# Labor Market Returns to Personality: A Job Search Approach to Understanding Gender Gaps

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**Abstract**

This paper investigates the effects of the so-called big five personality traits on labor market outcomes and on gender disparities within a job search, matching and bargaining model with heterogeneous workers. In the model, parameters pertaining to productivity, job offer arrival rates, job dissolution rates and the division of surplus from an employer-employee match depend on worker personality traits, education, and other demographics. The model's estimation is based on a German panel dataset. Parameter estimates show that four of the five personality traits are statistically significant determinants of job search parameters and labor market outcomes. Also, women and men are rewarded differently for two traits, conscientiousness and agreeableness, which largely explains gender labor market disparities. If women were to receive the same return that men receive for their personality traits, the wage gap would be eliminated.

# 1 Introduction

Despite substantial convergence in gender wage and employment differentials over the 1970s and 80s, significant differences remain with women earning on average 25 percent less than men (Blau and Kahn (2006), Flabbi (2010b)). A large empirical literature uses data from the US and from Europe to investigate the reasons for gender disparities. Individual attributes, such as years of education and work experience, account for a portion of gender

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wage and employment gaps, but a substantial unexplained proportion remains. Studies generally attribute residual gaps to unobserved productivity differences and/or labor market discrimination.

There is increasing recognition that non-cognitive skills, such as personality traits, are important determinants of labor market outcomes. The most commonly used noncognitive measurements are the so-called big five personality traits, which measure an individual's openness to experience, conscientiousness, extraversion, agreeableness and neuroticism (the opposite of emotional stability).[1] When we compare in Figure 1 the distribution of the big-5 personality traits in our data, we see that women are much more likely to score in the highest categories on openness, conscientiousness, and agreeableness and in the lowest categories on emotional stability. Such patterns are also supported by numerous empirical studies across different countries and these trait differences have been shown to be significantly associated with gender wage gaps (e.g. Nyhus and Pons (2005), Heineck (2011), Mueller and Plug (2006), Braakmann (2009), Cattan (2013)). However, the mechanisms through which personality traits affect labor market outcomes have not been explored in depth.

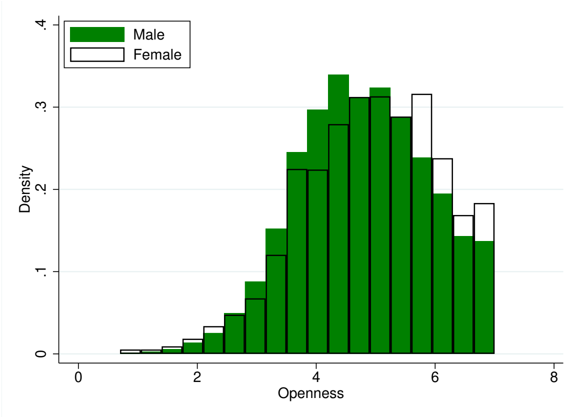
This paper analyzes the relationship between personality traits and labor market outcomes within a partial-equilibrium job search model. We develop and estimate a model in which personality traits potentially operate through multiple channels. Unemployed and employed workers who differ in both observed and unobserved characteristics stochastically receive employment opportunities from firms characterized in terms of idiosyncratic match productivity values. Firms and job searchers divide the match surplus using a Nash-bargaining protocol, with the fraction going to the worker determined by a bargaining power parameter. We propose a new way of incorporating individual heterogeneity by specifying job search parameters as index functions of a possibly high-dimensional set of characteristics. We use the model to explore how personality traits affect hourly wages, employment and labor market dynamics and to better understanding the factors underlying gender wage gaps.

Our model builds on traditional matching-bargaining models, such as Cahuc et al. (2006) and Dey and Flinn (2005). It also contributes to a smaller literature that uses job search models to understand gender wage gaps (e.g. Bowlus and Grogan (2008), Flabbi (2010a), Liu (2016), Morchio and Moser (2020), Xiao (2020), Amano-Patino et al. (2020)). Our modeling approach differs from prior studies by allowing job search parameters to depend in a flexible way on worker characteristics and by incorporating personality traits. We quantify the importance of workers' characteristics operating through four distinct channels: worker

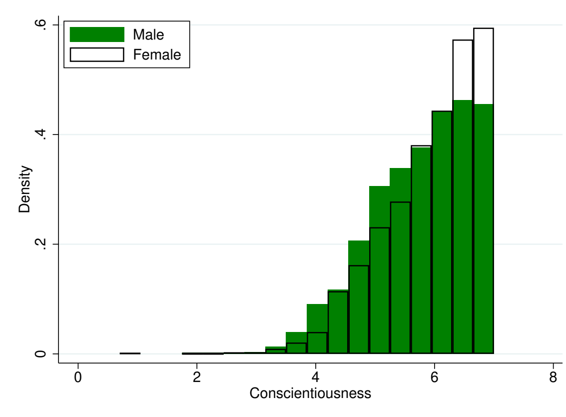
[1] The measures aim to capture patterns of thoughts, feelings and behavior that correspond to individual differences in how people actually think, feel and act (Borghans et al. (2008), Almlund et al. (2011)).

Figure 1: The distributions of “big five” personality traits by genders

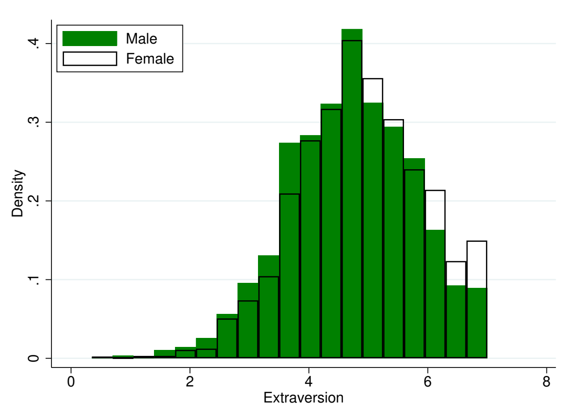
(a) Openness to experience



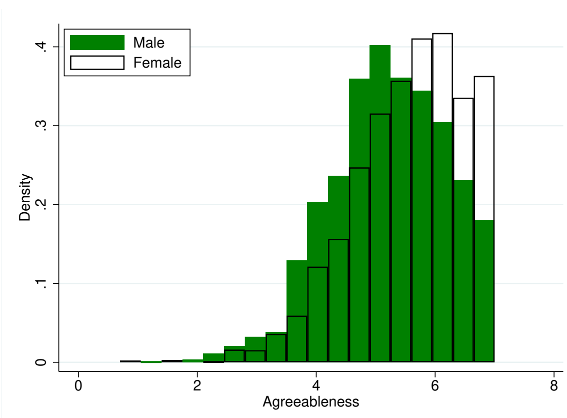

(b) Conscientiousness



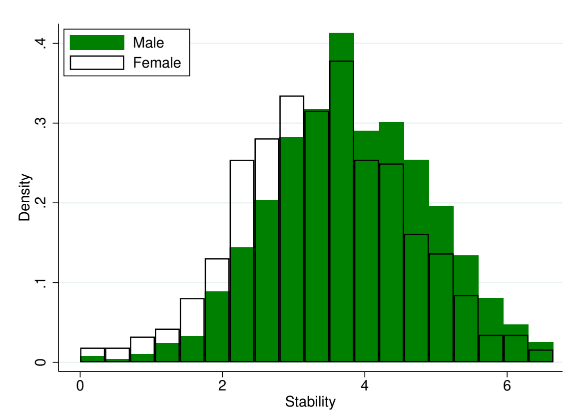

(c) Extraversion




(d) Agreeableness




(e) Emotional Stability




Notes: The measures are based on scores of individuals age 25 to 55 who reports personality traits in all waves of the IZA ED. All trait measures are defined on a scale of 1 to 7.

productivity, job finding rates, job exit rates, and bargaining power.[2]

Model parameters are estimated by maximum likelihood using panel data from the German IZA Evaluation Dataset, which follows individuals who became unemployed between 2007 and 2008 for up to three years. Our analysis sample includes men and women during prime-age working years (ages 25-55). The data contain the big five personality measures, which are significantly associated with job search behaviors and outcomes, such as the number of job applications, length of unemployment spells, and hourly wage rates. We use information on age, education, wages, and job transitions to estimate the model.

The job search literature develops alternative modeling frameworks that differ in the assumptions on how firms bargain with workers. In this paper, we estimate two model specifications that differ in the outside options used by worker-firm pairs in the wage-setting process. In the first specification, two firms competing for a worker are assumed to know the worker's value at both firms and to act as Bertrand competitors when bidding for the worker's services. In the second specification, it is assumed that firms cannot verify a worker's other employment opportunities, so the worker's outside option when bargaining with any employer is assumed to be the value of unemployment.[3] We use Vuong's (1989) test for nonnested models to compare the two model specifications and find that the model in which firms do not renegotiate wages provides a better fit to the data.[4] Using that model, we then estimate three different nested job search models that vary in the extent of individual heterogeneity. In the most general specification, worker productivity, job arrival rates, job exit rates, and bargaining parameters all depend, through indices, on worker characteristics. Likelihood ratio tests reject the more restrictive specifications in favor of the one that allows for the highest dimension of heterogeneity.

Using the model estimates, we simulate steady state labor market outcomes for men and women. The simulation reveals that men have many labor market advantages relative to women. For example, men have a higher job offer arrival rate which leads to an average unemployment spell that is about 1.25 months shorter than those of women. Men also receive higher wage offers and experience greater job-to-job wage growth. In addition, men's

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

[3] This outcome may also occur even when firms have full information regarding alternative employment opportunities. As soon as an individual rejects a competing offer, her outside option becomes the value of unemployment. Thus, the winning firm has an incentive to renege on the promised wage. Firms could be deterred from such behavior if there are reputation effects.

[4] Flinn and Mullins (2019) develop a model in which equilibria can exist in which some firms do not renegotiate and instead post wages while other firms negotiate with workers regarding their wage. Such an extension is beyond the scope of the current paper.

jobs are more secure; their average job spell is 0.8 months longer than a woman's average job spell. In the steady-state, a woman earns on average 86 percent of a man's wage.[5]

We perform a comparative statics exercise to analyze how each of the five personality traits influences labor market outcomes. In particular, we increase each trait by 1 standard deviation (SD) and examine the implied labor market outcome changes by gender. An increase in emotional stability affects men and women in similar ways, increasing reservation wages, average accepted wages, and the length of employment spells. Extroversion also affects men and women in similar ways, reducing wages, reducing the length of unemployment spells, and increasing the frequency of job changes. The impact of the openness to experience trait is not statistically significant for labor market outcomes. The remaining two traits, conscientiousness and agreeableness, affect men's and women's labor market outcomes in remarkably different ways. For men, a one SD increase of conscientiousness increases average wages, increases wage growth, decreases unemployment spells and promotes job and employment stability. For women, conscientiousness lowers reservation wages, lowers average wages and decreases the job spell length. A one SD change in agreeableness negatively impacts men's wages (-4.5 percent) but has little impact on women's wages. However, it substantially inhibits wage growth for women.

To assess the relative importance of personality traits and other characteristics in explaining gender wage gaps, we perform a Oaxaca-Blinder-type decomposition, adapted to a nonlinear model setting. Specifically, we simulate women's labor market outcomes if their education levels and personality traits were valued in the same way as those of men. We find that gender differences in the valuation of education are less important than differences in the valuation of personality traits in explaining the gender wage gap. Among different model channels, gender differences in the estimated bargaining parameters emerges as a primary factor. Further investigation shows that gender differences in the valuation of the agreeableness trait largely accounts for women's lower bargaining power, which is consistent with a long-standing literature that argues that wage gaps are partly attributable to gender differences in effectiveness in negotiation settings.

Lastly, we use the estimated model to conduct an "equal pay experiment" in which we simulate women's labor market outcomes using the model parameters estimated for men. We find the gender wage gap is totally eliminated under such simulation. We therefore conclude that gender differences in the labor market valuation of personality traits rather than in trait levels are the primary determinants of gender wage gap.

[5]Some other studies also find that women are disadvantaged not only in terms of wages but also in terms of job finding rates using datasets from different countries. (See e.g. Liu (2016) and Amano-Patino et al. (2020))

Our evidence adds to the literature analyzing gender differences in job search behaviors and outcomes. Most prior studies estimate different search parameters by gender and education groups (e.g. Bowlus (1997), Bowlus and Grogan (2008), Flabbi (2010a), Liu (2016), Morchio and Moser (2020), Amano-Patino et al. (2020)). In comparison, we allow job search model parameters to depend on a larger set of worker characteristics to account for both cognitive and noncognitive dimensions of individual heterogeneity. There are two studies that investigate the association between noncognitive traits and job search, Caliendo et al. (2015) and McGee (2015). The noncognitive measure used in both papers is "locus of control", which is a measure of how much individuals think success depends on "internal factors"(i.e. their own actions) verses "external factors."[6] We focus rather on the big five traits because, in our data, the "locus of control" measure exhibits little variation by gender. To the best of our knowledge, this is the first study to incorporate the big five personality traits into a job search matching and bargaining framework.

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

There are several studies in the workplace bargaining literature showing that women are less likely to ask for fair wages, both in lab experiments (e.g. Stuhlmacher and Walters (1999)) and survey data (e.g. Säve-Söderbergh (2007) and Card et al. (2015)). However, there is no consensus on the reason for this phenomenon. Possible explanations offered include gender differences in risk preferences (e.g. Croson and Gneezy (2009) ), attitudes towards competition (e.g. Lavy (2013); Manning and Saidi (2010)) and negotiation skills (e.g. Babcock et al. (2003)). Our results suggest that gender differences in personality traits could also be a key factor. Specifically, we find that the agreeableness trait is is strongly associated with lower bargaining power. Not only are women more agreeable than men on average, but they also receive a larger penalty for being agreeable through the bargaining channel of our model.

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

This paper proceeds as follows. The next section presents our baseline model. Section 3 describes the data. Section 4 discusses the model's econometric implementation. Section 5 presents the model coefficient estimates. Section 6 interprets the model estimates and present wage gap decomposition results. Section 7 concludes.

# 2 Model

We first introduce a baseline job search, matching and bargaining model and then discuss alternative model specifications derived under two different assumptions on the wage bargaining process. We estimate multiple specifications and use statistical tests to choose the one that best fits the data.

## 2.1 Setup and preliminaries

The model is set in continuous time, with a continuum of risk-neutral and infinitely lived agents: firms and workers. Workers are distinguished by different observable "types," denoted by the vector $z$. An unemployed worker meets firms at the rate $\lambda_U(z)$, and an employed worker meets new potential employers at the rate $\lambda_E(z)$, where both of these rates are assumed to be exogenously determined. The general productive ability of an individual is denoted by $a(z)$. When a worker matches with a firm, the match-specific productivity of the match is an i.i.d. draw from the distribution $G_z(\theta)$, which has a corresponding density function $g_z(\theta)$, both of which are defined on $R_+$. The productive ability of individual $z$ is given by [7]

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

The flow value of unemployment to the individual is assumed to be $a(z)\times b$, where $b$ can differ by gender.[8] Employment matches are dissolved at the exogenous rate $\eta(z)$. The common discount rate of all agents in the model, firms and workers, is $\rho$, which is a independent

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

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

of $z$.[9] The worker and the firm bargain over the wage $w$ using a Nash bargaining protocol, with the outside option of the individual dependent upon the particular bargaining protocol assumed.[10] The worker's flow payoff is $w$ and the firm's flow revenue is $y(z) - w$ from this match. The bargaining power of the individual is denoted by $\alpha(z)$.

In our application, the "type" $z$ corresponds to a combination of observed individual characteristics that include education level, birth cohort, and the big five personality trait assessments.[11] Because the model is stationary and our data are a short panel (three years), we assume that these characteristics are time-invariant.

## 2.2 A model of on-the-job search with renegotiation

In this section, we first present an on-the-job search model with renegotiation as our benchmark model and then discuss alternative modeling assumptions. A type $z$ worker with ability $a(z)$ receives job offers at the rate $\lambda_U(z)$ when unemployed and $\lambda_E(z)$ when employed. To simplify the notation, we for now suppress the notation that conditions the model parameters on $z$.[12] We reintroduce $z$ later when we discuss the parametric specifications.

Following Dey and Flinn (2005) and Cahuc et al. (2006), we assume firms are able to observe the worker's productivity at a competing firm, either directly or through the process of repeated negotiation. The firms behave as Bertrand competitors, with the culmination of the bidding process resulting in the worker going to the firm where her productivity is greatest. Because general ability $a$ is the same at all firms, the different productivity levels of the worker in the two firms are attributable to the different match qualities at the firms. When two firms compete for the same worker, their positions are symmetric. This means the incumbent has no advantage or disadvantage in retaining the worker with respect to the poacher.[13] Let $\theta$ and $\theta'$ denote the match productivity draws at the two firms. Let $\theta' > \theta$, in which case we will refer to $\theta'$ as the *dominant* match value and $\theta$ as the *dominated*

[9] There is some evidence that workers with different cognitive and non-cognitive ability tend to have different discount rates ( Dohmen et al. (2011)). However, we are not able to allow for such dependence, because the $(\rho, b)$ are not individually identified in the canonical search framework. See the discussion in section 4.3.1.

[10] If allowing for renegotiation between the worker and the firm, the outside option of the worker is the current job. However, if a worker is not allowed to renegotiate the contract with the firm, her outside option would be unemployment. We will discuss the model allowing for renegotiation as our leading case. The alternative model without renegotiation is described in Section 2.3.1.

[11] We incorporate gender as a state variable in a more flexible way than other observed characteristics. We will discuss its detailed specification in Subsection 2.4.

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

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

match value. When the firms engage in Bertrand competition in terms of wage negotiations, the firm associated with the dominated match value will attempt to attract the worker by increasing its wage offer to the point where it earns no profit from the employment contract. The firm with match value $\theta$ will offer a wage of $a\theta$ to attract the worker. The value of working in the dominated firm with wage $a\theta$ (equal to worker's productivity) then serves as the worker's outside option when engaging in Nash bargaining with the dominant firm.

We now derive the expression for the bargained wage. First, consider an employed worker with the state variable $(\theta', \theta)$. When offered a wage $w$, the value of employment can be written as

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

where $V_U(R)$ denotes the value of being unemployed under the Bertrand competition assumption. Term (1) corresponds to the case in which the current job paying $w$ is dissolved due to exogenous shock which occurs at rate $\eta$. Term (2) corresponds to the case in which a new firm is encountered with match productivity $x$, where $\theta < x \leq \theta'$, is drawn. In this case, the employee will remain at the current firm, but the wage will be renegotiated given the increased value of the employee's outside option, which has increased from $\theta$ to $x$. Term (3) reflects the case in which the new match productivity value $x$ exceeds the current match value $\theta'$. In this case, the individual moves to the new job, where their match productivity increases to $x$, and the new dominated match value becomes $\theta'$. In either case (2) or (3), the (potential) wage payment at the dominated firm is equal to the individual's productivity at that firm (and the firm's flow profit is 0). This is the same outcome as would occur in a special situation when their was no dominant match value, with match productivity at both firms given by $\theta$. When $\theta' = \theta$, equation 1 simplifies to

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

The value of the employment match to the firm given the value of the worker's outside option $\theta$ and a wage of $w$ is given by

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

where $a\theta'$ is the flow revenue to the firm and $a\theta' - w$ is the firm's flow profit. Note that when the match is exogenously terminated, which occurs at rate $\eta$, the value to the firm is the value of an unfilled vacancy, which by assumption is 0.

We assume that every job searcher with an idiosyncratic productivity value $a$ has a flow utility in the unemployment state equal to $ba$, where $b$ is a constant.[14] The value of unemployment is given by

$$\rho V_U(R) = ba + \lambda_U \int_{\theta^*_R} (V_E(x, \theta^*_R) - V_U(R))\, dG(x). \tag{4}$$

$\theta^*_R$ is the reservation match value, the one at which individual is indifferent between employment and continued search, which is defined as

$$V_U(R) = V_E(\theta^*_R, \theta^*_R). \tag{5}$$

After having defined these value functions, the Nash-bargained wage is given by

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

where the worker's outside option $V_E(\theta, \theta)$ is given in equation 2, the maximum value when working a job with match value $\theta$, the firm's outside option is 0 and the worker's share of the surplus is $\alpha$. The solution $w(\theta', \theta)$ and the reservation match value in the unemployment state $\theta^*$ can be found in Appendix A.1.1.

## 2.3 Alternative modeling assumptions

### 2.3.1 The renegotiation assumption

Although assuming Bertrand competition between firms is theoretically appealing, it is not clear how realistic this assumption is.[15] It can be shown that introducing a positive cost of negotiation discourages Bertrand competition and makes it unprofitable for firms to poach workers from other firms with better match values. Mortensen (2005) argues that

[14]This assumption greatly simplifies the solution to the steady state value functions, and is also made, for example, in Postel-Vinay and Robin (2002), Bartolucci (2013), and Flinn and Mullins (2015).

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

counteroffers are empirically uncommon.[16] Moscarini (2008) claims moral hazard concerns largely explain why firms do not match outside offers. Firms may credibly commit to ignoring outside offers that their employees receive to reduce other employees' incentives to search on the job.

In an environment where workers are not able to recall rejected job offers, a firm also has an incentive to renege on its offered wage once the potential competitor's offer has been withdrawn.[17] As a result, the outside option for the worker is unemployed search with value $V_U$.[18] In such case, all on-the-job wage bargaining uses the value of unemployment as the outside option, an option that is always available whether or not the wage contract is enforced.[19]

Due to skepticism that the Bertrand competition assumption characterizes actual labor market bargaining protocols, we next consider one way to alter this assumption. We describe an alternative protocol that does not allow for renegotiation. In this set-up, the "dominated" match value does not affect the bargained wage at the firm with the dominant productivity value $\theta'$. The value of employment $V_E(\theta')$ is a function of the current match value $\theta'$:

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

where $V_U(N)$ is the value of unemployment given no competition between firms when setting wages. The value to the firm of a filled job becomes

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

because the firm only loses an employee with match productivity value $\theta'$ when the employee encounters another firm where their match productivity is $\theta'' > \theta'$. The value of being

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

[17]This possibility exists in most dynamic models of bargaining. Typically problems of reneging are met by assuming that both sides of the bargain must agree to renegotiate the terms of a contract or by assuming that firms who do renege will not be able to hire workers in the future due to a negative reputation effect.

[18]It might be argued that the worker, being fully aware of the fact that the firm will renege on its wage offer once the other offer is withdrawn, would insist on a lump sum payment, or "signing bonus," to accept the employment contract. In such case, we might see a one time payment to the worker at any moment in which two firms are engaged in a competition for her labor services. However, the flow wage payment would be that specified in equation 11.

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

unemployed, $V_U(N)$, is given by

$$\rho V_U = ba + \lambda_U \int_{\theta_N^*} (V_E(x) - V_U(N))\, dG(x) \tag{9}$$

where $\theta_N^*$ is the reservation match value in the no-renegotiation case, the value at which individual is indifferent between employment and continued search, which is defined by

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

Note that $\theta_N^* \neq \theta_R^*$, so that the values of unemployment are different in the two specifications. It is important to recognize, however, that whether we assume Bertrand competition or not, both bargaining assumptions imply efficient mobility. This means that a worker will always accept employment at the firm where their idiosyncratic productivity is greatest. Although turnover decisions will be the same, the wage processes will differ.

In the case of no renegotiation, the bargained wage is

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

which can be written as

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

where we incorporate the efficient mobility implication that the worker accepts alternative job offers if and only if the alternative match quality $x > \theta$. The solution of the reservation value $\theta_N^*$ is given in the appendix A.1.2. Because the bargaining assumptions of this model are not consistent with the axioms underlying Nash bargaining, the parameter $\alpha$ should be thought simply as a surplus-sharing parameter. For practical purposes, this parameter has the same interpretation in both bargaining environments.

Clearly, the models with renegotiation and without renegotiation will yield different wage solutions even for identical values of the primitive parameters and identical match quantity distributions. We estimate both models and choose the preferred one based on the Vuong (1989) likelihood ratio test for non-nested models.

### 2.3.2 Allowing sector-specific match value distributions

In our baseline model, individuals do not target a specific occupational sector in their job search. However, as we will later show, there are differences in the occupational distribution by gender. We next describe a way of extending the previous framework to allow job offers to be sector-specific while still maintaining the tractability of a random search model. Assume the match value distribution is a mixture of $K$ sector-specific match value distributions:

$$g(\theta) = \sum_{k=1}^{K} p_k g_k(\theta)$$

where $p_k$ represents the proportion of jobs drawn from sector $k$, which could differ by gender. We assume that the match quality distribution is log normal within sectors:

$$\log(\theta_k) \sim N\left(\mu_k, \sigma_k^2\right).$$

We can allow $\mu_k$ and $\sigma_k$ to differ by gender to capture potential within-sector gender differences. In this case, the value of being unemployed is

$$\rho V_U(N) = ab + \sum_{k=1}^{K} \lambda_U p_k \int_{\theta_N^*} \left(V_E(x) - V_U(N)\right) dG_k(x)$$

It is worth noting that the reservation match value $\theta_N^*$ is the same across different sectors, as jobs from different sectors have exactly the same value for workers given the same matching quality $\theta$.[20] The term $\lambda_U p_k$ represents the arrival rate for jobs from a certain sector $k$. The value function for an employed worker at a current job with match value $\theta$ is

$$\rho V_E(\theta) = w(\theta) + \eta\left(V_U(N) - V_E(\theta)\right) + \sum_{k=1}^{K} \lambda_E p_k \int_{\theta} \left(V_E(x) - V_E(\theta)\right) dG_k(x)$$

The model allowing for sector-specific match value distributions is more general than the previous model. However, when we estimated both models, we found that allowing match value distributions to be sector-specific led to similar inferences. We therefore present results from the simpler model without sectors as our baseline and report the estimates from the multi-sector model as a robustness check in Appendix B.2.4.

### 2.3.3 Household search

In Flinn et al. (2018), we develop and estimate a model of household bargaining about time allocation decisions, using Australian data, and we argue that it is important to model

[20] This is obviously a limitation of this approach, since women may prefer occupations for other reasons besides wages. A full analysis of occupational choice with nonpecuniary job amenities would substantially complicate our current framework and is beyond the scope of this paper.

household interactions when examining gender wage differences. Because men and women often inhabit households together, their labor supply decisions can be thought of as being jointly determined. Gender differences in wages may reflect patterns of assortative mating in the marriage market as well as the manner in which household decisions are made.

We are able to circumvent this issue in this paper because of the linear flow utility assumption.[21] Both men and women are assumed to have flow utility functions given by their respective wages $w$ when employed and by the constants $ba$ when they are unemployed. The linear utility assumption allows the the household's maximization problem to be decentralized as the sum of two individual maximization problems as noted in Dey and Flinn (2008). Under this assumption, we do not have to be concerned with interdependence in household decision-making.[22]

## 2.4 Incorporating individual heterogeneity

So far, we described the search and bargaining model given a set of labor market parameters $\Omega = \{\lambda_U, \lambda_E, \eta, \alpha, a, b, \sigma_\theta\}$, where the parameter $\sigma_\theta$ denotes the standard deviation of distribution of $\ln \theta$, which is assumed to be normal (so that $\theta$ follows a lognormal distribution). We assume that the mean of $\ln \theta$ is equal to 0 for all individuals. We now reintroduce individual types $z$ and describe how we allow search parameters to depend on worker characteristics, that include education, personality traits, birth cohort and gender. For an individual $i$, we specify gender-specific "link" index functions between $z_i$ and $\Omega_i$ as follows:

$$
\begin{array}{rcc}
\lambda_U(i) & : & \exp(z_i^{'}\gamma^g_{\lambda_U}) \\
\lambda_E(i) & : & \exp(z_i^{'}\gamma^g_{\lambda_E}) \\
\alpha(i) & : & \frac{\exp(z_i^{'}\gamma^g_{\alpha})}{1+\exp(z_i^{'}\gamma^g_{\alpha})} \\
\eta(i) & : & \exp(z_i^{'}\gamma^g_{\eta}) \\
a(i) & : & \exp(z_i^{'}\gamma^g_{a}) \\
b(i), \sigma_\theta(i) & : & \text{differ only by gender}
\end{array}
\tag{12}
$$

where $z_i$ include all observed heterogeneity except for the gender. And $\gamma^g_j$ are gender-specific loading coefficients, where $g \in \{Male, female\}$ denotes the gender of worker $i$, and $j$ is

[21] Another reason that this assumption is made is that it obviates the need to include a specification of the capital markets within which individuals operate, because there is no demand for borrowing or saving under the risk neutrality assumption.

[22] Under the alternative assumption of non-linear utility, bargaining between spouses as well as with firms must be taken into account, which considerably complicates the analysis.

specific to the given model parameters. These gender-specific coefficients $\gamma_j^g$ allow to capture potential gender-asymmetric returns to observed characteristics including personality traits. Men and women may be subject to different labor market parameters

Because $z_i$ takes values on the entire real line, these index functions are necessary to restrict the parameters to the correct parameter space associated with the model. For example, the rate parameter $\lambda_U(i) \in R_+$, and the $\exp(\cdot)$ function insures that this is the case. The logit transform is used to map $z_i^{'}\gamma_\alpha^g$ into the unit interval, which is required given its interpretation as a bargaining power or surplus share parameter.

# 3 The IZA evaluation dataset

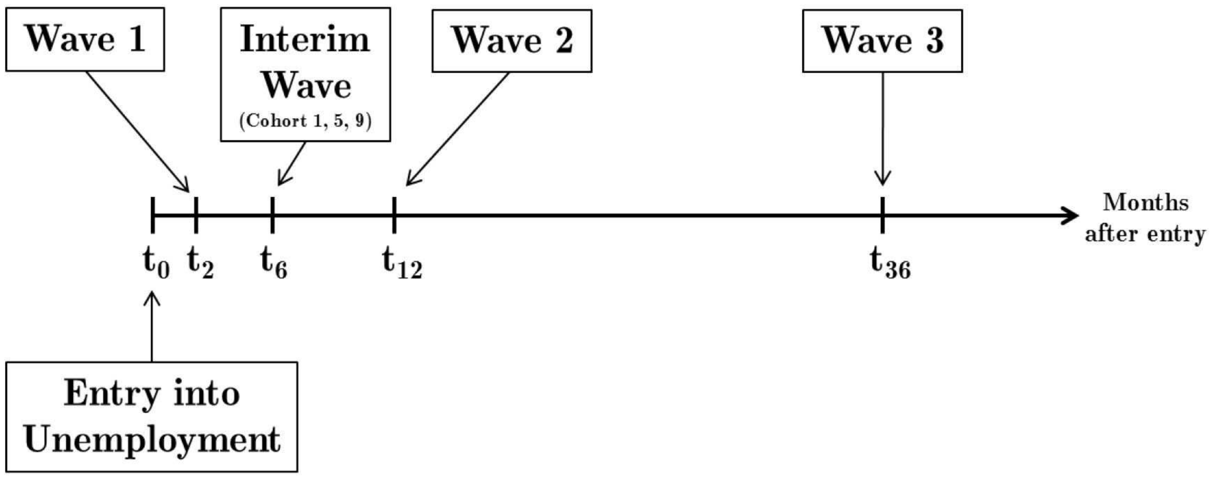
The IZA evaluation dataset survey (IZA ED) is a panel survey of 17,396 Germans who registered as newly unemployed with the Federal Employment Agency between mid-May 2007 and mid-May 2008. In each of 12 months, approximately 1,450 individuals are randomly selected to be interviewed based on their birthdays.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

The IZA ED is a monthly cohort-specific panel. Upon entry into unemployment, each cohort was interviewed at least three times. Most cohorts did their first interviews within 55 to 84 days after entering unemployment. The second and third interviews were scheduled one year and three years later. In addition, three cohorts (corresponding to months June and October 2007 and February 2008) were interviewed at an interim time, six months after their first interview. A graph of the panel structure is shown in figure 2.[23] In constructing our analysis sample, we drop individuals with missing information on age, gender, and education as well as missing personality trait information. We also exclude self-employed individuals, because our model pertains to firm-worker matches. These restrictions leave us with a final sample of 4,319 individuals.[24]

[23]One concern with regard to these data is whether the model's stationary assumption holds. We examine this assumption in appendix B.1.1. Although the stationarity assumption may not be ideal, it is less problematic in Germany in this time period than it would be for the US.

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

Figure 2: Panel Structure




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

The big five information in the IZA ED is based on a 15-item personality description. Respondents were asked to pick a number between 1 to 7 to indicate how well each description applies to them. The lowest number '1' denotes a completely opposite description and the highest number '7' denotes a perfect description. Each personality trait is constructed by the average scores of three items pertaining to that trait.[25]

The personality trait information is collected at each wave, including the interim wave. The completed big five personality traits are available for 5,601 respondents in wave 1, for 1,680 respondents for the interim wave, and for 5,747 and 5,732 respondents in waves 2 and 3, respectively. We include in our analysis individuals for whom personality traits were measured at least once. When there are multiple measures, we use the average value across the different waves, because differences observed within a 3-year time frame are likely due to measurement errors rather than fundamental changes in personality characteristics.[26] Cognitive skills are only measured for three cohorts that were selected to participate during the interim wave (June and October 2007, February 2008).

Table 1 presents summary statistics by gender. As seen in the last column, all of the gen-

effects on wages and employment prospects. We do not explicitly include information on ALMP in our analysis.

[25]In the beginning of the first wave interview, there were 10 personality items, but an additional 5 items become available beginning with the February (ninth) cohort. A detailed description of which items are used to construct each personality trait is provided in Appendix A.2

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

der differences are statistically significant at conventional levels. Males spend fewer months in unemployment, 2.41 on average in comparison to 2.67 for females, and more months in employment. The difference in labor market experience of men and women in our sample is not that large: 18 years for men in comparison to 16 years for women. The dataset contains information on actual wages, expected wages, and reported reservation wages. Men have on average an expected hourly wage equal to €9.51 in comparison to €8.26 for women. Their actual wage is also higher, €8.79 on average for men in comparison to €7.66 on average for women. Men also report on average a higher reservation wage than women; €8.26 for men compared to € 7.24 for women. The data also shows the gender-specific job distributions by industry sectors. Men are most likely to work in the manufacturing sector (39.6%) and the service sector (55.6%); the majority of women work in the service sector (80.7%).

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

Comparing the average wage for men and women, there is a 14.7 percent gender wage gap. At first glance, the wage gap may seem smaller than the wage gaps reported for Germany in other studies. For example, Blau and Kahn (2000) found a gender hourly gap in West Germany of 32 percent, placing West Germany in position 6 in a ranking of 22 industrialized countries. There are two explanations for the discrepancy. First, our sample of newly unemployed individuals tends to include more individuals from the lower part of the wage distribution. Second, the wages reported in IZA-ED are net earnings, which are different from the conventional gross earning measures that most other datasets report.

To better understand why the wage gap is lower in our data sample than in some other studies, we tabulated mean wages by gender using the German Socio-Economic Panel (GSOEP) data (a random representative sample) in Table 2, in which both net wages and gross wages are available.[27] Although the average wage in the newly unemployed sample is lower than the average wage in a representative sample (€8.87 vs. €11.55 for men and €7.72 vs. €9.11 for women), the smaller gender wage gap is mainly caused by the measured differences between net wages and gross wages. Due to the progressive nature of the Ger-

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

Table 1: Summary Statistics by Gender

| | Male | | | Female | | | Difference | |
|---|---|---|---|---|---|---|---|---|
| | Mean | Std. Dev. | Obs. | Mean | Std. Dev. | Obs. | Diff in mean | P-value |
| Labor market measures | | | | | | | | |
| Unemployment (Months) | 2.42 | 2.60 | 2490 | 2.68 | 3.05 | 2261 | -0.26 | 0.00 |
| Employment (Months) | 12.60 | 12.68 | 1664 | 11.50 | 12.47 | 1462 | 1.10 | 0.02 |
| Actual wage (€/$h$) | 8.79 | 4.43 | 1405 | 7.66 | 3.46 | 1161 | 1.12 | 0.00 |
| Wage during last employment(€/$h$) | 8.74 | 6.58 | 3632 | 7.59 | 4.74 | 3108 | 1.15 | 0.00 |
| Industry sectors | | | | | | | | |
| Agriculture and forestry, fishing | 0.05 | 0.22 | 1585 | 0.04 | 0.20 | 1375 | 0.01 | 0.35 |
| Manufacturing, production | 0.40 | 0.49 | 1585 | 0.15 | 0.36 | 1375 | 0.24 | 0.00 |
| Services, trade/banking/insurance | 0.56 | 0.50 | 1585 | 0.81 | 0.40 | 1375 | -0.25 | 0.00 |
| Previous accu. experience (years) | 18.28 | 9.98 | 3808 | 15.79 | 9.59 | 3293 | 2.49 | 0.00 |
| Expected wage (€/$h$) | 9.51 | 3.62 | 1915 | 8.26 | 3.33 | 2003 | 1.25 | 0.00 |
| Reservation wage (€/$h$) | 8.26 | 3.01 | 1428 | 7.24 | 2.73 | 1524 | 1.02 | 0.00 |
| Number of applications | 13.15 | 18.40 | 1615 | 12.76 | 17.07 | 1512 | 0.39 | 0.54 |
| Demographic characteristics | | | | | | | | |
| Age: mean | 37.94 | 8.65 | 2084 | 38.70 | 8.68 | 1965 | -0.76 | 0.01 |
| Birth cohorts | | | | | | | | |
| 1952-1962 | 0.38 | 0.49 | 2084 | 0.35 | 0.48 | 1965 | 0.03 | 0.06 |
| 1963-1972 | 0.35 | 0.48 | 2084 | 0.35 | 0.48 | 1965 | 0.01 | 0.69 |
| 1973-1982 | 0.27 | 0.44 | 2084 | 0.30 | 0.46 | 1965 | -0.04 | 0.02 |
| Education levels | | | | | | | | |
| Lower secondary school | 0.37 | 0.48 | 2084 | 0.24 | 0.43 | 1965 | 0.13 | 0.00 |
| (Adv.) middle sec. school | 0.37 | 0.48 | 2084 | 0.44 | 0.50 | 1965 | -0.07 | 0.00 |
| Upper sec. school (A-level) | 0.26 | 0.44 | 2084 | 0.33 | 0.47 | 1965 | -0.07 | 0.00 |
| Marriage | 0.44 | 0.50 | 2077 | 0.52 | 0.50 | 1960 | -0.08 | 0.00 |
| Dependent child (under age 18) | 0.32 | 0.47 | 2080 | 0.40 | 0.49 | 1964 | -0.09 | 0.00 |
| Personality traits | | | | | | | | |
| Cognitive ability | 1.77 | 0.57 | 530 | 1.89 | 0.52 | 550 | -0.12 | 0.00 |
| Emotional stability | 3.81 | 1.10 | 2084 | 3.40 | 1.15 | 1965 | 0.41 | 0.00 |
| Openness to experience | 4.76 | 1.11 | 2084 | 4.89 | 1.19 | 1965 | -0.14 | 0.00 |
| Conscientiousness | 5.71 | 0.82 | 2084 | 5.86 | 0.78 | 1965 | -0.15 | 0.00 |
| Agreeableness | 5.19 | 0.94 | 2084 | 5.51 | 0.91 | 1965 | -0.32 | 0.00 |
| Extraversion | 4.68 | 1.04 | 2084 | 4.82 | 1.06 | 1965 | -0.14 | 0.00 |
| Locus of control | 4.36 | 0.75 | 1895 | 4.31 | 0.72 | 1826 | 0.05 | 0.02 |

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

man tax system, the gap in net wages should be smaller than the gap in gross wages. In the GSOEP data for 2007 and for newly unemployed workers similar to the individuals in our sample, the net wage gap is 22.4 percent but the gross wage gap is 30.5 percent (the average wages are €13.52 for men and €10.36 for women).

A comparison of personality trait scores shows that men have higher emotional stability scores on average. But for all other traits, women have higher scores on average. The greatest gender differences occur for emotional stability (3.81 for males versus 3.40 for women) and agreeableness (5.19 for males versus 5.51 for females).[28] As previously noted, some studies focus on locus of control as a measure of an individual's noncognitive skills. As seen in the last row of the table, our sample shows very little gender difference in average locus of control (4.36 for men and 4.31 for women). Therefore, we focus on the big five personality measures as a potential source of labor market outcome disparities between men and women.[29]

Table 3 reports estimated coefficients from a linear regression of log hourly wages (at the last time of employment) on education, personality traits, cognitive ability, and reported labor market experience (before being unemployed) and its square. As seen in Table 3, the coefficient associated with education is similar for men and women (0.230 for women and 0.241 for men). Higher scores on emotional stability are associated with higher hourly wages for both men and women. Moreover, a higher score on conscientiousness is associated with higher wages for men but lower wages for women. Agreeableness is associated with lower wages, the effect is only statistically significant for men.

In our behavioral model, personality traits are allowed to affect the gender wage gap through the job search, productivity and wage bargaining channels. However, some other individual characteristics/choices such as occupation, marriage and fertility could also be relevant. Columns (2), (3), (5) and (6) of Table 3 add to the previous regression specification the following covariates: cognitive ability, a marriage indicator, the number of children, and industry sector indicators (agriculture/manufacturing/service). Both marriage status and occupation sector choices are significantly associated with hourly wage rates, but including these additional covariates does not significantly alter the association between personality traits and hourly wages.

Figure 3 shows estimated Kaplan-Meier survival functions associated with unemployment duration, by gender. Women exit unemployment more slowly than men. However, men are more likely to experience unemployment spells in excess of 12 months. About 50 percent of the sample experiences initial unemployment spells lasting less than six months.

[28] A more detailed comparison of personality trait distributions between genders can be found in Table 1.

[29] Additional information on the correlation between big five and locus of control can be found in Table B2 and Table B3.

Table 2: Mean comparisons for IZA ED and GSOEP

| | IZA ED | | GSOEP wave 2007 | | GSOEP newly unemployed | |
|---|---|---|---|---|---|---|
| | Male | Female | Male | Female | Male | Female |
| Gross hourly wage (€/$h$) | | | 17.77 | 14.24 | 13.52 | 10.36 |
| | | | (8.76) | (7.38) | (26.67) | (6.56) |
| Net hourly wage (€/$h$) | 8.87 | 7.73 | 11.55 | 9.11 | 7.99 | 6.53 |
| | (4.52) | (3.55) | (5.34) | (4.34) | (10.79) | (3.17) |
| Previous accu. experience (years) | 18.12 | 15.70 | 18.32 | 16.49 | 15.67 | 13.19 |
| | (9.93) | (9.65) | (8.91) | (8.74) | (10.00) | (8.69) |
| Age | 37.79 | 38.73 | 41.32 | 41.53 | 39.40 | 39.28 |
| | (8.61) | (8.68) | (8.19) | (8.35) | (9.20) | (9.41) |
| Birth cohorts | | | | | | |
| 1952-1962 | 0.38 | 0.35 | 0.23 | 0.23 | 0.34 | 0.34 |
| | (0.49) | (0.48) | (0.42) | (0.42) | (0.48) | (0.47) |
| 1963-1972 | 0.37 | 0.34 | 0.39 | 0.36 | 0.32 | 0.34 |
| | (0.48) | (0.47) | (0.49) | (0.48) | (0.47) | (0.48) |
| 1973-1982 | 0.25 | 0.31 | 0.38 | 0.41 | 0.34 | 0.32 |
| | (0.43) | (0.46) | (0.49) | (0.49) | (0.48) | (0.47) |
| Education levels | | | | | | |
| Lower secondary school | 0.38 | 0.22 | 0.29 | 0.21 | 0.42 | 0.24 |
| | (0.49) | (0.42) | (0.45) | (0.41) | (0.50) | (0.43) |
| (Adv.) middle sec. school | 0.40 | 0.43 | 0.36 | 0.45 | 0.43 | 0.52 |
| | (0.49) | (0.50) | (0.48) | (0.50) | (0.50) | (0.50) |
| Upper sec. school (A-level) | 0.22 | 0.34 | 0.36 | 0.35 | 0.15 | 0.24 |
| | (0.42) | (0.48) | (0.48) | (0.48) | (0.36) | (0.43) |
| Marriage status | 0.45 | 0.47 | 0.62 | 0.61 | 0.44 | 0.44 |
| | (0.50) | (0.50) | (0.49) | (0.49) | (0.50) | (0.50) |
| Dependent child (under age 18) | 0.34 | 0.36 | 0.45 | 0.45 | 0.40 | 0.50 |
| | (0.47) | (0.48) | (0.50) | (0.50) | (0.49) | (0.50) |
| Emotional Stability | 3.76 | 3.43 | 3.76 | 3.28 | 3.57 | 3.05 |
| | (1.07) | (1.11) | (1.06) | (1.10) | (1.07) | (1.14) |
| Openness to experience | 4.77 | 4.92 | 4.41 | 4.59 | 4.45 | 4.65 |
| | (1.04) | (1.05) | (1.01) | (1.10) | (1.04) | (1.11) |
| Conscientiousness | 5.68 | 5.84 | 5.54 | 5.65 | 5.55 | 5.50 |
| | (0.78) | (0.75) | (0.81) | (0.78) | (0.85) | (0.87) |
| Agreeableness | 5.17 | 5.52 | 4.85 | 5.16 | 4.90 | 5.08 |
| | (0.91) | (0.87) | (0.89) | (0.83) | (0.81) | (0.91) |
| Extraversion | 4.67 | 4.86 | 4.40 | 4.69 | 4.46 | 4.69 |
| | (1.01) | (0.98) | (1.05) | (1.04) | (1.13) | (1.10) |
| Obs. | 2,084 | 1,965 | 4,380 | 4,284 | 183 | 172 |

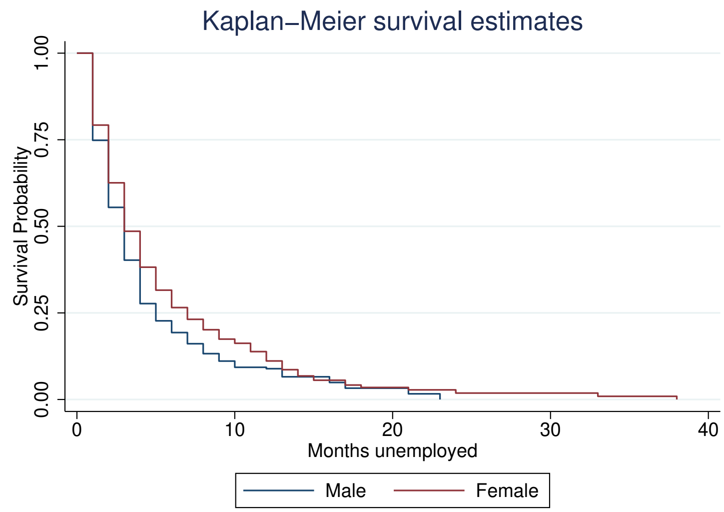
Source: IZA Evaluation Dataset (IZA ED) and German Socio-Economic Panel (GSOEP). We use a specific wave of GSOEP (Wave 24 in year 2007), which is close to the time when IZA ED was first conducted. We restricted both samples to persons in the labor force, age 25-55. "Big five" personality measures in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

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

| Outcome variable: | | Male | | | Female | |
|---|---|---|---|---|---|---|
| (log) hourly wage | (1) | (2) | (3) | (4) | (5) | (6) |
| Higher level sec. degree | 0.24*** | 0.23*** | 0.23*** | 0.23*** | 0.23*** | 0.23*** |
| (Baseline: sec. school or lower) | (0.03) | (0.03) | (0.03) | (0.03) | (0.03) | (0.03) |
| Emotional Stability | 0.01 | 0.02 | 0.02 | 0.027* | 0.02 | 0.02 |
| | (0.01) | (0.01) | (0.01) | (0.01) | (0.01) | (0.01) |
| Openness to experience | 0.01 | 0.01 | 0.01 | 0.02 | 0.02 | 0.02 |
| | (0.01) | (0.01) | (0.01) | (0.02) | (0.02) | (0.02) |
| Conscientiousness | 0.06*** | 0.05** | 0.05** | -0.07** | -0.07** | -0.07*** |
| | (0.02) | (0.02) | (0.02) | (0.02) | (0.02) | (0.02) |
| Agreeableness | -0.05*** | -0.05*** | -0.05*** | -0.01 | -0.01 | -0.01 |
| | (0.02) | (0.01) | (0.01) | (0.02) | (0.02) | (0.02) |
| Extraversion | -0.01 | -0.02 | -0.01 | -0.01 | -0.01 | -0.01 |
| | (0.01) | (0.01) | (0.01) | (0.02) | (0.02) | (0.02) |
| Cognitive Ability | | 0.06 | 0.06 | | 0.02 | 0.01 |
| | | (0.06) | (0.06) | | (0.06) | (0.06) |
| Marriage dummy | | 0.15*** | 0.14*** | | -0.10** | -0.10** |
| | | (0.03) | (0.03) | | (0.03) | (0.03) |
| Dependent child (any) | | 0.05 | 0.05 | | 0.04 | 0.05 |
| | | (0.03) | (0.03) | | (0.03) | (0.03) |
| Industry sector (Omitted: agriculture) | | | | | | |
| Manufacturing | | | 0.05 | | | -0.09 |
| | | | (0.07) | | | (0.07) |
| Services | | | -0.03 | | | -0.10 |
| | | | (0.07) | | | (0.07) |
| Number of Obs | 932 | 932 | 932 | 697 | 697 | 697 |
| $R^2$ | 0.07 | 0.12 | 0.13 | 0.12 | 0.13 | 0.14 |
| *Experience* | X | X | X | X | X | X |
| $Experience^2$ | X | X | X | X | X | X |
| Missing cognitive indicator | | X | X | | X | X |
| Missing industry indicator | | | X | | | X |

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

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




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

To summarize, we find significant gender differences in wage outcomes and labor market dynamics which are associated with observable characteristics. This descriptive evidence motives us to develop and estimate a job search and bargaining model that incorporates worker heterogeneity.

# 4 Estimation and identification

## 4.1 Measurement error in wages

In estimating the model, we will assume that observed wages are measured with error for three reasons. First, reporting errors are common in survey data. Second, individuals report one wage for each job spell and incorporating measurement error is one way to allow for some wage fluctuation within job spells. Third, measurement error is needed to explain why some job changes are not associated with wage increases. In both model specifications described in Section 3, job mobility is efficient in the sense of increasing the worker's productivity. In the model without wage renegotiation, all job-to-job moves should be associated with wage increases. In the model with wage renegotiation, wage declines can occur. We use a maximum likelihood estimator, so any wage decrease between jobs is a zero-probability event under the model without wage renegotation, which would lead to a degenerate likelihood. This is an important rationale for including measurement error in the model. In the data, the majority of job-to-job transitions are associated with wage increases, but some are not.[30]

The introduction of measurement error into nonlinear models is not without some cost, because it requires assuming a measurement error process. Adopting a standard classical measurement error assumption, we write observed wages $\tilde{w}$ as

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

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

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

where $\phi$ denotes the standard normal density, and where $\mu_\varepsilon$ and $\sigma_\varepsilon$ are the mean and standard deviation of $\ln \varepsilon$. We impose the restriction that $\mu_\varepsilon = -0.5\sigma_\varepsilon^2$, so that $E(\varepsilon|w) = 1$.[31] Therefore, the expectation of the observed wage is equal to the true wage, since

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

## 4.2 Constructing the individual likelihood contribution

We estimate the model parameters using maximum likelihood. In this subsection, we first discuss how we construct each individual likelihood $L_i, i = \{1, 2, .., N\}$ conditional on the individual-specific parameter values $\Omega_i$. In the next subsection, we will describe the mapping between individual characteristics $z_i$ and $\Omega_i$. To avoid notational clutter, we suppress the individual subscript $i$, but the reader should bear in mind that the underlying econometric model allows the search-environment parameters to vary across individuals.

As in Flinn (2002) and Dey and Flinn (2005), for example, the information used to construct the likelihood function is defined as an employment cycle. An employment cycle begins with an unemployment spell that is then followed by one or more jobs in the em-

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

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

ployment spell that follows. For computational simplicity, we limit attention to the first two jobs in the employment spell. Each individual contributes information on (at most) one employment spell to the likelihood function. In describing the individual likelihood contribution, it will be useful to distinguish between three types of individuals: (1) those with information only on the initial (incomplete) unemployment spell; (2) those with information on the (completed) unemployment spell and one job spell; and (3) those with information on the (completed) unemployment spell and with information on the first two job spells in the subsequent employment spell. The data used to define the likelihood contribution of an individual can be represented as

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

For the unemployment state, $t_U$ is the length of the unemployment spell and $r_U$ is an indicator variable that takes the value 1 if the unemployment spell is right-censored. In the following employment spell, which consists of up to 2 jobs, for each job spell $k \in 1, 2$, $t_k$ is the length of job $k$ in the employment spell, $\tilde{w}_k$ is the observed wage in job $k$, and $r_k = 1$ indicates that the duration of job $k$ is right-censored. As described in data section, every individual observation in our sample begins with an unemployment spell. Therefore, we avoid the common difficulty of having to take into account incomplete spells at the beginning of a sample period, otherwise known as the left-censoring problem.[32] In addition, we focus on up to the first two job spells in the following employment spell. This is done to ease the computational burden. Then, the individual likelihood function covers the following cases:

1. One right-censored unemployment spell ($r_U = 1$)
2. One completed unemployment spell ($r_U = 0$)
   (a) + first right-censored job spell ($r_1 = 1$)
   (b) + first completed job spell ending with unemployment ($r_1 = 0, q_1 = 0$)
3. One completed unemployment spell + first completed job spell ($r_1 = 0, q_1 = 1$)
   (a) + second right-censored job spell ($r_2 = 1$)
   (b) + second completed job spell ending with unemployment ($r_2 = 0, q_2 = 0$)

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

(c) + second completed job spell ending with third job ($r_2 = 0, q_2 = 1$)

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

(13)

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

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

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

where $\tilde{G} \equiv 1 - G$ is the complement of the cumulative distribution function, often referred to as the survivor function.

For the specification that does not allow for wage renegotiation, the likelihood contribution of an individual is

(14)

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

where $w\left(\theta; N\right)$ and $\theta_N^*$ are determined by equation (11) and (10). We compute the likelihood function by Monte Carlo integration using importance sampling.[33]

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

[33] We generate 2500 repetitions of the $(\theta_1, \theta_2)$ draws (50 draws of $\theta_1$ and 50 draws of $\theta_2$) for use in the importance sampling algorithm.

likelihood function $\ln L$ defined for the entire sample of size $N$ is

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

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

## 4.3 Identification

We begin by considering identification in the simpler case of a bargaining model with on-the-job search when the population is homogeneous, that is, all individuals share the same labor market parameters. We then extend this analysis to the situation in which (potentially) each individual has their own labor market parameters. We will mainly consider the case relevant for the data we analyze, which is one in which a short labor market history is available for each individual (large $N$, relatively small observation period).

### 4.3.1 Identification of parameters in a homogeneous search model

For the homogeneous case without on-the-job search and with the bargaining power parameter, $\alpha$, constrained to be equal to 1 (i.e., where the worker receives the full surplus of the match), model parameter identification was considered in Flinn and Heckman (1982).[34] For the case without measurement error in wages, Flinn and Heckman (1982) demonstrate that the accepted wage offer distribution is nonparametrically identified; however, in the absence of information on rejected wage offers, a parametric assumption is required to identify the full wage offer distribution. [35] Flinn and Heckman (1982) show that most parametric distributions can be identified even with systematically missing data on job offers.[36]

For the case without measurement error, they show that the minimum observed accepted wage, $\hat{w}_{(1)}$, is a superconsistent estimator of the reservation wage, that is $plim_{N\to\infty}\hat{w}_{(1)} = \rho V_U \equiv w^*$, with the rate of convergence being $N$ instead of $\sqrt{N}$. Given this estimator, they demonstrate that maximization of the concentrated log likelihood function yields $\sqrt{N}$

[34]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.

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

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

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 $b$.

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

Adding on-the-job search to the above framework only adds one additional parameter, $\lambda_E$, 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 $h_E(w) = \lambda_E \tilde{G}(w)$. 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 $h_E(w)/(h_E(w) + \eta)$. Because we observe a number of first job spells (after unemployment) that 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 (i.e., wage) currently occupied.

### 4.3.2 Identification of the bargaining power parameter $\alpha$

We now extend our argument to consider the estimation of the bargaining power parameter $\alpha$ under the Nash bargaining protocol, otherwise interpreted as the surplus division parameter in the no-renegotiation case. The wage distribution is not considered to be exogenous, although the productivity distribution $G(\theta)$ is. The bargaining parameter is difficult to identify given that we only observe the portion of the surplus received by workers in the form of wages, and not the profits earned by the firm. A given wage distribution may be consistent with a “small” surplus that is mainly captured by the worker (high $\alpha$) or a “large” surplus, with the worker obtaining a small share (low $\alpha$). As noted in Flinn (2006), with no OTJ search, the mapping from the worker’s productivity at the firm, $\theta$, to the wage, is linear and is given by

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

where $\theta^*$ is the reservation match value, which depends on the assumed bargaining protocol.[37] Because $\theta^*$ is a constant, the function $w(\theta)$ is linear, and the wage distribution is given by $F(w) = G(\frac{w-(1-\alpha)\theta^*}{\alpha})$. If $G$ is a location-scale distribution, so that $G(\theta) = G_0(\frac{\theta-c}{d})$, with $G_0$ a known function, $c$ the location parameter, and $d$ the scale parameter, the parameter $\alpha$ is not identified.[38] 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.

An alternative approach to imposing the restriction of the distribution of $\theta$ would be to use information on reported reservation wages $w^*$ in estimation. When both $w$ and $w^*$(which is $\theta^*$ given $a = 1$) are observed, $\alpha$ can be inferred from how wages vary in response to reservation wage variation. However, there are some empirical challenges to incorporating reservation wages directly in estimation. One is that previous studies found that some job seekers have biased beliefs about their employment prospects due to overconfidence ( Spinnewijn (2015)). Another is that individuals are often observed to accept jobs with wages below their reservation wage. In our estimation sample, 231 out of 490 workers report reservation wages that are higher than their actual wage rates in their first job out of unemployment. [39] Due to these empirical challenges, we estimated the model both with and without including reservation wage data in the likelihood function. The results were quite robust across the two models, so we report the model without using reservation wage data as our baseline specification and report the alternative model incorporating reservation wages as a robustness check in Appendix B.2.5.

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

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

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

where

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

Even if $\theta^*$ 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.

[39] We only have 490 workers have information about their reservation wage and first job wage.

#### 4.3.3 Introducing observed heterogeneity

If we had access to an indefinitely long labor market history for each individual $i$, we could estimate the identified model parameters separately for each $i$. In our case, we have access to only a short panel of observations for each of a large number of individuals, so allowing for heterogeneity requires positing restrictions on how parameters vary across individuals. In particular, we assume that each individual is characterized by the gender-specific index function

$$z_i \gamma_j^g,$$

where $j$ is specific to a given model parameter, g is the gender of worker $i$. The least restrictive version of the model we take to the data characterizes an individual $i$ in terms of the full vector of characteristics $z_i$ and specifies a gender-specific mapping between the characteristics $z_i$ and the job search model parameter values. The rate of arrival of job offers in the unemployment and employment states are given by

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

and the rate of exogenous job dissolution is

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

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.[40] In this case

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

[40] 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 $\mu = -0.5\sigma^2$. Because the variance of the lognormal is $Var(\theta) = [\exp(\sigma^2) - 1]\exp(2\mu + \sigma^2)$, upon substitution we have that

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

and

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

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

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

and we parameterize the standard deviation of the match distribution to be gender specific

$$\sigma_\theta(i) = \begin{cases} \sigma_\theta^m(i) & g_i = m \\ \sigma_\theta^f(i) & g_i = f, \end{cases} \tag{17}$$

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

Because the Nash bargaining weight $\alpha \in (0,1)$, we assume

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

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 $\gamma_j^g$ vectors due to the nonlinearity of the likelihood function in terms of the various components.[41] 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 $\gamma_a^g$ for individual $i$ is given by

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

As mentioned above, it is typically difficult to obtain precise estimates of $\alpha$ in a homogeneous

[41] In practise, $\gamma_j^m$ and $\gamma_j^f$ are separately estimated from male subsample and female subsample.

stationary search setting. In this case, the partial of $\ln L_i$ with respect to $\gamma_\alpha^g$ is

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

In terms of the first order conditions associated with $\gamma_a$ and $\gamma_\alpha$, we have

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

and

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

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

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

# 5 Model estimates

## 5.1 Comparing the two model specifications with alternative bargaining assumptions

As previously noted, we estimate multiple job search model specifications allowing for different assumptions on how firms bargain with workers to set wages. In the first model, when a worker receives a wage offer from an outside firm, the current firm can increase the wage to retain the worker. In the second model, firms do not match outside offers and the only way a worker can increase the wage is by switching jobs. In this section, we compare estimates obtained from both the renegotiation and the no-renegotiation specifications, both of which incorporate individual heterogeneity.

The results are presented in Table 4, which reports the mean parameter values across individuals by gender. Comparing the two sets of estimates, there are substantial differences in the estimated job arrival rates $\lambda_U$ and $\lambda_E$ and in the bargaining parameter $\alpha$. Specifically, when allowing for renegotiation, the arrival rate of job offers to unemployed workers is 1.30 for men and is 1.26 for women, and the arrival rate for employed men and women is 0.06 and 0.10, respectively. 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 0.18 for men and 0.15 for women in the model with renegotiation, which are much lower than the estimated $\alpha$ for the model without renegotiation (0.48 for men and 0.37 for women).

The low estimated value of the surplus division parameter $\alpha$ in the model that allows for renegotiation is a common finding in the literature (Cahuc et al. (2006); Bartolucci (2013); Flinn and Mullins (2015)). Under the renegotiable contract framework, the worker's share of surplus is determined by both the surplus division parameter $\alpha$ 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 that the worker obtains can increase over the job spell as the firm competes with other potential employers for the employee's services.

Lastly, our estimates indicate lower estimates of ability parameters in the specification with renegotiation than for the specification without renegotiation. The parameter values are $a$ are 8.25 for men and 6.50 for women in the former case and 12.07 and 11.17 in the latter case. This is to be expected. In the renegotiation case, the workers' outside option is the full surplus of first job when bargaining for the initial wage at the second job. This outside option is larger than the value of unemployment, which is 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 assumption.

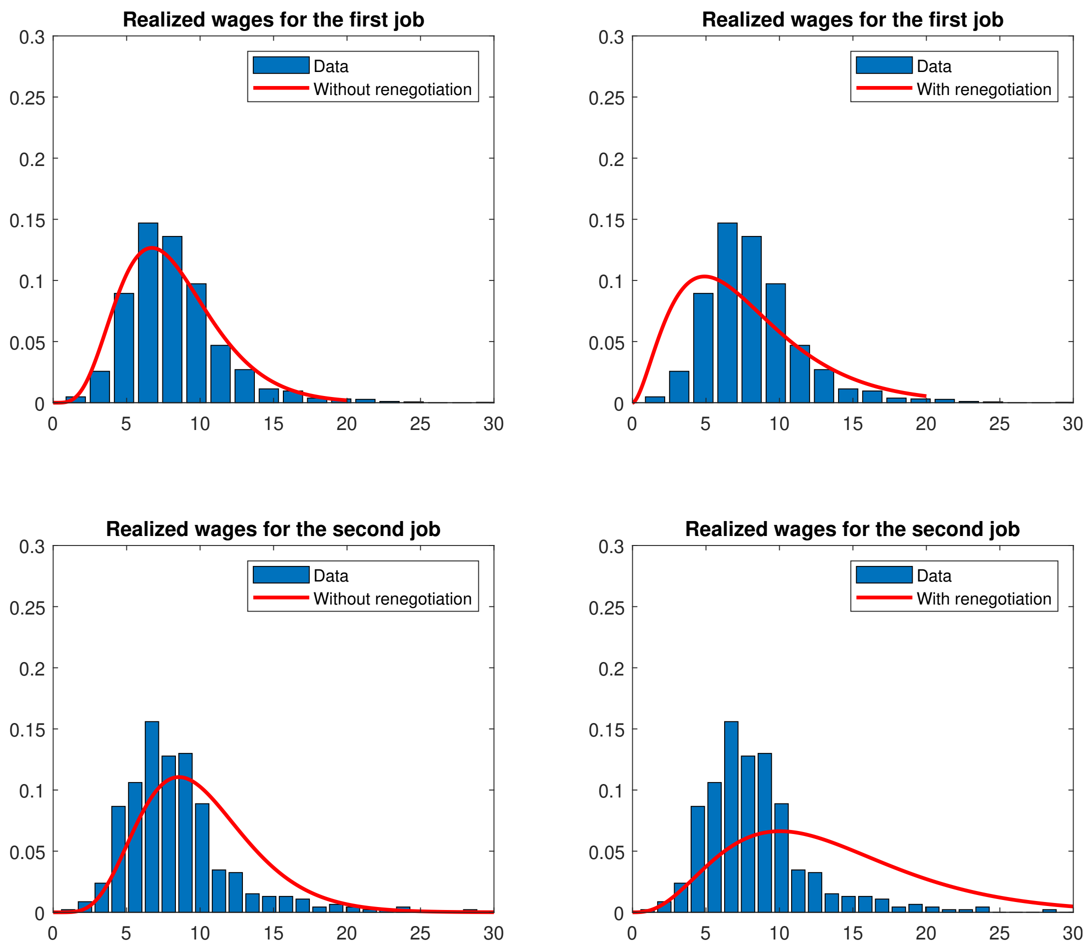
We next compare the goodness-of-fit of the no-renegotiation and the renegotiation specifications. The specifications are non-nested, so we apply the likelihood ratio test of Vuong (1989), which (strongly) selects the no-renegotiation model as providing a better fit to the data. Further examination reveals that the better fit arises mainly with regard to the wage distribution rather than the unemployment/employment spell distributions. Because both specifications imply efficient job-to-job mobility decisions, both model specifications repli-

Table 4: Parameter estimates under alternative bargaining assumptions

| Parameter | Description | With renegotiation | | Without renegotiation | |
|---|---|---|---|---|---|
| | | Male | Female | Male | Female |
| $a$ | time-invariant ability | 8.25 | 6.50 | 12.07 | 11.17 |
| | | (1.21) | (0.75) | (1.08) | (1.19) |
| $\lambda_u$ | offer arrival rate, in unemployment | 1.30 | 1.26 | 0.26 | 0.21 |
| | | (0.21) | (0.55) | (0.03) | (0.05) |
| $\lambda_e$ | offer arrival rate, in employment | 0.06 | 0.10 | 0.04 | 0.07 |
| | | (0.01) | (0.03) | (0.01) | (0.02) |
| $\eta$ | separation rate | 0.03 | 0.03 | 0.03 | 0.03 |
| | | (0.00) | (0.01) | (0.01) | (0.01) |
| $\alpha$ | surplus division | 0.18 | 0.15 | 0.48 | 0.37 |
| | | (0.05) | (0.06) | (0.05) | (0.05) |
| $b$ | flow utility when unemployed | 0.97 | 1.09 | -1.19 | -0.39 |
| | | (0.12) | (0.06) | (0.17) | (0.10) |
| $\sigma_\theta$ | $\theta \sim \log N\left(-\frac{\sigma_\theta^2}{2}, \sigma_\theta\right)$ | 0.41 | 0.41 | 0.32 | 0.35 |
| | | (0.01) | (0.01) | (0.02) | (0.02) |
| $\sigma_\epsilon$ | $\epsilon \sim \log N\left(-\frac{\sigma_\epsilon^2}{2}, \sigma_\epsilon\right)$ | 0.44 | 0.44 | 0.30 | 0.32 |
| | | (0.03) | (0.03) | (0.03) | (0.04) |
| $N$ | | 4,049 | | 4,049 | |
| $\log L$ | | -38,872 | | -36,298 | |
| Vuong test (p-value) | | | | 2.17e-60 | |

Data: IZA Evaluation Dataset. The parameter set $\{a, \lambda_U, \lambda_E, \eta, \alpha\}$ is heterogeneous and depends on individuals' characteristics vector. The table reports the mean values and the standard deviation across individuals in parentheses.

Figure 4: Observed and simulated wage distributions



cate the distributions of unemployment/employment spells reasonably well.[42] Figure 4 shows how both model specifications fit the wage data on the first and second jobs. The top and bottom left panels show the fit of the model without renegotiation for the first and second jobs. The top and bottom right panels show the fit of the model with renegotiation to the same data. The model without renegotiation fits better, particularly with regard to the first job wage distribution.

Simulations based on the model with renegotiation predict lower initial wages compared with the data. The wage growth from first job to second job (€7.19/$h$ to €12.45/$h$) predicted from the renegotiation model is much larger the wage growth observed in the data (€8.27/$h$ to €8.49/$h$). The wage growth predicted from the no-renegotiation model (€8.14/$h$ to €10.04/$h$) is closer to the data. This result is consistent with similar findings concerning these two types of specifications reported in Flinn and Mullins (2015).[43] Given that the model without renegotiation provides a substantially better fit, the remainder of our quantitative analysis will be based on that specification.

## 5.2 Estimated model parameters under alternative heterogeneity specifications

Many previous papers have estimated search models that allow parameters to differ by gender (e.g. Bowlus (1997), Bowlus and Grogan (2008), Flabbi (2010a), Liu (2016), Morchio and Moser (2020), Amano-Patino et al. (2020)). In this section, we estimate three different models that incorporate varying degrees of parameter heterogeneity. The estimates are reported in Table 5. In specification (1), all parameters are assumed to be the same 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 (also by gender) as a function of a vector of characteristics (e.g. education, personality traits, age cohort).

The results for specification 2 in Table 5 indicate that men and women have different labor market parameters. The estimated unemployment job arrival rate ($\lambda_U$) is lower for women, which implies a lower job finding rate and longer unemployment spells. On the other hand, the on-the-job arrival rate $\lambda_E$ is higher for women. Estimated job separation rates $\eta$ are similar for men and women.

Under the structure of our model, any persistent productivity gap by gender is captured

[42] See B.2.1 for a detailed comparison on distributions of unemployment spells/job spells.

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

by the ability parameter $a$.[44] Our results show that average female productivity is 11.17 in comparison to 12.07 for men. The 8 percent gap is smaller than the gap found in other studies (using other datasets). For example, Bowlus (1997) finds the productivity of females is 17 percent lower using NLSY79 data. Flabbi (2010a) finds a 21 percent differential in average productivity using CPS data.[45]

With regard to the surplus division parameter $\alpha$, we find the value is 0.48 for men and 0.37 for women. The estimated values are fairly consistent with papers in the search literature using similar modeling frameworks. For example, Bartolucci (2013) uses German matched employer-employee data and finds female workers have, on average, slightly lower bargaining power than their male counterparts, with an average $\alpha$ of 0.42 across genders. Flinn and Mabli (2009) use US employee-level data and find the overall bargaining power in the sample is approximately 0.45.

The two bottom lines of Table 5 report $p$-values for likelihood ratio (LR) tests where we test specification (2) against specification (1) and also test specification (3) against specification (2). The heterogeneous model nests the two homogeneous specifications. The tests reject the restrictive model specifications in favor of the model that allows for rich parameter heterogeneity (3).

### 5.3 Understanding the role of personality traits and other individual characteristics in a job search model

We next examine how education and personality traits affect job search parameters $\{\lambda_U, \lambda_E, \eta, \alpha, a\}$. In Table 6, we present the estimates for the heterogeneous model and explores the channels through which education, birth cohort and personality traits influence wage and employment outcomes. For men and women, education increases the unemployment job offer arrival rate ($\lambda_U$). Education decreases the on-the-job offer arrival rate ($\lambda_E$) for women. It lowers the job separation rate ($\eta$) for both men and women, with a much larger effect for women. As would be expected, education increases productivity ($a$) for both genders. With regard to the bargaining power parameter ($\alpha$), education increases the bargaining parameter for men but lowers it for women.

As seen in Table 6, four of the five personality traits are statistically significant determinants of job search parameters. For women, emotional stability increases job offer arrival rates, lowers the job separation rate, and enhances productivity. For men, emotional sta-

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

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

Table 5: Parameter estimates under alternative heterogeneity specifications

| Parameter | Description | (1) homogeneous | (2) homogeneous within gender | | (3) heterogeneous | |
|---|---|---|---|---|---|---|
| | | Combined | Male | Female | Male | Female |
| $a$ | time-invariant ability | 10.80 | 12.64 | 10.61 | 12.07 | 11.17 |
| | | (1.18) | (2.71) | (2.07) | (1.08) | (1.19) |
| $\lambda_U$ | offer arrival rate, in unemployment | 0.23 | 0.25 | 0.20 | 0.26 | 0.21 |
| | | (0.01) | (0.01) | (0.01) | (0.03) | (0.05) |
| $\lambda_E$ | offer arrival rate, in employment | 0.05 | 0.04 | 0.07 | 0.04 | 0.07 |
| | | (0.00) | (0.00) | (0.00) | (0.01) | (0.02) |
| $\eta$ | separation rate | 0.03 | 0.03 | 0.03 | 0.03 | 0.03 |
| | | 0.00 | (0.00) | (0.00) | (0.01) | (0.01) |
| $\alpha$ | surplus division | 0.46 | 0.43 | 0.42 | 0.48 | 0.37 |
| | | (0.11) | (0.15) | (0.16) | (0.05) | (0.05) |
| $b$ | flow utility when unemployed | -0.32 | -0.91 | -0.45 | -1.19 | -0.39 |
| | | (0.04) | (0.36) | (0.21) | (0.17) | (0.10) |
| $\sigma_\theta$ | $\theta \sim \log N\left(-\frac{\sigma_\theta^2}{2}, \sigma_\theta\right)$ | 0.34 | 0.32 | 0.32 | 0.32 | 0.35 |
| | | (0.03) | (0.03) | (0.03) | (0.02) | (0.02) |
| $\sigma_\epsilon$ | $\epsilon \sim \log N\left(-\frac{\sigma_\epsilon^2}{2}, \sigma_\epsilon\right)$ | 0.34 | 0.32 | 0.32 | 0.30 | 0.32 |
| | | (0.07) | (0.05) | (0.06) | (0.03) | (0.04) |
| $N$ | | 4,049 | 4,049 | | 4,049 | |
| $\log L$ | | -36,597 | -36,492 | | -36,298 | |
| LR tests | | | (1)&(2) | | (2)&(3) | |
| P-value | | | 0.00 | | 0.00 | |

NOTES: The likelihood ratio (LR) test tests the current specification against the previous specification (e.g. (2) against (1)). The monthly discount rate is set at 0.005.
In the heterogeneous specification, the parameters $\{a, \lambda_U, \lambda_E, \eta, \alpha\}$ depend on indices of individual characteristics. Column (3) reports the mean values and standard deviation of the parameters in parentheses.

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

Two traits - conscientiousness and agreeableness - affect men and women in different ways. Conscientiousness increases the unemployment job offer rate and lowers the job separation rate for both men and women. It also increases the employed job offer arrival rate for women. In terms of productivity, however, conscientiousness augments productivity for men but lowers it for women. Agreeableness lowers the unemployment job offer arrival rate. It enhances productivity for women but lowers productivity for men. Lastly, agreeableness has a large negative effect on the bargaining parameter for women. Extraversion generally increases job offer arrival rates and job separation rates for both men and women, with no significant effect on productivity or bargaining.

The job search model we estimate is stationary and we therefore do not condition on initial time-varying state space elements (such as labor market experience). However, we include birth cohort indicator variables to capture possible differences in the labor markets for older and younger workers. As seen in the bottom rows of Table 6, older workers experience lower job offer arrival rates, with the age penalty being larger for women. Workers who are age 35-44 (birth cohort 63-72 in 2007) have the lowest job destruction rate relative to younger or older workers. Age does not have a statistically significant effect on productivity or bargaining.

# 6 Interpreting model estimates

In this section, we use the estimated model to perform various model simulations that are aimed at understanding the effect of personality traits on labor market dynamics in general and the contribution of particular traits and particular model channels in explaining gender gaps.

## 6.1 Effects of personality traits on labor market outcomes

First, we use the estimated model to simulate outcomes for 500 months to obtain steady state values. Table 7 reports means and quantiles of the simulated labor market outcomes. It is reassuring that the reservation wages obtained from the estimated model (8.24 for men and 7.75 for women) are fairly close to reported reservation wage values in the data (8.26 for men and 7.26 for women), even though we did not use the reservation wage data in this estimation. The simulated average accepted wages are higher than the average wages in the

Table 6: Estimated index coefficients by gender in the heterogeneous specification

| | $\log\lambda_U$ | | $\log\lambda_E$ | | $\log\eta$ | | $\log a$ | | $\log\left(\frac{\alpha}{1-\alpha}\right)$ | |
|---|---|---|---|---|---|---|---|---|---|---|
| | Male | Female | Male | Female | Male | Female | Male | Female | Male | Female |
| *Cons.* | -1.55 | -1.82 | -3.32 | -3.52 | -3.08 | -3.20 | 2.27 | 2.19 | 0.62 | 0.94 |
| | (0.11) | (0.09) | (0.23) | (0.12) | (0.21) | (0.13) | (0.10) | (0.10) | (0.38) | (0.26) |
| *Edu* | 0.06 | 0.34 | 0.02 | -0.39 | -0.04 | -0.42 | 0.14 | 0.16 | 0.10 | -0.20 |
| | (0.04) | (0.04) | (0.07) | (0.07) | (0.06) | (0.07) | (0.04) | (0.08) | (0.21) | (0.24) |
| *Stb* | -0.01 | 0.03 | 0.13 | 0.08 | -0.12 | -0.07 | 0.03 | 0.03 | -0.12 | -0.05 |
| | (0.01) | (0.01) | (0.03) | (0.02) | (0.02) | (0.02) | (0.02) | (0.01) | (0.09) | (0.04) |
| *Opn* | 0.01 | 0.02 | 0.02 | 0.02 | -0.03 | 0.00 | 0.01 | 0.02 | 0.05 | 0.01 |
| | (0.02) | (0.01) | (0.03) | (0.02) | (0.03) | (0.03) | (0.02) | (0.01) | (0.10) | (0.03) |
| *Cos* | 0.05 | 0.02 | -0.02 | 0.07 | -0.07 | -0.02 | 0.04 | -0.04 | 0.03 | -0.02 |
| | (0.02) | (0.02) | (0.04) | (0.02) | (0.03) | (0.03) | (0.02) | (0.02) | (0.09) | (0.04) |
| *Agr* | -0.06 | -0.05 | -0.04 | 0.00 | -0.02 | -0.02 | -0.04 | 0.05 | -0.06 | -0.17 |
| | (0.01) | (0.01) | (0.03) | (0.02) | (0.03) | (0.03) | (0.02) | (0.01) | (0.10) | (0.04) |
| *Ext* | 0.05 | 0.05 | -0.02 | 0.05 | 0.12 | 0.04 | -0.01 | 0.00 | -0.07 | -0.06 |
| | (0.02) | (0.01) | (0.03) | (0.03) | (0.03) | (0.03) | (0.02) | (0.02) | (0.10) | (0.04) |
| Cohort (Omitted cat: 73-82) | | | | | | | | | | |
| 63-72 | -0.05 | -0.16 | -0.05 | -0.05 | -0.13 | -0.28 | 0.04 | 0.02 | -0.08 | -0.03 |
| | (0.04) | (0.04) | (0.06) | (0.06) | (0.06) | (0.07) | (0.04) | (0.03) | (0.18) | (0.08) |
| 52-62 | -0.10 | -0.16 | -0.07 | -0.06 | 0.12 | 0.11 | -0.01 | -0.02 | -0.07 | 0.05 |
| | (0.04) | (0.04) | (0.08) | (0.06) | (0.06) | (0.07) | (0.05) | (0.04) | (0.20) | (0.14) |

NOTE: Asymptotic standard errors in parentheses.

data, which is expected given that for the wages reported in the data are from the first and second jobs following an unemployment spell and do not correspond to average steady state values.

As seen in Table 7, men have advantages relative to women in multiple dimensions. Their average wages are higher, their average wage growth is higher and their average unemployment spells are shorter. An inspection of the quantiles shows that gender gaps tend to be larger at lower quantiles. For example, a female worker at the 25% quantile spends 1.5 months more time to search for a job compared with the 25% quantile male, whereas a female worker at the 75% quantile spends 0.6 months more than the comparable male. The gender gap in job spell length is also larger for female workers in the lower end of the distribution.

We now use the estimated model to explore the effects of a ceteris paribus change in each of the personality traits on the same labor market outcomes. We increase each trait by one standard deviation (across the whole sample) and report in Table 8 the implied changes in the outcomes. Emotional stability generally has a positive effect on labor market outcomes for men, increasing reservation wages and average wages. It also substantially increases wage growth, due to longer employment spells and more job to job transitions. For women, emotional stability also increases reservation wages and average wages. However, there is no effect on wage growth and the percentage increase in the average employment spell length is smaller than for men.

Increasing the conscientiousness trait affects men and women in remarkably different ways. For men, conscientiousness increases reservation wages, increases average wages, increases wage growth, decreases unemployment spells and promotes job and employment stability. For women, conscientiousness lowers reservation wages, lowers average wages and decreases the job spell length. As further discussed below, the dramatic gender differences in the labor market valuation of the conscientiousness trait make this trait one of the most important in explaining gender wage gaps.

Agreeableness is another trait where the estimates reveal substantial gender differences. For men, a ceteris paribus increase in the agreeableness trait lowers reservation wages and average wages and substantially increases the length of unemployment spells as well as job spells. For women, agreeableness also substantially increases the length of unemployment spells, but it has no effect on average wages and it has the effect of substantially inhibiting wage growth.

Table 7: Steady state labor market outcomes

| Statistics | Mean | 25% quantile | Median | 75% quantile |
|---|---|---|---|---|
| *Accepted wages* | | | | |
| Women | 8.39 | 6.78 | 8.08 | 9.70 |
| Men | 9.67 | 7.78 | 9.25 | 11.14 |
| Ratio | 0.87 | 0.87 | 0.87 | 0.87 |
| *Reservation wages when unemployed* | | | | |
| Women | 7.75 | 7.00 | 7.57 | 8.48 |
| Men | 8.24 | 7.46 | 8.12 | 8.92 |
| Ratio | 0.94 | 0.94 | 0.93 | 0.95 |
| *Job to job wage growth rate* | | | | |
| Women | 0.34 | 0.12 | 0.26 | 0.48 |
| Men | 0.35 | 0.13 | 0.28 | 0.50 |
| Ratio | 0.96 | 0.93 | 0.93 | 0.95 |
| *Length of unemployment spell (unit: months)* | | | | |
| Women | 5.12 | 6.24 | 4.88 | 3.81 |
| Men | 4.06 | 4.77 | 3.90 | 3.22 |
| Ratio | 1.26 | 1.31 | 1.25 | 1.18 |
| *Length of job spell (unit: months)* | | | | |
| Women | 17.98 | 13.68 | 16.52 | 20.82 |
| Men | 22.06 | 18.02 | 20.95 | 24.82 |
| Ratio | 0.82 | 0.76 | 0.79 | 0.84 |
| *Length of employment spell (unit: months)* | | | | |
| Women | 44.36 | 30.77 | 39.36 | 51.92 |
| Men | 43.19 | 32.31 | 39.73 | 49.78 |
| Ratio | 1.03 | 0.95 | 0.99 | 1.04 |

Table 8: Effects of a one SD change in each personality trait on labor market outcomes

| | Average wages | Reservation wages | Wage growth rate | Unemployment spells (months) | Job spell (months) | Employment spells (months) |
|---|---|---|---|---|---|---|
| *Effects on male workers* | | | | | | |
| Baseline | 9.66 | 8.24 | 0.35 | 4.03 | 22.02 | 43.10 |
| Emotional stability (+1 SD) | 2.74% | 7.66% | -1.43% | 2.53% | -2.47% | 10.37% |
| Openness (+1 SD) | 2.08% | 2.91% | 4.82% | 0.88% | 0.53% | 2.82% |
| Conscientiousness (+1 SD) | 4.67% | 4.70% | 1.73% | -3.09% | 3.18% | 4.66% |
| Agreeableness (+1 SD) | -4.53% | -4.58% | -0.08% | 7.15% | 3.27% | 2.27% |
| Extraversion (+1 SD) | -2.98% | -4.58% | -0.36% | -4.88% | -6.39% | -12.25% |
| *Effects on female workers* | | | | | | |
| Baseline | 8.39 | 7.75 | 0.33 | 5.09 | 17.86 | 44.89 |
| Emotional stability (+1 SD) | 2.22% | 5.10% | -0.15% | -3.05% | -1.95% | 4.59% |
| Openness (+1 SD) | 2.40% | 2.74% | 0.20% | -0.87% | -1.12% | -1.71% |
| Conscientiousness (+1 SD) | -3.22% | -2.11% | 1.66% | -1.27% | -2.23% | -0.68% |
| Agreeableness (+1 SD) | -0.73% | -0.15% | -3.56% | 6.02% | 1.64% | 1.97% |
| Extraversion (+1 SD) | -1.64% | -1.37% | -1.25% | -4.95% | -3.87% | -5.33% |

Note: The first row for each gender shows labor market outcomes in steady-state under baseline model. Rows (2)-(6) display the deviation from baseline outcomes from a one standard deviation unit increase in each personality traits.

Lastly, extroversion has negative effects on reservation wages and average wages, especially for men. It decreases the length of unemployment spells but also decreases job and employment stability.

## 6.2 Wage gap decomposition

We examine which channels of the model contribute most to the gender wage gap in Table 9. To generate the table, we simulate outcomes under the heterogeneous specification (specification (3) in Table 5) where we set a subset of the coefficients for women equal to those estimated for men. In particular, 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 division parameter $(\alpha)$, and productivity parameters $(a, \sigma_\theta)$ as men. We also perform a simulation in which we give women all of the estimated parameter values for men. In all of these simulations, women retain their characteristics (e.g. education, personality traits, birth cohort), but we change the way the 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 eliminates the gap in offered and accepted wages. Looking at the rows "All parameters, Education" and "All parameters, Personality," we see that giving women the male coefficients associated with education has almost no effect on the wage gap relative to the baseline. The main area in which women are being rewarded less is for their personality traits. Giving females the estimated male coefficients associated with personality traits completely eliminates the wage gaps.

The bottom three panels of the Table 9 examine which of the model components contributes most to explaining wage gaps. With regard to productivity $(a, \sigma)$, as seen in Table 6, the overall net effect of gender differences in education coefficients or in personality coefficients in explaining the wage gap is minor. Overall, gender differences in the estimated productivity parameters are not an important channel.

On the other hand, gender differences in the surplus division parameter $(\alpha)$ 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 largely eliminated. Women with higher education are also at a disadvantage with respect to men in terms of bargaining power.

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 close the wage gap. However, this channel is not nearly empirically as important as is the surplus division channel. These decompositions show that the area in which women appear to be at the biggest disadvantage is in terms of bargaining. Most of the gender difference in bargaining is attributed to gender-specific returns to their personality traits, in particular, the agreeableness trait.

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

In the column headed by $\alpha'$, we give women the bargaining penalty that men get for being agreeable. Their average bargaining power increases from 0.37 to 0.52, accounting for the entire gender gap in terms of bargaining power (0.48 (men) vs. 0.37 (women)). We conclude that the agreeableness trait largely explains the gender gap in bargaining power.[46] There is some discussion of the negative impact of agreeableness on negotiating economic outcomes in the psychology literature (e.g. Barry and Friedman (1998)); however, that literature does not discuss that the the labor market valuation of agreeableness differs for men and women.

To summarize, we present Figure 5, which shows the offered wage and accepted wage distributions for both the baseline and the counterfactual "equal pay experiment" in which women are paid according to the male labor market parameters. In the baseline model (upper

[46] A further decomposition to understand which personality trait matters for which channel can be found in the Online Appendix, Table B4.

Table 9: How the gender wage gap changes when women's coefficients are set equal to those of men

| Women/Men Ratio Generated by | Offered wage | Accepted wage |
|---|---|---|
| Baseline | 0.86 | 0.86 |
| All parameters | | |
| -Constant | 0.88 | 0.87 |
| -Personality | 1.10 | 1.08 |
| -Education | 0.85 | 0.86 |
| -Total | 1.00 | 0.99 |
| Productivity $(a, \sigma)$ | | |
| -Constant | 0.95 | 0.95 |
| -Personality | 0.85 | 0.85 |
| -Education | 0.85 | 0.86 |
| -Total | 0.93 | 0.93 |
| Surplus division $(\alpha)$ | | |
| -Constant | 0.79 | 0.79 |
| -Personality | 1.03 | 1.05 |
| -Education | 0.89 | 0.90 |
| -Total | 0.99 | 1.00 |
| Transitions $(\lambda_U, \lambda_E, \eta)$ | | |
| -Constant | 0.88 | 0.88 |
| -Personality | 0.91 | 0.89 |
| -Education | 0.84 | 0.84 |
| -Total | 0.87 | 0.85 |

Notes: We calculate the counterfactual women/men wage ratio setting the female parameters associated with a subset of the coefficients equal to the male estimated parameters.

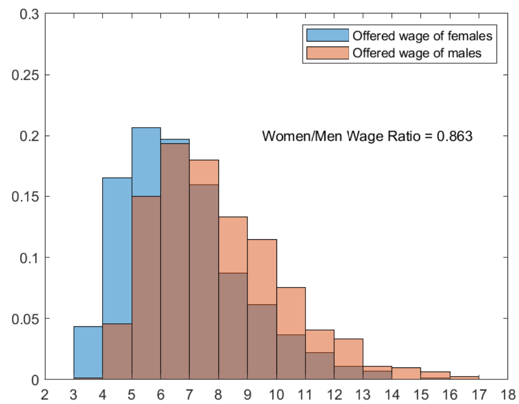
Table 10: How agreeableness affects surplus parameters $\alpha$ by gender

| Agreeableness | Male | | Female | | |
|---|---|---|---|---|---|
| | $\alpha$ | Proportion | $\alpha$ | $\alpha'$ | Proportion |
| (0,3] | 0.47 | 0.04 | 0.41 | 0.54 | 0.06 |
| [3,4) | 0.48 | 0.18 | 0.38 | 0.53 | 0.14 |
| [4,5) | 0.48 | 0.32 | 0.37 | 0.52 | 0.27 |
| [5,6) | 0.49 | 0.29 | 0.37 | 0.51 | 0.31 |
| [6,7) | 0.49 | 0.15 | 0.36 | 0.51 | 0.18 |
| Average | 0.48 | 1.00 | 0.37 | 0.52 | 1.00 |

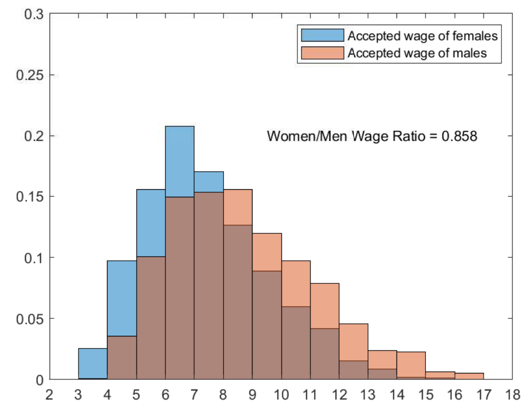
NOTE: The column named "$\alpha'$" reports the simulated bargaining weights after giving women men's penalty for being agreeable in the bargaining index.

Figure 5: Distributions of accepted wages and offered wages

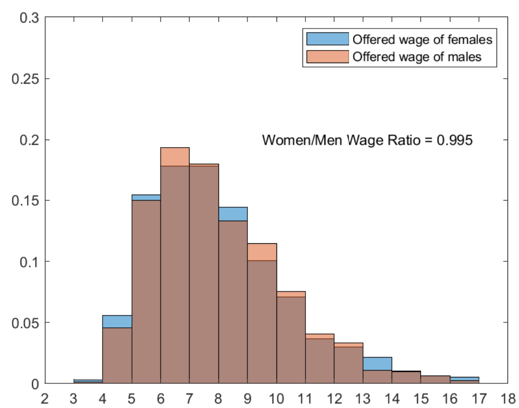
(a) Offered wages in baseline model




(b) Accepted wages in baseline model




(c) Offered wages under equal parameters




(d) Accepted wages under equal parameters


panel), the female wage distribution is more left-skewed than is the male wage distribution. Offered wages and accepted wages are lower for women than for men. However, the wage gap is totally eliminated under the simulation that gives women the estimated model parameters for men. (bottom panel).

## 6.3 External validation

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

As seen in Table 11, having a higher education level is associated with a greater number

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

| Outcome variable: | Male | | Female | |
|---|---|---|---|---|
| Arrival rates/Num. of Application | (1)log $\lambda_U$ | (2)Num | (3)log $\lambda_U$ | (4)Num |
| Higher level secondary degree | 0.06 | 2.98 | 0.34 | 0.36 |
| | (0.04) | (1.28) | (0.04) | (0.94) |
| Emotional Stability | -0.01 | 0.17 | 0.03 | 0.28 |
| | (0.01) | (0.54) | (0.01) | (0.38) |
| Openness to experience | 0.01 | 0.44 | 0.02 | 0.70 |
| | (0.02) | (0.55) | (0.01) | (0.39) |
| Conscientiousness | 0.05 | 2.17 | 0.02 | 2.31 |
| | (0.02) | (0.75) | (0.02) | (0.60) |
| Agreeableness | -0.06 | -0.39 | -0.05 | -1.10 |
| | (0.01) | (0.63) | (0.01) | (0.51) |
| Extraversion | 0.05 | 1.05 | 0.05 | 0.50 |
| | (0.02) | (0.61) | (0.01) | (0.45) |

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

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

# 7 Conclusions

This paper developed and estimated a job search model to investigate how individual heterogeneity in education, personality and other dimensions affect labor market outcomes for men and women. We considered two modeling specifications that had the same numbers of parameters but that differed in terms of assumptions on whether firms renegotiate wages when workers receive offers from competing firms. We find that the model that does not allow for renegotiation provides a better fit to the data and is selected by Vuong's (1989) non-nested model likelihood-based test.

We also considered three alternative model specifications that vary in the degree of parameter heterogeneity incorporated. Specification tests reject the more restrictive models in favor of the model allowing for rich parameter heterogeneity, which appears to be an important feature of these data. The heterogeneous model estimates show that education and personality traits are important determinants of productivity, bargaining and job offer arrival rates for both men and women.

We use the estimated model to simulate labor market outcomes in the steady state, which reveals significant gender inequalities in multiple dimensions. Men on average are more likely to find jobs, have higher wages, have greater job-to-job wage growth and experience more job stability. Clearly, analyses that solely focus on wages provide an incomplete picture of the extent of disadvantage that women experience in the labor market.

When we explore how changes in personality traits affect these labor market outcomes, we find that two of the personality traits affect men and women in similar ways. Greater emotional stability increases wages for both genders and promotes employment stability for men. Greater extraversion lowers wages and leads to shorter job spells for both men and women. The effect of the openness to experience trait is generally statistically insignificant.

Interestingly, two traits, conscientiousness and agreeableness, affect men and women in very different ways. An increase in conscientiousness increases males' wages, increases wage growth, and promotes job and employment stability. For women, conscientiousness decreases wages and reduces job spell length. The agreeableness trait negatively affects men's productivity and wages. For women, this trait has little impact on wages but it substantially reduces bargaining power and inhibits wage growth.

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

As discussed in the introduction, studies for many countries show that men and women differ in terms of personality traits. This paper shows that not only do traits differ in levels, but there are also substantial gender differences in how the labor market values the specific personality traits. In fact, gender differences in the estimated labor market parameters associated with conscientiousness and agreeableness emerge as primary factors accounting for gender wage and employment disparities. Our evidence adds to the growing body of literature demonstrating that noncognitive attributes are important determinants of adult labor market success and of gender inequality.

A natural question is what kinds of public policies could mitigate the observed gender disparities? Our results show that women are particularly disadvantaged in terms of bargaining, so any policy that makes it easier for women to bargain for higher wages could be effective. For example, in 2018 the UK adopted a policy whereby all firms registered in

Great Britain with at least 250 employees have to publicly disclose their gender pay gap and gender composition at different locations in the wage distribution. It is reasonable to believe that better information about one's own position in the wage distribution provides a better basis for requesting an increase in one's wage. An early study has already found that this policy significantly reduces the gender pay gap by 15 percent (Duchini et al., 2020). A few U.S. states recently have introduced policies that prohibit employers from asking applicants about their wages in prior jobs. The motivation for this restriction is to prevent low wages and/or low wage growth at a prior job, possibly for reasons of discrimination, from affecting future job prospects and wage outcomes. Generally, policies that reduce the scope for bargaining over wages or provide a more objective basis for bargaining are likely to be favorable to women.

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# A Appendices

## A.1 Model Solutions

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

This appendix provides further detail on how to solve for the bargained wage $w(\theta', \theta)$ and for the reservation match value $\theta^*$.

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

We use the bargaining protocol

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

which yields the expression

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

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

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

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

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

and the bargaining wage can be expressed as

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

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

To calculate the reservation match value $\theta^*$, we use the definition of $V_U$

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

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

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

By definition, $V_E(\theta^*,\theta^*) = V_U$, so setting the two equations to be equal we solve for $\theta^*$ as a fixed point problem

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

### A.1.2 Solving the reservation match value $\theta^*$ in the model without renegotiation

We next describe our approach to solving the model. First, we discretize the continuous $\theta$ interval into $L$ grid points $\{\theta_1, ..., \theta_L\}$ with probability $\{p_1, ..., p_L\}$. To initialize the algorithm, we set a initial value of unemployment $V_U$ to be equal to $ab$. The model is solved by the following steps:

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

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

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

with the wage

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

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

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

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

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

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

The value of employment at an acceptable match value $\theta_l$ is given by

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

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

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

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

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

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

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

### A.1.3 The likelihood function

We describe the likelihood contribution for individuals with different employment trajectories.

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

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

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

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

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

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

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

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

Let the match productivity value at the first job be given by $\theta_1$. We estimate the model under two different assumptions regarding the renegotiation of wages between workers and firms, in the case in which the worker has the possibility of working at either of two firms at a particular moment in time. While the wage $w(\theta_1; N)$ is strictly increasing in $\theta$ in the case without renegotiation, the bargaining wage $w(\theta_1, \theta_R^*; R)$ created by Bertrand competition may not be monotonic in $\theta$ in general. As the function $w(\theta_1, \theta_R^*; R)$ is not 1-1, we define the marginal distribution using the joint density of $\tilde{w}_1$ and $\theta_1$ rather than the joint density of $\tilde{w}_1$ and $w_1$.[47]

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

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

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

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

Because $w$ is a deterministic function, we have

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

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

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

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

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

of the sample period is

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

where

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

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

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

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

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

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

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

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

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

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

which can be simplified as

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

With renegotiation, we have

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

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

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

Under renegotiation, it is

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

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

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

Under renegotiation, the likelihood contribution becomes

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

## A.2 Sample construction

### A.2.1 Obtaining the dataset used in our analysis

This appendix describes the sample restrictions imposed to obtain the data subsample used for our analysis. First, we calculated durations of the unemployment and employment spells. The monthly unemployment/employment activities are recorded and updated retrospectively during each interview, starting at the last interview or at unemployment entry in case of the first interview. Therefore, we are able to calculate the duration of each of the spells based on the starting dates and ending dates of each activities. Unfortunately, IZA ED only records the months rather than the exact date of each activities. Therefore, we calculate the days of duration based on a randomly assigned date within that month. Thus, the spell durations are calculated based on "statistical months rather than calendar months. For example, we calculate the duration in months to equal 1 when the duration is less or equal to 30 days. After we calculate the duration spells, 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 17,395 individuals with 62,439 individual-spell observations. During the sample selection process, we drop individuals for the following reasons:

- We drop the same job spell but are double-counted in two different waves, reducing the number of individual-spell observations to 51,334.
- We drop any spells after the fourth spell, which leaves individual-spell 43,229 observa-

tions. (17,395 for the first spells, 13,269 for the second spells, 7,532 for the third spells and 5043 for the fourth spells)

- We drop observations with incorrect/missing starting or ending dates, reducing individual-spell observations to be 42,110. We assume the start year is no earlier than 2007 and the end year no later than 2011.
- We drop the individuals whose activities are out of labor force (e.g. attending school or other activities unrelated to the activities incorporated in our model) or whose unemployment benefits information is missing. These restrictions leave us with 34,230.
- We drop the individuals who ever had reported self-employment, which reduces the sample size to 31,111.
- We combine any consecutive unemployment spells across waves into one longer spell, which reduces the number of individuals to be 10,951 with 18,826 individual-spell observations.
- We further drop any individuals missing information on characteristics included in our model: age and gender, educational attainment and personality traits. We further restrict the age of individuals to be between 25 to 55. Our final estimation sample has 4,049 individuals with individual-spell 7,872 observations, consisting of 4,049 first unemployment spells, 2,267 first job spells, 1,053 second job spells and 503 third job spells.

### A.2.2 Personality trait questionnaire

The table below gives the survey questions used for the big five personality scores that are provided in the IZA ED database.

Table A1: Questions used to measure Big Five personality traits in the IZA ED

*The following statements describe different characteristics that a person can possess. Please tell me how much each statement applies to you. 1 means "it does not apply at all" and 7 means "it applies fully". You can gauge your evaluations with in-between values. I am someone who...*

*1) ... works thoroughly*
*2) ... is communicative, talkative*
*3) ... is sometimes rough to others (starting cohort 9)*
*4) ... is inventive, brings new ideas*
*5) ... worries often*
*6) ... can forgive easily (starting cohort 9)*
*7) ... is rather lazy (starting cohort 9)*
*8) ... can be an extrovert, sociable*
*9) ... places value on artistic experiences (starting cohort 9)*
*10) ... becomes nervous easily*
*11) ... carries out tasks effectively and efficiently*
*12) ... is cautious*
*13) ... deals with others in a considerate and friendly way (starting cohort 9)*
*14) ... has a vivid fantasy, imagination*
*15) ... is relaxed, can work well under stress*

*1: does not apply at all ... 7: applies fully, 97: refused, 98: do not know*
*Note: 5 additional items were added starting with No. 9 (February) cohort)*
Each of the personality traits are calculated as the average scores of three items. (The scores of 3, 5, 7, 10, 12 are reversed before calculating the average)

**Openness to experience**: 4, 9, 14
**Conscientiousness**: 1, 7, 11
**Extraversion**: 2, 8, 12
**Agreeableness**: 3, 6, 13
**Emotional stability (opposite to Neuroticism)**: 5, 10, 15

# B Online Appendices (Not For Publication)

## B.1 Additional Tables and Estimates

### B.1.1 Examining the stationarity assumption

We consider the labor market conditions in Germany during the years 2007-2010 when our sample was collected to see if the stationarity assumption is plausible. One concern, in particular, is how the German labor market was affected by the financial crisis of 2007-2008. Figure B.1 shows the unemployment rates for Germany, France, the UK, and the US. The unemployment rate in the US experienced a dramatic increase between 2007-2010 (purple dashed line), but the unemployment rates in Germany (DEU) remained much more stable during the same period (solid dotted line). In the right panel, we compare the unemployment rates obtained using two data sources (OECD and GSOEP). The trends are consistent with trends reported in Carrillo-Tudela et al. (2018). Our conclusion is that the stationarity assumption may not be ideal for this period of time in Germany, but that it is much less problematic than it would be if we were using data from the US during this period.

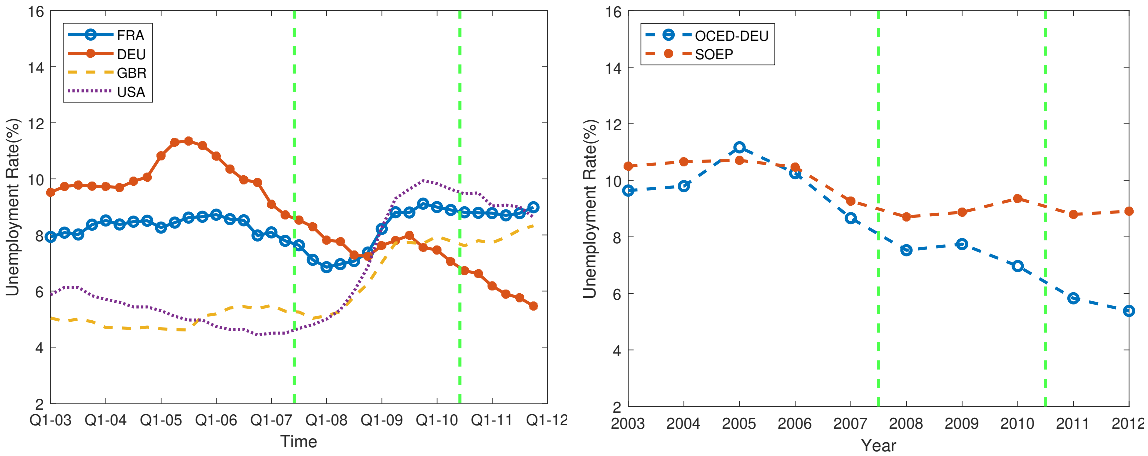
### B.1.2 Are measured personality traits affected by labor force status?

Our analysis assumes that personality traits are time invariant over our observation period, which is up to three years for each individual. It would be problematic if trait assessments were not stable and instead varied with factors such as job loss. In the table below, we report regression coefficients from regressing each of the personality trait measures on recent employment and unemployment durations as well as age and age-squared. All the regressors have coefficients that are statistically insignificantly different from zero, supporting the assumption that the traits are stable.

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

(a) The evolution of unemployment rate overt time

(b) The unemployment rate by different sources




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

Table B1: The effect of employment/unemployment experience on personality traits

| Changes between waves | (1) Opn | (2) Cos | (3) Agr | (4) Stb | (5) Ext |
|---|---|---|---|---|---|
| Employment duration | 0.00 | -0.01 | 0.00 | 0.00 | -0.01 |
| | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) |
| Unemployment duration | 0.00 | 0.00 | 0.00 | 0.00 | 0.01 |
| | (0.01) | (0.01) | (0.01) | (0.01) | (0.01) |
| Age | 0.01 | -0.01 | 0.00 | -0.01 | 0.04 |
| | (0.04) | (0.04) | (0.03) | (0.04) | (0.03) |
| $Age^2/100$ | -0.01 | 0.01 | -0.01 | 0.01 | -0.06 |
| | (0.05) | (0.05) | (0.04) | (0.05) | (0.04) |
| Constant | -0.27 | 0.30 | 0.12 | 0.14 | -0.73 |
| | (0.66) | (0.66) | (0.58) | (0.65) | (0.57) |
| Observations | 1003 | 1003 | 1003 | 1003 | 1003 |
| $R^2$ | 0.00 | 0.00 | 0.00 | 0.00 | 0.01 |

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

### B.1.3 Relationship between Big Five personality traits and internal locus of control

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

Table B2: The correlation between big five personality traits and internal locus of control

| | Emot. Stability | Openness to experience | Conscientiousness | Extrav. | Agreeableness | Locus of control |
|---|---|---|---|---|---|---|
| Emotional Stability | 1.00 | | | | | |
| Openness to experience | 0.06 | 1.00 | | | | |
| Conscientiousness | 0.09 | 0.18 | 1.00 | | | |
| Extraversion | 0.10 | 0.15 | 0.35 | 1.00 | | |
| Agreeableness | 0.21 | 0.35 | 0.29 | 0.16 | 1.00 | |
| Locus of control | 0.39 | 0.10 | 0.20 | 0.13 | 0.27 | 1.00 |

Source: IZA Evaluation Data Set, own calculations.

Table B3: The value of the big five personality traits by locus of control

| "Big 5" traits | LOC indicator External $N = 2,009$ | LOC indicator Internal $N = 1,943$ | Diff | p-value |
|---|---|---|---|---|
| Emotional Stability | 3.26 | 4.00 | -0.74 | 0.00 |
| Openness to experience | 4.75 | 4.95 | -0.21 | 0.00 |
| Conscientiousness | 5.65 | 5.90 | -0.26 | 0.00 |
| Agreeableness | 5.24 | 5.45 | -0.21 | 0.00 |
| Extraversion | 4.52 | 5.01 | -0.50 | 0.00 |

Notes: individuals are classified as being internal if their LOC scores are higher than the median and external otherwise.

## B.2 Additional model results

### B.2.1 Observed and simulated unemployment spells/job spells

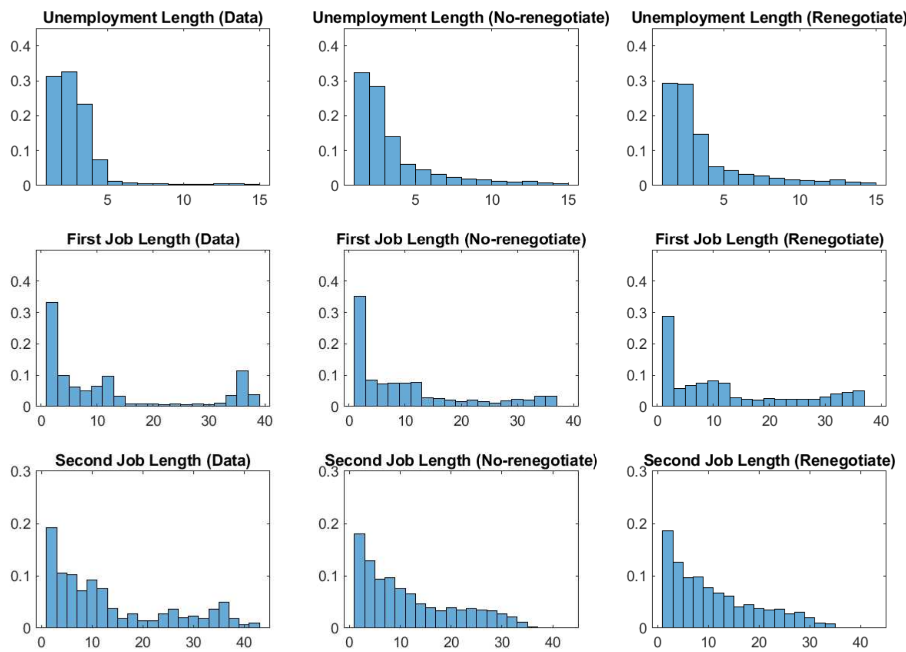
Figure B.2 reports the goodness-of-fit for the observed and simulated unemployment and job spell lengths (on the first and second jobs). The left panels show the histogram for the observed data spells. The top panel shows the length of unemployment spells, the middle panel shows the length of the first job spell, and the bottom panel shows the length of second job spell. The three middle panels show the histograms generated by simulating the model without renegotiation for the same time periods. The right three panels show the histograms for the model with renegotiation.

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

### B.2.2 Which personality traits matters for which channel

To further examine which personality traits matter most for each model channel, we perform the same decompositions as in Table 9 in the main context except now setting the female parameters associated with different personality traits equal to the male estimated parameters (across all model channels separately). Table B4 reports the difference between the resulting simulated gender wage ratio and the wage ratio in the baseline model (0.86). A value above 0.86 means men are being rewarded more (or penalized less) for that trait. As seen in the column (1), differences in the estimated parameters associated with consci-

Figure B.2: Observed and simulated unemployment spells/job spells




entiousness and agreeableness emerge as two most important traits in explaining the gender wage gap, but they affect the gender wage gap in opposite ways. Men are more highly rewarded for conscientiousness than women (primarily through the productivity channel), which widens the wage gap. With regard to agreeableness, both men and women receive a bargaining penalty for being agreeable (see column (2)). However, the penalty is greater for women. Concomitantly, men also receive a productivity penalty for agreeableness that women do not experience. On net, combining both the surplus division and the productivity channels, differences in the estimated agreeableness parameters reduce the gender wage gap.

### B.2.3 Parameter estimates for the heterogeneous model with renegotiation

Table B4: How the gender wage gap changes after equalizing coefficients for each trait and channel

| | All channels | Surplus division | Transitions | Productivity |
|---|---|---|---|---|
| "Big-five"' in total | 1.10 | 1.04 | 0.91 | 0.85 |
| Emotional stability | 0.84 | 0.81 | 0.87 | 0.88 |
| Openness to experience | 0.87 | 0.91 | 0.88 | 0.82 |
| Conscientiousness | 1.66 | 0.93 | 0.93 | 1.41 |
| Agreeableness | 0.64 | 1.01 | 0.86 | 0.55 |
| Extraversion | 0.79 | 0.85 | 0.83 | 0.84 |

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

Table B5: Other parameters in specification (3) under the renegotiation model: individual heterogeneity with gender-specific model coefficients

| | $\log \lambda_U$ | | $\log \lambda_E$ | | $\log \eta$ | | $\log a$ | | $\log\left(\frac{\alpha}{1-\alpha}\right)$ | |
|---|---|---|---|---|---|---|---|---|---|---|
| | Male | Female | Male | Female | Male | Female | Male | Female | Male | Female |
| *Cons.* | -0.25 | -0.04 | -2.87 | -3.97 | -3.35 | -3.21 | 2.11 | 2.11 | 0.14 | -0.47 |
| | (0.30) | (0.24) | (0.38) | (0.30) | (0.19) | (0.24) | (0.12) | (0.10) | (0.55) | (0.44) |
| *Edu* | 0.25 | -0.30 | -0.21 | -0.28 | -0.12 | 0.01 | 0.11 | 0.16 | 0.50 | 0.56 |
| | (0.13) | (0.08) | (0.10) | (0.06) | (0.04) | (0.05) | (0.05) | (0.04) | (0.19) | (0.16) |
| *Stb* | 0.00 | -0.03 | -0.01 | 0.13 | -0.03 | -0.07 | 0.08 | -0.01 | -0.03 | -0.04 |
| | (0.04) | (0.04) | (0.04) | (0.03) | (0.02) | (0.02) | (0.02) | (0.02) | (0.06) | (0.05) |
| *Opn* | 0.07 | 0.00 | 0.10 | 0.10 | 0.04 | 0.08 | -0.03 | 0.02 | -0.10 | 0.03 |
| | (0.05) | (0.04) | (0.05) | (0.03) | (0.02) | (0.03) | (0.02) | (0.02) | (0.06) | (0.05) |
| *Cos* | 0.06 | -0.05 | -0.03 | 0.05 | 0.02 | -0.01 | -0.09 | -0.07 | -0.02 | -0.01 |
| | (0.06) | (0.05) | (0.06) | (0.04) | (0.03) | (0.04) | (0.02) | (0.02) | (0.08) | (0.08) |
| *Agr* | -0.05 | 0.10 | -0.03 | 0.09 | -0.03 | -0.31 | 0.05 | 0.03 | -0.18 | -0.33 |
| | (0.05) | (0.05) | (0.05) | (0.04) | (0.02) | (0.03) | (0.02) | (0.02) | (0.06) | (0.05) |
| *Ext* | 0.00 | -0.09 | -0.01 | 0.03 | -0.01 | 0.19 | 0.01 | -0.02 | -0.02 | 0.10 |
| | (0.05) | (0.04) | (0.05) | (0.03) | (0.02) | (0.03) | (0.02) | (0.02) | (0.07) | (0.07) |
| Cohort (Omitted cat: 73-82) | | | | | | | | | | |
| 63-72 | 0.07 | 0.66 | 0.02 | -0.15 | -0.21 | 0.26 | -0.07 | -0.01 | -0.12 | 0.13 |
| | (0.11) | (0.10) | (0.09) | (0.06) | (0.05) | (0.07) | (0.04) | (0.05) | (0.12) | (0.18) |
| 52-62 | 0.00 | 0.93 | 0.09 | -0.27 | -0.09 | 0.20 | -0.06 | -0.09 | -0.19 | 0.13 |
| | (0.10) | (0.11) | (0.12) | (0.06) | (0.05) | (0.07) | (0.05) | (0.04) | (0.14) | (0.19) |

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.

### B.2.4 Parameter estimates for the extended model allowing for sector-specific match distributions

In this section, we extend the match quality distribution $G(\theta)$ to be a mixture over three industry sectors (agriculture/manufacturing/service sector) as described in the text to account for the potential gender wage gap generated by different gender occupation distributions. In our empirical implementation, we allow $p_k$ and $g_k(\theta)$ to differ by gender. Jobs are drawn from three different sectors: $k=1$ service sector, $k=2$ manufacturing sector, $k=3$ agriculture sector.[48] The likelihood function in this case is

(18)

$$l\left(t_U, r_U, \tilde{w}_1, k_1, t_1, r_1, q_1, \tilde{w}_2, k_2, t_2, r_2, q_2; \Omega, N\right) = \int_{\theta_N^*}\int_{\theta_1} \lambda_U \exp\left(-h_{U,N} t_U\right)$$
$$\times \left\{\exp\left(-h_E(\theta_1)t_1\right)\left(\lambda_E^{1-q_1}\eta^{q_1}\right)^{1-r_1} m\left(\tilde{w}_1 | w\left(\theta_1; N\right)\right)\right\}^{1-r_u}$$
$$\times \left\{\exp\left(-h_E(\theta_2)t_2\right)\left(\left(\lambda_E \tilde{G}(\theta_2)\right)^{1-q_2}\eta^{q_2}\right)^{1-r_2} m\left(\tilde{w}_2 | w\left(\theta_2; N\right)\right)\right\}^{1-(r_1+q_1)} \frac{p_{k2}g_{k2}(\theta_2)}{\tilde{G}(\theta_1)^{r_1}}\frac{p_{k1}g_{k1}(\theta_1)}{\tilde{G}(\theta_N^*)^{r_U}} d\theta_2 d\theta_1$$

where $k_1$ is the sector of the first job, $k_2$ is the sector of the second job. And $\tilde{G}(\theta) = \sum_{k=1}^{3} p_k \tilde{G}_k(\theta)$ is defined as the truncated distribution of match values higher than $\theta$. $p_{k1}g_{k1}(\theta_1)$ and $p_{k2}g_{k2}(\theta_2)$ capture the likelihood contribution of finding a first job in sector $k_1$ with match value $\theta_1$ and a second job in sector $k_2$ with match value $\theta_2$, respectively.

We report the estimated sector-specific distributions of match values by gender in figure B.3. The agriculture sector has the lowest match values on average for both genders. For men, the average match values drawing from manufacturing sector is slightly higher than match values from service sector. For women it is the opposite. Table B7 compares the effects of personality traits in the sector-specific model with the effects estimated under the baseline model. In general, the effects of personality traits are quite robust across these two model specifications. For example, when women have men's estimated parameters, the average wage of women exceeds men's average by 14%, in comparison to 10% in the baseline model. Differences in the estimated parameters associated with conscientiousness and agreeableness emerge as two most important traits in explaining the gender wage gap, but they affect the gender wage gap in opposite ways. Men are more highly rewarded for conscientiousness than are women (primarily through the productivity channel), which widens the wage gap. Agreeableness remains as the single important channel to explain the gender gap in the bargaining channel.

[48] About 5% workers (117 out of 2267) did not report their sectors when finding their first job out of unemployment. We drop these part of workers when estimating the model.

Figure B.3: Sector-specific distributions of (log) match values by genders

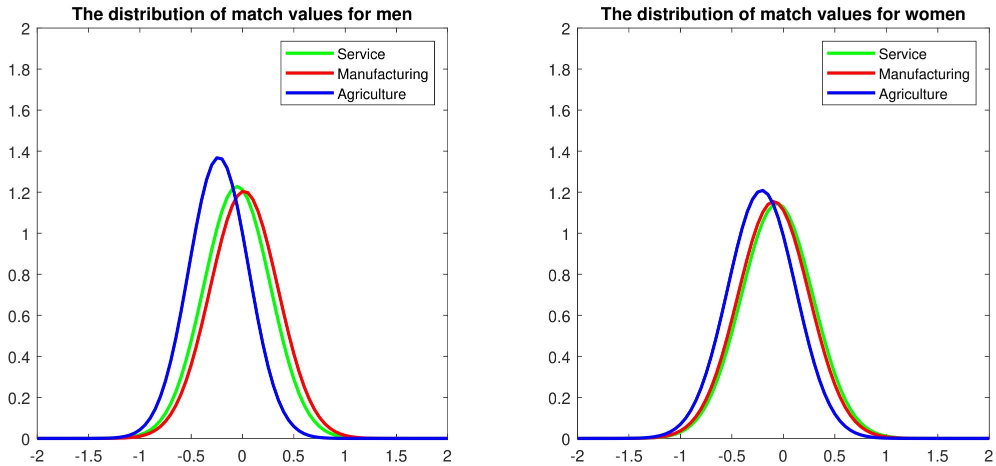



Table B6: Estimated index coefficients by gender when allowing match value distributions to be sector-specific

| | $\log \lambda_U$ | | $\log \lambda_E$ | | $\log \eta$ | | $\log a$ | | $\log\left(\frac{\alpha}{1-\alpha}\right)$ | |
|---|---|---|---|---|---|---|---|---|---|---|
| | Male | Female | Male | Female | Male | Female | Male | Female | Male | Female |
| *Cons.* | -1.55 | -1.82 | -3.33 | -3.52 | -3.04 | -3.20 | 2.27 | 2.19 | 0.62 | 0.94 |
| | (0.12) | (0.10) | (0.25) | (0.18) | (0.20) | (0.19) | (0.12) | (0.10) | (0.47) | (0.27) |
| *Edu* | 0.03 | 0.33 | 0.00 | -0.44 | -0.05 | -0.44 | 0.14 | 0.16 | 0.11 | -0.14 |
| | (0.04) | (0.04) | (0.07) | (0.07) | (0.06) | (0.07) | (0.05) | (0.08) | (0.22) | (0.24) |
| *Stb* | -0.01 | 0.03 | 0.13 | 0.07 | -0.12 | -0.07 | 0.03 | 0.03 | -0.12 | -0.05 |
| | (0.01) | (0.01) | (0.03) | (0.03) | (0.03) | (0.02) | (0.02) | (0.01) | (0.10) | (0.03) |
| *Opn* | 0.01 | 0.01 | 0.03 | 0.02 | -0.03 | 0.01 | 0.00 | 0.02 | 0.05 | 0.02 |
| | (0.02) | (0.01) | (0.03) | (0.02) | (0.03) | (0.03) | (0.02) | (0.01) | (0.10) | (0.04) |
| *Cos* | 0.05 | 0.02 | -0.02 | 0.07 | -0.07 | -0.02 | 0.04 | -0.04 | 0.03 | -0.03 |
| | (0.02) | (0.02) | (0.04) | (0.02) | (0.03) | (0.03) | (0.02) | (0.02) | (0.10) | (0.04) |
| *Agr* | -0.06 | -0.05 | -0.04 | 0.00 | -0.02 | -0.02 | -0.04 | 0.05 | -0.06 | -0.17 |
| | (0.02) | (0.02) | (0.04) | (0.03) | (0.03) | (0.03) | (0.02) | (0.02) | (0.11) | (0.04) |
| *Ext* | 0.05 | 0.05 | -0.02 | 0.05 | 0.12 | 0.04 | -0.01 | 0.00 | -0.07 | -0.06 |
| | (0.02) | (0.02) | (0.03) | (0.03) | (0.03) | (0.03) | (0.02) | (0.01) | (0.10) | (0.04) |
| Cohort (Omitted cat: 73-82) | | | | | | | | | | |
| 63-72 | -0.05 | -0.15 | -0.05 | -0.05 | -0.13 | -0.26 | 0.04 | 0.02 | -0.08 | -0.02 |
| | (0.04) | (0.04) | (0.07) | (0.06) | (0.06) | (0.07) | (0.05) | (0.03) | (0.18) | (0.07) |
| 52-62 | -0.10 | -0.16 | -0.07 | -0.06 | 0.12 | 0.13 | -0.01 | -0.02 | -0.08 | 0.07 |
| | (0.04) | (0.04) | (0.08) | (0.07) | (0.06) | (0.07) | (0.06) | (0.04) | (0.23) | (0.14) |

NOTE: this table reports estimated index coefficients by gender when allowing match value distributions to be sector-specific. Asymptotic standard errors using numerical scoring function are reported in parentheses. Data: IZA Evaluation Dataset.

Table B7: The counterfactual gender wage ratios after equalizing coefficients for each trait and channel

| | All channels | | Surplus division | | Transitions | | Productivity | |
|---|---|---|---|---|---|---|---|---|
| | Base | Sec. | Base | Sec. | Base | Sec. | Base | Sec. |
| "Big-five"' in total | 1.10 | 1.14 | 1.04 | 1.11 | 0.91 | 0.96 | 0.85 | 0.87 |
| Emotional stability | 0.84 | 0.86 | 0.81 | 0.85 | 0.87 | 0.90 | 0.88 | 0.91 |
| Openness to experience | 0.87 | 0.90 | 0.91 | 0.95 | 0.88 | 0.92 | 0.82 | 0.85 |
| Conscientiousness | 1.66 | 1.82 | 0.93 | 1.00 | 0.93 | 1.00 | 1.41 | 1.50 |
| Agreeableness | 0.64 | 0.68 | 1.01 | 1.06 | 0.86 | 0.91 | 0.55 | 0.58 |
| Extraversion | 0.79 | 0.85 | 0.85 | 0.90 | 0.83 | 0.89 | 0.84 | 0.89 |

NOTE: columns named "Base" report gender wage ratios calculated using the baseline model and columns named "Sec." report gender wage ratios calculated using the alternative model when allowing match value distributions to be sector-specific.

### B.2.5 Estimation results when incorporating reservation wages

In this section, we incorporate the reported reservation wage $w^*$ as additional information incorporated into the likelihood. As previously noted, information on reservation wages can be incorporated in the estimation. However, the previous literature studying reservation wages found job seekers may have biased beliefs about their employment prospects (Spinnewijn (2015)) and that the bias differs by gender (Caliendo et al. (2017a)). Consistent with the literature, we also find some evidence of over-confidence in our data: 231 out of 490 workers report reservation wages that are higher than their actual wage rates in their first job out of unemployment.[49]

To tackle this empirical challenge, we assume the following relationship between reported reservation wage $\tilde{w}^*$ and the reservation wage implied by the model $w^*$:

$$\log \tilde{w}^* = \gamma_{0j} + \gamma_{1j} \log w^* + \zeta_j, j \in \{M, F\} \tag{19}$$

where the term $\gamma_{0j} > 0$ captures the level of over-confidence when workers report their reservation wages, $\gamma_{1j}$ captures the marginal effect of "true" reservation wages on the reported reservation wages. This parametric assumption help us to address the potential over-confidence issue yet preserve the meaningful correlation between the reported reservation wage and worker's characteristics. The error term $\zeta_j$ follows a normal $\zeta_j \sim N\left(0, \sigma^2_{\zeta j}\right)$. Our specification nests the special case in which workers have unbiased reports on their reservation wages with classical measurement errors ($\gamma_{0j} = 0, \gamma_{1j} = 1$).

The likelihood function including the reservation wage extension becomes

$$\begin{aligned} l\left(\tilde{w}^*, t_U, r_U, \tilde{w}_1, t_1, r_1, q_1, \tilde{w}_2, t_2, r_2, q_2; \Omega, N\right) = f(\tilde{w}^*|\theta_N^*) \int_{\theta_N^*} \int_{\theta_1} \lambda_U \exp\left(-h_{U,N} t_U\right) \\ \times \left\{ \exp\left(-h_E(\theta_1) t_1\right) \left(\lambda_E^{1-q_1} \eta^{q_1}\right)^{1-r_1} m\left(\tilde{w}_1 | w\left(\theta_1; N\right)\right) \right\}^{1-r_u} \\ \times \left\{ \exp\left(-h_E(\theta_2) t_2\right) \left( \left(\lambda_E \tilde{G}(\theta_2)\right)^{1-q_2} \eta^{q_2} \right)^{1-r_2} m\left(\tilde{w}_2 | w\left(\theta_2; N\right)\right) \right\}^{1-(r_1+q_1)} \frac{g(\theta_2)}{\tilde{G}(\theta_1)^{r_1}} \frac{g(\theta_1)}{\tilde{G}(\theta_N^*)^{r_U}} d\theta_2 d\theta_1. \end{aligned} \tag{20}$$

where the additional term $f(\tilde{w}^*|\theta_N^*)$ captures the contribution from the observed reservation wage to the likelihood function

$$f(\tilde{w}^*|\theta_N^*) = \phi\left(\frac{\log(\tilde{w}^*) - (\gamma_{0j} + \gamma_{1j} \log a\theta_N^*)}{\sigma_{\zeta j}}\right)$$

The estimates from equation 19 are reported in table B8.[50] The constant term $\gamma_{0j}$ is larger

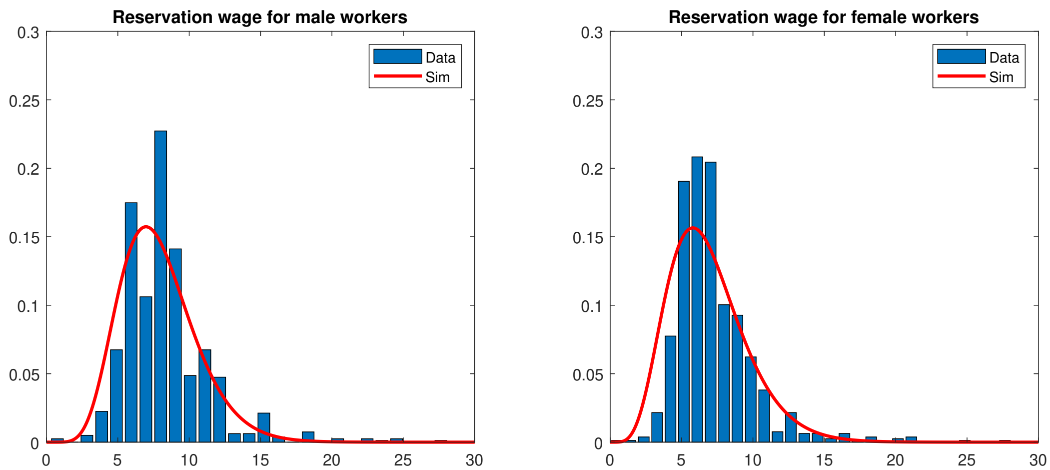
[49] We only have 490 workers have information about their reservation wage and first job wage.

[50] Other model estimates are reported in Appendix B.2.5.

Table B8: New estimates from equation 19

| | Men | Women |
|---|---|---|
| $\gamma_{0j}$ | 0.99 | 0.83 |
| | (0.23) | (0.13) |
| $\gamma_{1j}$ | 0.69 | 0.75 |
| | (0.15) | (0.09) |
| $\sigma_{\zeta j}$ | 0.32 | 0.40 |
| | (0.00) | (0.00) |

Figure B.4: The goodness of fit for reservation wages by genders




for men than for women, which is consistent with the empirical pattern that men on average are more over-confident than women. Meanwhile, the variance of measurement error term is smaller for men than for women.(Niederle and Vesterlund, 2007; Buser et al., 2014) We show the goodness of model fit for the reservation wages by gender in Figure B.4. The model fits the distribution of reservation wages reasonably well.

We now compare the impact of personality traits in our baseline model and the alternative model with additional reservation wage measures in B10. Standard errors for the index coefficients under the reported alternative model in table B9 are smaller than ones under the baseline model reported in table 6, especially for the coefficients associated with the bargaining power $\alpha$. However, the findings regarding effects of personality traits on gender wage gap are robust to the inclusion of reservation wages in the estimation. Differences in the estimated parameters associated with conscientiousness and agreeableness emerge as two most important traits in explaining the gender wage gap. The bargaining channel is the most important channel in explaining the gender wage gap, and agreeableness is the most important personality trait within the bargaining channel. The estimated penalty of being agreeable is even larger in the model that incorporates reservation wage data compared to the baseline model.

Table B9: Estimated index coefficients by gender in the extended model incorporating data on reservation wages

| | $\log \lambda_U$ | | $\log \lambda_E$ | | $\log \eta$ | | $\log a$ | | $\log\left(\frac{\alpha}{1-\alpha}\right)$ | |
|---|---|---|---|---|---|---|---|---|---|---|
| | Male | Female | Male | Female | Male | Female | Male | Female | Male | Female |
| *Cons.* | -1.53 | -1.86 | -3.38 | -3.02 | -3.07 | -3.13 | 2.28 | 2.20 | 0.66 | 0.97 |
| | (0.07) | (0.05) | (0.13) | (0.09) | (0.14) | (0.10) | (0.07) | (0.06) | (0.20) | (0.04) |
| *Edu* | -0.02 | 0.33 | -0.14 | -0.33 | -0.36 | -0.41 | 0.16 | 0.14 | 0.19 | 0.06 |
| | (0.03) | (0.03) | (0.06) | (0.06) | (0.06) | (0.06) | (0.04) | (0.02) | (0.16) | (0.06) |
| *Stb* | -0.01 | 0.03 | 0.13 | 0.07 | -0.18 | -0.02 | 0.03 | 0.05 | -0.16 | -0.10 |
| | (0.01) | (0.01) | (0.03) | (0.02) | (0.02) | (0.02) | (0.01) | (0.01) | (0.06) | (0.02) |
| *Opn* | 0.00 | 0.02 | -0.02 | 0.02 | -0.02 | 0.02 | 0.01 | 0.02 | -0.04 | -0.15 |
| | (0.01) | (0.01) | (0.03) | (0.02) | (0.02) | (0.02) | (0.01) | (0.01) | (0.05) | (0.02) |
| *Cos* | 0.04 | 0.02 | 0.04 | 0.02 | -0.08 | -0.05 | 0.03 | -0.05 | 0.04 | -0.02 |
| | (0.01) | (0.01) | (0.03) | (0.03) | (0.03) | (0.03) | (0.01) | (0.01) | (0.07) | (0.01) |
| *Agr* | -0.04 | -0.07 | -0.04 | 0.00 | 0.00 | 0.00 | -0.03 | 0.05 | -0.06 | -0.22 |
| | (0.01) | (0.01) | (0.03) | (0.03) | (0.02) | (0.03) | (0.01) | (0.01) | (0.06) | (0.02) |
| *Ext* | 0.05 | 0.05 | -0.02 | 0.01 | 0.17 | 0.02 | 0.01 | 0.01 | 0.04 | 0.09 |
| | (0.02) | (0.01) | (0.03) | (0.02) | (0.03) | (0.03) | (0.01) | (0.01) | (0.05) | (0.02) |
| Cohort (Omitted cat: 73-82) | | | | | | | | | | |
| 63-72 | -0.04 | -0.07 | -0.03 | -0.14 | -0.13 | -0.30 | 0.05 | 0.01 | -0.43 | -0.06 |
| | (0.04) | (0.03) | (0.07) | (0.06) | (0.06) | (0.06) | (0.02) | (0.02) | (0.11) | (0.05) |
| 52-62 | -0.13 | -0.06 | -0.08 | -0.07 | 0.10 | 0.03 | -0.02 | -0.02 | -0.07 | 0.00 |
| | (0.04) | (0.03) | (0.07) | (0.04) | (0.06) | (0.05) | (0.02) | (0.02) | (0.11) | (0.10) |

NOTE: this table reports estimated index coefficients by gender in the extended model allowing for reservation wages. Asymptotic standard errors using numerical scoring function are reported in parentheses. Data: IZA Evaluation Dataset.

Table B10: The counterfactual gender wage ratios after equalizing coefficients for each trait and channel

| | All channels | | Surplus division | | Transitions | | Productivity | |
|---|---|---|---|---|---|---|---|---|
| | Base | Res. | Base | Res. | Base | Res. | Base | Res. |
| "Big-five"' in total | 1.10 | 1.07 | 1.04 | 1.13 | 0.91 | 0.84 | 0.85 | 0.79 |
| Emotional stability | 0.84 | 0.78 | 0.81 | 0.79 | 0.87 | 0.88 | 0.88 | 0.80 |
| Openness to experience | 0.87 | 0.92 | 0.91 | 0.96 | 0.88 | 0.85 | 0.82 | 0.79 |
| Conscientiousness | 1.66 | 1.49 | 0.93 | 0.91 | 0.93 | 0.86 | 1.41 | 1.33 |
| Agreeableness | 0.64 | 0.70 | 1.01 | 1.05 | 0.86 | 0.85 | 0.55 | 0.55 |
| Extraversion | 0.79 | 0.76 | 0.85 | 0.78 | 0.83 | 0.80 | 0.84 | 0.85 |

NOTE: columns named "Base" report gender wage ratios calculated using the baseline model and columns named "Res." report gender wage ratios calculated using the alternative model allowing for reservation wages.