Online Appendix

GENDER DIFFERENCES IN JOB SEARCH: TRADING OFF COMMUTE AGAINST WAGE

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This online appendix has four sections. In Appendix A, we conduct robustness analyses to alternative interpretations of the declared reservation wage and reservation commute measures. In Appendix B, we show further insights using job application data. Appendix C includes extra figures, while Appendix D includes extra tablees.

A Robustness to alternative interpretations of the declared reservation wage and reservation commute measures

In this section, we provide a robustness analysis in which we adopt alternative interpretations (other than Interpretation 1 of the main text) for job seekers' answers to the reservation wage and maximum commute questions. We consider Interpretation 2 and its variant that we denote Interpretation 2 bis.

Under Interpretation 2, we interpret the reported reservation wage as the absolute lowest wage that the job seeker would be ready to accept, i.e. the minimum acceptable wage for a job next door: $\phi(0)$. Similarly, we interpret the self-reported maximum acceptable commute as the commute that the job seeker would be ready to accept for her maximum achievable wage: $\bar{\tau}$ s.t. $\phi(\bar{\tau}) = \bar{w}$. The definition of $\bar{\tau}$ and $\bar{w}$ yields: $\alpha = (\bar{w} - \phi(0)) / \bar{\tau}$. Empirically we define the maximum achievable wage for individual i as the 90th percentile in the distribution of wages of individuals with the same characteristics. Under Interpretation 2, we observe $\phi^* = \phi(0)$ and $\tau^* = \bar{\tau}$. If we know $\bar{w}$, we can identify the slope of the job seeker's indifference curve (see Panel (b) of Appendix Figure C7 for an illustration). Under Interpretation 2 bis, the identification strategy follows the same lines. Job seekers report the reservation wage $\phi(\tau_{25})$ corresponding to the first quartile of potential commute τ_{25} and the reservation commute $\phi^{-1}(w_{75})$ corresponding to the third quartile in the potential wage distribution w_{75}. Similarly, the definition of the log reservation wage curve yields: $\alpha = (w_{75} - \phi(\tau_{25})) / \left(\phi^{-1}(w_{75}) - \tau_{25}\right)$.

In both cases, we can define a mapping between the reported ϕ^*, τ^*, the distributions of wage offers F, and of commute offers G, and α.

$$\hat{\alpha}(\phi^*, \tau^*, F, G) = \frac{w^q(F) - \phi^*}{\tau^* - \tau^q(G)} \tag{5}$$

where $w^q(F)$ is the 90th quantile of F in Interpretion 2, and the 75th quantile of F in Interpretation 2 bis; and $\tau^q(G)$ is 0 in Interpretation 2 and the 25th quantile of G in Interpretation 2 bis.

Gender gap in commute valuation. In practice, we compute estimates of α under these interpretations as follows:

a. We estimate quantile regressions of entry wages and of commute on job seekers' characteristics (female, age, education, experience, occupation and year). This delivers a mapping between a vector X_i of individual characteristics and some predicted percentiles of the wage and commute distributions of individuals with characteristics X_i. We predict the 90th percentile $\hat{w}_{90}(X_i)$ for Interpretation 2, and the first and third quartiles $\hat{\tau}_{25}(X_i)$ and $\hat{w}_{75}(X_i)$ for Interpretation 2 bis.

b. We compute the $\hat{\alpha}$ using the definition of $\hat{\alpha}(\phi^*, \tau^*, F, G)$ in Equation (5) above, where we replace $w^q(F)$ and $\tau^q(G)$ by the quantities corresponding to the respective interpretation.

We obtain average values of α for men around 0.021. To compensate, workers for one extra kilometer in commute (one way), monthly wages must be increased by 2 log points. This is broadly consistent with the main estimate in Section IV.. We estimate the gender gap in willingness to pay for shorter commute in Tables A1 and A2. We present the result of regressions of the log of WTP ($\log \alpha$) on gender dummies under Interpretation 2 and under Interpretation 2 bis (respectively). In the preferred specification (column 3), we control for a variety of workers' characteristics that may confound the gender effect. We find that the indifference curve inferred from the declared job-search strategy of women is significantly steeper than that of similar men. Under Interpretation 2, female WTP is 23.8% larger than male WTP. Under Interpretation 2 bis, it is 15% larger. This leads us to conclude that the estimate of the gender gap in commute valuation is robust to the alternative interpretations. In column (4) of both Tables A1 and A2, we further find that the gender gap in WTP increases with marriage and children.

Model calibration and decomposition of the gender wage gap. What is the share of the gender wage gap explained by gender differences in commute valuation, under the alternative interpretations of job seekers' answers? We proceed as in Section V. and calibrate the job search model under these alternative interpretations of the reservation wage and commute. According to Interpretations 2 and 2 bis, we observe ϕ^* and τ^* in the data. We assume that the distribution of the log-wage F is a gamma distribution and estimate the shape k_F and the scale θ_F of this

Table A1: Gender differentials in commute valuation by family situation: Interpretation 2 of the reservation wage and the maximum acceptable commute measures

	(1)	(2)	(3)	(4)
	Slope of the log-reservation wage curve (in log) log((log w_{90}-log ResW) / Max. commute)			
Female	0.131***	0.116***	0.238***	
	(0.00442)	(0.00444)	(0.00875)	
F. $\times$ single, no children				0.129***
				(0.00931)
F. $\times$ married, no children				0.298***
				(0.0143)
F. $\times$ single, with children				0.354***
				(0.0173)
F. $\times$ married, with children				0.423***
				(0.0114)
Control w_i^{90}		X	X	X
Control indiv. worker			X	X
Observations	143,669	143,669	143,669	143,669
R-squared	0.009	0.0011	0.256	0.261

Note: Controls include past wage and past job attributes (commute, occupation, industry, part-time, contract type), unit of reservation commute (kilometers v. minutes), commuting zone fixed effects, and quarter fixed effect. From column (2) on, we add worker's maximum wage offer (w^{90}). From column (3) on, we include workers' characteristics (age, education, family structure, work experience), and potential benefit duration. Robust standard errors in parenthesis.

Table A2: Gender differentials in commute valuation by family situation: Interpretation 2 bis of the reservation wage and the maximum acceptable commute measures

	(1)	(2)	(3)	(4)
	Slope of the log-reservation wage curve (in log)			
	log((log w_{75} - log ResW) / (Max. commute - τ_{25}))			
Female	0.111***	0.101***	0.151***	
	(0.00502)	(0.00513)	(0.00918)	
F. × single, no children				0.0408***
				(0.00998)
F. × married, no children				0.214***
				(0.0162)
F. × single, with children				0.265***
				(0.0197)
F. × married, with children				0.361***
				(0.0125)
Control w_i^{75}		X	X	X
Control indiv. worker			X	X
Observations	134,930	134,930	134,930	134,930
R-squared	0.004	0.005	0.207	0.212

Note: Controls include past wage and past job attributes (commute, occupation, industry, part-time, contract type), unit of reservation commute (kilometers v. minutes), commuting zone fixed effects, and quarter fixed effect. From column (2) on, we add worker's maximum wage offer (w^{75}). From column (3) on, we include workers' characteristics (age, education, family structure, work experience), and potential benefit duration. Robust standard errors in parenthesis.

distribution, for women. For the distribution of commute offer G, we assume the same distribution as above, defined over the support 0 to 100 km:

$$g(\tau) = \gamma(\tau; k_G, \theta_G) + \tau.$$

We use the empirical measures of the expectation and variance of the log of the new wage w^n and commute τ^n to pin down the four parameters F and G. The theoretical moments also depend on α (see for example Equation (3) in the main text), and α is well defined for given values of $(k_F, \theta_F, k_G, \theta_G, \phi^*, \tau^*)$ (see Equation (5) above). At the end of this step, we then obtain the four parameters of distributions F and G, as well as an estimate for α. The final steps from section *V.A.* are the same as before: we obtain λ and b.

The decomposition exercises are unchanged. We start from the values of α for women, keep all other structural parameters equal, and decrease α to match the gender difference in α estimated in Tables A1 and A2, i.e. 24% under Interpretation 2 and 15% under Interpretation 2 bis. We simulate the job search model to predict the gender gap in wage and commute of the next job; we report how much of the observed gaps these predicted gaps explained. Results are shown in Table A3. In the simulations, we explain between 9.4 and 14.6% of the gender wage gap. This is broadly in line with the results in Table VI.

Table A3: Contribution of gender differences in commute valuation to gender gaps in wage and commute: Alternative interpretations of the reservation wage and reservation commute measures

	Contribution to the observed gender gaps in		Commute valuation
	Wage	Commute	shock
Interpretation 2	14.6%	180%	24%
Interpretation 2 bis	9.4%	137.5%	15%

Note: This table computes the share of the empirical gender gaps in reemployment wage and commute explained by gender differences in commute valuation, under alternative interpretations of the reservation wage and maximum acceptable commute measures. We shock the commute valuation parameter of women by the difference in α estimated in Table A1 and Table A2 column (3). We simulate the job search model to predict the gender gaps in the wage and commute of the next job; we show in columns (1) and (2) how much this explains the observed gaps in reemployment wage and commute.

B Further insights from application data

Elasticity of posted wages with respect to commute distance

In this subsection we analyze the application data from the job seeker's perspective. We present estimates of the elasticity of the posted wages with respect to the distance between the vacancy workplace and the job seeker's residence. They are obtained from the following regression at the application level of worker i for vacancy j (at date $t(i,j)$):

$$\log PostedWage_{i,j} = \nu_i + \alpha \log Commute_{i,j} + \delta \log Commute_{i,j} \times Female_i + \gamma Female_i + \beta X_i + \mu Udur_{t(i,j)} + \psi V_j + \epsilon_{i,j}$$

where $PostedWage_{i,j}$ is the log posted wage (gross full-time equivalent in euros) of vacancy j and $Commute_{i,j}$ is the log commute distance between the workplace of vacancy j and applicant i 's residence. As above, the commute is computed as the distance between the centroids of the workplace and residence municipalities. Our main parameter of interest is the gender gap in elasticity (δ). We include worker fixed effects ν_i, so the average gender gap in posted wage (γ) and the coefficients on permanent worker characteristics (β) are not identified. The only identified coefficient from the worker's perspective (μ) is the posted wage profile with unemployment duration, defined as the difference between the application and unemployment registration dates. We also control for vacancy characteristics V_j that could confound the relationship between posted wages and commute distances: calendar months of when the vacancy is first posted, 3-digit occupation dummies, a dummy for temporary contracts, required hours worked, qualification, education and work experience. Standard errors are clustered at both the applicant and vacancy levels.

Table B1 presents the estimation results for different specifications and samples. In column (1), we see that the male elasticity is significantly positive: a 10% increase in commute is associated with a 0.05% increase in the posted wage. The gender gap in this elasticity is insignificant. However, as in the main estimation of the slope of the indifference curve in Section IV., the wage elasticity with respect to commute in application data is attenuated by the binding legal minimum wage. We thus restrict the sample to above minimum wage occupations in columns 2 and

3. We compute the share of vacancies posting a wage equal to the minimum wage within each 3-digit occupation (around 500 occupation categories). The median occupation has 37% of vacancies posting minimum-wage jobs. We include in the above minimum wage sample all workers whose preferred occupation has fewer minimum wage jobs than the median occupation. In column (2), the gender gap in elasticity becomes positive and statistically significant. Jobs to which women apply have posted wages that increase when they are further away from home at a faster rate than men. This is in line with women having steeper indifference curves in the wage-commute plane. We obtain a similar pattern when we control for the other vacancy characteristics in column (3).

The estimates of the elasticity of posted wages with respect to commute are significantly lower than those of the slope of the reservation wage curve in Section IV.. This is expected as posted wages to which workers apply are above the reservation wage curve in the wage-commute plane. For small commuting distances, average posted wages are further up from the reservation wage curve than for high commuting distances. This highlights that gender gaps in posted wage elasticity with respect to commute mostly inform us about the sign of the gender gap in commute valuation.

What about labor demand?

Figure VII in the main text shows that the reduction in hiring rate with distance looks similar for men and women. In this appendix, we document this finding in a regression framework. We run the following regression at the application level of worker i to vacancy j :

$$H_{i,j} = \psi_j + \delta Female_i + \beta X_i + \phi Z_{i,j} + f_0(Commute_{i,j}) + f_1\left(Commute_{i,j}\right) \times Female_i + \epsilon_{i,j}$$

where $H_{i,j}$ is a dummy indicating whether worker i is hired on vacancy j. ψ_j is a vacancy fixed effect. $Female_i$ indicates the gender of applicant i and X_i is a vector of other covariates (incl. age, education level, work experience, qualification and nationality). $Z_{i,j}$ is a vector of characteristics that depends on the worker-vacancy pair: $Z_{i,j}$ includes whether worker i has the education level required by the job ad (if present), whether she has the work experience required by the employer, and whether she states the occupation advertised on the vacancy as her desired

Table B1: Elasticity of posted wages with respect to commute distance between the vacancy workplace and the jobseeker's residence, by gender

	(1)	(2)	(3)	(4)
	Log vacancy wage			
Log commute	0.0147***	0.00526***	0.007***	0.00319***
	(0.00021)	(0.00017)	(0.00023)	(0.00022)
Female	-0.00875***			
	(0.00028)			
Female $\times$ log Commute	-0.00214***	-0.00007	0.00391***	0.00202***
	(0.00028)	(0.00024)	(0.00042)	(0.00039)
Worker Control		Y	Y	Y
Worker FE		Y	Y	Y
Vacancy Controls				Y
Sample			$>$min W	$>$min W
Observations	2,893,586	2,765,311	1,329,862	1,329,862
R-squared	0.062	0.356	0.377	0.439

Note: Baseline controls include dummies for the month when vacancy is posted and commuting zone of the applicant. Worker controls include unemployment duration. Vacancy controls are occupation, temporary contracts, required hours worked, qualification, education and work experience. Standard errors in parenthesis are clustered at both the applicant and vacancy levels. In columns (3) and (4), the estimation sample is restricted to applicants whose preferred occupation has a share of vacancies posted at the min wage below 37%.

occupation. $Z_{i,j}$ does not include the geographical distance $Commute_{i,j}$. $f_0(.)$ is a polynomial function capturing the relationship between hiring and commuting distance for male applicants, while $f_1(.)$ is its deviation for female applicants. $f_1(.)$ is our main object of interest. We cluster standard errors at the vacancy level j, as outcomes of competitors to the same tournament are correlated. The fixed effect ψ_j also accounts for variations in the average hiring rate across vacancies that depends on the number of applicants, and their fit to the job.

Table B2 presents the estimates of $f_1(.)$, $f_0(.)$ and δ for different sets of controls. The relationship between hiring rate and commuting distance for men is stable across the first three columns and decreases a bit in column (4) where we introduce vacancy fixed effects. We estimate second-order deviations in the hiring-commute relationship for women, which are statistically significant at the 5% level, only in column (3). To assess the economic magnitude of these gender differences, we compute the marginal effects of commute on hiring rates, separately for men and women (at the average of the commuting distance). Column (1) shows that a 10km increase in commute reduces the hiring rate of men by 0.72 percentage point (from an average of 5%). For women, the same marginal effect is -0.75, suggesting a slightly steeper decrease, but the small difference between the two marginal effects is not statistically significant. Marginal effects barely change when we introduce applicants or vacancy controls. The gender difference in the marginal effect of a 10km commute increase is never greater than 0.08 p.p across specifications, and it is not statistically significant at the 5% level in our preferred specification of column (4). Overall, we find that firms do not specifically lower their hiring of women compared to men when applicants live further away.

Table B2: Effect of commute to the vacancy's workplace on the hiring probability, by gender

	(1)	(2)	(3)	(4)
	Hiring rate			
Commute	-.000975***	-.00101***	-.000933***	-.000602***
	(2.16e-05)	(3.00e-05)	(2.99e-05)	(5.03e-05)
Commute-sq	6.78e-06***	7.17e-06***	6.48e-06***	4.11e-06***
	(2.19e-07)	(2.86e-07)	(2.85e-07)	(5.47e-07)
Female	.00418***	.00613***	.00534***	.00719***
	(.000716)	(.000765)	(.000759)	(.000835)
Commute $\times$ Female	-6.43e-05	-7.63e-05*	-11.6e-05***	-10.6e-05*
	(4.26e-05)	(3.14e-05)	(4.21e-05)	(6.23e-05)
Commute-sq $\times$ Female	7.76e-07*	7.16e-07*	10.2e-07**	7.19e-07
	(4.21e-07)	(4.18e-07)	(4.17e-07)	(6.66e-07)
Marginal effect of Commute				
Men	-.000720	-.000740	-.000689	-.000447
	(1.99e-05)	(1.99e-05)	(1.98e-05)	(3.25e-05)
Women	-.000755	-.00079	-.000767	-.000527
	(2.03e-05)	(2.03e-05)	(2.01e-05)	(3.31e-05)
Women-Men	-3.50e-05	-4.93e-05*	-7.82e-05***	-7.96e-05*
	(2.84e-05)	(2.84e-05)	(2.82e-05)	(4.63e-05)
Applicant controls		X	X	X
Appl. satisfies Vac. requirements			X	X
Vacancy Fixed Effects				X
Observations	3,103,522	3,103,522	3,103,522	712,654
# of vacancies				214,248

Sample: applications to vacancy/job ads posted at the PES.
Note: In this table, we regress the hiring dummy on the commuting distance (and its square), on a female dummy and on their interactions. Commute is the distance between the applicant's residence and the vacancy's workplace. We report regression coefficients and marginal effects on hiring rate of an increase in commuting distance for men and for women. We finally compute the gender gap in the marginal effects on hiring. All regressions include dummies for application month. From column (2) onwards, we include applicant controls (age, education, work experience, foreigner). From column (3) onwards, we include dummies indicating whether applicant has the required education, or experience levels and whether she states the occupation advertised on the vacancy as her desired occupation. In column (4), we add vacancy fixed effects. Standard errors are clustered at both the vacancy and applicant levels.

C Extra Figures

Figure C1: Screenshot of the section dedicated to the desired occupation / reservation wage / maximum acceptable commute on the public employment service website at registration

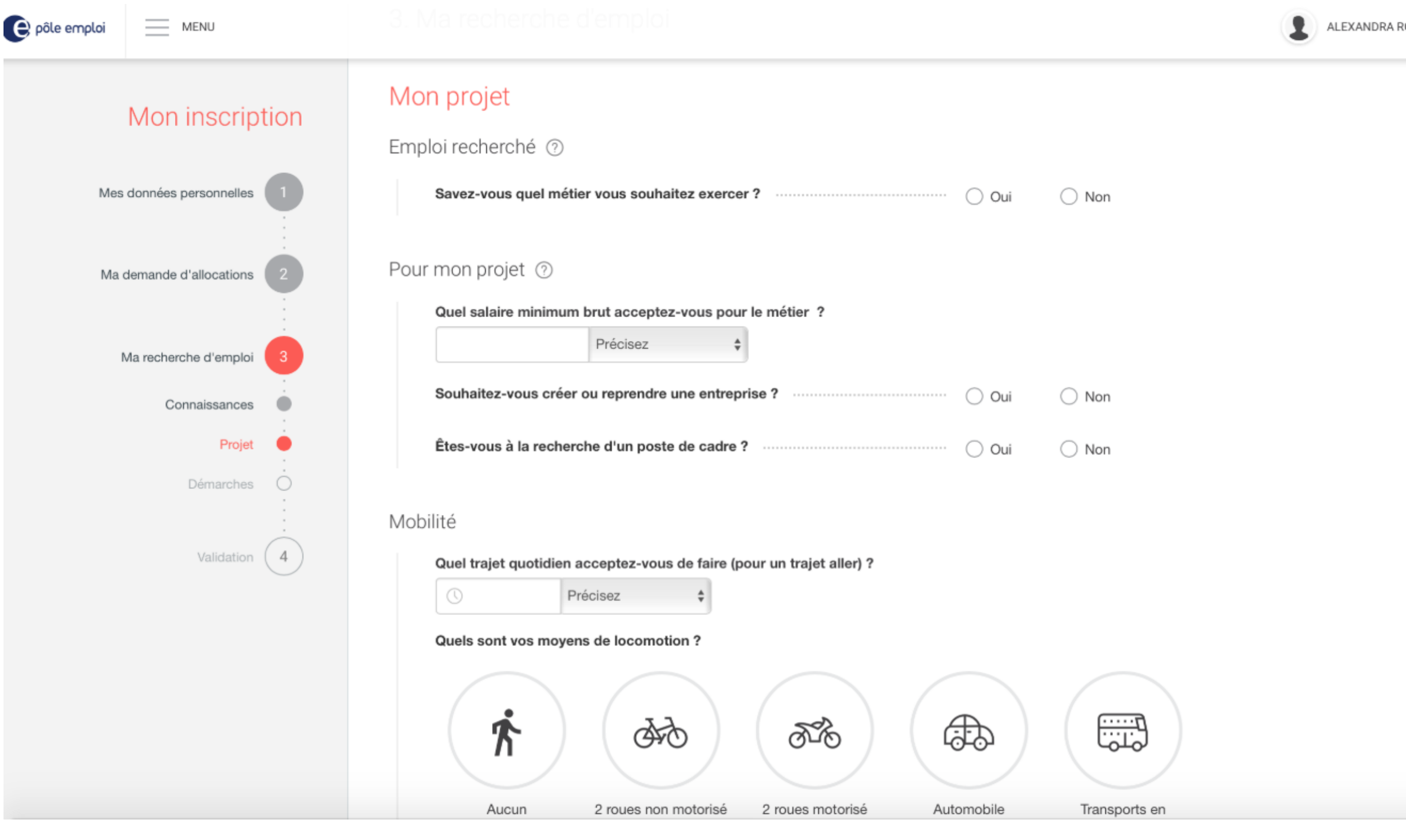


Figure C2: Screenshot of the section dedicated to desired hours worked and type of labor contract on the public employment service website at registration

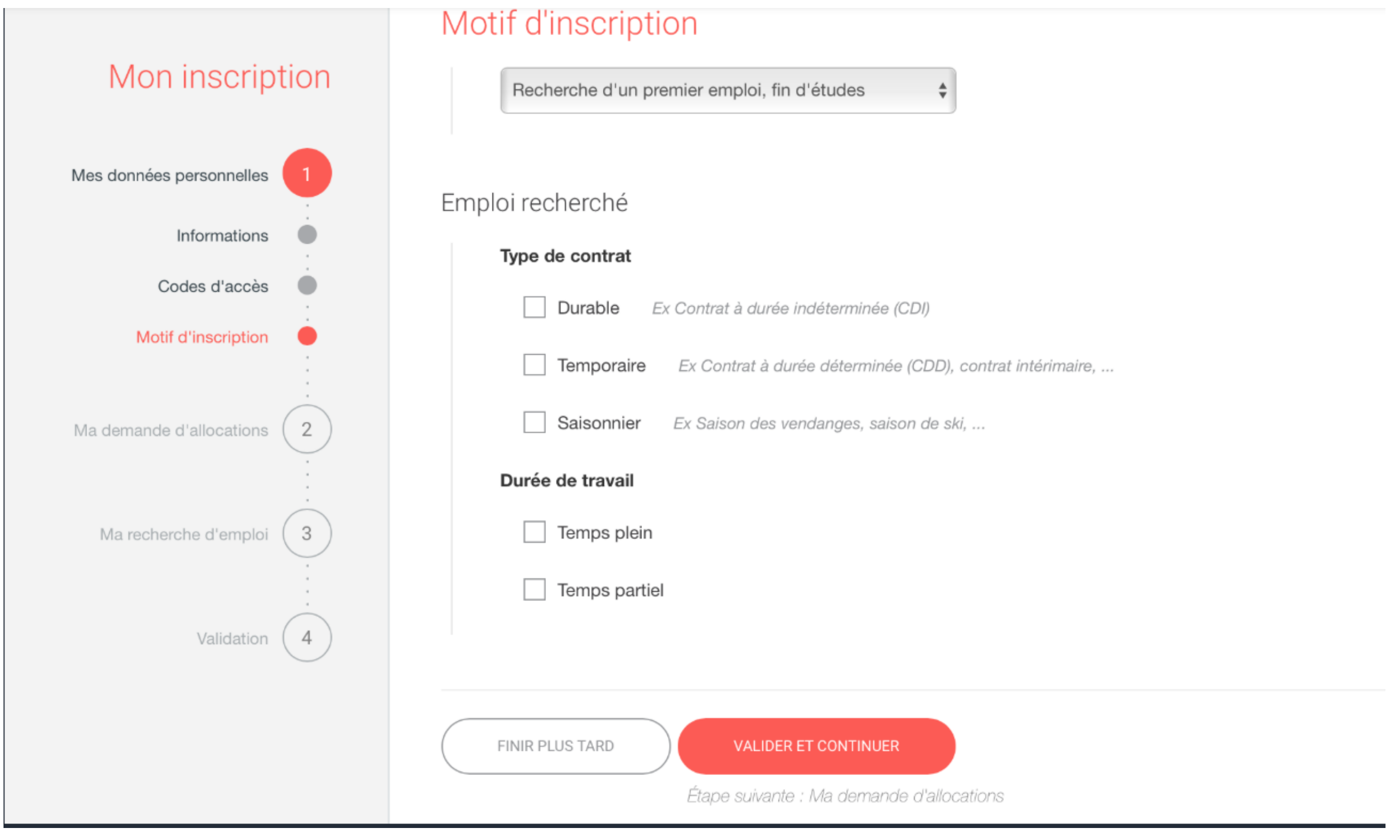
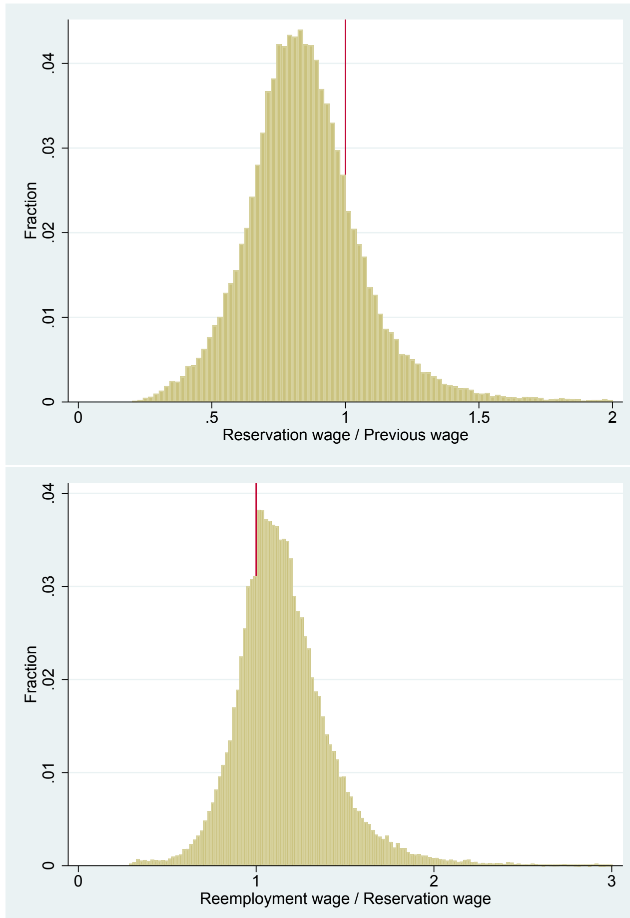


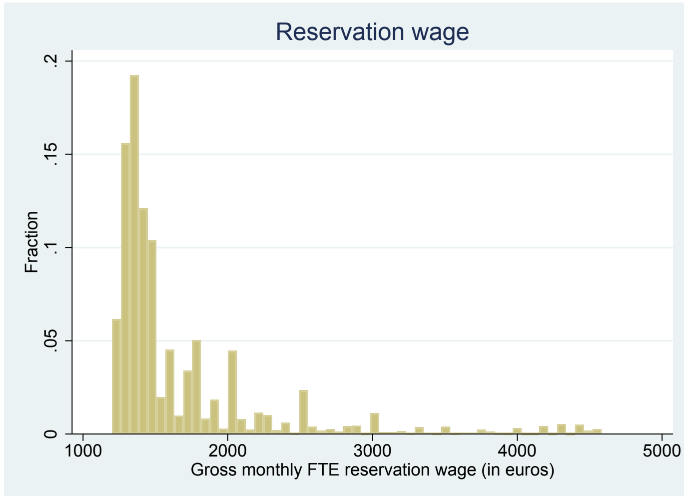
Figure C3: Reservation wage over previous wage and reemployment wage over reservation wage, excluding minimum wage workers



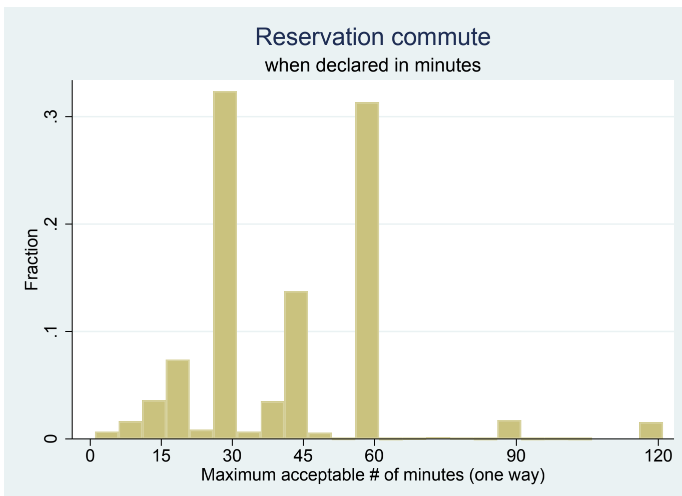
Note: The figure plots the distributions of search criteria and employment outcomes for our main sample of unemployed people restricted to those who find jobs within two years. Compared to Figure II, we exclude minimum-wage workers. The left-hand panel plots the distribution of the ratio of the unemployed's reservation wage over the full-time-equivalent gross monthly wage in her previous job. The right-hand panel plots the ratio of the reemployment (FTE gross monthly) wage over the reservation wage.

Figure C4: Reservation wage and maximum acceptable commute

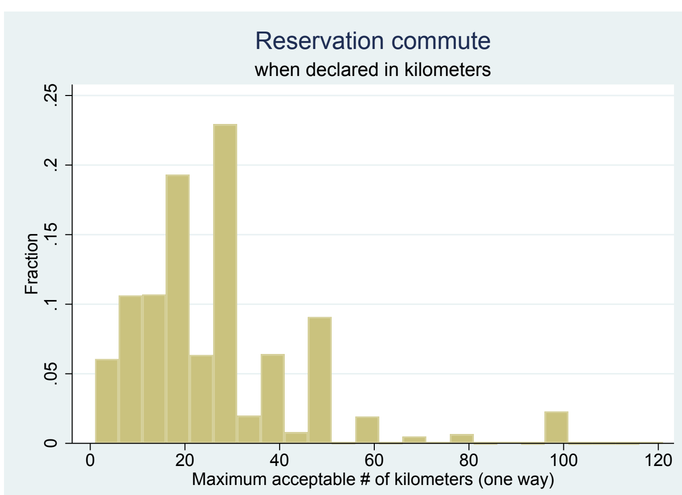
(a) Reservation wage



(b) Maximum acceptable commute (in minutes)



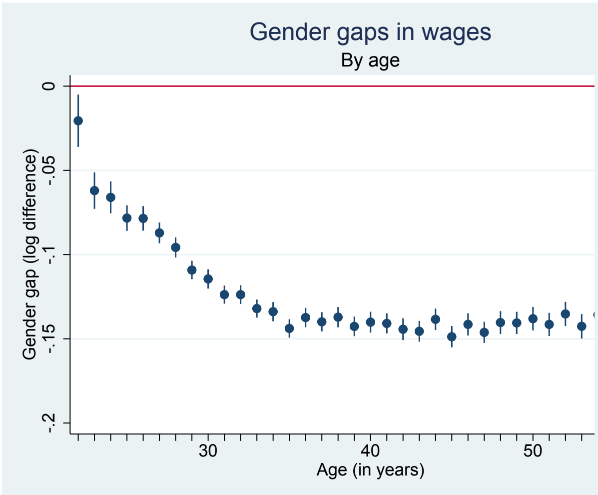
(c) Maximum acceptable commute (in kilometers)



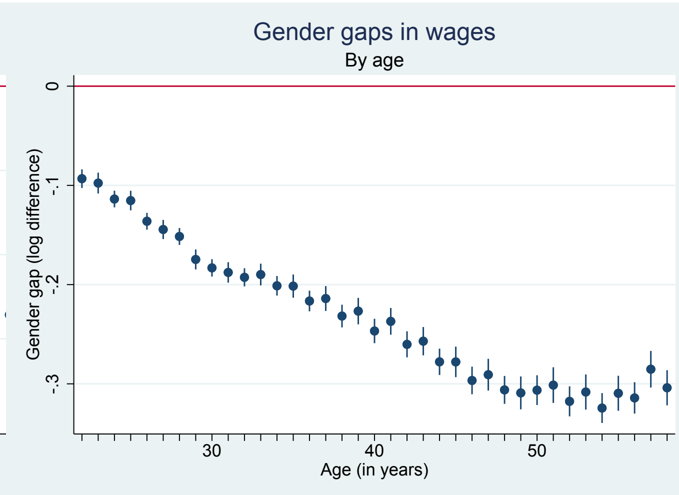
Note: The figure plots the distributions of search criteria for our main sample of unemployed people. Panel (a) plots the distribution of the gross monthly FTE reservation wage in euros, panel (b) the reservation commute for those who declare it in minutes, and panel (c) the reservation commute for those who declare it in kilometers.

Figure C5: Age effects in gender wage gaps, over different periods

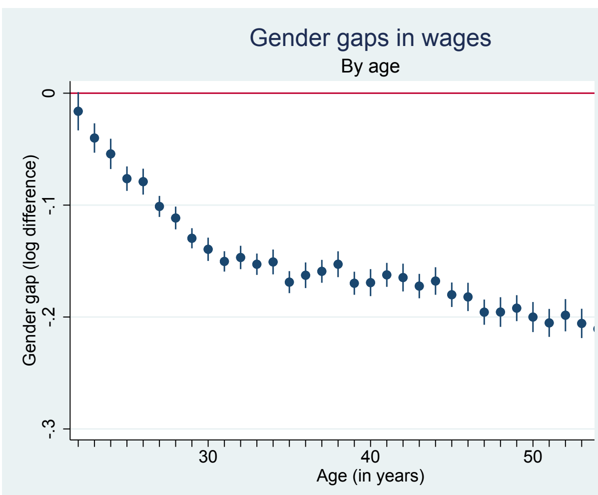
(a) FTE monthly wages, 1993-2010



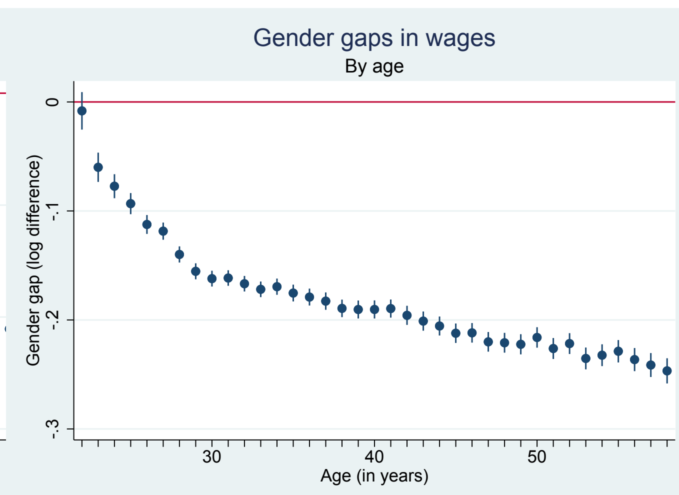
(b) Daily wages, 1976-1992



(c) Daily wages, 1993-2001



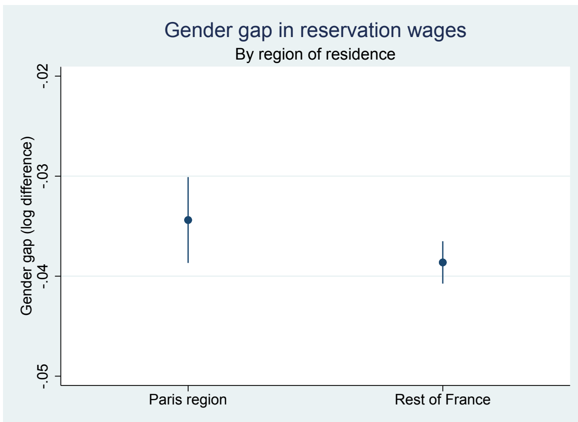
(d) Daily wages, 2002-2010



Note: We regress log-wages on a female dummy interacted with age. The figures plot the corresponding regression coefficients. Realized wages come from a random subsample of all private sector yearly employment spells in France (DADS-EDP data). We control for education, age, marital status, children, experience and its square, and year $\times$ industry $\times$ CZ fixed effects. We include a part-time dummy and occupation dummies. Vertical lines for 95% confidence intervals. In Panel (a), wages are full-time equivalent monthly gross wages, while we analyze daily gross wages in Panels (b), (c) and (d). Before 1993, exact hours worked, and detailed occupation and industry are not available. The sample in Panel (a) runs from 1993 to 2010; in Panel (b), from 1976 to 1992; in Panel (c), from 1993 to 2001; in Panel (d), from 2002 to 2010.
Panel (a) reports the same plot as Figure IV but using almost 20 years of data, 1993-2010. If cohort effects are large, expanding the sample should flatten the age profile but we see no evidence of that. Panels (b) through (c) report gender gaps in daily wages, respectively for the period 1976-1992, 1993-2001 and 2002-2010. Again, whatever the period, we find a quite similar age profile suggesting that the patterns of Figure IV reflect age effects, rather than cohort effects.

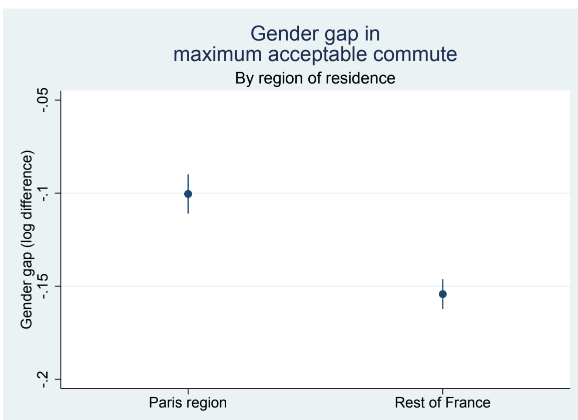
Figure C6: Gender gaps are smaller in the Paris region than in the rest of France

(a) Reservation wage

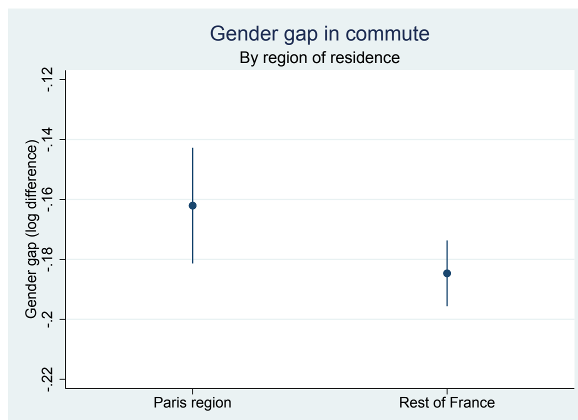


(b) Wage

(c) Maximum acceptable commute



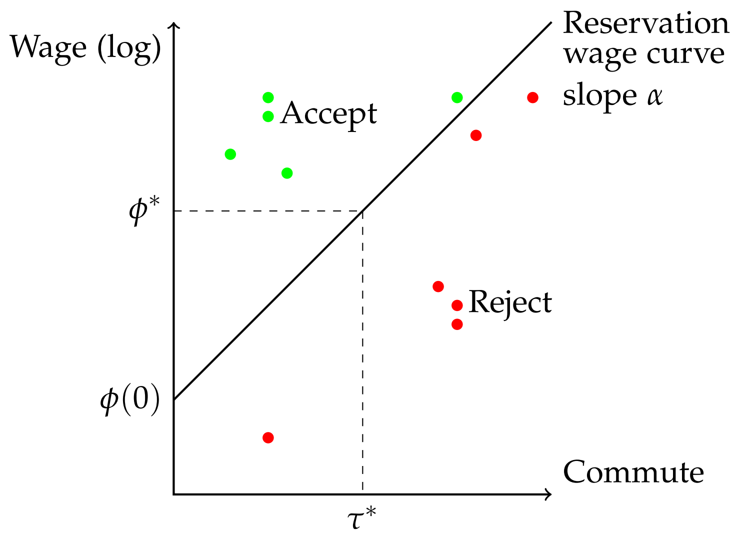
(d) Commute



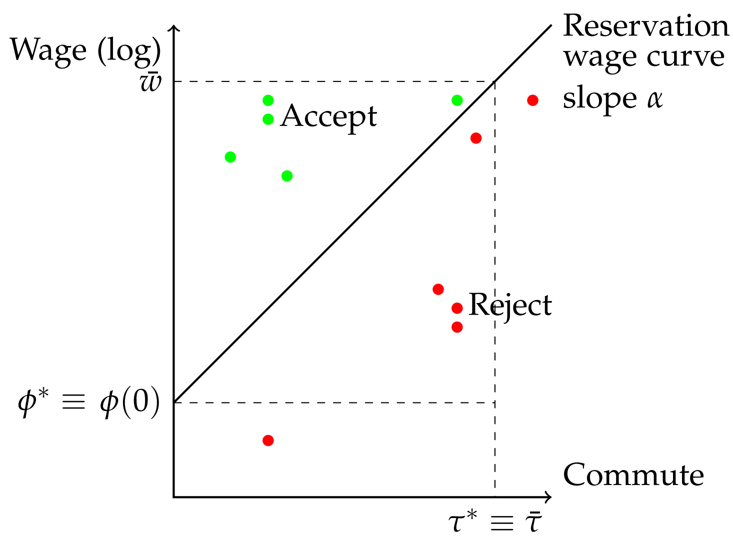
Note: These figures plot regression coefficients of a female dummy interacted with two region dummies, on the log of the FTE gross monthly reservation wage (panel a), the log of FTE gross monthly wages (panel b), the log of the maximum acceptable commute (panel c) and the log of commute distances (panel d). The two region dummies are for the Paris region and for the rest of France. Search criteria analyzed in panels (a) and (c) are based on our main sample comprising 319,000 job seekers. Realized wages and commutes in panels (b) and (d) come from a sample of 4% of all private sector yearly employment spells in France between 2003 and 2010 (DADS-EDP data). We control for education, age, marital status, children, and year $\times$ industry $\times$ CZ fixed effects. When analyzing searched criteria, we also control for potential benefit duration, and previous job characteristics (contract, hours, occupation, wage bins). When analyzing realized outcomes we include a part-time dummy and occupation dummies. Vertical lines for 95% confidence intervals.

Figure C7: Interpretation of the reported reservation wage ϕ^* and maximum acceptable commute τ^*

(a) Interpretation 1

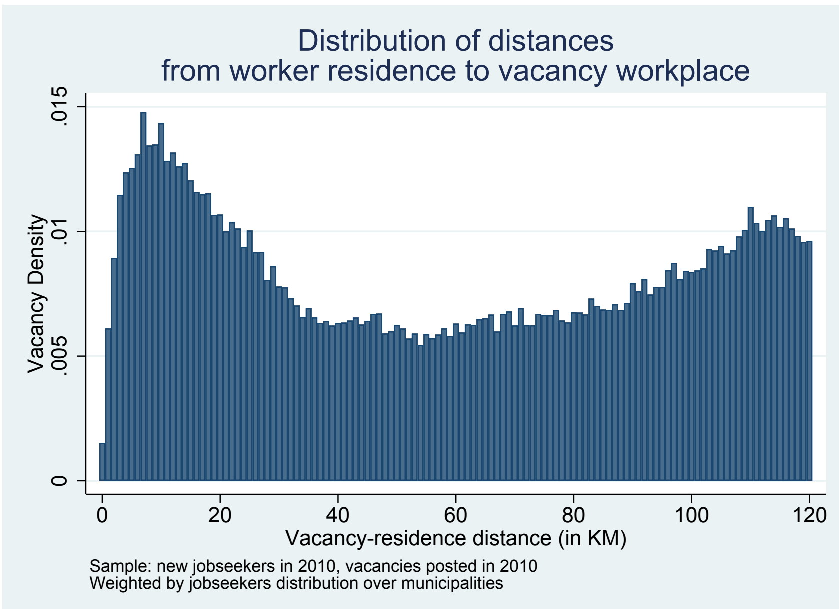


(b) Interpretation 2



Note: These figures draw the reservation strategy of job seekers in the log-wage-commute plane. The reservation wage curve intercepts the y-axis at $\phi(0)$ and has a slope α. Workers accept job bundles above the reservation wage curve (green dots) and reject jobs below (red dots). Panel (a) draws the reservation wage ϕ^* and maximum acceptable commute τ^* reported to the public employment service under interpretation 1 explained in Section IV.B.. Panel (b) draws the reported search criteria under interpretation 2, where we denote $\bar{w}$ the upper bound of the wage offer distribution and $\bar{\tau} = \phi^{-1}(\bar{w})$.

Figure C8: Distribution of distances between workers' residence and vacancies' workplace



Note: The figure plots the distribution of distances between workers' residence and vacancies' workplace. The distribution is not conditional on workers' application, nor on any match between workers and vacancy characteristics.

D Extra Tables

Table D1: Declared search criteria and probability to be sanctioned

	Sanctions		
Reservation wage	1.77e-05		2.34e-05
	(0.000916)		(0.000917)
Max. accept. commute		-0.000130	-0.000118
		(0.000266)	(0.000266)
Mean: sanction rate	0.5%	0.5%	0.5%
Observations	319,902	319,902	319,902
R-squared	0.195	0.195	0.195

Sample: New claimants from 2006-2012.
Note: In this table, we estimate a linear probability model of being sanctioned by the PES for failing to search for jobs on search criteria. All regressions control for previous job characteristics (20 wage bin dummies, 3 digit occupation, hours, contract, distance to home), Quarter X previous industry X CZ FE, and worker characteristics (age dummies, education, experience, family status, potential benefit duration).
Take-away: The coefficients of reservation wage and commute are insignificant.

Table D2: Summary statistics for the sample of job finders

Variable	Men	Women
	Pre-unemployment variables	
Age	30.8	30.9
Married	0.334	0.357
Child	0.291	0.375
Education (in years)	11.5	12.2
Experience (in years)	5.7	4.8
Past wage (monthly, gross, euros)	2,020	1,908
Past commuting distance (km)	21.4	17.2
Past job is full-time	0.865	0.723
Past contract is open-ended	0.392	0.277
Number of obs.	81,162	68,744
	Search-related variables	
Reservation wage (monthly, gross, euros)	1,703	1,566
Max commute dist. accepted (km)	34.0	28.2
Max commute time accepted (min)	46.1	41.8
Looking for a full-time job	0.980	0.910
Looking for an open-ended contract	0.921	0.905
Looking for same occupation (3-digit)	0.192	0.209
Found a job within 2 years	1	1
Non-employment duration (in days)	287	285
Number of obs.	81,162	68,744
	Reemployment outcomes	
Next-job wage (monthly, gross, euros)	1,947	1,825
New commuting distance (km)	21.3	16.6
Next job is full-time	0.841	0.712
Next-job contract is open-ended	0.377	0.343
Finding in same occupation as prev. job	0.262	0.304
Number of obs.	81,162	68,744

Note: The sample consists in job finders starting an unemployment spell between 2006 and 2012 (subsample from FH-DADS). *Child* indicates whether workers have at least one child. Wages are full-time-equivalent gross monthly wages. Commuting distances are for one-way trips. *Looking for same occupation* is a dummy for whether workers state as their desired occupation the occupation of their pre-unemployment job. *Finding in same occupation* is a dummy for whether workers' occupation in their new job is the same as their occupation in their pre-unemployment job.

Table D3: Gender effect on attributes of the job searched for: Robustness on subsamples

	Log ResW	Log max. commute	Full-time	Same occup.
	Panel A: Whole sample			
Female	-0.0356***	-0.140***	-0.0649***	0.00659***
	(0.000927)	(0.00351)	(0.00143)	(0.00198)
Mean: males	1,741€	32 km	0.966	0.283
Observations	319,902	319,902	319,902	319,902
R-squared	0.730	0.434	0.277	0.397
	Panel B: Non-minimum wage sample			
Female	-0.0466***	-0.137***	-0.0471***	0.0108***
	(0.00167)	(0.00495)	(0.00188)	(0.00317)
Observations	121,399	121,399	121,399	121,399
R-squared	0.687	0.447	0.301	0.443
	Panel C: Workers previously full-time			
Female	-0.0382***	-0.144***	-0.0440***	0.00353
	(0.00112)	(0.00416)	(0.00143)	(0.00238)
Observations	193,631	193,631	193,631	193,631
R-squared	0.757	0.442	0.238	0.421
	Panel D: Workers finding jobs			
Female	-0.0332***	-0.123***	-0.0395***	0.00416
	(0.00141)	(0.00554)	(0.00194)	(0.00316)
Observations	149,952	149,952	149,952	149,952
R-squared	0.750	0.459	0.272	0.443

Note: The table reports regression coefficients of a female dummy on the log of the FTE gross monthly reservation wages (column 1), on the log of the maximum acceptable commute (column 2), on a dummy indicating whether workers search for a full-time job (column 3) and on a dummy indicating whether the desired occupation is the same as the previous occupation (column 4). Controls include previous wage bins (20 dummies), 3 digit previous occupation dummies, other characteristics of the previous job (full-time, type of contract and distance to home), log potential benefit duration, commuting zone times quarter times industry fixed effects, age dummies, experience and education dummies. Standard errors clustered at worker level in parenthesis.
The sample in Panel A is the whole sample used in Table II. Panel B restricts the analysis to the sample used for Section *IV.B.*, i.e. job seekers with reservation wage at least 5% above the minimum wage prevailing at registration. In Panel C, we include only job seekers who worked full-time in their previous job. In Panel D, we restrict to job seekers finding a new job within two years.

Table D4: Gender effect on the probability to find a job

	(1)	(2)	(3)	(4)
	Found a job within 2 years			
	Inflows 2006-2012		Inflows 2006-2010	
Female	-0.0239***	-0.000100	-0.0286***	-0.00145
	(0.00241)	(0.00277)	(0.00299)	(0.00346)
Log ResW		-0.0192***		-0.0308***
		(0.00640)		(0.00792)
Log Max. Commute		0.0351***		0.0383***
		(0.00162)		(0.00198)
Search criteria		X		X
Mean: males	0.480	0.480	0.480	0.480
Observations	319,902	319,902	184,142	184,142
R-squared	0.343	0.349	0.310	0.324

Note: In this table, we regress a dummy indicating whether workers find a job within two years after their unemployment registration on a female dummy. Controls include previous wage bins (20 dummies), 3 digit previous occupation dummies, other characteristics of the previous job (full-time, type of contract and distance to home), log potential benefit duration, commuting zone times quarter times industry fixed effects, age dummies, experience and education dummies, marital status and number of children. In columns (2) and (4), we control for the attributes of the job searched for: reservation wage, maximum acceptable commute, desired occupation, part-time job and labor contract. Robust standard errors in parenthesis.
Columns (1) and (2) include the full main sample, while columns (3) and (4) exclude the inflows from 2011 and 2012 where end-of-data censoring may be an issue.
The estimation drops singleton observations within CZ x Quarter x Industry cells, so that the effective sample size in Columns (1) and (2) is 270,934.

Table D5: Gender effect on reemployment outcomes: Robustness on subsamples

	(1) Log wage	(2) Log commute	(3) Full-time	(4) Same occup.
	Panel A: All sample, without search related controls			
Female	-0.0367***	-0.118***	-0.0812***	-0.00169
	(0.00190)	(0.00975)	(0.00342)	(0.00349)
Mean: males	1,948 €	21.3 km	0.39	0.19
Observations	149,952	149,952	149,952	149,952
R-squared	0.543	0.346	0.305	0.322
	Panel B: All sample, with search related controls			
Female	-0.0162***	-0.0529***	-0.0471***	0.00160
	(0.00212)	(0.0113)	(0.00390)	(0.00367)
R-squared	0.578	0.359	0.321	0.424
	Panel C: Non-minimum wage sample			
Female	-0.0404***	-0.148***	-0.0354***	0.00403
	(0.00326)	(0.0152)	(0.00478)	(0.00567)
R-squared	0.571	0.385	0.293	0.357
	Panel D: Job seekers whose municipality of residence did not change			
Female	-0.0362***	-0.130***	-0.0782***	-0.00103
	(0.00213)	(0.0106)	(0.00382)	(0.00390)
R-squared	0.556	0.373	0.317	0.331

Note: In this table, we regress the log of reemployment FTE wages (column 1), the log of reemployment commuting distances (column 2), a dummy indicating whether the new job is full-time (column 3), and a dummy indicating whether the next-job occupation is the same as the pre-unemployment occupation (column 4) on a female dummy. Controls include previous wage bins (20 dummies), 3 digit previous occupation dummies, other characteristics of the previous job (full-time, type of contract and distance to home), log potential benefit duration, commuting zone times quarter times industry fixed effects, age dummies, experience and education dummies, marital status and number of children. Standard errors clustered at worker level in parenthesis.

Panel A replicates estimation results of Table III columns (1) and (2). Panel B adds search criteria as controls as in columns (5) and (6) of Table III. Panel C restricts the sample to non-minimum wage workers. In Panel D, we exclude job seekers who move from one municipality to another when finding their new job.

Table D6: Gender effect on attributes of the job searched for and on reemployment outcomes, controlling for municipality fixed effects

	(1) Log ResW	(2) Log max. commute	(3) Log wage	(4) Log commute
Female	-0.0348***	-0.148***	-0.037***	-0.148***
	(0.000998)	(0.00362)	(0.00216)	(0.0106)
Municipality FE	X	X	X	X
Mean: males	1,741 €	32 km	1,948 €	21.3 km
Observations	319,902	319,902	149,952	149,952
R-squared	0.750	0.501	0.730	0.437

Note: This table adds fixed effects for the job seeker's municipality of residence to the regressions of Table II and III.

We regress the log of the reservation wage (column 1), the log of the maximum acceptable commute (column 2), the log of the reemployment FTE wage (column 3) and the log of the reemployment commuting distance (column 4) on a female dummy. Controls include previous wage bins (20 dummies), 3 digit previous occupation dummies, other characteristics of the previous job (full-time, type of contract and distance to home), log potential benefit duration, commuting zone times quarter times industry fixed effects, age dummies, experience and education dummies, marital status and presence of children. We add municipality fixed effects. Standard errors clustered at worker level in parenthesis. The estimation drops singleton observations. The effective sample size in columns (1) and (2) is 261,513. The effective estimation sample size in columns (3) and (4) is 105,261.

Table D7: Gender effect on attributes of the job searched for, by family size

	(1) Log ResW	(2) Log max. commute	(3) Full-time	(4) Same occup.
Female × Single, no child	-0.0214***	-0.0768***	-0.0199***	0.00514**
	(0.00111)	(0.00446)	(0.00171)	(0.00248)
Male × Married, no child	0.0177***	0.0273***	0.00787***	-0.000986
	(0.00187)	(0.00652)	(0.00222)	(0.00365)
Female × Married, no child	-0.0328***	-0.149***	-0.0744***	0.0104***
	(0.00166)	(0.00638)	(0.00308)	(0.00374)
Male × Single, with child	0.0234***	0.0427***	0.0111***	-0.00579
	(0.00242)	(0.00826)	(0.00263)	(0.00488)
Female × Single, with child	-0.0233***	-0.138***	-0.0770***	-0.00357
	(0.00157)	(0.00632)	(0.00310)	(0.00364)
Male × Married, with child	0.0271***	0.0628***	0.0127***	-0.000546
	(0.00139)	(0.00486)	(0.00159)	(0.00282)
Female × Married, with child	-0.0288***	-0.174***	-0.133***	0.0106***
	(0.00139)	(0.00544)	(0.00272)	(0.00310)
Mean: males	1,741 €	32 km	0.966	0.283
Observations	319,902	319,902	319,902	319,902
R-squared	0.730	0.436	0.284	0.397

Note: The table reports regression coefficients of a female dummy interacted with different household structure dummies, on the log of the FTE gross monthly reservation wage (column 1), the log of the maximum acceptable commute (column 2), on a dummy indicating whether the desired job is full-time (column 3) and on a dummy indicating whether the preferred occupation is the same as the previous occupation (column 4). Controls include previous wage bins (20 dummies), 3 digit previous occupation dummies, other characteristics of the previous job (full-time, type of contract and distance to home), log potential benefit duration, commuting zone times quarter times industry fixed effects, age dummies, experience and education dummies. The reference individual is a single man without children. Standard errors clustered at worker level in parenthesis. The estimation drops singleton observations within CZ x Quarter x Industry cells, so that the effective sample size is 270,934.
Columns (1) and (2) provide the estimation results of the left-hand panels of Figure III.

Table D8: Gender effect on reemployment outcomes, by family status

	(1) Log wage	(2) Log commute	(3) Full-time	(4) Same occup.
	Panel A: Without search related controls			
Female × Single, no child	-0.0307***	-0.102***	-0.0680***	0.00132
	(0.00226)	(0.0119)	(0.00419)	(0.00416)
Male × Married, no child	-0.00477	0.00668	0.00570	0.000474
	(0.00382)	(0.0192)	(0.00598)	(0.00661)
Female × Married, no child	-0.0420***	-0.109***	-0.0616***	0.00596
	(0.00363)	(0.0184)	(0.00694)	(0.00705)
Male × Single, with child	0.0123**	-0.0150	-0.000884	0.00527
	(0.00520)	(0.0253)	(0.00784)	(0.00926)
Female × Single, with child	-0.0394***	-0.138***	-0.102***	-0.0258***
	(0.00357)	(0.0182)	(0.00704)	(0.00681)
Male × Married, with child	0.00684**	0.0347**	0.00613	-0.00706
	(0.00292)	(0.0143)	(0.00460)	(0.00515)
Female × Married, with child	-0.0377***	-0.122***	-0.111***	-0.00823
	(0.00304)	(0.0154)	(0.00579)	(0.00585)
R-squared	0.543	0.346	0.306	0.323
	Panel B: With search related controls			
Female × Single, no child	-0.0142***	-0.0523***	-0.0408***	0.00226
	(0.00241)	(0.0131)	(0.00453)	(0.00417)
Male × Married, no child	-0.00604*	-0.00289	0.00463	-0.00166
	(0.00366)	(0.0190)	(0.00595)	(0.00600)
Female × Married, no child	-0.0229***	-0.0421**	-0.0309***	0.00739
	(0.00364)	(0.0191)	(0.00711)	(0.00670)
Male × Single, with child	0.00446	-0.0285	-0.00552	0.000956
	(0.00495)	(0.0252)	(0.00783)	(0.00816)
Female × Single, with child	-0.0202***	-0.0696***	-0.0636***	-0.0201***
	(0.00363)	(0.0190)	(0.00727)	(0.00646)
Male × Married, with child	4.05e-05	0.0163	0.00267	-0.00746
	(0.00280)	(0.0142)	(0.00460)	(0.00470)
Female × Married, with child	-0.0162***	-0.0413**	-0.0656***	-0.00143
	(0.00313)	(0.0166)	(0.00612)	(0.00570)
R-squared	0.578	0.359	0.321	0.424
Mean: single males	1861 €	20.9 km	0.83	0.18
Observations	149,952	149,952	149,952	149,952

Note: The table reports regression coefficients of a female dummy interacted with different household structure dummies, on the log of the reemployment FTE wage (column 1), the log of the reemployment commuting distance (column 2), on a dummy indicating whether the new job is full-time (column 3) and on a dummy indicating whether the reemployment occupation is the same as the previous occupation (column 4). Controls include previous wage bins (20 dummies), 3 digit previous occupation dummies, other characteristics of the previous job (full-time, type of contract and distance to home), log potential benefit duration, commuting zone times quarter times industry fixed effects, age dummies, experience and education dummies, marital status and number of children. Standard errors clustered at worker level in parenthesis. The effective estimation sample size, dropping singletons, is 114,394.

Table D9: Gender effect on reemployment outcomes, for non-minimum wage job seekers

	(1) Log wage	(2) Log commute	(3) Full-time	(4) Same occup.
Female × Single, no child	-0.0361***	-0.119***	-0.0120**	0.00741
	(0.00404)	(0.0192)	(0.00595)	(0.00698)
Male × Married, no child	-0.00391	0.0283	0.0172**	0.00654
	(0.00553)	(0.0257)	(0.00743)	(0.00922)
Female × Married, no child	-0.0432***	-0.137***	-0.0278***	0.00923
	(0.00645)	(0.0296)	(0.00999)	(0.0119)
Male × Single, with child	0.0107	-0.00279	0.00524	0.00417
	(0.00717)	(0.0332)	(0.00967)	(0.0122)
Female × Single, with child	-0.0439***	-0.169***	-0.0430***	-0.00775
	(0.00645)	(0.0296)	(0.0103)	(0.0115)
Male × Married, with child	0.00996**	0.0371*	0.0162***	-0.00580
	(0.00420)	(0.0192)	(0.00577)	(0.00711)
Female × Married, with child	-0.0323***	-0.155***	-0.0627***	-0.00373
	(0.00539)	(0.0247)	(0.00816)	(0.00970)
Mean: single males	2036 €	23.2 km	0.87	0.22
Observations	75,189	75,189	75,189	75,189
R-squared	0.571	0.385	0.294	0.357

Note: Everything is similar to Table D8 panel A, except that the sample is restricted to non-minimum wage workers (sample used for estimation in Section *IV.B.*, i.e. job seekers with a reservation wage at least 5% above the minimum wage prevailing at registration). The effective estimation sample size, dropping singletons, is 50,778.

Table D10: Gender reservation wage gaps in the literature

	Estimate	Std. errors	Sample size	Country
Krueger and Mueller (2016)	-.083	(.016)	3,841	US
Feldstein and Poterba (1984)	-.051	(.04)	246	US
Caliendo, Lee, and Mahlstedt (2017)	-.052	(.013)	1,974	GER
Caliendo, Schmidl, and Uhlendhorff (2011)	-.103	na		GER
Brown, Roberts, and Taylor (2011)	-.068	na	12,921	UK
Koenig, Manning, and Petrongolo (2018)	-.102	(.011)	14,847	UK
Koenig, Manning, and Petrongolo (2018)	-.188	(.018)	11,221	GER
This paper	-.036	(.0009)	319,902	FR

Estimates obtained in regression of log reservation wage ratio (over past wage) for Krueger and Mueller (2016) and Feldstein and Poterba (1984). Caliendo, Lee, and Mahlstedt (2017) and Brown, Roberts, and Taylor (2011) rather control for past wages. Koenig, Manning, and Petrongolo (2018) do not control for past wages.
Krueger and Mueller (2016): Column (1) of Table 1.
Feldstein and Poterba (1984): Column (1) of Table 4.
Caliendo, Lee, and Mahlstedt (2017): Column (8) of Table 4
Caliendo, Schmidl, and Uhlendhorff (2011): Colmun (2) of Table AV
Brown, Roberts, and Taylor (2011): Column (1) of Table 1
Koenig, Manning, and Petrongolo (2018): Columns (2) and (4) of Table A2

Table D11: Gender effect on employment outcomes in job-to-job transitions

	(1) Log wage	(2) Log commute	(3) Log wage	(4) Log commute
Female	-0.0417***	-0.121***	-0.1076***	-0.230***
	(0.0007)	(0.0030)	(0.0008)	(0.0030)
Past job controls.	X	X		
Observations	973,762	973,337	973,765	973,765
R-squared	0.672	0.260	0.305	0.050

Sample: job-to-job transitions, where workers do no register to unemployment rolls, and where non-employment duration (between the two jobs) is inferior to six months.

Note: The table reports regression coefficients of a female dummy on the log of the full-time-equivalent gross monthly wage (columns 1 and 3) and on the log of the commuting distance (columns 2 and 4). In columns (1) and (2), controls include previous wage bins (20 dummies), 3 digit previous occupation dummies, other characteristics of the previous job (full-time, type of contract and distance to home), commuting zone $\times$ quarter $\times$ industry fixed effects, age dummies, experience and education dummies. In columns (3) and (4) we remove all controls related to the past job, as well as experience and industry. Standard errors clustered at worker level in parenthesis.

Table D12: Elasticity of wage with respect to commute along the reservation wage curve: Heterogeneity Paris region vs rest of France

	(1) All	(2) Paris	(3) Rest of France
Women	0.148***	0.241***	0.127***
	(.0045)	(.0148)	(.0048)
Men	0.121***	0.226***	0.099***
	(.0046)	(.0210)	(.0044)
Gender gap	0.027***	0.015	0.028***
	(.0073)	(.0260)	(.0065)
Obs.	75,071	17,942	57,226

Note: This table presents estimates of the elasticity of wages with respect to commute along the reservation wage curve. Estimation minimizes the criteria in Equation (4). We restrict the sample to job finders and to non-minimum-wage workers who declare a reservation wage at least 5% above the minimum wage. In column (2), we further restrict the sample to the Parisian region (*Ile-de-France*); in column (3), we exclude the Parisian region. We use inverse probability weighting to balance the covariates of women and men. Bootstrapped standard errors in parenthesis.

Table D13: Wage elasticity with respect to commute along the reservation curve: Robustness to minimum wage worker definition

	(1) Baseline	(2) Selection on occ. X pastW	(3) Selection on ResW > 1.15 minW	(4) Including min wage workers
Women	0.148***	0.139***	0.164***	0.113***
	(.0045)	(.0037)	(.0054)	(.0025)
Men	0.121***	0.12***	0.125***	0.105***
	(.0046)	(.0027)	(.049)	(.0037)
Gender gap	.027***	0.019***	0.039***	0.008*
	(.0073)	(.0052)	(.0074)	(.0046)
Obs.	75,071	74,635	56,165	148,190

Note: This table presents estimates of the elasticity of wages with respect to commute along the reservation wage curve. Estimation minimizes the criteria in Equation (4). The sample is restricted to job finders, and to non-minimum-wage workers, except in column (4) that also includes minimum-wage workers. We define non-minimum wage workers as those who declare a reservation wage at least 5% above the minimum wage in column (1). In column (2), non-minimum wage workers are those searching in an occupation X past wage cell where the share of workers declaring a reservation wage below 5% the minimum wage is below the median. In column (3), we define non-minimum wage workers as those who declare a reservation wage at least 15% above the minimum wage. We use inverse probability weighting to balance the covariates of women and men. Bootstrapped standard errors are in parenthesis.

Table D14: Wage elasticity with respect to commute along the reservation curve - Robustness

	(1) All	(2) Max commute in km	(3) Selection on max commute	(4) Min absolute distance to resW curve	(5) Previously full-time	(6) Adding white noise
Women	0.148***	0.119***	0.160***	0.163***	0.139***	0.124***
	(.0045)	(.0061)	(.0074)	(.0039)	(.0044)	(0.004)
Men	0.120***	0.095***	0.114***	0.148***	0.121***	0.107***
	(.0023)	(.0055)	(.0077)	(.0045)	(.0049)	(0.004)
Gender gap	.028***	0.024***	0.046***	0.015**	0.018***	0.017***
	(.0073)	(.0080)	(.011)	(.0063)	(.0061)	(0.006)
IPW		X	X	X	X	X
Obs.	75,071	46,900	42,403	75,071	118,794	75,071

Note: This table presents estimates of the elasticity of wages with respect to commute along the reservation wage curve. Estimation minimizes the criteria in Equation (4), except in column (4) where the distance to the indifference curve is not squared but taken in absolute value. The sample is restricted to job finders, and to non-minimum-wage workers. We define non-minimum wage workers as those who declare a reservation wage at least 5% above the minimum wage. In column (2), we restrict the sample to job seekers who declare their maximum acceptable commute in kilometers (rather than minutes). In column (3), we select workers whose accepted commute is between -150% and +150% of their declared maximum commute. In column (5), we restrict to job seekers, whose previous job is full-time. In column (6), we add white noise to the estimation data (log reservation and accepted wages and commutes). The variance of the simulated measurement error is 5% of the variance of the underlying variable. We use inverse probability weighting to balance the covariates of women and men, except in column (1). Bootstrapped standard errors are in parenthesis.

Table D15: Calibration of the model

Notation	Comment	Value
Moments		
ϕ^*	Log reservation wage, from data (ratio to min wage)	0.24
τ^*	Maximum acceptable commute, from data (in x00 km)	0.3
$E(w^n)$	Expected log wage in new job, from data (ratio to min. wage)	0.34
$E(\tau^n)$	Expected commute in new job, from data (in x00 km)	0.088
$V(w^n)$	Variance log wage in new job, from data (ratio to min. wage)	0.037
$V(\tau^n)$	Variance commute in new job, from data (in x00 km)	0.036
jfr	Job-finding rate, from data	0.16
Structural parameters		
r	Annual discount rate 12%	0.011
q	Inverse of job spell duration, from data	0.11
α	Estimation of α, see supra	-1.7
F: k_F	Matches the first two moments of next wage w^n	3.2
F: θ_F	(id.)	0.1
G: k_G	Matches the first two moments of next commute τ^n	3.6
G: θ_G	(id.)	0.017
λ	Matches the job-finding rate	0.28
b	Solution of Equation (1)	-0.86

Note: The table reports the values of the model moments and parameters, when calibrated for the sample of women. In column (2), we provide a short comment for each quantity. The model has a monthly frequency. The distribution G is a mixture of a gamma and a linear component; the weight of the linear component is normalized to one. For the sake of robustness to outliers, we use the median of accepted wages and commutes as the empirical quantities to match.

Table D16: Calibration of the model: values for all subgroups

	(1)	(2)	(3)	(4)
Married	0	1	0	1
Children	0	0	1	1
q	0.12	0.11	0.11	0.085
α	-1.6	-1.8	-1.9	-1.7
ϕ_0	-0.24	-0.3	-0.34	-0.24
F: k_F	3.1	3.4	3	3.5
F: θ_F	0.1	0.098	0.11	0.098
G: k_G	3	3.6	3.5	3.6
G: θ_G	0.019	0.018	0.015	0.019
λ	0.3	0.3	0.23	0.24
b	-0.82	-0.97	-0.9	-0.88

Each of the four columns represents a subsample on which we calibrate the model. The characteristics of the sample are given in the two first rows, and the calibrated/estimated parameters are in the following rows. Notations are the same as in Table D15.

Table D17: Decomposition of the gender wage gap: assuming differences in α explain all the observed gender gap in reemployment commute

	Gender gap in next-job wage		Gender gap in
	Empirical $\Delta \log w^n$	Explained share (in %)	commute valuation $\frac{\Delta\alpha}{\alpha}$
With all controls	-0.039	10.1%	-14.1%
Removing previous job controls	-0.077	10.6%	-19.9%
	Broken down by family status, with all controls		
Single, no kids	-0.028	9.9%	-9.9%
Married, no kids	-0.037	11.3%	-16.2%
Single, with kids	-0.048	8.3%	-15.8%
Married, with kids	-0.039	13.7%	-18%

Note: This table computes the share of the empirical gender gap in reemployment wages explained by gender differences in commute valuation. Column (1) reports the empirical gender gap in residualized wages to be explained. The decomposition is based on the job search model in Section IV.. First, gender differences in commute valuation α are estimated to match the empirical gender gap in commute. The estimated gender gap in commute valuation is reported in column (3). Second, we simulate the job search model to predict the gender gap in the wages of the next job; we show in column (2) what share of the empirical wage gap this predicted share represents.

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