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ABSTRACT

The Gender Wage Gap: Does a Gender Gap in Reservation Wages Play a Part?*

This paper focuses on re-examining the gender wage gap and the potential role that reservation wages play. Based on two waves of rich data from the IZA Evaluation Dataset Survey we examine the importance of gender differences in reservation wages to explain the gender gap in realized wages for a sample of newly unemployed individuals actively searching for a full-time job in Germany. The dataset includes measures for education, socio-demographics, labor market history, psychological factors and job search characteristics allowing us to perform a decomposition analysis including these potentially influential factors. Our results suggest that the gender wage gap disappears once we control for reservation wages. We also find a close correspondence between the two gaps for certain subgroups. For example, those with low labor market experience show no gender gap in reservation wages and also no corresponding gap in observed wages. In an attempt to better understand how the initial gender gap in reservation wages arises, we also decompose the gender gap in reservation wages and draw some preliminary conclusions on the nature of the unobservable traits that reservation wages might be capturing.

JEL Classification: J16, J31

Keywords: wages, gender gap, reservation wages, discrimination

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* This study uses the IZA Evaluation Dataset Survey (for more information, see Arni, Caliendo, Künn, and Zimmermann, 2014). We thank the participants at ESPE 2013 (Aarhus), EALE 2013 (Torino) and the COSME-FEDEA Workshop on Gender Economics 2013 (Madrid) for valuable comments.

1 Introduction

The decomposition of gender and racial wage gaps can arguably be considered to be the Holy Grail in labor economics. In the case of the gender wage gap, despite numerous attempts by economists in the past, there typically still remains a sizeable unexplained gap (e.g. Altonji and Blank, 1999; Blau and Kahn, 2006). Meta-analysis studies of the gender wage gap estimate the raw mean gap to be between 32% to 35% of the female wage (Stanley and Jarrell, 1998; Jarrel and Stanley, 2004). Briefly summarizing the vast literature on this topic, proposed logical explanations include the institutional wage structure (e.g. Blau and Kahn, 2003), gender differences in experience and tenure (e.g. Blau and Kahn, 1997), occupations (e.g. Groshen, 1991; Macpherson and Hirsch, 1995), qualifications (e.g. Blau and Kahn, 1997), college major (e.g Brown and Corcoran, 1997; Machin and Puhani, 2003), promotion rates (e.g. Booth, Francesconi, and Frank, 2003) and the penalty on women for having children (e.g. Waldfogel, 1997). The unexplained gap could potentially reflect discrimination against women or possibly arise due to omitted variables in estimating the wage equation.

In the last ten years, new classes of explanations for gender differences in labor market outcomes have been proposed (see the discussion in Bertrand, 2010). These include gender differences in psychological attributes and risk preferences (e.g. Croson and Gneezy, 2009), gender differences in attitudes towards competition (e.g. Lavy, 2012; Manning and Saidi, 2010) and negotiation (e.g. Babcock and Lascheyer, 2003), and gender differences in personality (e.g. Mueller and Plug, 2006). These new explanations help provide micro-foundations for understanding why women may choose alternative career paths than men or why they might be less committed to particular career paths. However, to date, most evidence has been based on laboratory experiments and real world evidence is generally lacking. Bertrand (2010) states that more empirical evidence will be important in determining whether these explanations will have a lasting impact in the study of gender wage gaps.

In this paper, we contribute to this more recent literature searching for new explanations for the gender gap in wages. We do so by examining the importance of gender differences in reservation wages in explaining the gender gap in realized wages for a sample of newly unemployed job applicants in Germany. The key research question we focus on is if any observed wage gap between men and women is simply an empirical realization of an initial gender gap in reservation wages.

In particular, the novel contribution of the paper is including the reservation wage into the decomposition of the gender gap in wages. We determine the extent to which gender differences in aspirations and expectations regarding wages can be a self-fulfilling prophecy. In the general equilibrium search literature, although there has been previous work that attempts to decompose gender wage differentials that accounts for gender differences in reservation wages (e.g. Bowlus, 1997; Bowlus and Grogan, 2009), search models have no actual data on reservation wages and must infer them from observed outcomes in the data, such as the lowest observed wage. Previous empirical work involving reservation wages has generally been concerned with macro-labor issues such as unemployment insurance and unemployment rates (e.g. Feldstein and Poterba, 1984; Shimer and Werning, 2007). Others have been concerned with estimating the determinants of reservation wages. For example, Brown, Roberts, and Taylor (2010b) use the BHPS data to examine the role of health in determining reservation wages. Similarly, Prasad (2003) and Humpert and Pfeifer (2013) use data from the German Socio-Economic Panel (SOEP) to analyze the determinants of reservation wages of German workers.

By having data on both reservation wages and wages on the same individual in a panel data set, we can determine the extent to which gender differences in aspirations and expectations regarding wages can be a self-fulfilling prophecy and lead to gender differences in actual wages. Moreover, we also attempt to explain why there exists a gender gap in reservation wages in the first place. We focus on unemployed men and women actively searching for full-time employment in order to mitigate the common problem that men and women may self-select differently in deciding whether or not to participate in the labor market. Additionally, our dataset allows us to compare men and women at the same time of their unemployment spell.

Previewing our main findings, we find as is typical in the literature that men earn more than women, with the raw gender gap in hourly wages estimated to be about 11.9%. Although the inclusion of standard human capital variables, personality traits, labor market history variables and job search characteristics reduces the gender gap in realized wages somewhat, the gap still remains statistically significant. The inclusion of reservation wages, however, makes the gender gap insignificant. As we find that controlling for reservation wages reduces the gender wage gap significantly, we also take a closer look at the determinants of reservation wages in an attempt to better understand how this initial gender gap in reservation wages arises.

The rest of this paper is organized as follows. Section 2 describes the data in more detail. Section 3 presents the methods used and the main results about the wage gap. In Section 4, we examine the reservation wage gap and also perform some robustness analysis. Finally, Section 5 concludes.

2 Data, Descriptive Statistics and the Reservation Wage

2.1 The IZA Evaluation Dataset S

This study uses the IZA Evaluation Dataset S which consists of survey information on individuals who entered unemployment between June 2007 and May 2008 in Germany (see Caliendo et. al, 2011, for details). The dataset contains a 9% random sample from the monthly unemployment inflows of approximately 206,000 individuals identified in the administrative records who are selected for an interview. From this gross sample of individuals aged between 16 and 54 years, representative samples of about 1,450 individuals are interviewed each month so that twelve monthly cohorts are gathered after one year. The first wave of interviews takes place shortly after the entry into unemployment. Besides the extensive set of individual-level characteristics and labor market outcomes, the individuals are asked a variety of non-standard questions regarding search behavior, social networks, psychological factors, cognitive and non-cognitive skills, subjective assessments on future outcomes, and attitudes. Altogether, a total of 17,396 interviews were obtained in this initial round of the survey (wave 1), with a time lag from seven to fourteen weeks between the unemployment registration and the interview. One year later, 8,915 individuals were interviewed again for a second wave (wave 2).[1]

For the purposes of this paper we restrict the sample to individuals who are still unemployed at the moment of the first interview and are actively searching for full-time employment. That is we exclude all individuals who do not actively search for a new job or contemplate part-time employment. This restriction is expected to reduce potential selection issues compared to other gender wage gap studies.[2] We further exclude those individuals whose reported hourly reservation wages and benefit levels are in the lowest or highest percentile of the distribution and who have missing values for reservation wage, search intensity or the control variables. For the estimation of the reservation wage in the first wave we end up with an estimation sample of 6,169 individuals comprising of 3,893 men and 2,276 women. For examining labor market outcomes, employment status and realized wages in the second wave, our estimation sample is based on 3,234 individuals (2,023 men and 1,211 women).

[1] In order to investigate whether panel attrition might bias our results we re-estimate our model for different estimation samples, whenever this is possible. Further details on the IZA Evaluation Dataset S can be found in the user manual (Arni, Caliendo, Künn, and Zimmermann, 2014).

[2] Since one can also argue that women searching for full-time employment are a 'positive selection' of all women, while this form of selection does not appear among men, we include also individuals searching for part-time employment into a sensitivity analysis.

2.2 Differences in Reservation Wages and Labor Market Outcomes

The reservation wage is defined as the lowest wage rate at which a job-seeker would accept a job offer. We measure an individual's reservation wage in several steps. First, individuals are asked for their expected monthly income in a prospective job and how many hours they expect to work at such a job per week. The hourly reservation wage is than defined as the ratio of the expected income and the expected weekly working hours divided by 4.33. Second, individuals are also asked if they are willing to work for less than the expected wage. If so, they are asked for the minimum amount they would be willing to work for and the expected weekly hours of work. For all individuals who are willing to work for less than the expected wage, we replace the reservation wage by this minimum wage if it is lower than the expected wage defined before.[3]

[Insert Table 1 about here]

The top panel of Table 1 presents the corresponding average answers for each of the previous questions separated by gender. Women expect a significant lower monthly income but at the same time also want to work fewer hours per week for such a job. This leads to an expected hourly wage of €7.49 which is substantially lower than the one for men with €8.57. In the follow-up question, a higher share of women state that they are willing to work for less than their expected wage that had just been computed (74% of women are willing to do, as compared to 72% of men). For both these reasons we end up with significantly lower reservation wages for women (€6.61) than for men (€7.57). Furthermore, there is also a significant gender gap in wages in the most recent previous job, which is close to the gender gap in reservation wages. Figure 1 presents the relative distribution of reservation wages and previous wages. There is a higher fraction of women in the lower part of the distribution, which indicates that women expect lower reservation wages for given previous wages. We argue that former discrimination will find expression in previous wages. Hence, the result is a first indicator that women set lower reservation wages even conditional on previous wages.

[Insert Figures 1 and 2 about here]

In the bottom panel of Table 1, we show the labor market outcomes in wave 2. Due to our restriction on individuals actively searching for a job we observe no differences in labor market participation rates. Men and women face the same employment probability one year

[3] This is similarly defined as the ratio of the minimum monthly income and the expected working hours divided by 4.33.

after entering unemployment. We observe, however, a big gender gap in realized wages. Women receive significantly lower hourly wages than men (€7.93 compared to €9.27). This is also illustrated by the distribution of the realized log wages in Figure 2, where it can be seen that there is a higher share of men in the upper part of the log wage distribution. Moreover, just over 30% of individuals accept a wage offer below their reservation wage, with there being no significant gender differences. Overall, the difference between the reservation wage and the accepted wage is about €1 on average. Search theoretic models suggest that the longer the duration of unemployment while searching for a job, the more likely individuals will lower their reservation wages. We find this to be the case for nearly half of all individuals still searching for work after one year. The decrease in the reservation wage between waves 1 and 2, however, is quantitatively very small (€0.01 for males and €0.08 for females).

2.3 Differences in Observed Characteristics

Explanations for gender differences in observed wages often involve differences in human capital and other observable characteristics. Therefore, before proceeding to our decomposition analysis, we first examine gender differences in these characteristics. Table 2 shows the differences between men and women for some selected control variables measured in wave 1 for our estimation sample.

[Insert Table 2 about here]

With respect to our extensive set of control variables, we define four groups of covariates. First, the *educational variables* include information on the school leaving degree and the type of vocational training. In our sample, women generally have higher school leaving degrees than men. For example, 29% of women hold a (specialized) upper secondary school degree, whereas only 21% of men do. The second category comprises *socio-demographic characteristics* and the local labor market conditions. There are no gender differences with respect to age, citizenship or marital status. However, we observe a lower share of women with children than men. For example, 77% of the women are without children whereas this is the case for only 73% of the men. Similarly, only 7% of the women have two or more children, as compared to 11% of the men. These differences are likely to be due to our focus on individuals who are searching for full-time employment only.[4]

[4]Women are more likely to perform parenting duties and either search only for part-time employment or remain out of the labor force. Therefore women with children are more likely to be excluded from our estimation sample.

The third group of control variables summarizes the individual *labor market history* using several measures, such as the employment status before entering unemployment and the time spent in employment in the past. Generally, women are less likely to enter unemployment from regular jobs (66% vs. 71%) and have less work experience relative to their age.[5] Furthermore, we observe whether individuals receive unemployment benefits and what these benefit amounts are. According to the classical job search model, the amount of unemployment benefits is one of the key variables explaining a job seekers reservation wage. Since unemployment benefits in Germany are directly related to previous net income, this information should give us an approximation of the previous income and related unobserved variables influencing labor market outcomes. In our sample, we observe significantly higher unemployment benefits for men than for women, but no significant gender differences in unemployment benefit receipt.

The last group of covariates, the *personality and job search characteristics*, contains some non-standard information, including the 'Big Five' personality traits (e.g. Mueller and Plug, 2006), locus of control (e.g. Caliendo, Cobb-Clark, and Uhlendorff, 2014) and job search behavior, like the number of applications or the use of different search channels. As can be seen in Table 2, women report significantly higher levels of openness, conscientiousness, extraversion, neuroticism and have a lower internal locus of control. They also have a lower willingness to move in order to find a new job. There are, however, no reported differences with respect to job search intensity and the search channels used.

3 Decomposition of the Gender Wage Gap

3.1 Empirical Strategy

The most common approach employed in the literature on gender gaps is the decomposition proposed by Blinder (1973) and Oaxaca (1973). In the standard Blinder-Oaxaca (BO) decomposition, separate regressions are estimated for group A ($Y_i = \beta_A X_i + \epsilon_i$) and for group B ($Y_i = \beta_B X_i + \epsilon_i$), where X are individual level characteristics that help explain differences in Y. The average gap in outcomes ($\bar{Y}_A - \bar{Y}_B$) can be expressed as the sum of two components: $\beta_A(\bar{X}_A - \bar{X}_B) + (\beta_A - \beta_B)\bar{X}_B$. The first part is attributed to differences in average characteristics between the two groups (i.e., the explained component). The second part is due to differences in average returns to the individual characteristics, which may reflect discrimination (i.e., the unexplained gap).

Much has been written about how best to express the appropriate counterfactual and

[5]This is measured by the months in employment standardized by an individual's age minus 18.

whether one should use group A or group B as the reference group when performing the decomposition in order to examine the extent to which characteristics matter. Following the suggestion of Elder, Godderis, and Haider (2009), as our benchmark approach, we adopt a straightforward way of estimating the gender gap in employment and wages. We refer to this as the pooled regression decomposition approach as this approach simply uses the coefficient on a group indicator from an OLS regression in order to obtain a single measure of the unexplained gap in wages between men and women. As discussed by Elder, Godderis, and Haider (2009), this coefficient can essentially be viewed as a weighted average of the two different ways of doing a BO decomposition.

In order to decompose the gender gap in wages at different quantiles of the distribution, we also use the method based on the Recentered Influence Function (RIF) regressions proposed by Firpo, Fortin, and Lemieux (2009). One would think that one could simply use quantile regression to perform a decomposition at different quantiles, analogous to how linear regression is used in a BO decomposition to perform a decomposition at the mean. However, quantile regression provides conditional quantile estimates. In other words, in a regression where Y denotes the outcome of interest and X are the regressors, it can only provide coefficients that can be interpreted as the effect of increasing X on a particular conditional quantile of Y given X. These coefficients are not able to be interpreted as the effect of increasing X on a particular quantile of Y that is not conditional on X. As noted in the recent survey by Firpo, Fortin, and Lemieux (2009), this property of quantile regressions has limited the usefulness of quantile regression in decomposition applications until recently. The RIF approach has the advantage that it generates unconditional quantile estimates; its estimated coefficients can usefully be interpreted as the effect of increasing the mean value of X on any unconditional quantile of Y that is of interest. Implementing the RIF decomposition approach consists of two steps. In the first step, the RIF is estimated for each sample quantile of interest (e.g., 10^{th}, 20^{th}, ..., 90^{th} percentile) using kernel regression methods. Once an estimate of the RIF is obtained for each observation in the data set, we replace the original outcome variable with this estimate of the RIF and perform a BO decomposition for that respective quantile. Then, just as in the BO decomposition, we are able to decompose the gender gap in wages in to an explained component and an unexplained part. In summary, the RIF decomposition therefore allows us to examine in more detail the extent to which characteristics matter at different points in the wage distribution.

One potential problem with including reservation wages on the right hand side of a decomposition analysis is that reservation wages might be correlated with unobserved characteristics.

For example, it is possible that higher ability individuals set higher reservation wages as well as earn correspondingly higher wages. Although a conventional solution to such endogeneity problems is to use instrumental variable methods, in practice, it is difficult to find a variable that is correlated with reservation wages but has no influence on the realized wage. However, as we are not interested in the causal effect of reservation wages but the wage gap between men and women, the reservation wage should be included in the decomposition of the wage gap when they differ between men and women and simultaneously affect realized wages. This is similar to variables such as education, occupation or work experience which are usually regarded as exogenous variables in BO decompositions even though they are possibly endogenous as well. The endogeneity of reservation wages can even be ignored if unobserved ability is correlated with reservation wages but the correlation is the same for both men and women (see Fortin, Lemieux, and Firpo, 2011). Although the contribution of reservation wages and abilities cannot be disentangled in this instance, the estimate of the aggregate unexplained gap is valid. Another argument mitigating the concern that reservation wages are potentially endogenous is the fact that we use reservation wages measures from wave 1 on the right hand side and observed wages measured in wave 2 on the left hand side. This time ordering of the data reduces the likelihood of observed wages affecting reservation wages, as compared to the case of working with pure cross-sectional data.

As we have seen in Table 2, individuals do adjust their reservation wages between waves 1 and 2 and an individual's reservation wage should therefore not be viewed as a static phenomenon. However, it is still possible that women may anticipate that they will receive lower wages in the future and adjust their reservation wages downwards accordingly. In the models where we examine the determinants of reservation wages, we therefore include the last observed wage as an additional explanatory variable to explore the possibility of reverse causality. Additionally, we concentrate on a subsample of individuals with only little labor market experience relative to their age. The idea is that those individuals have not experienced discrimination so far, which makes them less likely to adjust their reservation wages.

3.2 Baseline Results - The Gender Gap in Labor Market Outcomes

We have seen in Section 2.2 a raw gender wage gap that can be caused by differences in observed characteristics. Thus, we include several groups of control variables using the pooled OLS decomposition approach described in the previous section to see if this helps to eliminate the gender gap. In the first step, we estimate the employment probability to ensure that the gender wage gap is not affected by differences in labor market participation rates. This involves estimating the employment status for all individuals actively searching for full-time employment in wave 1 and being interviewed at wave 2. Next, we estimate the gender wage gap and perform some wage decompositions for all individuals employed at wave 2. For the ease of exposition, we use the four groups of covariates already defined in the previous section.

The upper part of Table 3 presents the OLS estimates of the gender gap in the probability of being employed in wave 2. There are only small and insignificant effects on the probability of being employed, irrespective of the set of control variables that are used in columns (1)-(5). The lack of evidence for a gender gap in employment, which is likely to be caused by our focus on individuals actively seeking work, reduces the likelihood that endogenous selection into employment may bias our estimation results. In contrast to the prediction from a job search model, we find a positive significant effect of reservation wages on the probability of being employed in wave 2 in column (6).[6] This result is likely due to reservation wages having a positive correlation with unobserved abilities. For this reason, we also include an interaction term of the gender dummy and log reservation wages in column (7). We observe a positive significant effect of the interaction term, while there is no longer a significant effect for the reservation wage itself. This indicates that reservation wages might be a proxy for women's unobserved abilities, while this is not the case for men.

[Insert Table 3 about here]

However, when we examine log hourly wages for individuals who are employed at wave 2 (see bottom panel of Table 3), we observe significant gender differences. The raw gap, which is simply the mean difference in log hourly wages, is about 11.9%. Thus, women earn significantly less than men without controlling for any characteristics. Next, we sequentially include the four groups of control variables. Since women are on average better educated than men, conditioning the decomposition on the educational level slightly increases the unexplained part of the wage gap (column (1) in Table 3). Including the other groups of control variables reduces the wage gap, where we find that the labor market history variables seem to contribute the highest explanatory power. When all groups of control variables are included, the wage gap drops from 11.9% to 5.3% in column (5). Finally, we also add the reservation wages as an additional control variable. The striking result is that by including the reservation wage

[6] Since the exit rate from unemployment is defined as the job offer arrival rate times the probability that an offered wage exceeds the reservation wage, a higher reservation wage ceteris paribus reduces the probability of starting a new job.

in the wage decomposition, the gender gap in observed wages disappears in column (6).[7] In light of the fact that numerous previous wage decomposition studies have not accounted for the gender gap in reservation wages, one possible interpretation is that reservation wage is a key omitted variable that has been missing in previous decomposition exercises. Including an interaction term between the gender dummy and the reservation wage in column (7) has no significant influence which makes us confident that the correlation between reservation wages and realized wages is similar for men and women.

Comparing our results with previous studies, the gender wage gap for our sample of newly unemployed individuals in Germany is substantially lower than that of the full population (e.g. Bauer and Sinning, 2010) and also lower than that of highly educated individuals holding an university degree (Machin and Puhani, 2003). Bauer and Sinning (2010) find a raw gender wage gap of about 33% using SOEP data from 2004, with an unexplained gap of 11% left after controlling for observed characteristics. Machin and Puhani (2003) observe a raw gap of 28% for graduates, which decreases to 18% by including control variables. The unexplained gender gap for our estimation sample is only half the full population gap and one third of the gap for graduates.[8] One potential explanation is the fact that we observe a larger number of individual characteristics, especially labor market history and personality traits. However, the raw gender gap is also substantially lower for our sample (about 12%), which indicates that the differences are not entirely caused by the control variables. Assuming that our sample of newly unemployed individuals represents the lower part of the wage distribution, while the sample of graduates used by Machin and Puhani (2003) represents the upper part of the distribution, the increasing unexplained gender gap suggests the presence of glass ceiling effects in Germany, which is in line with the results of Arulampalam, Booth, and Bryan (2007) who detect an increasing gender gap within the wage distribution for Germany. However, their estimates – without controlling for reservation wages – also suggest a higher gender gap (12-20%) than our results.

[7]Our main analysis focuses on individuals searching for full-time employment in order to mitigate issues related to selection into the labor market. One can argue, however, that women searching for full-time employment are a selective sample of all women while this type of selection is less likely to occur for men. Therefore, we also present our main estimation results for a sample including all individuals searching for any type of employment in Table A.1 in the Appendix. The overall pattern is generally similar to the sample of job-seekers searching for full-time only.

[8]For this comparison, we consider the estimates of log wage equation including all covariates but not the reservation wage (column (5) of Table 3).

4 Examine the Gender Gap in Reservation Wages

4.1 Why do Women Have Lower Reservation Wages?

Reservation wages can be viewed as a measure of a person's eagerness or reluctance to accept employment. The level of the reservation wage plays a key role in theoretical models of job search and labor market participation (Mortensen, 1986). For unemployed persons, it helps determine the unemployment duration and the speed at which they will be reintegrated into the labor market (e.g. Rogerson, Shimer, and Wright, 2005). In research that focuses on examining the role of search behavior differences in determining gender wage differentials, wage differentials across groups can stem from three distinct sources: (i) exogenous differences in reservation wages, (i.e. different preferences for leisure), (ii) differences in search friction (i.e. differences in labor market behavior), and (iii) differences in productivity.

Bowlus (1997) finds that 20-30% of the US male-female wage differential can be explained by the first two factors. For the UK, Bowlus and Grogan (2009) find that reservation wages contribute to explaining 25% of the gender wage differential for university educated full-time workers and 33% of the gender gap for O-level educated workers. Given their estimated model parameters, they argue that the only way their search model can explain such a gender gap is that females have a much smaller value of non-market time while unemployed than males. On the other hand, Sulis (2011) points out the importance of differences with respect to search frictions which is an important source of the observed gender wage differential.[9]

Search theory also suggests that gender differences in wage offer distributions could give rise to gender differences in reservation wages. In an equilibrium search model, gender wage differentials can emerge because heterogeneous firms can have different pay policies and offer different wages to men and women. For example, Blackaby, Booth, and Frank (2005) show that, in the UK academic labor market, male-female differences in the arrival rate of outside offers are associated with females obtaining relatively low pay for a given rank. Thus, women who have experienced such discrimination in the past might adjust their reservation wages downwards to increase their future employment prospects. It is therefore possible that gender differences with respect to reservation wages might be a simple realization of the expected

[9]In order to account for differences with respect to the job search behavior, we include information on the usage of different search channels, the willingness to apply for vacancies which involve a relocation and the search intensity, as control variables into our estimations. However, these variables do not seem to be an important factor in explaining the gender reservation wage gap in our data.

discrimination against women in the labor market.[10]

It appears plausible that reservation wages might be interpreted as an important omitted variable proxying for both expectations and unobserved ability in our wage decompositions. The reservation wage depends on the job offer arrival rate, the job destruction rate and the wage offer distribution (e.g. Mortensen and Neumann, 1988). To the extent that individuals with lower productivity receive fewer wage offers and experience longer unemployment spells, leading them to lower their expectations and reservation wages, we would see a positive correlation between ability and reservation wages. Applying a job search model on U.S. data, Flabbi (2010) estimates women's productivity to be 6.5% lower, while two-thirds of the earning differential can be explained by discrimination. However, in contrast to previous studies, our results suggest that expected discrimination, instead of actual discrimination, might be sufficient to induce a gender wage gap. Once these difficult to quantify variables are controlled for, the gender gap in wages disappears. In related research on the black-white wage gap, Neal and Johnson (1996) report that controlling for abilities via the use of the Armed Forces Qualification Test eliminates the wage gap for young women and much of it for young men. The authors argue that this is because the test scores serve as an racially unbiased measure of basic skills that helps predict actual job performance. Just as Neal and Johnson (1996) find that large skill gaps between blacks and whites are important determinants of the wage gap between blacks and whites, we find that a gender gap in reservation wages is an important determinant of the gender wage gap. The difference is that in our context, reservation wages likely proxy for more than just ability and potentially also proxy for differing expectations.

4.2 Decomposition of the Reservation Wage Gap

A natural question that arises from our analysis of the gender wage is whether the lower observed wages for women are an empirical realization of having lower reservation wages. As an attempt to get to the root of the problem, we examine in more detail the gender gap in reservation wages at wave 1. Corresponding to the analysis done in the bottom part of Table 3 which examined the gender wage gap for those currently employed (n=1,974), we first examine the gender gap in reservation wages for this same sample of individuals (top panel of Table 4). Next, we perform the same decomposition for two alternative larger samples whose sample sizes are provided in Table 1 in order to examine whether sample attrition and selection into

[10] However, estimating the contribution of differences in the arrival rate of job offers to gender wage differentials is difficult in a reduced form econometric setting as the wage offer distribution is not observed. Note that the wage offer distribution is not the same as the observed wage distribution of workers at a given point in time as workers tend to move up the wage range. This implies that the observed wage distribution would be to the right of the offer distribution.

employment have an effect on our results. These are individuals interviewed in wave 1 and individuals interviewed in wave 2 (see middle and bottom panel of Table 4).

The raw gender gap is similar for all samples and is about 13%, implying that women expect significantly lower wages than men. Note that this is very close to the raw gender wage gap of 11.9% we saw in Table 3. We again sequentially add the four groups of control variables in columns (1)-(5). Since women in our sample are generally better educated but have lower reservation wages the gap increases slightly by adding the educational variables in column (1). Socio-demographics, as well as personality and search variables have only a small impact in reducing the gender gap in reservation wages, while again the labor market history variables in column (3) seem to have the highest explanatory power. In general, we can explain a larger part of the reservation wage gap for those individuals who are employed in the second wave. When we include all four groups of covariates, a gender gap in reservation wages of 10.5% emerges for all individuals interviewed in wave 1, whereas it drops to 7.1% when we focus on those who are employed in wave 2.

[Insert Table 4 about here]

The previous results show a big and significant gender gap in reservation wages that is linked to the subsequent gender gap in realized wages. However, it is not clear whether reservation wages affect wages or vice versa. For instance, based on former experiences and outside information, women anticipate that they are likely to receive a lower wage than comparable men and may thus reduce their reservation wages to increase their employment prospects. Therefore, it is not clear whether the gender wage gap arises due to an initial reservation wage gap or because the wage gap induces the reservation wage gap. In order to estimate the relative importance of past wage levels on current reservation wages, we use information about the last wage before entry into unemployment. It is possible that women who are confronted with relatively low wages in the past might reduce their expectations regarding future earnings and set lower reservation wages. By including the previous wage in a model explaining the determinants of reservation wages, we hope to get a good idea of how much reservation wages are influenced by former realized wages. In column (6) of Table 4, we can see that including the previous wage reduces the reservation wage gap but not by a considerable amount. A significant wage gap of 8.5% is found for all individuals interviewed in wave 1. For those employed in wave 2, a gap of 5.6% still remains unaccounted for. Including additionally some measure for the individual expectations about future employment prospects, expected program participation and life satisfaction in column (7) has nearly no impact on the reservation wage gap.

Finally, the reservation wages gap could simply express gender differences with respect to preferences or personality traits we do not observe in our survey, for example the tendency for males to be overconfident (see Barber and Odean, 2001) or to the fact that women generally tend to be more risk averse (Eckel and Grossmann, 2008). This risk preference could manifest itself in terms of lower reservation wages. Pannenberg (2010) uses the SOEP and finds that risk aversion and reservation wages are negatively correlated, where risk averse job seekers are found to have 40% lower reservation wages. Moreover, Kleinjans and Fullerton (2013) show that women have a stronger preference for occupations with higher social prestige, which results in lower reservation wages. Goldin (2014) argues that women's lower wages could be a result of their higher preference for more workplace flexibility. This not only includes the number of working hours but also the continuity of these working hours. As a desire for a flexible schedule comes with a price, such preferences are likely to be reflected in their wage expectations and reservation wages. We explore this latter interpretation by including some additional personality characteristics for a smaller sub-sample of 1,353 individuals for whom these variables are available. This includes attributes on risk-behavior, trust, patience and reciprocity.[11] As shown in Table A.2 in the Appendix, the gender gap in reservation wages for this subsample is slightly smaller than for the full estimation sample, while including the additional personality traits has nearly no impact on the reservation wage gap. Women still have significantly lower reservation wages of about 6.8% statistically significant at the 1%-level. Within the context of the BO decomposition we are able to explain about 40% of the gender gap in reservation wages.

4.3 Heterogeneity in the Wage and Reservation Wage Gap

In order to take a closer look at the role of the gender gap in reservation wages in influencing the gender gap in observed wages, we re-estimate the gender gap in reservation wages and realized wages for different subgroups and at different quantiles of the distribution. The idea is that if it is possible to find a subgroup where there is no gender gap in reservation wages, then if reservation wages do indeed play a key role in explaining wage gaps, we might not find a gender gap in observed wages either. Table 5 presents the subgroup estimates for decomposing the wage and reservation wage gaps, including all individual characteristics and the previous wage as control variables.

[11] As in our baseline model, we also include measures for openness, conscientiousness, extraversion, neuroticism and the locus of control which allows us to control in a very detailed way for potential gender differences in attitudes and personality traits.

Heterogeneity by Age First, we compare the gender gap for different subgroups based on individuals age. For the youngest subgroup, job seekers younger than 25 years, the reservation wage gap of 3.8% is below that of the full sample (5.6%) and statistically insignificant. Interestingly, we find that there is no gender gap in reservation wages for those who are younger. Furthermore, there is also no corresponding gender gap in observed wages in wave 2 for this subgroup. The gender gap in reservation wages appears to increase with age. This is consistent with Goldin (2014) who observes that something happens to women's earnings relative to men as they age.

[Insert Table 5 about here]

Heterogeneity by Labor Market Experience Differing expectations regarding discrimination are another plausible explanation for the gender gap in reservation wages. Assuming that these expectations are related to one's own labor market experiences, it is useful to distinguish between people with low/high labor market experience (which we define as below/above the median in our data). Clearly, labor market experience will be correlated with age but due to the different educational attainments between men and women in our data and fertility spells for women, this subgroup analysis based on experience is not equivalent to a subgroup analysis based on age. We expect women who have spent only a short time in employment to be less likely to have experienced discrimination and hence also be less likely to expect discrimination in future jobs. Our measure of experience is computed using the ratio of months spent in employment and the individual age in years minus 18 in order to disentangle potential age and experience effects. Based on using median experience as the dividing line, we estimate gender gaps for those with low experience and those with high experience. Columns (3) and (4) in Table 5 show that there is no gender gap in reservation wages for those with low experience and also no corresponding gender gap in observed wages in wave 2. This is consistent with the findings we have just seen for the age subgroups and not surprising, given that younger workers are also expected to have less labor market experience. For those with more experience, a significant gender gap in reservation wages emerges.

Heterogeneity by Education As educational qualifications can influence wage expectations and wage offers, we also examine the gender gap for individuals with A-level qualifications or higher, and those with less than A-level qualifications. Here, we again find a pairing of there being no gender gap in reservation wages and observed wages for those with higher than A-level qualifications, reinforcing the notion that the two gaps could be closely related.

Heterogeneity by Family Status Finally, we also examine subgroups based on whether the individual has any children. Recently, Brown, Roberts, and Taylor (2010a) suggest that a potential gender reservation wage differential may lead to different labor market participation rates between men and women. As the presence of children in a household might raise the opportunity cost of accepting work outside the home, and if this affects women more so than men (because women are more likely to be the ones taking care of the children), it is possible that children could increase the reservation wages of women relative to those of men. This implies that women with children might have more difficulties receiving job offers above their reservation wage and consequently be less likely to find employment. As women tend to have more children at home than men, children should narrow the reservation wage gap. However, our estimation results in Table 5 suggest that the reservation wage gap for individuals without any children (3.9%) is below that of the full-sample, while the presence of children increases the reservation wage gap substantially. A potential explanation for why our results differ to those reported by Brown, Roberts, and Taylor (2010a) is our focus on unemployed individuals searching for full-time employment only. As highlighted by Kunze and Troske (2012), gender differences in job search behavior occur mainly among workers aged 24 to 35 as these are the prime child bearing and rearing ages for women. It is plausible that the presence of children influences women's job search behavior by making them less likely to seek full-time employment. This implies that many women with children will not be included in our analysis sample. The unemployed mothers in our sample who do actually seek full-time employment might be doing so because they are under financial pressure to do so, which makes them more likely to accept lower paid jobs.

[Insert Table 6 about here]

RIF Quantile Decomposition In order to investigate the gender gap heterogeneity among the (reservation) wage distribution we apply the RIF decomposition, introduced in Section 3.1. Table 6 summarizes the decomposition results of realized wages in wave 2 and reservation wages in wave 1 for several alternative specifications. By way of comparison, the first column shows the decomposition results at the mean based on the BO decomposition. We find that 47.3% of the raw gender gap can be explained by educational attainment, socio-demographic characteristics and labor market history. When personality traits and job search characteristics are included, the explained part of the wage gap increases up to 55.3%. Including the reservation wage as a control variable increases the wage gap that is explained by observed characteristics up to 79.0%. This implies the reservation wage explains 23.7% of the gender wage gap, leaving the remaining 21.0% of the gap to be accounted for by discrimination and unobserved abilities.

In order to get an idea of the nature of the heterogeneity, the other columns presents the estimates of the RIF decomposition for different percentiles of the log wage distribution (top panel) and the log reservation wage distribution (bottom panel). Women earn between 6.8% and 18.2% less than men, with the highest difference at the 90^{th} percentile. We estimate the RIF decomposition again for several alternative specifications. Model 1 is the baseline specification, including only educational variables, socio-demographics and labor market history. Adding personality traits and job search characteristics (Model 2) does not increase the explained part of the wage gap substantially. The explained part of the gender wage gap improves only for the 90^{th} percentile by 23.2%. Overall, between 21.3% and 66.9% of the wage gap can be explained by the control variables. Including the reservation wage as an explanatory variable (Model 3) increases the explained portion of the gap substantially for all percentiles. Regarding the median, this gain is about 33.4%. The model does especially well in explaining the gender wage gaps at the 20^{th}, 50^{th}, 60^{th} and 90^{th} percentiles.

Regarding the unconditional gender wage gap we find some evidence for the glass ceiling hypothesis (a higher gender gap in the upper part of the wage distribution) in line with Albrecht, Björklund, and Vroman (2003) and Arulampalam, Booth, and Bryan (2007). However, this effect completely disappears when control variables are included. Looking at the gap for the 80th and 90th percentiles when including all control variables and reservation wages, there is some evidence in our data for a decrease in the size of the gap at the tail of the distribution. As our sample focuses on unemployed workers, perhaps a more appropriate comparison to make is with the results in De la Rica, Dolado, and Llorens (2008) who analyse the gender wage gap for less-educated workers in Spain. Instead of a glass ceiling, they report the opposite finding that the wage gap decreases along the wage distribution, similar to our decomposition of the gender wage gap when controlling for reservation wages. Due to our focus on the newly unemployed, we are essentially examining the gender pay gap at the lower to middle quantiles of the wage distribution of the overall working population. Individuals at the very top of the wage distribution are not likely to be included in our sample, which limit potential glass ceiling effects from emerging.

Performing the BO and the RIF decompositions of the reservation wage gap, we find that the control variables explain less of the reservation wage gap than of the gap in observed wages.[12] Based on the BO decomposition, the baseline covariates (education, socio-demographics and labor market history) are able to explain 35.5% of the gap, while controlling for personality traits and job search characteristics increases the percentage of the gap explained up to 43.4%. Including the last observed wage helps to explain a further 11.6% of the reservation wage gap. When we employ the RIF quantile decomposition on the reservation wage gap, We find that the gap varies between 7.1% and 15.9%, with the highest difference for the 20$^{\text{th}}$ percentile. By including all control variables with the exception of the previous wage (Model 2), we can explain between 19.0% and 91.8% of the reservation wage gap. Relative to the other percentiles, the model does especially well in explaining the reservation wage gap for the 80$^{\text{th}}$ percentile. A large part of the gap, however, remains unexplained in other quantiles of the reservation wage distribution.

5 Conclusion

The economic literature typically finds a persistent wage gap between men and women. In this paper, based on a sample of newly unemployed persons seeking work in Germany, we find that the gender wage gap disappears once we control for reservation wages in a wage decomposition exercise. Despite a concern with reservation wages being potentially endogenous, we believe that the exploratory results in our paper can help one better understand what the driving forces are behind the gender wage gap. As the gender gap in actual wages appears to mirror the gender gap in reservation wages, there is a clear need to better understand why there are gender differences in the way reservation wages are set in the first place. Whereas a gender gap in actual wages could reflect either productivity differences or discrimination, a gender gap in reservation wages essentially reflects either productivity differences or differing expectations. Since we have been only partially successful to explain the gender gap in reservation wages for our sample, it is possible that reservation wages measure some characteristics that are not easily quantifiable and that could be obtained from a single question in a survey questionnaire. We can think of several different explanations.

First, reservation wages are likely to be correlated with unobserved productivity differences between men and women. As reservation wages reflect a worker's own valuation of their time while employed, high productivity workers are likely to set relatively higher reservation wages. On the other hand, lower productivity workers will tend to receive fewer wage offers and experience longer unemployment spells (e.g. by virtue of signaling lower observable ability

[12] This is not very surprising since otherwise the reservation wage could not have that much explanatory power within the wage equation.

in a job interview). This will lead them to lower their reservation wages over time in order to increase their employment prospects. In our data, we find that individuals with higher reservation wages are more likely to be employed even though there is no corresponding gender gap in employment prospects. The most plausible explanation for this finding is that there exist some unobserved characteristic such as productivity that helps determine reservation wages and employment prospects simultaneously.

On the other hand, differing expectations can be important in explaining the reservation wage gap and might arise for various reasons. Our empirical findings that the gender gap in reservation wages appears to increase with age and labor market experience suggests that expectations are changing over time in a non-symmetric fashion for men and women. In addition, the search theory literature suggests that a gender gap in reservation wages might exist because females have a much smaller value of non-market time while unemployed than males, or that they encounter different wage offer distributions and work in segmented labor markets. Differing expectations in reservation wages could also arise due to gender differences in preferences or personality traits. One can speculate that higher reservation wages for males could reflect their tendency to be more competitive or overconfident, which could translate to better wage outcomes from salary negotiations. However, accounting for both expectations and attitudes using measures such as risk-behavior, trust, patience and reciprocity has no impact on the gender gap in reservation wages. To the extent that past discrimination matters, it might also be the case that women expect lower wages for performing the same job as men.

Therefore, at this point, we conclude that both productivity differences and differing expectations appear to matter in explaining the gender gap in reservation wages. Future research might want to focus on designing survey questions that better elicit information on the nature of such differing expectations to help disentangle between these factors. For example, questions can be asked regarding expectations for flexible time at work and on the continuity of work hours, and how these might change over the life course. Finally, as our sample only includes unemployed individuals seeking work, we are not able to generalize our results to all working age men and women. As such, future research might also want to gather survey data on reservation wages from all labor market participants and not just those currently unemployed and seeking work. We are not aware of any data sets that do so.

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Tables and Figures

Table 1: Reservation Wages and Labor Market Outcomes

	Men	Women	p-value
Soliciting the reservation wage in wave 1			
No. of observations: Interviewed in wave 1	3893	2276	
Step 1:			
Expected monthly net income	1571	1305	0.00
Expected weekly hours of work	42.34	40.23	0.00
Step 2:			
Willing to work for less than expected wage	0.72	0.74	0.08
Monthly minimum income	1280	1040	0.00
Expected weekly hours of work for min. income	39.77	37.45	0.00
Resulting reservation wage (in Euro)	7.57	6.61	0.00
Wage per hour in last job[1]	7.83	6.82	0.00
Ratio of reservation and previous wages[1]	1.12	1.09	0.09
Labor market outcomes in wave 2			
No. of observations: Interviewed in wave 2	2022	1212	
Employed at wave 2	0.63	0.63	0.86
No. of observations: Employed in wave 2	1235	739	
Realized wage in wave 2 (in Euro)	9.27	7.93	0.00
Accepting an wage below the reservation wage	0.34	0.32	0.39
Difference between reservation wage and accepted wage	1.22	0.93	0.41
No. of observations: Searching for employment in wave 2	508	308	
Reservation wage in wave 2	7.60	6.19	0.00
Reservation wage in wave 2 $<$ wave 1	0.46	0.45	0.78
Difference between reservation wage wave 1 and wave 2	-0.01	-0.08	0.65

Note: The upper part of the table shows the generation process of the reservation wage. In a first step the individuals are asked for their expected monthly income and how many hours they expect to work for such a job. In a second step they are asked if they are willing to work for less than this expected income and how many hours of work they expect for this job. p-values are based on t-tests on mean euqality.

[1]Observed for 3336 men and 1847 women who were employed before.

Table 2: Selected Descriptive Statistics by Gender

	Men	Women	p-value
Number of observations	3893	2276	
Education			
School leaving degree			
None, special needs, other	0.03	0.02	0.00
Lower secondary school	0.38	0.23	0.00
Middle secondary school	0.38	0.47	0.00
Specialized upper secondary school	0.21	0.29	0.00
Vocational training			
None	0.10	0.10	0.74
Internal or external professional training, others	0.70	0.71	0.60
Technical college or university degree	0.20	0.19	0.40
Socio-demographic characteristics			
West Germany	0.67	0.67	0.68
German citizenship	0.95	0.95	0.41
Migration background	0.15	0.15	0.59
Age	35.30	35.26	0.89
Married (or cohabiting)	0.34	0.32	0.19
Children			
No children	0.73	0.77	0.00
One child	0.16	0.16	0.75
Two (or more) children	0.11	0.07	0.00
Labor market history			
Unemployment benefit recipient	0.82	0.81	0.45
Level of unemployment benefits in €	630.30	519.80	0.00
Months in unemployment (div. by age-18)	0.83	0.76	0.20
Months in employment (div. by age-18)	9.08	7.60	0.00
Employment status before unemployment			
Employed	0.71	0.66	0.00
Subsidized employment	0.07	0.06	0.08
School, apprentice, military, etc.	0.14	0.18	0.00
Maternity leave	0.00	0.03	0.00
Personality and job search characteristics			
Openness	5.01	5.11	0.00
Conscientiousness	6.19	6.39	0.00
Extraversion	5.09	5.30	0.00
Neuroticism	3.55	3.97	0.00
Locus of control	5.08	4.98	0.00
Number of own applications (mean)	17.29	17.22	0.93
Job search by contacting friends, acquaintances, family etc.	0.84	0.84	0.82
Applied for vacancies for which you would have to move	0.32	0.29	0.05

Note: All numbers are shares unless indicated otherwise. Variables are measured at entry into unemployment. Personality traits are measured with different items on a 7-Point Likert-Scale. p-values are based on t-tests on mean euqality. Additional variables that are not listed here, but will be used later on in the decompoistion analysis: local labor market conditions (unemployment rate), month of entry into unemployment and the time between the entry into unemployment and the interview.

Table 3: Decomposition of the gender gap in labor market outcomes

	Raw gap	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Employed in wave 2								
Female	0.003	-.004	0.005	0.01	0.024	0.018	0.024	-.154
	(0.018)	(0.018)	(0.018)	(0.018)	(0.017)	(0.018)	(0.017)	(0.097)
Log reservation wage							0.065^{**}	0.031
							(0.035)	(0.035)
Female × Log reservation wage								0.094^{*}
								(0.005)
No. of observations	3234	3234	3234	3234	3234	3234	3234	3234
R^2	9.63e-06	0.03	0.021	0.031	0.089	0.143	0.144	0.145
Adjusted R^2	-.0003	0.028	0.017	0.023	0.087	0.129	0.13	0.131
Log hourly wage in wave 2								
Female	$-.119^{***}$	$-.127^{***}$	$-.100^{***}$	$-.055^{***}$	$-.101^{***}$	$-.053^{**}$	-.025	-.075
	(0.022)	(0.021)	(0.021)	(0.021)	(0.022)	(0.021)	(0.020)	(0.109)
Log reservation wage							0.398^{***}	0.388^{***}
							(0.034)	(0.040)
Female × Log reservation wage								0.026
								(0.056)
No. of observations	1974	1974	1974	1974	1974	1974	1974	1974
R^2	0.015	0.122	0.12	0.209	0.051	0.298	0.346	0.346
Adjusted R^2	0.014	0.119	0.114	0.198	0.046	0.279	0.327	0.327
Control variables								
Education		✓				✓	✓	✓
Socio-demographics			✓			✓	✓	✓
Labor market history				✓		✓	✓	✓
Personality and search variables					✓	✓	✓	✓

Note: Depicted are decomposition results using OLS. */**/*** indicate statistically significance at the 10%/5%/1%-level. Standard errors are shown in parenthesis.

Table 4: Decomposition of the reservation wage gap in wave 1

	Raw gap	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Sample: Employed in wave 2								
Female	-.125***	-.130***	-.110***	-.070***	-.109***	-.071***	-.056***	-.052***
	(0.016)	(0.015)	(0.015)	(0.014)	(0.016)	(0.014)	(0.012)	(0.012)
Log previous wage							0.316***	0.316***
							(0.016)	(0.016)
No previous wage							2.073***	2.076***
							(0.106)	(0.106)
No. of observations	1974	1974	1974	1974	1974	1974	1974	1974
R^2	0.03	0.204	0.194	0.312	0.081	0.436	0.530	0.535
Adjusted R^2	0.03	0.202	0.189	0.302	0.077	0.42	0.517	0.520
Sample: Interviewed in wave 2								
Female	-.133***	-.134***	-.126***	-.096***	-.119***	-.097***	-.080***	-.077***
	(0.012)	(0.012)	(0.011)	(0.011)	(0.013)	(0.011)	(0.010)	(0.010)
Log previous wage							0.284***	0.285***
							(0.012)	(0.012)
No previous wage							1.838***	1.844***
							(0.079)	(0.079)
No. of observations	3234	3234	3234	3234	3234	3234	3234	3234
R^2	0.034	0.191	0.21	0.256	0.073	0.409	0.496	0.500
Adjusted R^2	0.034	0.19	0.206	0.25	0.071	0.399	0.487	0.490
Sample: Interviewed in wave 1								
Female	-.133***	-.136***	-.126***	-.102***	-.122***	-.105***	-.085***	-.083***
	(0.009)	(0.009)	(0.008)	(0.008)	(0.009)	(0.008)	(0.007)	(0.007)
Log previous wage							0.283***	0.283***
							(0.009)	(0.009)
No previous wage							1.820***	1.815***
							(0.059)	(0.059)
No. of observations	6169	6169	6169	6169	6169	6169	6169	6169
R^2	0.034	0.175	0.198	0.199	0.069	0.37	0.457	0.461
Adjusted R^2	0.033	0.174	0.196	0.195	0.067	0.365	0.452	0.455
Control variables								
Education		✓				✓	✓	✓
Socio-demographics			✓			✓	✓	✓
Labor market history				✓		✓	✓	✓
Personality and search variables					✓	✓	✓	✓
Expectations								✓

Note: Depicted are decomposition results of the gender gap in reservation wages in wave 1 using OLS. */**/*** indicate statistically significance at the 10%/5%/1%-level. Standard errors are shown in parenthesis. Expectation variables in column (7) include: Life satisfaction, expected probability to participate in active labor market policies and expected probability to find a new job in the next 6 months.

Table 5: Decomposition of the gender gap for different subgroups

	Age in years		LM experience[1]		A-level		Children	
	≤25	>25	Low	High	No	Yes	No	Yes
Sample: Employed in wave 2	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Log reservation wage in wave 1								
Female	-.038	-.059***	-.018	-.101***	-.081***	-.020	-.039***	-.130***
	(0.031)	(0.014)	(0.018)	(0.016)	(0.015)	(0.025	(0.014)	(0.035))
Log previous wage	0.206***	0.341***	0.335***	0.301***	0.319***	0.313***	0.28***	0.314***
	(0.051)	(0.018)	(0.026)	(0.02)	(0.019)	(0.032)	(0.019)	(0.044)
No previous wage	1.345***	2.279***	2.279***	1.874***	2.039***	2.152***	1.853***	2.025***
	(0.310)	(0.118)	(0.17)	(0.136)	(0.123)	(0.212)	(0.124)	(0.287)
No. of observations	353	1621	989	985	1369	605	1426	345
R^2	0.328	0.542	0.546	0.569	0.479	0.539	0.488	0.608
Adjusted R^2	0.211	0.526	0.519	0.544	0.457	0.495	0.468	0.536
Log hourly wage in wave 2								
Female	-.053	-.061**	-.021	-.097***	-.070***	-.024	-.049**	-.027
	(0.049)	(0.024)	(0.028)	(0.032)	(0.026)	(0.036)	(0.024)	(0.054)
No. of observations	353	1621	989	985	1369	605	1426	345
R^2	0.207	0.307	0.367	0.271	0.24	0.362	0.252	0.466
Adjusted R^2	0.076	0.284	0.331	0.229	0.21	0.304	0.224	0.373
Control variables								
Education	✓	✓	✓	✓	✓	✓	✓	✓
Socio-demographics	✓	✓	✓	✓	✓	✓	✓	✓
Labor market history	✓	✓	✓	✓	✓	✓	✓	✓
Personality and search variables	✓	✓	✓	✓	✓	✓	✓	✓

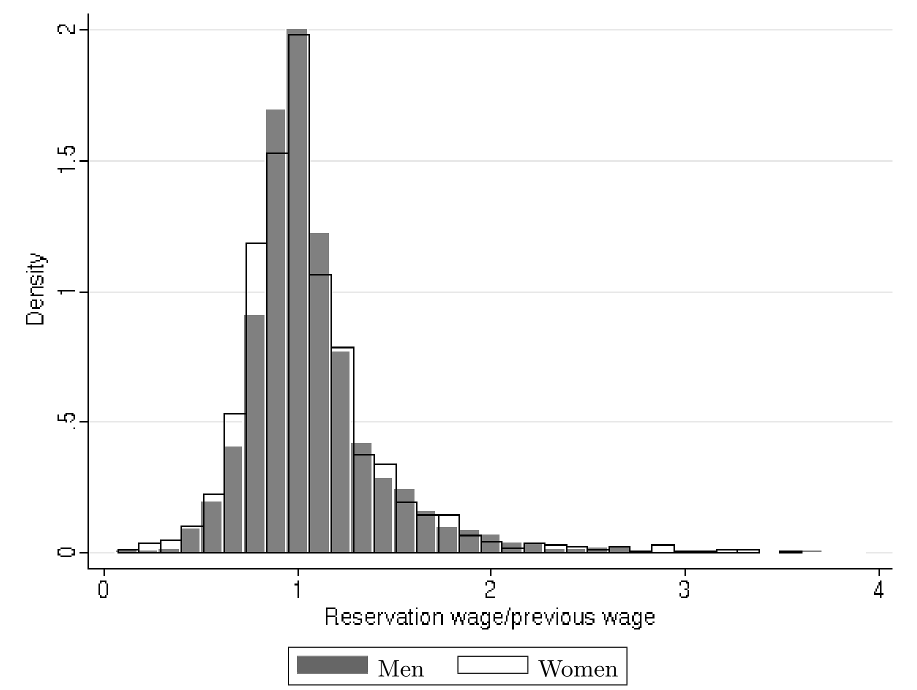
Note: Depicted are decomposition results of the gender gap in reservation wages in wave 1 (upper part) and the realized wage in wave 2 (lower part) using OLS. The decomposition of the realized wage gap does not explicitly not include the reservation wage as control variable. */**/*** indicate statistically significance at the 10%/5%/1%-level. Standard errors are shown in parenthesis.
[1]Labor market (LM) experience refers to the lifetime months in employment divided by age-18. Low (High) LM experiences contains all values below (above) the median.

Table 6: Decomposition of the Gender Gap in Realized Wages and Reservation Wages

Sample: Employed in wave 2	Mean	Quantile 10th	20th	30th	40th	50th	60th	70th	80th	90th
Log hourly wages										
Male	2.100	1.669	1.797	1.913	2.011	2.103	2.191	2.318	2.437	2.625
Female	1.981	1.564	1.729	1.831	1.906	2.022	2.082	2.150	2.275	2.443
Gender Gap	0.119	0.105	0.068	0.082	0.105	0.081	0.109	0.168	0.162	0.182
Model 1:										
Explained	0.056	0.023	0.035	0.033	0.032	0.043	0.051	0.069	0.067	0.093
	47.3%	22.1%	51.3%	41.0%	30.3%	52.8%	46.7%	41.2%	41.6%	50.9%
Unexplained	0.063	0.082	0.033	0.048	0.073	0.038	0.058	0.099	0.095	0.089
Control Variables:	education, socio-demographics, labor market history									
Model 2:										
Explained	0.066	0.022	0.04	0.032	0.032	0.047	0.058	0.078	0.079	0.122
	55.3%	21.3%	58.5%	38.9%	30.1%	57.5%	53.4%	46.5%	48.4%	66.9%
Unexplained	0.053	0.083	0.028	0.05	0.074	0.034	0.051	0.09	0.084	0.06
Control variables:	education, socio-demographics, labor market history, personality traits, job search characteristics									
Model 3:										
Explained	0.094	0.039	0.06	0.054	0.057	0.074	0.084	0.106	0.114	0.164
	79.0%	36.9%	88.6%	65.8%	54.6%	90.9%	77.6%	63.0%	70.4%	90.1%
Unexplained	0.025	0.066	0.008	0.028	0.048	0.007	0.024	0.062	0.049	0.018
Control variables:	education, socio-demographics, labor market history, personality traits, job search characteristics, reservation wage									
No. of observations	1974	1974	1974	1974	1974	1974	1974	1974	1974	1974
Log reservation wage										
Male	2.010	1.649	1.789	1.829	1.938	1.975	2.063	2.166	2.260	2.465
Female	1.885	1.549	1.630	1.758	1.830	1.867	1.972	2.033	2.172	2.307
Gender Gap	0.125	0.099	0.159	0.071	0.108	0.108	0.091	0.133	0.089	0.158
Model 1:										
Explained	0.044	0.024	0.022	0.027	0.032	0.036	0.046	0.048	0.064	0.059
	35.5%	24.1%	13.8%	38.0%	29.5%	33.5%	50.7%	36.0%	72.4%	37.4%
Unexplained	0.08	0.075	0.137	0.044	0.076	0.072	0.045	0.085	0.024	0.099
Control Variables:	education, socio-demographics, labor market history									
Model 2:										
Explained	0.054	0.024	0.03	0.035	0.042	0.052	0.059	0.062	0.081	0.072
	43.4%	24.0%	19.0%	49.1%	38.6%	47.9%	65.1%	46.5%	91.8%	45.8%
Unexplained	0.071	0.075	0.129	0.036	0.066	0.056	0.032	0.071	0.007	0.086
Control variables:	education, socio-demographics, labor market history, personality traits, job search characteristics									
Model 3:										
Explained	0.069	0.032	0.038	0.045	0.052	0.063	0.07	0.076	0.097	0.091
	55.0%	32.8%	24.0%	62.5%	48.3%	58.3%	77.6%	56.8%	109.9%	57.6%
Unexplained	0.056	0.067	0.121	0.027	0.056	0.045	0.02	0.058	-.009	0.067
Control variables:	education, socio-demographics, labor market history, personality traits, job search characteristics, previous wage									
No. of observations	1974	1974	1974	1974	1974	1974	1974	1974	1974	1974

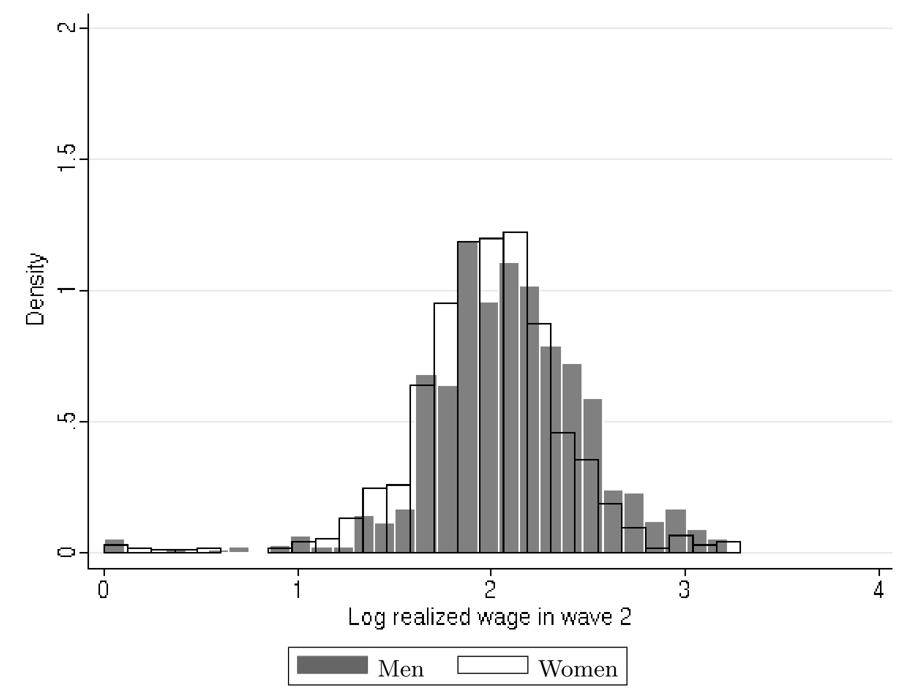
Note: The first column reports BO decomposition results at the average, while the other columns show RIF decomposition results for each quantile of the log (reservation) wage distribution. Full estimation results are available on request.

Figure 1: Ratio of Reservation Wage and Previous Wage



Note: Depicted is the ratio or reservation wages in wave 1 and previous wages if these are observed (n=5,183).

Figure 2: Log Wage Distribution by Gender



Note: Depicted is the log wage distribution for those individuals who are employed in wave 2 (n=1,974).

A Supplementary Tables

Table A.1: Decomposition of the gender gap (incl. part-time employment job seekers)

Sample: Employed in wave 2	Raw gap	(1)	(2)	(3)	(4)	(5)	(6)
Log reservation wage in wave 1							
Female	-.112***	-.111***	-.137***	-.051***	-.089***	-.066***	-.044***
	(0.013)	(0.012)	(0.012)	(0.012)	(0.014)	(0.013)	(0.012)
Log previous wage							0.323***
							(0.014)
No previous wage							2.103***
							(0.089)
No. of observations	2909	2909	2909	2909	2909	2909	2909
R^2	0.025	0.179	0.162	0.249	0.069	0.381	0.488
Adjusted R^2	0.024	0.177	0.159	0.242	0.065	0.369	0.476
Log hourly wage in wave 2							
Female	-.098***	-.099***	-.129***	-.028	-.073***	-.043**	-.017
	(0.018)	(0.017)	(0.017)	(0.017)	(0.02)	(0.018)	(0.018)
Log reservation wage							0.398***
							(0.026)
No. of observations	2909	2909	2909	2909	2909	2909	2909
R^2	0.011	0.117	0.103	0.173	0.044	0.272	0.327
Adjusted R^2	0.01	0.115	0.099	0.165	0.04	0.258	0.314
Control variables							
Education		✓				✓	✓
Socio-demographics			✓			✓	✓
Labor market history				✓		✓	✓
Personality and search variables					✓	✓	✓

Note: Depicted are decomposition results of the gender gap in reservation wages in wave 1 and realizeg wages in wave 2 for all individuals who search for any employment in wave 1 (including also part-time job seekers) and are employed in wave 2. */**/*** indicate statistically significance at the 10%/5%/1%-level. Standard errors are shown in parenthesis. In addition to our previous specifications, we also include control variables for the type of job search (full- or part-time employment).

Table A.2: Decomposition of the reservation wage gap in wave 1 (three cohorts of entry)

Sample: Interviewed in wave 1	Raw gap	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Female	-.113***	-.132***	-.118***	-.065***	-.100***	-.087***	-.076***	-.069***	-.068***
	(0.019)	(0.018)	(0.017)	(0.017)	(0.019)	(0.016)	(0.015)	(0.015)	(0.016)
Log previous wage							0.22***	0.221***	0.219***
							(0.02)	(0.02)	(0.02)
No previous wage							1.460***	1.462***	1.450***
							(0.128)	(0.128)	(0.129)
No. of observations	1353	1353	1353	1353	1353	1353	1353	1353	1353
R^2	0.025	0.187	0.208	0.309	0.067	0.447	0.497	0.506	0.508
Adjusted R^2	0.025	0.183	0.2	0.299	0.061	0.428	0.479	0.486	0.485
Control variables									
Education		✓				✓	✓	✓	✓
Socio-demographics			✓			✓	✓	✓	✓
Labor market history				✓		✓	✓	✓	✓
Personality and search variables					✓	✓	✓	✓	✓
Expectations								✓	✓
Risk, trust, patience and reciprocity									✓

Note: Depicted are decomposition results of the gender gap in reservation wages in wave 1 for only 3 cohorts of entry (June 2007, October 2007 and February 2008), for which we observe an additional set of personality traits on risk behavior, trust, patience and reciprocity. */**/*** indicate statistically significance at the 10%/5%/1%-level. Standard errors are shown in parenthesis.