Gender Discrimination and Promotions in a Labor Search Model

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Abstract

This paper presents a replication of Flabbi 2010 on Current Population Survey (CPS) data collected in 1995 as well as a re-estimation with data from the German Socio-Economic Panel (SOEP) collected in 2017. An extension to Flabbi's model is explored in which employees experience an exogenous promotion shock that occurs to women at prejudiced employers less frequently than women at unprejudiced employers and men. An identification strategy for the extension utilizing features in the SOEP data is suggested.

1 Introduction

According to the Bureau of Labor Statistics (BLS) women earn 82 cents on the dollar compared to their male counterparts in 2017; this is an improvement from the first year that complete earnings data was available, 1979, in which women only earned 62 cents on the dollar. Following this trend, we have another forty years until women's earnings will reach parity. Furthermore, the BLS reports that in 2016 approximately half of the management, professional, and related occupations were held by women, but only 27% of the chief executives were female. Understanding how women can enter positions of higher occupational levels would assist in decreasing the gender pay gap (*Women in the labor force* 2019).

In the United States, female labor force participation has greatly expanded with increased participation at younger ages and more time spent in the labor force (Goldin and Mitchell 2017). However, research has shown that there exists a glass ceiling for women (e.g. Maume 2004; Hultin 2003; Yap and Konrad 2009). A glass ceiling is defined by four criteria: an artificial barrier to the advancement of women, a gender difference that is more pronounced at higher levels, which carries over to the advancement (promotions and pay raises), and the inequality increases over the course of one's career (Cotter et al. 2001). A cross-national study found that there exists variation in the authority gender gap at all levels of management independent of differences in personal attributes and employment settings (Wright, Baxter, and Birkelund 1995).

Women are able to break through the glass ceiling to top management positions in companies with an increased proportion of females in lower- and middle-level management and decreased average management salary (Goodman, Fields, and Blum 2003). When increasing the proportion of women in managerial positions, especially at the highest levels, there is a reduction of the gender wage gap (Cohen and Huffman 2007). Specifically in non-manufacturing industries, the presence of women in top management positions leads to an increase in the proportion of females in lower-level management and an increased emphasis on employee development and promotion (Goodman, Fields, and Blum 2003). However this result is not representative, as there is evidence from Germany and the United States that female managers in gender-balanced industries face a wage penalty (Busch and Holst 2011; Cohen, Huffman, and Knauer 2009).

The economic literature has distinguished gender gaps as either being a product of wage discrimination or occupational segregation. Wage discrimination occurs when the returns to an employee's characteristics differ by the group the employee identifies with (in this paper, the group distinction is gender). Occupational segregation is said to be present when the distribution of occupations within one group are different from another. Occupational segregation has been decreasing over time and within cohorts in the United States, and this change has been attributed to better education for women and potentially less labor market discrimination for younger cohorts (Blau, Brummund, and Liu 2013). It has been argued that women are more risk averse and are less competitive than their male counterparts (Croson and Gneezy 2009), which has led some researchers to believe that there is a comparative disadvantage to women up for promotion, and companies overlook the better qualified female candidate (Lazear and Rosen 1990). However, these studies are outdated and there has not been economic research on the effects of job movements on wages for women compared to men.

In order to promote the advancement of professional women, we need to better understand the process by which women can earn promotions in both job title and salary. Does the presence of prejudiced employers lead to a decrease in wages for women? Could this distaste for women by prejudiced employers cause a reduced promotion rate for women, further extending the gender wage gap?

This paper explores these questions through a re-estimation of the model created by Flabbi 2010 in which the presence of prejudiced employers who experience a disutility from working with women lead to reduced wages for women. By including a proportion of prejudiced employers into the standard search-match-bargaining model, there is a reduction in the outside option for women inducing them to accept a job at a lower wage compared to men. After re-estimation, the model is extended to include a promotion shock impacting a worker's productivity that occurs with less frequency for women working for prejudiced employers. An estimation strategy is proposed with a discussion of variables that can be used for identification.

The organization of the paper is as follows. Section 2 presents the replication of Flabbi 2010 on data from the United States in 1995 (2.1) and Germany in 2017 (2.2). Then the extension of the model is presented in Section 3, with a description of the environment (3.1), value functions (3.2), wage equations (3.3), and equilibrium (3.4) prior to suggesting an identification strategy (3.5). Conclusions and future refinements are discussed in Section 4.

2 Replication of Flabbi 2010

To study the effect of employer prejudice on the labor market, Flabbi 2010 develops a search model that allows for the presence of prejudiced employers who have taste-based discrimination against women. By including some proportion of employers who experience a disutility from working with women, the model predicts a lower wage for women caused by a lower outside option. Through the mechanism of the flow disutility prejudiced employers face when working with female employees, the ex-ante reservation match productivity for women is higher at this meeting. Furthermore, this mechanism reduces the flow value of unemployment for women, shifting down the wage schedule for women compared to their male counterparts.

The continuous time random search-match-bargaining model has male and female workers ($J \in \{M, F\}$) and prejudiced and non-prejudiced employers ($I \in \{P, N\}$). There is a proportion p of prejudiced employers in the market who experience a flow disutility d of working with women. Workers can be employed or unemployed. Firms meet with unemployed workers following a Poisson process with arrival rate λ and there is an exogenous termination shock following a Poisson process with arrival rate η. Upon meeting, the types are revealed and a match-specific productivity x is drawn from a distribution with cumulative distribution function G. If a match is formed, wages w are determined through Nash bargaining with bargaining power coefficient α. The value of unemployment is ρU which equals the reservation wage rate. The hazard rate of unemployment is calculated and denoted by h.

The model is estimated using data on employment status, gender, wage (if employed) and on-going unemployment duration (if unemployed). Solving for the equilibrium and identifying the employed and unemployed data contributions leads to the following log-likelihood function

$$
\begin{aligned}
\ln L(\Omega; w, t) = {} & N_M \ln \frac{h_M}{\eta_M + h_M} + N_{UM} \ln \eta_M - h_M \sum_{i \in U_M} t_i + \sum_{i \in E_M} \ln \frac{\frac{1}{\alpha} g_M \left(\frac{w_i - (1-\alpha)\rho U_M}{\alpha} \right)}{\tilde{G}_M(\rho U_M)} \\
& + N_F \ln \frac{h_F}{\eta_F + h_F} + N_{UF} \ln \eta_F - h_F \sum_{i \in U_F} t_i \\
& + \sum_{i \in E_F} \ln \left(\frac{\frac{(1-p)}{\alpha} g_F \left(\frac{w_i - (1-\alpha)\rho U_F}{\alpha} \right)}{\tilde{G}_F(\rho U_F)} + \frac{\frac{p}{\alpha} g_F \left(\frac{w_i + \alpha d - (1-\alpha)\rho U_F}{\alpha} \right)}{\tilde{G}_F(\rho U_F + d)} \right)
\end{aligned} \tag{1}
$$

The log-likelihood function assumes that the only parameter in common between men and women is the discount rate ρ. The productivity distribution G is assumed to be the lognormal distribution with location and scale parameters as functions of μ and σ, which can be gender-specific.

The model is estimated through maximizing the log-likelihood function. Estimations were done using Python and the code is available on Github.[1] The identifying functions in Flabbi 2010 were written by hand with minimal use of Python packages. The optimization was conducted by minimizing the absolute value of the log-likelihood initiated at the estimation values in Flabbi 2010 using the BFGS algorithm.

2.1 United States' Current Population Survey, 1995

First the model is estimated using the same data as in Flabbi 2010 collected by the Current Population Survey (CPS) in 1995. The sample includes white individuals who are either working full time or unemployed, have a college degree or more, and are between the ages of 30 to 55. These sample restrictions ensure homogeneity in line with the ex-ante identical assumption in the model. For each individual, the econometrician is given their gender and employment status; if the individual is employed the hourly wage is provided, otherwise we observe the on-going unemployment duration in months. The data set contains 2,179 observations and descriptive statistics are presented in Table 1.

The proportion of unemployed individuals in the sample is 2.06% overall, with women having a higher unemployment probability of 2.71% compared to men's 1.51%. The expected unemployment duration for women is 3.84 months with a standard deviation of 3.34. The expected unemployment duration for men is higher, at 4.92 months with a standard deviation of 4.69.

Due to unrealistically low values for wage, the data is trimmed to remove the bottom fifth percentile of wage observations. The cut-off value is calculated separated for men and women. The

[1] The repository with data and code can be found at https://github.com/meganmccoy/masters-thesis.

Table 1: Descriptive Statistics, CPS 1995

Sample Moments	N	$P(i \in U)$	$E(w_i \mid i \in E)$	$SD(w_i \mid i \in U)$	$E(t_i \mid i \in U)$	$SD(t_i \mid i \in U)$
			Without trimming			
All	2,179	0.0206	19.15	9.49	4.27	3.92
Women	993	0.0271	16.60	8.31	3.84	3.34
Men	1,186	0.0151	21.26	9.89	4.92	4.69
Women/men ratio	0.837	1.794	0.780	0.840	0.780	0.712
			With trimming			
All	2,071	0.0217	19.91	9.13	4.27	3.92
Women	944	0.0286	17.26	8.00	3.84	3.34
Men	1,127	0.0162	22.81	9.15	4.92	4.69
Women/men ratio	0.851	1.765	0.756	0.874	0.780	0.712

Wage is hourly earnings in dollars, duration is the monthly unemployment duration. Data is trimmed to remove the bottom 5th percentile of wage observations, calculated separately for men and women. The lowest wage observation is 7.4 for men and 5.775 for women.

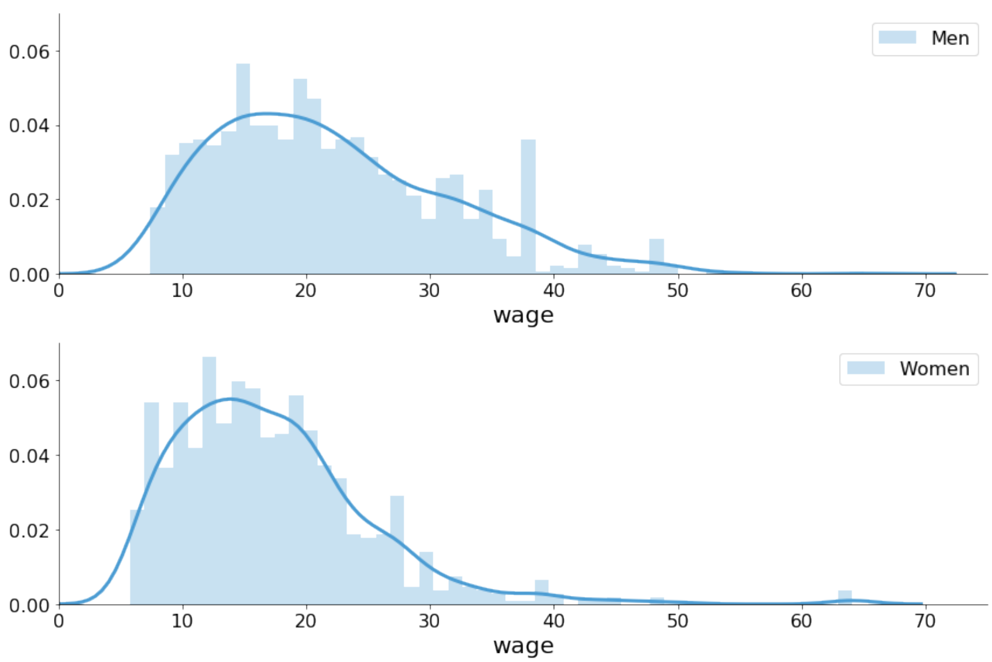

Figure 1: Accepted Wage Distribution for Men and Women, CPS 1995

minimum wage the trimmed data set is 7.27 dollars per hour for men and 5.756 dollars per hour for women.[2] Trimming reduces the estimation sample to 2,071.

By removing observations of employed individuals, the unemployment probabilities increase by no more than 0.15 percentage points. The impact of trimming is on the wages, increasing the average hourly wage for all individuals from 19.15 dollars to 19.91 dollars. The expected hourly wage for women increases by 0.66 dollars, and increases for men by 1.55 dollars. Prior to trimming the expected wage of women was 78% of their male counterparts, but trimming reduces this ratio to 75.6%. By removing the lowest fifth percentile of wage observations we have increased the gender wage gap by 2.4 percentage points.

The distribution of observed wages after trimming are presented in Figure 1. The mass of women's wages are lower than that of men, providing a visual representation of the lower expected wage for women. Women's wages are more centralized around the mean compared to men. The higher expected wage for men can be seen through the mass at a greater wage value as well as the increased variance to the right of the mean.

Estimation results of parameters based on equation (1) are presented in Table 2. Specifications (1)-(3) allow for the same meeting rate λ and termination rate η for men and women, while specifications (4)-(6) let these parameters be gender-specific. Specifications (1) and (4) do not have discrimination ($p = 0$, $d = 0$) so differences between men and women are based only on differences in the location and scale parameters, functions of μ and σ, of the match-specific productivity distributions. Specifications (2) and (5) require the same match-specific productivity distributions for men and women ($\mu_M = \mu_F = \mu$; $\sigma_M = \sigma_F = \sigma$), estimating the proportion of prejudiced employers p and degree of disutility d as the only cause for the gender wage gap. Specifications (3) and (6) allow for differences in productivity and the presence of prejudiced employers. The parameter estimates from each specification are used to predict labor market measures presented in Table 3.

Estimates of the arrival rate of individual and firm meetings λ is consistent across the estimates that maintain a common arrival rate. When allowing for differences by gender, we see that men have a lower meeting rate than women. The same pattern occurs for the rate of termination η. Men have a lower termination rate than women when allowing for the parameters to be gender-specific.

Specifications (1) and (4) that allow for varying productivity distributions between men and women show that women's match-specific productivity distribution has a lower location parameter than men's. However, the scale variable shows that there is approximately the same spread by gender. Thus, the distribution of the match-specific productivity for women will have a similar shape to the men's distribution, but it will be centered at a lower mean. Indeed, we see that the predicted expected productivity for men is greater than that of women, which leads to employed men having a greater expected wage. When allowing for there to be prejudice as well as productivity differences (specifications (3) and (6)), men and women have approximately the same average productivity, with women having a lower variance of their productivity distribution. The estimated expected productivity between men and women are closer when there is some prejudice.

The estimates of the degree of disutility faced by prejudiced employers as well as the proportion of prejudiced employers varies greatly depending on whether the model allows for common productivity distributions (specifications (2) and (5)) or not (specifications (3) and (6)). When the match-specific productivity distribution is the same by gender, most of the employers are prejudiced (94.6% to 97.0%) but have a relatively low disutility of working with women. When we allow for the productivity distributions to differ, the level of disutility almost doubles and the proportion

[2]The wage data is not trimmed at the upper limit because the CPS top-coded the wage values.

Table 2: Maximum Likelihood Estimates, CPS 1995

	(1)	(2)	(3)	(4)	(5)	(6)
λ	0.2353	0.2382	0.2482			
	(0.0972)	(0.1403)	(0.1507)			
λ_M				0.2041	0.2038	0.2041
				(0.1998)	(0.2385)	(0.1936)
λ_F				0.2620	0.2682	0.2770
				(0.1905)	(0.1521)	(0.1561)
η	0.0052	0.0052	0.0052			
	(0.1273)	(0.2099)	(0.2138)			
η_M				0.0033	0.0033	0.0033
				(0.2470)	(0.3381)	(0.2824)
η_F				0.0077	0.0077	0.0077
				(0.2748)	(0.2307)	(0.2186)
μ		3.4342			3.4343	
		(0.0155)			(0.0148)	
σ		0.5233			0.5234	
		(0.0189)			(0.0186)	
μ_M	3.4571		3.4569	3.4570		3.4570
	(0.0170)		(0.0170)	(0.0171)		(0.0172)
σ_M	0.5605		0.5606	0.5605		0.5605
	(0.0230)		(0.0228)	(0.0229)		(0.0228)
μ_F	3.2027		3.4637	3.2027		3.4614
	(0.0191)		(0.0679)	(0.0185)		(0.0507)
σ_F	0.5682		0.4118	0.5681		0.4128
	(0.0259)		(0.0644)	(0.0247)		(0.0617)
d		5.901	13.4936		5.7387	13.4352
		(0.2262)	(0.1879)		(0.1800)	(0.1565)
p		0.9462	0.5406		0.9707	0.5376
		(0.1708)	(0.3245)		(0.1870)	(0.1901)
N	2,071	2,071	2,071	2,071	2,071	2,071
ln$L$	-5972.056	-5976.973	-5954.048	-5969.797	-5974.802	-5952.053
LR test p value	0.0000	0.0000	0.0900	0.0000	0.0000	

Standard errors in parentheses. Data: CPS 1995; College graduate or more; 30-55 years old; white. Reservation values estimated by the minimum observed earning in the distribution of each group: $\hat{w}^*_M = 7.4$ and $\hat{w}^*_F = 5.775$. The likelihood ratio (LR) test is a specification test against specification (6).

Table 3: Predicted Values, CPS 1995

	Same Arrival and Termination Rates			Different Arrival and Termination Rates			
	No Prejudice (1)	Full Prejudice (2)	Estimated Prejudice (3)	No Prejudice (4)	Full Prejudice (5)	Estimated Prejudice (6)	Sample
			Productivity				
$E(x)$		35.56			35.56		
$V(x)$		398.26			398.62		
$E_M(x)$	37.12		37.12	37.12		37.12	
$V_M(x)$	508.47		508.58	508.55		508.55	
$E_F(x)$	28.91		34.76	28.91		34.69	
$V_F(x)$	318.41		223.30	318.34		223.61	
			Earnings				
$E_M(w\|E)$	22.33	21.52	22.33	22.33	21.53	22.33	22.81
$E_F(w\|E)$	17.41	18.27	17.25	17.41	18.26	17.25	17.26
			Unemployment				
u_M	0.022	0.021	0.021	0.016	0.016	0.016	0.016
$E_M(t\|U)$	4.177	4.121	3.964	4.844	4.844	4.844	4.92
u_F	0.022	0.022	0.022	0.029	0.029	0.029	0.028
$E_F(t\|U)$	4.180	4.230	4.189	3.728	3.728	3.728	3.84

Predicted values from specifications (1)-(6) reported in Table 2. Standard errors are not presented due to calculation problems.

of prejudiced employers is halved. By assuming a common distribution, the observed wage gap is explained entirely by prejudice. By allowing for differences in the productivity distributions, we see that there is a larger disutility from prejudiced employers working with women but only 53.7% to 54.0% of the employers are prejudiced.

The specifications that allow for productivity differences and prejudice, (3) and (6), show that there is a smaller difference in expected productivity by gender compared to the specification with no prejudice, but a larger wage gap than the specification with full prejudice. By estimating the amount of prejudice in the market, we see that the gender wage gap can be attributed to a proportion of prejudiced employers that experience a disutility of working with women. The estimated prejudice specification calculates expected earnings very close to the averages seen in the sample.

The estimation results presented in Table 2 are very close to those presented in Flabbi 2010. Key differences are in the in the proportion of prejudiced employers in the specification without productivity differences. Flabbi 2010 estimate that 81.1% of employers are prejudiced if we assume that men and women have the same productivity distributions, but the estimation procedure in this paper finds that 94.6% to 97.0% are prejudiced. Predicted values in Table 3 have the same pattern as in Flabbi 2010; differences in estimated values can be attributed to variations in the maximum likelihood estimates.

Table 4: Descriptive Statistics, SOEP 2017

Sample Moments	N	$P(i \in U)$	$E(w_i \mid i \in E)$	$SD(w_i \mid i \in U)$	$E(t_i \mid i \in U)$	$SD(t_i \mid i \in U)$
			Without winsorizing			
All	2,226	0.186	19.51	9.01	1.97	2.45
Women	857	0.226	16.81	7.44	2.18	2.80
Men	1,369	0.162	21.06	9.46	1.79	2.09
Women/men ratio	0.626	1.395	0.798	0.786	1.217	1.139
			With winsorizing			
All	2,226	0.186	19.30	7.60	1.97	2.45
Women	857	0.226	16.67	5.89	2.18	2.80
Men	1,369	0.162	20.82	8.06	1.79	2.09
Women/men ratio	0.626	1.395	0.800	0.730	1.217	1.139

Wage is hourly earnings in euros, duration is the monthly unemployment duration. Wage data is winsorized with a lower limit of the minimum wage in Germany for 2017, 8.84 euros per hour, and an upper limit calculated separately using Tukey's fences: 41.8267 euros per hour for men and 31.5159 euros per hour for women.

2.2 Germany's Socio-Economic Panel, 2017

The model presented in Flabbi 2010 is also estimated on data from the Socio-Economic Panel (SOEP) collected by the German Institute for Economic Research, DIW Berlin. The SOEP is a representative longitudinal study of private households in Germany that started in 1984 and was expanded in 1990 to include a representative sample of households in East Germany. Annually approximately 15,000 households and about 30,000 individuals are surveyed by the SOEP. Respondents include Germans living in both the former East and West Germany, foreign citizens living in Germany, and a new sample of migrants. Survey topics include household composition, education, employment, earnings, and satisfaction indicators (Goebel et al. 2019). This paper uses variables from a subset of the SOEP-Core, v34.[3]

The sample is restricted to 2017 for the re-estimation of Flabbi 2010. The estimation sample follows the similar restrictions as in the original paper:[4] individuals who were either employed full time or unemployed holding the equivalent of a college degree or more[5] between the ages of 30 and 55. The original number of observations from survey year 2017 was 31,360. The refinements reduced the sample size to 2,226 observations.

The continuous variables used for the employed workers are net monthly labor income (in euros) and agreed upon hours per week; hourly wage was calculated by dividing four times the hours per week from monthly income. The continuous variable for unemployed individuals is the unemployment duration measured by unemployment experience in months. The descriptive statistics are presented in Table 4.

Compared to the CPS data, there is a higher probability of being unemployed in the SOEP of 22.6% for women and 16.2% for men. The women to men ratio of unemployment is smaller for the SOEP than it was in the CPS. The average wage of women is approximately 80% of men in the sample. Women also have a longer expected unemployment duration compared to men.

Instead of trimming data as in Flabbi 2010, outliers are dealt with winsorizing: a method in which values outside of a limit are re-coded to be at the limit's boundary. Rather than deleting

[3]Socio-Economic Panel (SOEP), data for years 1984-2017, version 34, SOEP, 2019, doi: 10.5684/soep.v34.
[4]The sample was not restricted to individuals of the same race/ethnicity.
[5]UNESCO Institute for Statistics 2012 provides details for the classification of education level equivalents.

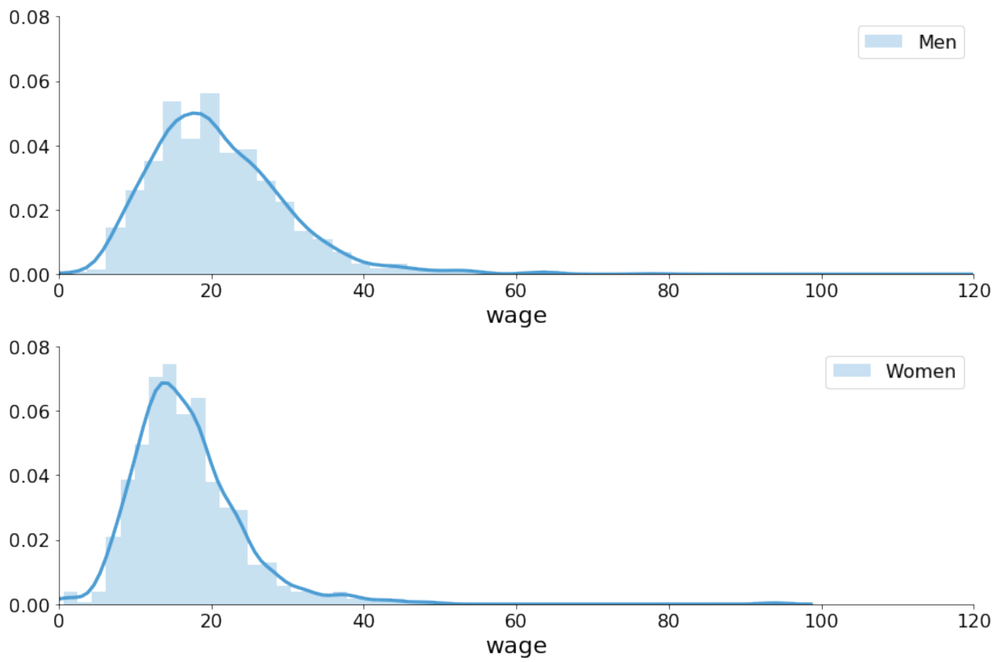

Figure 2: Accepted Wage Distribution

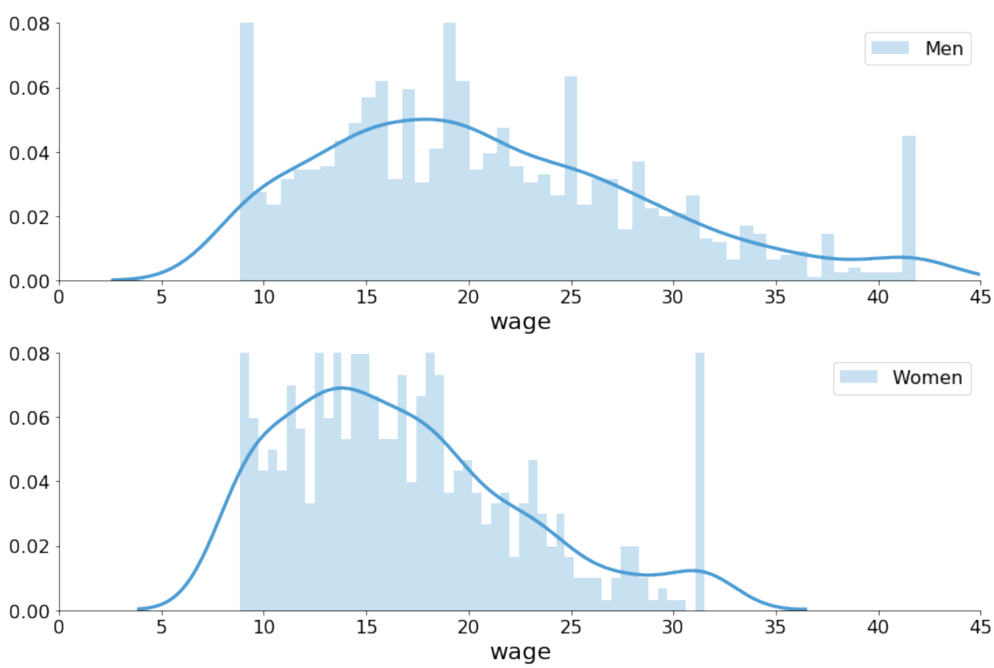

Figure 3: Winsorized Accepted Wage Distribution

data, winsorizing includes the outliers at a boundary so that the estimation strategy is able to place weight on the boundaries that have non-zero mass. If the outliers were deleted, the model's estimation would be excluding data from real-world outcomes and ignoring weight in the tails. If outliers were included, they could distort the model's estimates by placing disproportionate explanatory power in the tails. Winsorizing allows for the model to handle outliers through the non-zero mass at the boundary, but it does not allow distortion in the estimation when trying to explain fat tails. For example, in Figure 2 we see that there are observations far to the right of the central mass. Winsorizing redefines these outliers at the upper boundary, leading to a positive mass at the boundary (see Figure 3).

The upper boundary is calculated by Tukey's fences for each distribution.[6] The benefit of Tukey's fences is that the values do not depend on a distributional assumption nor the mean and standard deviation values; the outliers are identified using the box-plot (Seo n.d.). The upper boundary is calculated to be 41.8267 euros per hour for men and 31.5159 euros per hour for women. The lower limit was calculated to be -1.2414 for men and 0.8066 for women. As these were unrealistically small, the minimum wage in Germany for 2017, 8.84 euros per hour, was imposed as the lower boundary. The distribution of accepted wages by gender prior and post winsorizing are presented in Figures 2 and 3, respectively.

The descriptive statistics with winsorizing shows a slight decrease in the expected wage for men and women, suggesting that there was distortion in the sample moments due to the outliers in the tail to the right of the central mass of wage observations. In the winsorized sample, the expected wage for women is 16.67 euros per hour compared to 16.81 euros per hour in the raw sample. The expected wage for men in the winsorized sample is 20.82 euros per hour compared to 21.06 euros per hour in the raw sample.

Estimation results of parameters based on equation (1) with the SOEP 2017 data are presented in Table 5. Specifications (1)-(3) allow for the same meeting rate λ and termination rate η for men and women, while specifications (4)-(6) let these parameters be gender specific. Specifications (1) and (4) do not have discrimination ($p = 0$, $d = 0$) so differences between men and women are based only on differences in the location and scale parameters, functions of μ and σ, of the match-specific productivity distributions. Specifications (2) and (5) require the same match-specific productivity distributions for men and women ($\mu_M = \mu_F = \mu$; $\sigma_M = \sigma_F = \sigma$), estimating the proportion of prejudiced employers p and degree of disutility d as the only cause for the gender wage gap. Specifications (3) and (6) allow for differences in productivity and the presence of prejudiced employers. The parameter estimates from each specification are used to predict labor market measures presented in Table 6.

Estimates of the common arrival rate of individual and firm meetings λ is least when there is no prejudice in the model, and greatest when there is both prejudice and productivity differences. When allowing for differences by gender, the meeting arrival rate for men is greater than women's when there is no prejudice, but less otherwise. The women's meeting arrival rate follows the same trend as the common arrival rate. There is greater variation in the meeting arrival rate in the SOEP data compared to the CPS, and the values are larger for the SOEP. The rate of termination η is consistent across the specifications. The common termination rate is double the CPS estimate. Men have a lower termination rate than women when allowing for the parameters to be gender-specific.

Specifications (1) and (4) that allow for varying productivity distributions between men and women show that women's match-specific productivity distribution has a lower location parameter

[6] The upper boundary of Tukey's fences is calculated by adding the third quartile value to one and a half times the interquartile range, i.e. upper limit = Q3 + 1.5 × IQR. The lower boundary is calculated by subtracting one and a half times the interquartile range from the first quartile, i.e. lower limit = Q1 − 1.5 × IQR.

Table 5: Maximum Likelihood Estimates, SOEP 2017

	(1)	(2)	(3)	(4)	(5)	(6)
λ	0.5368	0.6010	0.6236			
	(0.0285)	(0.0868)	(0.0823)			
λ_M				0.5703	0.5667	0.5703
				(0.0707)	(0.0655)	(0.0459)
λ_F				0.4973	0.7485	0.7977
				(0.0806)	(0.1026)	(0.1019)
η	0.1174	0.1189	0.1188			
	(0.1210)	(0.1233)	(0.1033)			
η_M				0.1080	0.1080	0.1080
				(0.1025)	(0.1610)	(0.0774)
η_F				0.1340	0.1340	0.1340
				(0.1147)	(0.0984)	(0.0628)
μ		3.3166			3.3168	
		(0.0138)			(0.0198)	
σ		0.5279			0.5260	
		(0.0238)			(0.0212)	
μ_M	3.3309		3.3306	3.3292		3.3292
	(0.0184)		(0.0188)	(0.0262)		(0.0175)
σ_M	0.5664		0.5689	0.5681		0.5681
	(0.0257)		(0.0256)	(0.0366)		(0.0250)
μ_F	2.9686		3.3377	2.9884		3.3490
	(0.0000)		(0.0416)	(0.0472)		(0.0247)
σ_F	0.5894		0.3387	0.5740		0.3392
	(0.0228)		(0.0442)	(0.0403)		(0.0447)
d		12.5443	39.3736		18.0916	60.0461
		(0.0996)	(0.1691)		(0.1854)	(0.1526)
p		0.9180	0.3987		0.7988	0.4278
		(0.0561)	(0.2434)		(0.1156)	(0.1250)
ln$L$	-6490.085	-6489.272	-6448.114	-6484.240	-6487.694	-6444.983
LR test p value	0.0000	0.0000	0.1117	0.0000	0.0000	

Standard errors in parentheses. Data: SOEP 2017; College graduate or more; 30-55 years old. Reservation values estimated by the minimum wage for Germany in 2017: $\hat{w}^* = 8.84$ euros per hour. The likelihood ratio (LR) test is a specification test against specification (6).

Table 6: Predicted Values, SOEP 2017

	Same Arrival and Termination Rates			Different Arrival and Termination Rates			
	No Prejudice (1)	Full Prejudice (2)	Estimated Prejudice (3)	No Prejudice (4)	Full Prejudice (5)	Estimated Prejudice (6)	Sample
			Productivity				
$E(x)$		31.69			31.66		
$V(x)$		322.75			319.59		
$E_M(x)$	32.83		32.87	32.81		32.81	
$V_M(x)$	407.55		412.84	409.97		409.97	
$E_F(x)$	23.16		29.82	23.41		30.16	
$V_F(x)$	222.69		108.04	213.87		110.94	
			Earnings				
$E_M(w\|E)$	21.11	20.46	21.13	21.10	20.44	21.10	20.82
$E_F(w\|E)$	16.80	17.89	16.74	16.83	17.90	16.68	16.67
			Unemployment				
u_M	0.183	0.167	0.163	0.162	0.162	0.162	0.162
$E_M(t\|U)$	1.480	1.470	1.477	1.501	1.493	1.501	1.79
u_F	0.194	0.218	0.234	0.226	0.226	0.226	0.226
$E_F(t\|U)$	1.651	1.834	1.970	1.690	1.690	1.690	2.18

Predicted values from specifications (1)-(6) reported in Table 5. Standard errors are not presented due to calculation problems.

than men's. However, the scale variable shows that there is approximately the same spread by gender. Thus, the distribution of the match-specific productivity for women will have a similar shape to the men's distribution, but it will be centered at a lower mean. These results are very similar to the estimation with the CPS data. Indeed, we see that the predicted expected productivity for men is greater than that of women, which leads to employed men having a greater expected wage. When allowing for there to be prejudice as well as productivity differences (specifications (3) and (6)), men and women have approximately the same average productivity, and women have a smaller variance, reducing the spread of their productivity distribution. The estimated expected productivity between men and women are closer when there is some prejudice.

The estimates of the degree of disutility faced by prejudiced employers as well as the proportion of prejudiced employers varies greatly depending on whether the model allows for common productivity distributions (specifications (2) and (5)) or not (specifications (3) and (6)). The proportion of prejudiced employers is the greatest in the specification with common arrival and termination rates and no productivity differences. All of the gender differences are attributed to prejudice, leading to an estimate of 91.8% of employers are prejudiced; however, this specification has the lowest degree of disutility of working with women. Allowing for separate arrival and termination rates decreases the proportion of prejudiced employers to 79.8%, but increases their level of disutility. Allowing for productivity differences further reduces the proportion of prejudice to 39.8% and 42.7%. However, the degree of disutility is smaller for the estimation with common arrival and termination rates compared to when these parameters are gender-specific.

The specifications that allow for productivity differences and prejudice, (3) and (6), show that there is a smaller difference in expected productivity by gender compared to the specification with no prejudice, but a larger wage gap than the specification with full prejudice. By estimating the amount of prejudice in the market, we see that the gender wage gap can be attributed to a proportion of prejudiced employers that experience a disutility of working with women. The estimated prejudice specification calculates expected earnings very close to the sample averages.

3 Extended Model

The model presented by Flabbi 2010 and estimated above is a continuous time search-match-bargaining model with observed heterogeneity in the workers and firms. To explore gender wage discrimination, Flabbi has male and female workers interacting with firms that are either prejudiced or unprejudiced. Prejudiced firms experience a flow disutility when hiring female employees that affects the reservation value of the match-specific productivity when a prejudiced employer and woman employee meet. The model predicts that the presence of prejudiced firms cause a gender wage gap by reducing the value of the outside option for female workers.

To further explore the effects of prejudiced employers on the gender gap in wage, the model will be expanded to include a random shock in job title, akin to a promotion, with the arrival rate dependent on the type of match. If the match is discriminatory, the promotion shock will occur at a lower rate than in a non-discriminatory match. Therefore, when a woman chooses to work for a prejudiced firm, she knows that she will have a lower probability of an upgrade in her job title. This framework follows the work by Bobba et al. 2019, which explores human capital accumulation as a function of job formality in Mexico. The inclusion of a promotion shock will explore the gender wage gap from the framework of women being unable to ascend the job-ladder at their position thus further widening the gap.

3.1 Environment

The extension is a stationary, continuous time search-match-bargaining model with male and female workers ($J \in \{M, F\}$) and prejudiced and non-prejudiced employers ($I \in \{P, N\}$). The proportion of prejudiced employers in the market is p and they experience a flow disutility d of working with women. Workers can be employed or unemployed. When unemployed, workers and firms meet randomly following a Poisson process with arrival rate λ. Upon meeting types are revealed and a match specific productivity x is drawn from a distribution with cumulative distribution function G. If a match is realized, wages are determined through Nash bargaining with bargaining power α. Matches are terminated by an exogenous shock following a Poisson process with rate η. Death of individuals occurs exogenously, following a Poisson process with rate δ, and all agents discount the future at rate ρ.

Workers are endowed with a position level a_1 that impacts their productivity to the firm $y(x, k) = a_k x$. While in a match, employees can experience a promotion shock from a_k to $a_{k'}$, $k' > k$, $k, k' \in \{1, 2, ..., K\}$ following a Poisson process with rate $\tau_{\mathbf{I}_{\{F,P\}},k}$. The rate is dependent on the current position level k and whether there is a discriminatory match between a female employee and prejudiced employer. Discriminatory matches have a lower rate of promotion, i.e. $\tau_{0,k} > \tau_{1,k}$ $\forall k$. Position levels do not depreciate over time or during unemployment.[7] When a promotion shock

[7] It is reasonable to assume that the position level does not depreciate because a promotion leading to a title change is infinitely lived on a resume; as a signal, it gives information about the achieved productivity of a worker while in a job.

occurs, the worker's productivity changes and there is a renegotiation of wages. Utility is linear in wages for workers and profits for firms.

3.2 Value Functions

The value of being employed and unemployed are presented below. The value of being employed is dependent on the realized match-specific productivity and whether the match is discriminatory (female employee with a prejudiced employer) or not. The value of unemployment depends on the individual's sex as well as the continuation value of potentially matching with a firm in the future.

While working, an employee faces three events: staying employed with no change, experiencing a promotion shock, or experiencing a termination shock (all other possibilities are encapsulated in the $o(\Delta)t$ term). The discrete time approximation, with period length Δt, of the value of being employed is

$$\begin{aligned} W_J(w_{JI}(x;k)) = w_{JI}(x;k)\Delta t + \frac{1-\delta\Delta t}{1-\rho\Delta t}\Bigg[&\eta\Delta t U_J(k) \\ &+ (1-\eta\Delta t)\Bigg((1-\tau_{\mathbf{I}_{\{F,P\}},k}\Delta t)W_J(w_{JI}(x;k)) \\ &+ \tau_{\mathbf{I}_{\{F,P\}},k}\Delta t\sum_{k'=k+1}^{K} W_J(w_{JI}(x;k'))P(k'|k)\Bigg) + o(\Delta t)\Bigg]. \end{aligned}$$

The above equation states that the value of employment is given by the wage received in this period plus the expected value of termination or a promotion, with all other possible events happen with a negligible probability $o(\Delta t)$. Using the property of the Poisson process that $\lim_{\Delta t\to 0}\frac{o(\Delta t)}{\Delta t}$, we are able to estimate the discrete time approximation into continuous time, yielding the following value function for employed individuals:

$$W_J(w_{JI}(x;k)) = \frac{w_{JI}(x,k) + \eta U_J(k) + \tau_{\mathbf{I}_{\{F,P\}},k}\sum_{k'=k+1}^{K} W_J(w_{JI}(x;k'))P(k'|k)}{\tilde{\rho} + \eta + \tau_{\mathbf{I}_{\{F,P\}},k}} \tag{2}$$

where $\tilde{\rho} \equiv \rho + \delta$. Employed individuals receive their wage in the current period and face the potential for a promotion or a lay-off in the next period. With probability $\tau_{\mathbf{I}_{\{F,P\}},k}$ the employee experiences a promotion shock that triggers a renegotiation of the wage as a function of the higher position level. With probability η, the employee-firm match is terminated and the employee returns to the unemployed state in order to search for a new job.

While unemployed, an individual faces three events: not meeting an employer, meeting a prejudiced employer, and meeting an unprejudiced employer, with a negligible probability of other events. The discrete time approximation of the value of unemployment is given by the current (dis)utility of being unemployed plus the discounted expected value of potential future outcomes

$$\begin{aligned} U_J(k) = b\Delta t + \frac{1-\delta\Delta t}{1-\rho\Delta t}\Bigg(&(1-\lambda\Delta t)U_J(k) + \lambda\Delta t p\int \max\{W_j(w_{JP}(x;k)), U_J(k)\}dG(x) \\ &+ \lambda\Delta t(1-p)\int \max\{W_j(w_{NJ}(x;k), U_J(k)\}dG(x) + o(\Delta t)\Bigg). \end{aligned}$$

Using the properties of the Poisson process yields the continuous time formulation of the unemployed's value function

$$\tilde{\rho} U_J(k) = b + \lambda \Bigg(p \int \max\{W_j(w_{JP}(x;k)) - U_J(k), 0\} dG(x) \\ + (1-p) \int \max\{W_j(w_{NJ}(x;k)) - U_J(k), 0\} dG(x) \Bigg). \tag{3}$$

The value function of unemployed individuals shows the flow utility of unemployment with the expectation of meeting with a firm in the future. The individual will choose to enter the match if the value of employment is greater than (or equal to) the value of unemployment. The continuation value of being employed depends on the type of match that is created; the value of being employed is dependent on whether the match is discriminatory or not.

The value of employment W_J is increasing in wage and the value of unemployment U_J is constant in wage, so there will be a reservation value property in the agent's optimal decision: a reservation wage w^*_{JI} exists such that $W_J(w^*_{JI}) = U_J$ for every position level k.

3.3 Wages

The wages are determined by Nash bargaining; the firm and the individual maximize their surplus. The individual's surplus is the discounted value from being employed less the value of unemployment. The firm's surplus is the discounted productivity less the wage paid out and any disutility experienced by the employer. The wage maximizes these surpluses while taking into account the bargaining power parameter α. The wage optimization equation is

$$w_{JI}(x, U_J; k) = \arg\max_w \left\{ \left[\frac{W_J(x;k) - U_J(k)}{\tilde{\rho} + \eta + \tau_{\mathbf{I}_{\{F,P\}},k}} \right]^{\alpha} \left[\frac{y(k,x) - d\mathbf{I}_{F,P} - w}{\tilde{\rho} + \eta} \right]^{(1-\alpha)} \right\}.$$

Solving for the optimal wage yields the wage schedule in equation (4) as a function of the type of match and expectations over future promotion shocks, match-specific productivity, position level, and the value of unemployment.

$$w^*_{JI}(x, U_J; k) = \alpha\big(y(k,x) - d\mathbf{I}_{F,P}\big) \\ + (1-\alpha) \left((\tilde{\rho} + \tau_{\mathbf{I}_{\{F,P\}},k}) U_J(k) + \tau_{\mathbf{I}_{\{F,P\}},k} \sum_{k'=k+1}^{K} W_J(w_{JI}(x;k')) P(k'|k) \right) \tag{4}$$

Men's wages are a convex combination of their productivity and the expected future payoff of employment. The wage schedule for men is independent of the type of employer in the match. Men have a constant probability of promotion $\tau_{0,k}$ given their current position level k.

$$w^*_{MI}(x, U_M; k) = \alpha y(k,x) + (1-\alpha) \left((\tilde{\rho} + \tau_{0,k}) U_M(k) + \tau_{0,k} \sum_{k'=k+1}^{K} W_M(w_M(x;k')) P(k'|k) \right)$$

The wage for women in a non-discriminatory match differs from men only in the value of unemployment U_F and the continuation value on the expectation of a promotion $W_F(w_{FN}(x;k'))$.

Women at an unprejudiced employer face the same rate of promotion shock as men, so the only potential for a decreased wage comes from the gender-specific value of unemployment.

$$w^*_{FN}(x, U_F; k) = \alpha y(k, x) + (1-\alpha)\left((\tilde{\rho} + \tau_{0,k})U_F(k) + \tau_{0,k} \sum_{k'=k+1}^{K} W_F(w_{FN}(x; k'))P(k'|k)\right)$$

Women in a discriminatory match have a wage smaller than their counterparts at a non-prejudiced employer. When working for a prejudiced employer, the disutility of working with women is "paid" by the woman herself in the productivity term. Her wages are further reduced by the smaller rate of promotion $\tau_{1,k}$ that reduces the proportion of wages from the value of unemployment and the continuation value of expected promotion.

$$w^*_{FP}(x, U_F; k) = \alpha(y(k, x) - d) + (1-\alpha)\left((\tilde{\rho} + \tau_{1,k})U_F(k) + \tau_{1,k} \sum_{k'=k+1}^{K} W_F(w_{FP}(x; k'))P(k'|k)\right)$$

When a promotion shock occurs from a_k to $a_{k'}$, $k' > k$, the employee and employer renegotiate the wages to $w^*_{JI}(x, U_J; k')$ as defined by equation (4).

3.4 Equilibrium

Given a vector $(\rho,\ \delta,\ \eta,\ \lambda,\ \tau_{\mathbf{I}_{F,P},k},\ b,\ \alpha)$ and distributions $(G(x), \{a_k\}_{k=1}^K)$, an equilibrium is a vector of values of unemployment $U^*(k) = (U^*_M(k), U^*_F(k))$ satisfying equations (2), (3), and (4) for $J = \{M, F\}$, $k \in \{1, 2, ..., K\}$. The equilibrium vector $U^*(k)$ define the reservation values that determine agent's decision rules.

The reservation values given in equation (5) are determined for each match and each position level k numerically through value function iteration depending on the distribution of position levels. The value function iteration will solve for a fixed point vector $\{U^*(k)\}_{k=1}^K$ for the reservation values.

$$\begin{aligned}\tilde{\rho}U^*_J(k) = b + \lambda\Bigg[p\int\left(\frac{w^*_{JN}(x,k) + \eta U^*_J(k) + \tau_{0,k}\sum_{k'=k+1}^{K} W_J(w^*_{JN}(x;k'))P(k'|k)}{\tilde{\rho} + \eta + \tau_{0,k}}\right)dG(x)\\ + (1-p)\int\left(\frac{w^*_{JP}(x,k) + \eta U^*_J(k) + \tau_{\mathbf{I}_{\{F,P\}},k}\sum_{k'=k+1}^{K} W_J(w^*_{JP}(x;k'))P(k'|k)}{\tilde{\rho} + \eta + \tau_{\mathbf{I}_{\{F,P\}},k}}\right)dG(x)\Bigg].\end{aligned} \tag{5}$$

For men, we see that the reservation value simplifies to equation (6). The existence of prejudiced employers do no affect men, so their decision is only a function of their position level, wage, and outside option.

$$\tilde{\rho}U^*_M(k) = b + \lambda\int\left(\frac{w^*_M(x,k) + \eta U^*_M(k) + \tau_{0,k}\sum_{k'=k+1}^{K} W_M(w^*_M(x;k'))P(k'|k)}{\tilde{\rho} + \eta + \tau_{0,k}}\right)dG(x) \tag{6}$$

Women's reservation value is presented in equation (7). If there is a strictly positive proportion of prejudiced employers in the market, women will have a smaller reservation value than men at every position level k through the decreased wage in a discriminatory match and the decreased rate of promotion $\tau_{1,k} < \tau_{0,k}$.

$$\begin{aligned}\tilde{\rho}U_F^*(k) = b + \lambda\Bigg[p\int\left(\frac{w_{FN}^*(x,k) + \eta U_F^*(k) + \tau_{0,k}\sum_{k'=k+1}^{K} W_F(w_{FN}^*(x;k'))P(k'|k)}{\tilde{\rho}+\eta+\tau_{0,k}}\right)dG(x) \\ + (1-p)\int\left(\frac{w_{FP}^*(x,k) + \eta U_F^*(k) + \tau_{1,k}\sum_{k'=k+1}^{K} W_F(w_{FP}^*(x;k'))P(k'|k)}{\tilde{\rho}+\eta+\tau_{1,k}}\right)dG(x)\Bigg]\end{aligned} \tag{7}$$

The reduced reservation values of women induces women to accept wages at a lower rate than men. Moreover, the wages offered to women are a function of the value of unemployment; as it is less than men, women experience a lower offered wage regardless of firm type. The gender wage gap arises by the presence of prejudiced employers experiencing a disutility of working with women and by women having a lower exogenous probability of promotion when in a discriminatory match. The unprejudiced employers benefit from the presence of prejudice through the decreased value of the outside option.

3.5 Identification Strategy

The identification of the model follows the strategy of Bobba et al. 2019 closely. The model can be estimated using the Method of Simulated Moments. The model will be reparameterized to ($\tilde{\rho}U(k)$, η, λ, $\tau_{\mathbf{I}_{\{F,P\}},k}$, α) for estimation.[8]

The match-specific productivity distribution $G(x)$ will be assumed to be lognormal. As the data only includes accepted wages, we use the recoverability feature of the lognormal distribution. The distribution of the position transitions $\{a_k\}_{k=1}^K$ will be determined by defining an upper and lower bound prior to discretizing the range in equal intervals. Bobba et al. 2019 set a_1 to one use robustness checks to determine a_K and the optimal number of intervals.

The meeting rate λ and termination rate η will be identified through the unemployment duration lengths in the same manner as Flabbi 2010. The Nash bargaining power coefficient α will be assumed to equal 0.5 as there is no employer data. The position shocks $\tau_{\mathbf{I}_{\{F,P\}},k}$ are identified through two channels: a promotion induces a renegotiation of wages and a change in position level. Both wage growth and a title change will jointly identify the position shock.

The model will be identified on panel data from SOEP. Homogeneity measures will be included to meet the model's assumption of ex-ante identical workers. Necessary data is gender, employment status, unemployment duration if unemployed, and wage and job title if employed. The SOEP has a measure that asks if the individuals has experienced a job change, and if so, what type of change (see Table 7). The responses for job change include: changed positions within a company, first job, returned to past employer after a break, taken on by company after temporary work, started a new position with a different employer and new job as self-employed. Only responses of "changed positions within a company" will be considered when defining a promotion shock.

In addition to excluding the other job change options, further measures will be taken to ensure that the job change captures a promotion rather than a demotion or a life event that would change an individual's position or title. The data will only include participants who are either employed full-time or unemployed, thus removing the possibility of a reduction in hours or change to a part-time position in the company. Also, an occupation change will be associated with an increase in

[8]Given equilibrium equation (5), we can only jointly identify $\tilde{\rho} = \rho + \delta$, $U_J^*(k)$, and b.

Table 7: Frequency of responses to promotion variables, SOEP 2007-2017

Have you changed jobs or started a new one in the last year? (n=150,763)		
	Observations	Percent
No	123,516	81
Yes	27,247	18
What type of occupational change was that? (n=155,364)		
	Observations	Percent
Changed positions within the same company	2,173	2

Note: Table presents frequencies from full sample of SOEP responses, 2007-2017; homogeneity measures have not been applied. Other possible responses to type of occupation change include: first job, returned to past employer after a break, taken on by company after temporary work, started a new position with a different employer and new job as self-employed.

wages to ensure that there was a renegotiation of wages after the promotion shock in line with the model assumptions. Finally, the SOEP has data on the occupation and position which can be explored to ensure that the change reflects an increase in title.

4 Conclusion

This paper presented a re-estimation of the model created by Flabbi 2010 in which the presence of prejudiced employers who experience a disutility from working with women lead to reduced wages for women. The presence of prejudiced employers reduces the outside option for women, thus causing them to accept a job at a lower wage compared to men. Then the model was extended to include a promotion shock that affects a worker's productivity that occurs with less frequency for women working for prejudiced employers. An estimation strategy was proposed using the SOEP data.

This paper can be refined to include the standard errors for the predicted values in the re-estimation of Flabbi 2010. Also, further homogeneity measures could be implemented in the SOEP re-estimation, such as common race/ethnicity across individuals. Finally, the extended model could have been solved for a two-position levels case to conduct rudimentary comparative statistics of the impacts of the promotion mechanism on wage.

Extensions of this paper could include other methods to explore the impact of prejudiced employers on promotion rates and the resulting gender wage gap. One option is to utilize a promotion process following the mechanism presented in Postel–Vinay and Robin 2002 while still allowing for different arrival rates of offers for men and women. The results from such an analysis could be compared to estimations from the extended model presented in this paper to explore the extent to which promotion rates differ by gender and the resulting impact the gender wage gap.

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