<td>0.061</td>
<td>-3.852</td>
<td>-3.035</td>
<td>-3.548</td>
<td>-2.509</td>
<td>2.029</td>
<td>1.850</td>
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<tr>
<td></td>
<td>(0.687)</td>
<td>(0.444)</td>
<td>(0.650)</td>
<td>(0.648)</td>
<td>(0.337)</td>
<td>(0.437)</td>
<td>(0.235)</td>
<td>(0.175)</td>
<td>(0.847)</td>
</tr>
<tr>
<td>Edu</td>
<td>-0.229</td>
<td>0.113</td>
<td>0.023</td>
<td>-0.454</td>
<td>-0.869</td>
<td>-0.177</td>
<td>0.197</td>
<td>0.210</td>
<td>-0.941</td>
</tr>
<tr>
<td></td>
<td>(0.180)</td>
<td>(0.211)</td>
<td>(0.149)</td>
<td>(0.164)</td>
<td>(0.094)</td>
<td>(0.083)</td>
<td>(0.071)</td>
<td>(0.069)</td>
<td>(0.213)</td>
</tr>
<tr>
<td>Stb</td>
<td>0.039</td>
<td>-0.018</td>
<td>0.083</td>
<td>0.122</td>
<td>0.036</td>
<td>-0.108</td>
<td>0.006</td>
<td>0.018</td>
<td>0.017</td>
</tr>
<tr>
<td></td>
<td>(0.081)</td>
<td>(0.084)</td>
<td>(0.070)</td>
<td>(0.061)</td>
<td>(0.035)</td>
<td>(0.040)</td>
<td>(0.028)</td>
<td>(0.026)</td>
<td>(0.092)</td>
</tr>
<tr>
<td>Opn</td>
<td>-0.016</td>
<td>0.081</td>
<td>0.065</td>
<td>0.047</td>
<td>0.080</td>
<td>0.078</td>
<td>-0.025</td>
<td>0.078</td>
<td>0.015</td>
</tr>
<tr>
<td></td>
<td>(0.080)</td>
<td>(0.084)</td>
<td>(0.072)</td>
<td>(0.070)</td>
<td>(0.038)</td>
<td>(0.041)</td>
<td>(0.026)</td>
<td>(0.028)</td>
<td>(0.088)</td>
</tr>
<tr>
<td>Cos</td>
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<td>-0.045</td>
<td>0.096</td>
<td>-0.009</td>
<td>-0.029</td>
<td>-0.282</td>
<td>0.010</td>
<td>-0.037</td>
<td>0.037</td>
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<tr>
<td></td>
<td>(0.102)</td>
<td>(0.112)</td>
<td>(0.088)</td>
<td>(0.089)</td>
<td>(0.052)</td>
<td>(0.063)</td>
<td>(0.037)</td>
<td>(0.038)</td>
<td>(0.114)</td>
</tr>
<tr>
<td>Agr</td>
<td>-0.085</td>
<td>0.010</td>
<td>0.002</td>
<td>0.061</td>
<td>-0.040</td>
<td>0.002</td>
<td>-0.021</td>
<td>0.001</td>
<td>-0.085</td>
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<td>(0.097)</td>
<td>(0.124)</td>
<td>(0.087)</td>
<td>(0.085)</td>
<td>(0.041)</td>
<td>(0.053)</td>
<td>(0.030)</td>
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<td>(0.110)</td>
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<tr>
<td>Ext</td>
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<td>0.024</td>
<td>-0.038</td>
<td>-0.020</td>
<td>0.114</td>
<td>0.014</td>
<td>-0.055</td>
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<tr>
<td></td>
<td>(0.095)</td>
<td>(0.105)</td>
<td>(0.080)</td>
<td>(0.088)</td>
<td>(0.045)</td>
<td>(0.050)</td>
<td>(0.032)</td>
<td>(0.033)</td>
<td>(0.105)</td>
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</tbody>
</table>

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.
Appendix Table A.3 - The effect of employment/unemployment experience on personality traits

<table>
<thead>
<tr>
<th>Changes between waves</th>
<th>(1) Opn</th>
<th>(2) Cos</th>
<th>(3) Agr</th>
<th>(4) Stb</th>
<th>(5) Ext</th>
</tr>
</thead>
<tbody>
<tr>
<td>Employment experience</td>
<td>0.004</td>
<td>-0.007</td>
<td>0.000</td>
<td>-0.001</td>
<td>-0.006</td>
</tr>
<tr>
<td></td>
<td>(0.004)</td>
<td>(0.004)</td>
<td>(0.004)</td>
<td>(0.004)</td>
<td>(0.004)</td>
</tr>
<tr>
<td>Unemployment experience</td>
<td>0.001</td>
<td>-0.001</td>
<td>0.004</td>
<td>0.004</td>
<td>0.008</td>
</tr>
<tr>
<td></td>
<td>(0.007)</td>
<td>(0.007)</td>
<td>(0.006)</td>
<td>(0.007)</td>
<td>(0.006)</td>
</tr>
<tr>
<td>Age</td>
<td>0.008</td>
<td>-0.009</td>
<td>0.000</td>
<td>-0.008</td>
<td>0.044</td>
</tr>
<tr>
<td></td>
<td>(0.035)</td>
<td>(0.035)</td>
<td>(0.031)</td>
<td>(0.035)</td>
<td>(0.030)</td>
</tr>
<tr>
<td>Age²/100</td>
<td>-0.011</td>
<td>0.012</td>
<td>-0.008</td>
<td>0.010</td>
<td>-0.059</td>
</tr>
<tr>
<td></td>
<td>(0.045)</td>
<td>(0.045)</td>
<td>(0.040)</td>
<td>(0.045)</td>
<td>(0.039)</td>
</tr>
<tr>
<td>Constant</td>
<td>-0.268</td>
<td>0.303</td>
<td>0.117</td>
<td>0.138</td>
<td>-0.729</td>
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<td>(0.658)</td>
<td>(0.659)</td>
<td>(0.579)</td>
<td>(0.652)</td>
<td>(0.569)</td>
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<td>Observations</td>
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<td>1003</td>
<td>1003</td>
<td>1003</td>
<td>1003</td>
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<tr>
<td>R²</td>
<td>0.001</td>
<td>0.004</td>
<td>0.004</td>
<td>0.001</td>
<td>0.010</td>
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</tbody>
</table>

NOTE: sample for this regressions is restricted to all individuals whose personality traits are measured both in wave 2 and wave 3. This table reports estimates from regressions of the changes of “big five” personality traits on the indicated variables. Standard errors are reported in parentheses. Significance levels: *p < 0.05, **p < 0.01, ***p < 0.001.
References


# Tables

## Table 1: Summary Statistics by Gender

<table>
<thead>
<tr>
<th></th>
<th>Male</th>
<th></th>
<th></th>
<th>Female</th>
<th></th>
<th></th>
<th>Difference</th>
<th>P-value</th>
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<tr>
<td><strong>Labor market records</strong></td>
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<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Unemployment (Months)</td>
<td>2.411</td>
<td>2.547</td>
<td>2674</td>
<td>2.659</td>
<td>3.048</td>
<td>2385</td>
<td>-0.248</td>
<td>0.002</td>
</tr>
<tr>
<td>Employment (Months)</td>
<td>12.375</td>
<td>12.499</td>
<td>1918</td>
<td>11.216</td>
<td>12.208</td>
<td>1633</td>
<td>1.159</td>
<td>0.005</td>
</tr>
<tr>
<td>Actual wage (£/h)</td>
<td>8.264</td>
<td>2.512</td>
<td>1355</td>
<td>7.544</td>
<td>2.449</td>
<td>1125</td>
<td>0.719</td>
<td>0.000</td>
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<tr>
<td>Expected wage (£/h)</td>
<td>9.237</td>
<td>2.482</td>
<td>1981</td>
<td>8.147</td>
<td>2.421</td>
<td>1980</td>
<td>1.090</td>
<td>0.000</td>
</tr>
<tr>
<td>Reservation wage (£/h)</td>
<td>8.023</td>
<td>2.169</td>
<td>1474</td>
<td>7.088</td>
<td>2.051</td>
<td>1528</td>
<td>0.934</td>
<td>0.000</td>
</tr>
<tr>
<td>Number of applications</td>
<td>13.200</td>
<td>18.046</td>
<td>1752</td>
<td>12.548</td>
<td>16.722</td>
<td>1608</td>
<td>0.652</td>
<td>0.279</td>
</tr>
<tr>
<td><strong>Individual’s characteristics</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Education levels</td>
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<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Lower secondary school</td>
<td>0.355</td>
<td>0.479</td>
<td>2244</td>
<td>0.229</td>
<td>0.421</td>
<td>2075</td>
<td>0.126</td>
<td>0.000</td>
</tr>
<tr>
<td>(Adv.) middle sec. school</td>
<td>0.363</td>
<td>0.481</td>
<td>2244</td>
<td>0.429</td>
<td>0.495</td>
<td>2075</td>
<td>-0.066</td>
<td>0.000</td>
</tr>
<tr>
<td>Upper sec. school (A-level)</td>
<td>0.282</td>
<td>0.450</td>
<td>2244</td>
<td>0.341</td>
<td>0.474</td>
<td>2075</td>
<td>-0.059</td>
<td>0.000</td>
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<tr>
<td>Cognitive Ability</td>
<td>1.788</td>
<td>0.571</td>
<td>569</td>
<td>1.892</td>
<td>0.525</td>
<td>572</td>
<td>-0.104</td>
<td>0.002</td>
</tr>
<tr>
<td>Emotional Stability</td>
<td>3.820</td>
<td>1.097</td>
<td>2244</td>
<td>3.411</td>
<td>1.162</td>
<td>2075</td>
<td>0.409</td>
<td>0.000</td>
</tr>
<tr>
<td>Openness to experience</td>
<td>4.769</td>
<td>1.121</td>
<td>2244</td>
<td>4.923</td>
<td>1.188</td>
<td>2075</td>
<td>-0.154</td>
<td>0.000</td>
</tr>
<tr>
<td>Conscientiousness</td>
<td>5.696</td>
<td>0.823</td>
<td>2244</td>
<td>5.858</td>
<td>0.792</td>
<td>2075</td>
<td>-0.162</td>
<td>0.000</td>
</tr>
<tr>
<td>Agreeableness</td>
<td>5.181</td>
<td>0.945</td>
<td>2244</td>
<td>5.512</td>
<td>0.906</td>
<td>2075</td>
<td>-0.331</td>
<td>0.000</td>
</tr>
<tr>
<td>Extraversion</td>
<td>4.696</td>
<td>1.047</td>
<td>2244</td>
<td>4.840</td>
<td>1.064</td>
<td>2075</td>
<td>-0.145</td>
<td>0.000</td>
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</tbody>
</table>

Source: IZA Evaluation Data Set, own calculations. The whole sample includes individuals between age 25 to 55 and divided into two groups by gender: male and female. P-value refers to a two-sided t-test of mean equality between both groups at confidence level of 5%.
Table 2: The effects of personality traits on hourly wages (by gender)

<table>
<thead>
<tr>
<th>Outcome variable:</th>
<th>Not including cognitive</th>
<th>Including cognitive</th>
</tr>
</thead>
<tbody>
<tr>
<td>(log) hourly wage</td>
<td>Male</td>
<td>Female</td>
</tr>
<tr>
<td>Higher level sec. degree</td>
<td>0.131***</td>
<td>0.176***</td>
</tr>
<tr>
<td>(Baseline: sec. school or lower)</td>
<td>(0.027)</td>
<td>(0.028)</td>
</tr>
<tr>
<td>Emotional Stability</td>
<td>0.019*</td>
<td>0.021</td>
</tr>
<tr>
<td></td>
<td>(0.010)</td>
<td>(0.011)</td>
</tr>
<tr>
<td>Openness to experience</td>
<td>0.011</td>
<td>0.014</td>
</tr>
<tr>
<td></td>
<td>(0.010)</td>
<td>(0.012)</td>
</tr>
<tr>
<td>Conscientiousness</td>
<td>0.030*</td>
<td>-0.061***</td>
</tr>
<tr>
<td></td>
<td>(0.014)</td>
<td>(0.018)</td>
</tr>
<tr>
<td>Agreeableness</td>
<td>-0.030*</td>
<td>0.014</td>
</tr>
<tr>
<td></td>
<td>(0.012)</td>
<td>(0.015)</td>
</tr>
<tr>
<td>Extraversion</td>
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<td>0.005</td>
</tr>
<tr>
<td></td>
<td>(0.011)</td>
<td>(0.013)</td>
</tr>
<tr>
<td>Cognitive Ability</td>
<td>0.061</td>
<td>0.022</td>
</tr>
<tr>
<td></td>
<td>(0.045)</td>
<td>(0.050)</td>
</tr>
</tbody>
</table>

| Joint test p – value    | 0.018      | 0.008     | -      | 0.019      | 0.008     | -      |
| Number of Obs           | 893        | 667       | 1,560  | 893        | 667       | 1,560  |
| Work experience         | X          | X         | X      | X          | X         | X      |
| Missing cognitive indicator | X          | X         | X      | X          | X         | X      |

Notes: all columns displays the results using OLS regressions by gender. Source: IZA Evaluation Data Set, own calculations. The whole sample includes unemployed workers between age 25 to 55 and divided into two groups by gender: male and female. Standard Errors in parentheses. p < 0.1*, p < 0.05**, p < 0.01***.
Table 3: Cox proportional hazard model for exiting unemployment (by gender)

<table>
<thead>
<tr>
<th>Outcome variable:</th>
<th>Male</th>
<th>Female</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1)</td>
<td>(2)</td>
</tr>
<tr>
<td>Unemployment duration</td>
<td>0.044</td>
<td>0.023</td>
</tr>
<tr>
<td>Higher level secondary degree</td>
<td>0.041</td>
<td>0.041</td>
</tr>
<tr>
<td>(Baseline: secondary school or lower)</td>
<td>0.023</td>
<td>0.022</td>
</tr>
<tr>
<td>Emotional Stability</td>
<td>0.022</td>
<td>0.026</td>
</tr>
<tr>
<td>Openness to experience</td>
<td>-0.049</td>
<td>-0.052</td>
</tr>
<tr>
<td>Conscientiousness</td>
<td>-0.032</td>
<td>-0.036</td>
</tr>
<tr>
<td>Agreeableness</td>
<td>0.008</td>
<td>0.000</td>
</tr>
<tr>
<td>Extraversion</td>
<td>0.238*</td>
<td>0.134</td>
</tr>
<tr>
<td>Cognitive Ability</td>
<td>0.025</td>
<td>0.025</td>
</tr>
<tr>
<td>Joint test $p – value$</td>
<td>0.145</td>
<td>0.106</td>
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<td>Number of Obs</td>
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<td>2,060</td>
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<td>Working experience</td>
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<td>X</td>
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<tr>
<td>Missing cognitive indicator</td>
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<td>X</td>
</tr>
</tbody>
</table>

Source: IZA Evaluation Data Set. Estimation based on the whole sample includes unemployed workers between age 25 to 55 divided by gender. Standard Errors in parentheses. $p < 0.1^*$, $p < 0.05^{**}$, $p < 0.01^{***}$. 
<table>
<thead>
<tr>
<th>Outcome variable:</th>
<th>Male (1)</th>
<th>Female (2)</th>
<th>Male (3)</th>
<th>Female (4)</th>
</tr>
</thead>
<tbody>
<tr>
<td>First job duration</td>
<td>(3)</td>
<td>(4)</td>
<td>(3)</td>
<td>(4)</td>
</tr>
<tr>
<td>Higher level secondary degree</td>
<td>-0.542***</td>
<td>-0.503***</td>
<td>-0.324*</td>
<td>-0.329*</td>
</tr>
<tr>
<td>(Baseline: secondary school or lower)</td>
<td>(0.132)</td>
<td>(0.135)</td>
<td>(0.148)</td>
<td>(0.150)</td>
</tr>
<tr>
<td>Emotional Stability</td>
<td>-0.044</td>
<td>-0.031</td>
<td>-0.142*</td>
<td>-0.143*</td>
</tr>
<tr>
<td></td>
<td>(0.049)</td>
<td>(0.050)</td>
<td>(0.056)</td>
<td>(0.056)</td>
</tr>
<tr>
<td>Openness to experience</td>
<td>0.027</td>
<td>0.033</td>
<td>-0.038</td>
<td>-0.036</td>
</tr>
<tr>
<td></td>
<td>(0.052)</td>
<td>(0.053)</td>
<td>(0.061)</td>
<td>(0.061)</td>
</tr>
<tr>
<td>Conscientiousness</td>
<td>-0.012</td>
<td>-0.015</td>
<td>0.017</td>
<td>0.022</td>
</tr>
<tr>
<td></td>
<td>(0.070)</td>
<td>(0.069)</td>
<td>(0.091)</td>
<td>(0.091)</td>
</tr>
<tr>
<td>Agreeableness</td>
<td>0.097</td>
<td>0.088</td>
<td>0.122</td>
<td>0.122</td>
</tr>
<tr>
<td></td>
<td>(0.061)</td>
<td>(0.061)</td>
<td>(0.082)</td>
<td>(0.083)</td>
</tr>
<tr>
<td>Extraversion</td>
<td>-0.136*</td>
<td>-0.149**</td>
<td>0.009</td>
<td>0.010</td>
</tr>
<tr>
<td></td>
<td>(0.054)</td>
<td>(0.054)</td>
<td>(0.069)</td>
<td>(0.069)</td>
</tr>
<tr>
<td>Cognitive Ability</td>
<td>-0.212</td>
<td></td>
<td>-0.130</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.234)</td>
<td></td>
<td>(0.258)</td>
<td></td>
</tr>
<tr>
<td>Joint test $p - value$</td>
<td>0.061</td>
<td>0.054</td>
<td>0.071</td>
<td>0.066</td>
</tr>
<tr>
<td>Number of Obs</td>
<td>1,282</td>
<td>1,282</td>
<td>1,038</td>
<td>1,038</td>
</tr>
<tr>
<td>Working experience</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
</tr>
<tr>
<td>Missing cognitive indicator</td>
<td>X</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Source: IZA Evaluation Data Set. Estimation based on the between 25 to 55 who were able to find their first jobs in the sample period divided by gender. Standard Errors in parentheses. $p < 0.1*$, $p < 0.05**$, $p < 0.01***$.  


Table 5: Parameter estimates under alternative bargaining assumptions

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Description</th>
<th>With renegotiation</th>
<th>Without renegotiation</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Male</td>
<td>Female</td>
<td>Male</td>
</tr>
<tr>
<td>$a$</td>
<td>time-invariant ability</td>
<td>7.459 (0.732)</td>
<td>6.729 (1.029)</td>
</tr>
<tr>
<td>$\lambda_u$</td>
<td>offer arrival rate, in unemployment</td>
<td>1.011 (0.150)</td>
<td>1.127 (0.131)</td>
</tr>
<tr>
<td>$\lambda_e$</td>
<td>offer arrival rate, in employment</td>
<td>0.079 (0.013)</td>
<td>0.090 (0.023)</td>
</tr>
<tr>
<td>$\eta$</td>
<td>separation rate</td>
<td>0.025 (0.008)</td>
<td>0.027 (0.008)</td>
</tr>
<tr>
<td>$\alpha$</td>
<td>surplus division</td>
<td>0.221 (0.065)</td>
<td>0.152 (0.055)</td>
</tr>
<tr>
<td>$b$</td>
<td>flow utility when unemployed</td>
<td>0.020 (0.083)</td>
<td>1.045 (0.104)</td>
</tr>
<tr>
<td>$\sigma_\theta$</td>
<td>$\theta \sim \log N\left(-\frac{\sigma_\theta^2}{2}, \sigma_\theta\right)$</td>
<td>0.268 (0.017)</td>
<td>0.276 (0.017)</td>
</tr>
</tbody>
</table>

$N$ | 4,319 | 4,319 |
$0.282$ | -21,629 | -18,950 |

NOTES: Asymptotic standard errors in parentheses. Data: IZA Evaluation Dataset. The location parameter of match quality distribution $\mu_\theta$ 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.
Table 6: Parameter estimates under alternative model specifications

<table>
<thead>
<tr>
<th>Parameter Description</th>
<th>Combined (1)</th>
<th>Male (2)</th>
<th>Female (3)</th>
<th>Male (4)</th>
<th>Female (5)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(0.709)</td>
<td>(0.297)</td>
<td>(0.351)</td>
<td>(0.614)</td>
<td>(0.582)</td>
</tr>
<tr>
<td>offer arrival rate, in unemployment</td>
<td>0.249</td>
<td>0.248</td>
<td>0.208</td>
<td>0.273</td>
<td>0.211</td>
</tr>
<tr>
<td></td>
<td>(0.005)</td>
<td>(0.008)</td>
<td>(0.007)</td>
<td>(0.021)</td>
<td>(0.021)</td>
</tr>
<tr>
<td>offer arrival rate, in employment</td>
<td>0.051</td>
<td>0.051</td>
<td>0.062</td>
<td>0.053</td>
<td>0.067</td>
</tr>
<tr>
<td></td>
<td>(0.002)</td>
<td>(0.003)</td>
<td>(0.003)</td>
<td>(0.009)</td>
<td>(0.009)</td>
</tr>
<tr>
<td>separation rate</td>
<td>0.026</td>
<td>0.025</td>
<td>0.026</td>
<td>0.025</td>
<td>0.027</td>
</tr>
<tr>
<td></td>
<td>(0.001)</td>
<td>(0.001)</td>
<td>(0.001)</td>
<td>(0.004)</td>
<td>(0.004)</td>
</tr>
<tr>
<td>surplus division</td>
<td>0.518</td>
<td>0.496</td>
<td>0.474</td>
<td>0.558</td>
<td>0.371</td>
</tr>
<tr>
<td></td>
<td>(0.040)</td>
<td>(0.044)</td>
<td>(0.079)</td>
<td>(0.027)</td>
<td>(0.024)</td>
</tr>
<tr>
<td>flow utility when unemployed</td>
<td>-2.226</td>
<td>-2.084</td>
<td>-1.213</td>
<td>-1.074</td>
<td>-0.184</td>
</tr>
<tr>
<td></td>
<td>(0.903)</td>
<td>(0.623)</td>
<td>(0.998)</td>
<td>(0.006)</td>
<td>(0.019)</td>
</tr>
<tr>
<td>( \theta \sim \log N \left( -\frac{\sigma^2 \theta}{2}, \sigma \theta \right) )</td>
<td>0.367</td>
<td>0.330</td>
<td>0.369</td>
<td>0.321</td>
<td>0.375</td>
</tr>
<tr>
<td></td>
<td>(0.054)</td>
<td>(0.026)</td>
<td>(0.020)</td>
<td>(0.001)</td>
<td>(0.001)</td>
</tr>
<tr>
<td>( \epsilon \sim \log N \left( -\frac{\sigma^2 \epsilon}{2}, \sigma \epsilon \right) )</td>
<td>0.284</td>
<td>0.255</td>
<td>0.285</td>
<td>0.242</td>
<td>0.282</td>
</tr>
<tr>
<td></td>
<td>(0.079)</td>
<td>(0.038)</td>
<td>(0.035)</td>
<td>(0.006)</td>
<td>(0.007)</td>
</tr>
</tbody>
</table>

Additional notes:

- Asymptotic standard errors using numerical scoring function are reported in parentheses.
- Data: IZA Evaluation Dataset.
- The first likelihood ratio (LR) test is the current specification test against the previous specification.
- The monthly discount rate is set ex ante to be 0.005.
- The location parameter of match value distribution \( \mu \) is predetermined to be \( \mu_\theta = -0.5\sigma_\theta^2 \).
Table 7: Other parameters in specification (3): Individual heterogeneity with gender-specific model coefficients.

<table>
<thead>
<tr>
<th></th>
<th>$\log \lambda_U$ Male</th>
<th>$\log \lambda_U$ Female</th>
<th>$\log \lambda_E$ Male</th>
<th>$\log \lambda_E$ Female</th>
<th>$\log \eta$ Male</th>
<th>$\log \eta$ Female</th>
<th>$\log a$ Male</th>
<th>$\log a$ Female</th>
<th>$\log \left( \frac{a}{\alpha} \right)$ Male</th>
<th>$\log \left( \frac{a}{\alpha} \right)$ Female</th>
</tr>
</thead>
<tbody>
<tr>
<td>Cons.</td>
<td>-1.600</td>
<td>-1.905</td>
<td>-3.355</td>
<td>-3.528</td>
<td>-3.132</td>
<td>-3.207</td>
<td>2.180</td>
<td>1.980</td>
<td>0.720</td>
<td>0.889</td>
</tr>
<tr>
<td></td>
<td>(0.005)</td>
<td>(0.005)</td>
<td>(0.004)</td>
<td>(0.004)</td>
<td>(0.005)</td>
<td>(0.004)</td>
<td>(0.070)</td>
<td>(0.081)</td>
<td>(0.004)</td>
<td>(0.005)</td>
</tr>
<tr>
<td>Edu</td>
<td>0.083</td>
<td>0.048</td>
<td>-0.227</td>
<td>-0.235</td>
<td>-0.042</td>
<td>-0.447</td>
<td>0.107</td>
<td>0.166</td>
<td>0.070</td>
<td>-0.217</td>
</tr>
<tr>
<td></td>
<td>(0.025)</td>
<td>(0.004)</td>
<td>(0.029)</td>
<td>(0.008)</td>
<td>(0.015)</td>
<td>(0.007)</td>
<td>(0.021)</td>
<td>(0.024)</td>
<td>(0.025)</td>
<td>(0.008)</td>
</tr>
<tr>
<td>Stb</td>
<td>-0.004</td>
<td>0.002</td>
<td>0.137</td>
<td>0.074</td>
<td>-0.094</td>
<td>-0.008</td>
<td>0.020</td>
<td>0.021</td>
<td>-0.028</td>
<td>-0.076</td>
</tr>
<tr>
<td></td>
<td>(0.003)</td>
<td>(0.002)</td>
<td>(0.004)</td>
<td>(0.004)</td>
<td>(0.004)</td>
<td>(0.002)</td>
<td>(0.009)</td>
<td>(0.010)</td>
<td>(0.002)</td>
<td>(0.003)</td>
</tr>
<tr>
<td>Opn</td>
<td>-0.006</td>
<td>0.014</td>
<td>0.024</td>
<td>0.009</td>
<td>-0.023</td>
<td>0.008</td>
<td>0.013</td>
<td>0.012</td>
<td>0.003</td>
<td>0.035</td>
</tr>
<tr>
<td></td>
<td>(0.003)</td>
<td>(0.003)</td>
<td>(0.002)</td>
<td>(0.003)</td>
<td>(0.002)</td>
<td>(0.002)</td>
<td>(0.009)</td>
<td>(0.010)</td>
<td>(0.002)</td>
<td>(0.002)</td>
</tr>
<tr>
<td>Cos</td>
<td>0.042</td>
<td>0.052</td>
<td>-0.005</td>
<td>0.059</td>
<td>-0.059</td>
<td>-0.056</td>
<td>0.022</td>
<td>-0.022</td>
<td>0.034</td>
<td>0.027</td>
</tr>
<tr>
<td></td>
<td>(0.003)</td>
<td>(0.003)</td>
<td>(0.002)</td>
<td>(0.003)</td>
<td>(0.003)</td>
<td>(0.003)</td>
<td>(0.013)</td>
<td>(0.016)</td>
<td>(0.003)</td>
<td>(0.002)</td>
</tr>
<tr>
<td>Agr</td>
<td>-0.031</td>
<td>-0.049</td>
<td>-0.018</td>
<td>-0.002</td>
<td>-0.035</td>
<td>-0.042</td>
<td>-0.031</td>
<td>0.015</td>
<td>-0.062</td>
<td>-0.198</td>
</tr>
<tr>
<td></td>
<td>(0.003)</td>
<td>(0.002)</td>
<td>(0.002)</td>
<td>(0.003)</td>
<td>(0.002)</td>
<td>(0.003)</td>
<td>(0.010)</td>
<td>(0.014)</td>
<td>(0.003)</td>
<td>(0.005)</td>
</tr>
<tr>
<td>Ext</td>
<td>0.053</td>
<td>0.046</td>
<td>-0.011</td>
<td>0.058</td>
<td>0.095</td>
<td>0.055</td>
<td>-0.024</td>
<td>0.009</td>
<td>-0.062</td>
<td>-0.071</td>
</tr>
<tr>
<td></td>
<td>(0.003)</td>
<td>(0.003)</td>
<td>(0.002)</td>
<td>(0.003)</td>
<td>(0.004)</td>
<td>(0.002)</td>
<td>(0.011)</td>
<td>(0.013)</td>
<td>(0.002)</td>
<td>(0.003)</td>
</tr>
</tbody>
</table>

NOTE: this table reports the gender-specific coefficients of education and personality traits in specification (4). Asymptotic standard errors using numerical scoring function are reported in parentheses. Data: IZA Evaluation Dataset.
Table 8: The effects of personality traits on search efforts (by gender)

<table>
<thead>
<tr>
<th>Outcome variable:</th>
<th>Male</th>
<th></th>
<th>Female</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>log $\lambda_U$</td>
<td>Num</td>
<td>log $\lambda_U$</td>
<td>Num</td>
</tr>
<tr>
<td>Arrival rates/Num. of Application</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Higher level secondary degree</td>
<td>0.083</td>
<td>2.848</td>
<td>0.048</td>
<td>0.792</td>
</tr>
<tr>
<td></td>
<td>(0.025)</td>
<td>(1.215)</td>
<td>(0.004)</td>
<td>(0.877)</td>
</tr>
<tr>
<td>Emotional Stability</td>
<td>-0.004</td>
<td>-0.038</td>
<td>0.002</td>
<td>0.276</td>
</tr>
<tr>
<td></td>
<td>(0.003)</td>
<td>(0.510)</td>
<td>(0.002)</td>
<td>(0.366)</td>
</tr>
<tr>
<td>Openness to experience</td>
<td>-0.006</td>
<td>0.371</td>
<td>0.014</td>
<td>0.671</td>
</tr>
<tr>
<td></td>
<td>(0.003)</td>
<td>(0.514)</td>
<td>(0.003)</td>
<td>(0.378)</td>
</tr>
<tr>
<td>Conscientiousness</td>
<td>0.042</td>
<td>2.149</td>
<td>0.052</td>
<td>2.465</td>
</tr>
<tr>
<td></td>
<td>(0.003)</td>
<td>(0.706)</td>
<td>(0.003)</td>
<td>(0.589)</td>
</tr>
<tr>
<td>Agreeableness</td>
<td>-0.031</td>
<td>-0.230</td>
<td>-0.049</td>
<td>-1.191</td>
</tr>
<tr>
<td></td>
<td>(0.003)</td>
<td>(0.597)</td>
<td>(0.002)</td>
<td>(0.497)</td>
</tr>
<tr>
<td>Extraversion</td>
<td>0.053</td>
<td>1.063</td>
<td>0.046</td>
<td>0.585</td>
</tr>
<tr>
<td></td>
<td>(0.003)</td>
<td>(0.579)</td>
<td>(0.003)</td>
<td>(0.431)</td>
</tr>
<tr>
<td>Number of Obs</td>
<td>2,244</td>
<td>1,711</td>
<td>2,075</td>
<td>1,709</td>
</tr>
</tbody>
</table>

Notes: all columns displays the results using OLS regressions by gender. Source: IZA Evaluation Data Set, own calculations. The whole sample includes unemployed workers between age 25 to 55 and divided into two groups by gender: male and female. Standard Errors in parentheses.
Table 9: How the gender wage gap changes when women’s coefficients are set equal to those of men

<table>
<thead>
<tr>
<th>Women/Men Ratio Generated by</th>
<th>Offered wage</th>
<th>Accepted wage</th>
<th>Value of unemployment</th>
</tr>
</thead>
<tbody>
<tr>
<td>Baseline</td>
<td>0.892</td>
<td>0.898</td>
<td>0.957</td>
</tr>
<tr>
<td>All parameters</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>- Constant</td>
<td>0.900</td>
<td>0.899</td>
<td>0.936</td>
</tr>
<tr>
<td>- Personality</td>
<td>1.057</td>
<td>1.080</td>
<td>1.140</td>
</tr>
<tr>
<td>- Education</td>
<td>0.863</td>
<td>0.867</td>
<td>0.907</td>
</tr>
<tr>
<td>- Total</td>
<td>0.975</td>
<td>0.987</td>
<td>0.978</td>
</tr>
<tr>
<td>Productivity ((a, \sigma))</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>- Constant</td>
<td>0.927</td>
<td>0.928</td>
<td>0.963</td>
</tr>
<tr>
<td>- Personality</td>
<td>0.876</td>
<td>0.883</td>
<td>0.941</td>
</tr>
<tr>
<td>- Education</td>
<td>0.872</td>
<td>0.878</td>
<td>0.935</td>
</tr>
<tr>
<td>- Total</td>
<td>0.890</td>
<td>0.891</td>
<td>0.925</td>
</tr>
<tr>
<td>Surplus division ((\alpha))</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>- Constant</td>
<td>0.860</td>
<td>0.864</td>
<td>0.918</td>
</tr>
<tr>
<td>- Personality</td>
<td>1.010</td>
<td>1.037</td>
<td>1.110</td>
</tr>
<tr>
<td>- Education</td>
<td>0.909</td>
<td>0.919</td>
<td>0.981</td>
</tr>
<tr>
<td>- Total</td>
<td>1.009</td>
<td>1.035</td>
<td>1.105</td>
</tr>
<tr>
<td>Transitions ((\lambda_U, \lambda_E, \eta))</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>- Constant</td>
<td>0.919</td>
<td>0.926</td>
<td>1.005</td>
</tr>
<tr>
<td>- Personality</td>
<td>0.919</td>
<td>0.926</td>
<td>1.003</td>
</tr>
<tr>
<td>- Education</td>
<td>0.860</td>
<td>0.862</td>
<td>0.900</td>
</tr>
<tr>
<td>- Total</td>
<td>0.925</td>
<td>0.924</td>
<td>1.008</td>
</tr>
</tbody>
</table>

Notes: The simulation results are based on specification (3), Table 7. Except for the indicated parameter subset, others are set at female values.
Table 10: Wage differential decomposition by each trait and channel

<table>
<thead>
<tr>
<th></th>
<th>All channels</th>
<th>Surplus division</th>
<th>Transitions</th>
<th>Productivity</th>
</tr>
</thead>
<tbody>
<tr>
<td>“Big-five” in total</td>
<td>1.057</td>
<td>1.010</td>
<td>0.919</td>
<td>0.876</td>
</tr>
<tr>
<td>Emotional stability</td>
<td>1.009</td>
<td>0.926</td>
<td>0.963</td>
<td>0.915</td>
</tr>
<tr>
<td>Openness to experience</td>
<td>0.898</td>
<td>0.863</td>
<td>0.923</td>
<td>0.911</td>
</tr>
<tr>
<td>Conscientiousness</td>
<td>1.330</td>
<td>0.930</td>
<td>0.876</td>
<td>1.319</td>
</tr>
<tr>
<td>Agreeableness</td>
<td>0.776</td>
<td>1.017</td>
<td>0.900</td>
<td>0.682</td>
</tr>
<tr>
<td>Extraversion</td>
<td>0.741</td>
<td>0.911</td>
<td>0.856</td>
<td>0.768</td>
</tr>
</tbody>
</table>

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

Figure 1. Panel Structure

Figure 2. Unemployment duration: Kaplan-Meier Survival Estimates

Figure 3. Employment duration: Kaplan-Meier Survival Estimates

Figure 4. Observed and simulated wage distributions

Figure 5. Observed and simulated unemployment spells/job spells

Figure 6. Distributions of accepted wages and offered wages
Note: 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.

Figure 2: Unemployment duration: Kaplan-Meier Survival Estimates

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

Note: Source: IZA Evaluation Data Set. The sample includes unemployed workers between age 25 to 55. Log-rank test for equality of survivor functions: $p = 0.000$ (left) and $p = 0.000$ (right).
Figure 3: Employment duration: Kaplan-Meier Survival Estimates

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

Note: Source: IZA Evaluation Data Set. The sample includes workers between 25 to 55 who were able to find their first jobs in the sample period. Log-rank test for equality of survivor functions: $p = 0.259$ (left) and $p = 0.000$ (right).
Figure 5: Observed and simulated unemployment spells/job spells
Figure 6: Distributions of accepted wages and offered wages

(a) Offered wages in baseline model

(b) Accepted wages in baseline model

(c) Offered wages in equal pay experiment

(d) Accepted wages in equal pay experiment