Gender Differences in Job Search: Trading off Commute Against Wage

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Abstract

In this paper we relate gender differences in willingness to commute to the gender wage gap. Using unique administrative data on job search criteria, we first document that unemployed women have a lower reservation wage than comparable men and that the maximum commute they are willing to accept is smaller. We also find that they get lower wages and shorter commutes in their next job. We then identify indifference curves between wage and commute using the joint distributions of reservation job attributes and of accepted job bundles. Indifference curves are steeper for women, who value commute 22% more than men. Through the lens of a job search model where commuting matters, we estimate that around 10% of the gender wage gap is accounted for by gender differences in the willingness to pay for a shorter commute. Finally, we use job application data to test the robustness of our results and to show that female workers do not receive less demand from far-away employers, confirming that most of the gender gap in commute is supply-side driven.

Keywords: Gender wage gap, commute. **JEL Codes:** J16, J22, J31, J64, R20.

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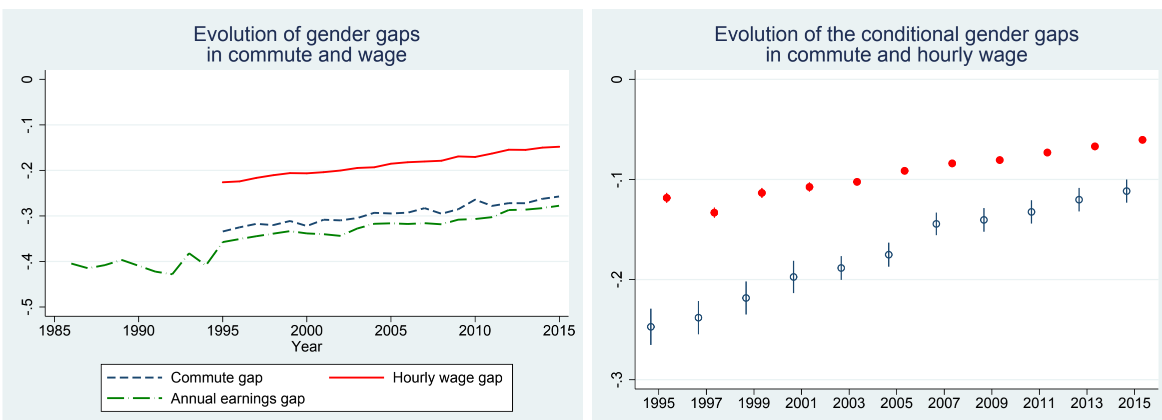
1 Introduction

The gender wage gap used to be decreasing but is now mostly stagnating and still substantial (see, for the latest evidence, Olivetti and Petrongolo, 2016; Blau and Kahn, 2017). Several non-exclusive mechanisms have been recently advanced to explain its persistence, such as gender differences in time flexibility (e.g., Bertrand et al., 2010; Goldin, 2014) and the so-called child penalty (e.g., Adda et al., 2017; Kleven et al., 2018). This paper explores a somewhat overlooked yet related aspect: gender differences in willingness to commute. Indeed, commute is a job attribute with large gender differences. In OECD countries, women on average have a 33% shorter commute than men.[1] In France, after controlling for workers' observable characteristics, the gender commute gap still amounts to 10 to 15%. Gender differentials in commute decreased over time in a similar manner as gender gaps in annual earnings or in hourly wages, even when adjusted for workers' experience, occupation, industry and part-time status (Figure 1).

Figure 1: Gender gaps in wages and commuting distances over time in France



Note: These figures plot the evolution of gender gaps over time. The left panel plots the raw log-difference of the annual earnings, of the hourly wage rate and of the commuting distance between women and men. Reliable data on commuting and hours are available since 1995. The right panel plots the adjusted gender gaps in hourly wage (red dots), and in commuting distance (blue circles). We run separate regressions of both commuting and hourly wage every year. We include as controls age, occupation, experience, part-time dummy, industry and commuting zone fixed effects.
Sample: 1/60th sample of all private sector employment spells in France (DADS data).

In this paper, we estimate how much wage men and women are willing to trade off for a shorter commute and study the relationship between gender differences in this commute

[1] Statistics compiled from Table LMF2.6.A of the OECD family database available at http://www.oecd.org/els/family/database.htm .

valuation and the gender wage gap.[2] Average wage compensating differentials are difficult to identify from realized labor market outcomes, because equilibrium outcomes are pinned down by marginal workers and because standard datasets cannot measure all relevant job attributes and worker productivity that may confound the wage effect of the attribute of interest (Brown, 1980; Hwang et al., 1992).[3] Moreover, frictions in the matching between workers and jobs often blur the compensating differentials of job attributes (Altonji and Paxson, 1992; Bonhomme and Jolivet, 2009; Rupert et al., 2009). To overcome these difficulties, recent research makes use of survey choice experiments to directly estimate the workers' willingness-to-pay for certain job attributes (Wiswall and Zafar, 2017; Maestas et al., 2018). Mas and Pallais (2017) further incentivize workers' choices over different job bundles, as their choice experiment is part of a real recruitment process.[4]

In this paper, unlike most work in this strand of literature, we focus on the gender heterogeneity in valuation for commute.[5] We also rely on incentivized elicitation of preferences by exploiting a unique feature of French institutions: when they start an unemployment spell, French job seekers must declare to the Public Employment Service (PES) their reservation wage, the maximum commute they are willing to accept, the occupation sought and their willingness to accept part-time work and/or fixed-term labor contracts. As their statements matter for the job search services provided by the PES, they have an incentive to be attentive and answer truthfully. We thus combine the advantages in terms of incentives from field experiments such as Mas and Pallais (2017), and the large sample and external validity of administrative data.

Using a sample of around 300,000 workers, we document gender differentials in the reservation wage, the maximum acceptable commute and other dimensions of the job searched for. The data is combined with matched employer-employee registers such that we can finely control for the characteristics of the previous job and check whether these differentials in reported search criteria translate into differences in the attributes of the job following the unemployment spell. Using the joint distributions of reservation wage and commute and of reemployment wage and commute, we then identify the willingness to pay for a

[2] We do not take a stand on whether differences in commute valuation come from individual intrinsic preferences or other sources, e.g. constraints resulting from household decisions.

[3] Contrary to other job attributes, the literature analyzing realized outcomes documents mostly positive correlation between wages and commuting time (e.g. Madden, 1985; Zax, 1991; Fu and Ross, 2013). However, the estimated returns to commute decrease substantially when controlling for workers productivity (e.g. Manning, 2003).

[4] Flory et al. (2014) is another prominent example of a field experiment designed to identify gender preferences over job attributes, in this case mostly competition.

[5] The closest analysis to commute can be found in Mas and Pallais (2017) who document that women prefer working from home. However, working from home is also related to other job attributes, for example monitoring from employers.

shorter commute for men and women separately. Eventually we build a job-search model to decompose the share of the gender wage gap that can be accounted for by these gender differentials in commute valuation.

We find that unemployed women have a lower reservation wage than men, controlling finely for the characteristics of the previous job (wage bins, three digit occupation, etc.) and for the job opportunities available (commuting zone times industry times quarter fixed effects). Women also search for jobs closer to their place of residence. The gender gap in the maximum acceptable commute, as declared at the start of the unemployment spell, is 7.7% for single individuals without children and 23.7% for married individuals with children.[6] These gender differences in reservation job attributes translate into women getting lower wages and shorter commutes upon reemployment. Moreover gender differences in commute and wage are not specific to unemployment-to-job transitions. We show that similar magnitudes are observed when looking at job-to-job transitions. They are also not specific to France. In particular, using the Krueger and Mueller (2016) survey data on 4,000 unemployed in the US, we also find in this setting a substantial gender gap in the maximum acceptable commute (26%) and, as reported in their paper, a gender gap in reservation wages of 8.3%.[7]

The fact that gender gaps in search criteria closely parallel the gender gaps observed for wages and commute in the overall working population suggests that supply-side considerations may be an important driver of the latter. We therefore introduce a search model where the commute matters, similar to van den Berg and Gorter (1997), i) to guide our identification of whether women have steeper indifference curves between wage and commute than comparable men, and ii) to assess the extent to which the gender wage gap is accounted for by gender differences in willingness to pay for a shorter commute. We assume that utility when employed depends positively on the wage and negatively on the commute time and that the distaste for commute is summarized by a key parameter α which may differ between women and men. The model yields a reservation wage curve that gives for every commute the lowest wage that the job seeker would accept. The slope of the reservation wage curve is equal to the commute distaste parameter α.

Using reemployment outcomes, in deviation from the reservation wage and commute, we draw the acceptance frontier of jobs, separately for men and women. We show that for

[6] Furthermore, women declare more often that they are willing to accept part-time and/or temporary work. We show that controlling for differences in these other job attributes hardly affects the gender gap in reservation wage and in reservation commute.

[7] Survey evidence on gender gap in reservation wages can also be found in Brown et al. (2011) for the UK, and in Caliendo et al. (2017) for Germany.

non-minimum wage workers the acceptance frontier indeed identifies the reservation wage curve. We then estimate the commute distaste parameter for women and men, and we obtain that it is significantly higher for women. We find that the value of commuting time amounts to 80% of the hourly gross wage for men and 98% for women. The above identification exercise relies on our interpretation that job seekers declare one given point of the reservation wage curve to the public employment service. We check the robustness of our results to other interpretations of how job seekers declare multi-dimensional reservation strategies in a series of questions where each dimension is asked independently.

We feed the commute distaste estimate for women into the job search model and calibrate the other parameters (unemployment flow utility, job offer arrival rate, and wage and commute offer distributions) in line with our data, again for women. Fixing all other parameters, we simulate a shock reducing α by 18.2%, equal to the residualized gender difference in commute valuation that we have estimated, and look at the impact of this shock on the next-job wage and commute. We find that this difference in α allows us to explain between 9% and 16% of the gender wage gap. This suggests that the contribution of gender differences in commute valuation to the gender wage gap is of the same order of magnitude as other well-studied job attributes such as flexible working time and/or job security.[8]

Finally, we perform two robustness exercises using data from around three millions job applications to vacancies posted at the French public employment service.[9] First, we study the characteristics of the vacancies to which men and women apply. Within-applicant regressions show that the elasticity of posted wages with respect to the distance between the vacancy's workplace and the applicant's home is larger for women than men. This reinforces our finding that distaste for jobs that are further from home is greater among women. Second, we study hiring decisions by employers in response to job applications. Within-vacancy regressions show that the hiring rate decreases with the commute distance of the applicant, but not at a significantly faster rate for women. This suggests that labor demand is not specifically tilted towards close-by candidates for women compared to men. This supports our view that gender gaps in commute are primarily driven by supply-side considerations.

This paper relates to several lines of research. First we bring gender differences in com-

[8] Wiswall and Zafar (2017) finds that accounting for gender differences in students preferences for future earnings growth, dismissal probability, and work hours flexibility, account for one quarter of the gender earnings gap.

[9] See Behaghel et al. (2015) for previous analysis of application data at the French Public Employment Services. Vacancies posted at PES represent 60% of all hires in France (authors' calculation).

muting distances into the prominent literature on the gender wage gap (Bertrand, 2011; Goldin, 2014; Olivetti and Petrongolo, 2016; Blau and Kahn, 2017).[10] Gender differences in commuting time/distances have been documented by the urban planning (MacDonald, 1999; Crane, 2007) and the health and well-being literature (Roberts et al., 2011; Clark et al., 2019; Stutzer and Frey, 2008) but have not been analyzed in relation to the gender wage gap. Recent research on the gender wage gap provides event-study evidence that the birth of the first child creates a large deterioration of labor market outcomes for women relative to men (Angelov et al., 2016; Kleven et al., 2018, 2019). Our paper sheds light on a potential mechanism for this child penalty: namely the fact that women prefer shorter commutes, maybe to be able to drop off/pick up children from school/daycare more easily. However our paper also suggests that gender differences in the value of commute time is not only driven by children. Even among single individuals without children, we find a gender gap in commute valuation that is statistically significant. Moreover, although the commute channel may have similar origins to the hours flexibility channel (Bertrand et al., 2010; Goldin, 2014; Goldin and Katz, 2016; Bolotnyy and Emanuel, 2019), we show that the commute contributes to the gender wage gap on top of gender differences in hours preferences.[11]

Second, our paper is related to the literature on compensating differentials, and in particular gender differences in compensating differentials (Filer, 1985; Mas and Pallais, 2017; Wiswall and Zafar, 2017; Maestas et al., 2018). Prior work on the trade-off between wages and commuting does not document gender heterogeneity (Van Ommeren et al., 2000; Mulalic et al., 2014; Guglielminetti et al., 2015)[12], with the exception of Manning (2003), who found in the cross-section in the UK that the wage effect of commuting was larger for women with children than for men.[13] A methodological contribution of our paper is to show how data on the joint distribution of reservation job attributes and of realized job bundles can be used to identify the key preference parameter for the wage vs. commute trade-off. We provide the first estimates of the heterogeneity of this parameter across gender.[14]

[10] Regarding the gender pay gap in our French context, a recent paper shows that 11% of it can be accounted for by sorting in lower-paying firms while none of it seems attributable to bargaining (Coudin et al., 2018), in contrast to the Portuguese results of Card et al. (2016).

[11] Our paper is also related to Danieli and Caldwell (2019) who show that commute distances are an important component of women's more restricted employment opportunity set.

[12] The large literature in transport economics on the value of travel time tend to focus on income heterogeneity rather than gender differences (See for a review Small, 2012).

[13] Van Ommeren and Fosgerau (2009) also find that the marginal costs of commuting are larger for women than for men, but the difference is not precisely estimated and insignificant.

[14] Black et al. (2014) analyze the link between commute and labor force participation of women.

Section 2 describes the data. Section 3 presents the reduced-form evidence on gender differences in job search criteria and reemployment outcomes separately. Section 4 explains how the commute valuation can be identified from the joint distribution of search criteria and realized outcomes and shows that women have steeper indifference curves between wage and commute than men. Section 5 estimates that around 10% of the gender wage gap can be accounted for by gender differences in willingness to pay for a shorter commute. Section 6 provides further evidence, using application data, that gender differences in commute are *not* primarily driven by weaker demand for women than comparable men to fill jobs that involve a long commute. Section 7 concludes.

2 Data description

2.1 Data source and sample

Our sample is drawn from a matched dataset of French unemployment and employment registers. Information on unemployment spells derives from the *fichier historique* (FH) of the French public employment service (*Pole Emploi*), while that on employment spells comes from the *déclarations administratives de données sociales* (DADS) built by the French Institute of Statistics (*Insee*) from firms' fiscal declarations. Legal protection of private information allows the matching for a subpopulation with a sampling rate of 1 in 12.

We select an inflow of unemployment insurance (UI) claimants whose unemployment spell starts between 2006 and 2012.[15] We restrict the sample to people who lost their jobs involuntarily, be it a permanent or a temporary/fixed-term contract. We observe their employment history from 2004 to 2012, from which we define: i) the last job before unemployment (last employment spell ending before they become unemployed) and ii) the next job after unemployment (first employment spell starting after their unemployment spell starts).[16] Our main sample comprises around 320,000 unemployment spells.

[15] We focus on new claims from the regular UI rules, excluding workers in the culture and arts industries *-intermittents du spectacle-* and from temporary help agencies *-interimaires*.

[16] We apply the standard restrictions in the employment registers, in order to analyze meaningful jobs. We exclude jobs tagged as annex by the data producer. We restrict the sample to employers from the private sector.

2.2 Desired occupation, reservation wage and maximum acceptable commute

When registering as unemployed in France, people are asked about the type of job they are seeking, their reservation wage and maximum acceptable commute.[17] Appendix Figure C1 is a screenshot of the current online registration form. First, people are asked which occupation they are looking for. The preferred occupation may be different from their previous one. Second, in response to the reservation wage question: "What minimum gross wage do you accept to work for?", they indicate an amount and choose a unit (hourly, monthly or annual). Third, people are asked for their maximum acceptable commute or reservation commute: "What length of daily commute (one way) would you accept?" Job seekers can reply either in minutes or in kilometers. They cannot move on to the next page of the registration website without having reported this information.[18] Before job seekers answer the questions on their desired occupation, reservation wage and maximum commute, they state whether they are willing to accept a temporary contract or a part-time job (see the screenshot in Appendix Figure C2).

All this information enables caseworkers from the public employment service to select the vacancies they will propose to job seekers. If browsing through vacancies is costly, standard theory suggests that the best response of job seekers is to reveal their true reservation wage and other job characteristics to the PES. Moreoever we are confident that the monitoring/sanctioning role of the PES does not lead job seekers to misreport their reservation wage and commute. Indeed, when controlling the search effort of job seekers, caseworkers are legally required to compare the posted wages of vacancies for which job seekers apply to their *past wage* – and not to their reservation wage. As for the commute, they compare it to predetermined targets (1 hour or 30 kilometers), not to the stated reservation commute. Whether the desired number of working hours and type of labor contract are used for monitoring/sanctions purposes is less clear. The law states that "If the desired job is full-time, job seekers cannot be forced to accept part-time jobs", which may induce UI claimants to 'strategically' report that they are seeking a full-time job. Regarding the labor contract, there are no published/explicit guidelines. We therefore focus on the reservation wage and commute questions for which we are confident that there is no strategic reporting bias. That being said, such concerns are minimal because in practice no sanctions are imposed. Only 0.51% of the observed unemployment spells are ended (either temporary

[17] This section follows closely the description of the reservation wage data in Le Barbanchon et al. (2019).

[18] At the bottom of the screenshot in Figure C1, people are also asked whether they have a bike, car, etc. We do not have access to this information.

or permanently) by the PES for failing to comply with job-search requirements. Moreover, search criteria are not significant predictors of being sanctioned.[19]

2.3 Summary statistics

Table 1 contains the raw summary statistics from our sample. Prior to being unemployed, workers earn on average €2,018 gross per month (full-time equivalent) and their average commute is 19 kilometers. Our commute measure in the employment registers is the distance between the centroids of the municipality of the workplace and the municipality of residence. There are over 34,000 municipalities in France, so municipality centroids proxy well for actual locations.[20] When workers reside and work in the same municipality (24.7% of the sample), we proxy for their commute by the average distance between two random locations within the municipality.

The average monthly gross reservation wage (full-time equivalent) of job seekers in our sample is €1,665 and the maximum acceptable commute (one way) is 29 kilometers for those who report in distance (two thirds of the sample) and 43 minutes for those who report in time (the remaining third). Upon reemployment, the average commuting distance remains similar to that of the previous job, while the average wage falls to €1,885. Both before and after unemployment, 75% of job seekers are full-time workers and around 40% have a permanent contract. Over 90% of job seekers state that they are looking for a full-time job and a permanent contract. Around half the sample find a job within two years. On average unemployment spells last 430 days.

Figure 2 plots the distribution of our main variables of interest. The four panels are restricted to people who found a job within two years in order to keep the same sample whether we look at reemployment outcomes or reservation job characteristics. Panel (a) shows the reservation wage, divided by the previous wage. Four out of five workers specify a reservation wage lower than their previous wage. The excess mass at 1 reflects the fact that 12% of our sample anchor their reservation wage on their prior wage. This is mostly driven by minimum-wage workers, as shown in Appendix Figure C3. Panel (b) of Figure 2 shows the reemployment wage divided by the reservation wage. 81.1% of workers find a

[19] The coefficients on reservation wage and commute are insignificant in a regression of a dummy of being sanctioned on search criteria, controlling for workers' characteristics, attributes of previous job and commuting zone $\times$ industry $\times$ quarter fixed effects.

[20] For the largest cities in France we use the centroids of a finer geographical unit, *arrondissements*. For instance, central Paris is divided into 20 *arrondissements*.

job above their reservation wage.[21] Panel (c) shows the reservation commute divided by the commute in the previous job. Most job seekers (91%) report a maximum acceptable commute greater than their previous commute (median of 2.7). Panel (d) shows the commute upon reemployment divided by the reservation commute: 81% of unemployed individuals end up commuting less than their reservation commute.

3 Gender differences in job search criteria and reemployment outcomes

In this section, we document how job search criteria and reemployment outcomes vary across gender. We first estimate average gender gaps in reservation and accepted job attributes. Second, we document the heterogeneity in gender gaps by family structure and worker's age. Third, we provide evidence in support of the external validity of our results, by looking at job-to-job transitions and by using survey data on US job seekers.

3.1 Average gender gaps in reservation wage and commute, and in reemployment outcomes

We first estimate gender gaps in reservation wage and in reservation commute. Table 2 shows results from regressions of a reservation job attribute on a female dummy. In columns (1) and (3) the outcome is the reservation wage, in logs, while in columns (2) and (4) it is the maximum acceptable commute, also in logs. All specifications control for worker characteristics (age dummies, years of education dummies, marital status, parenthood, and past work experience), the characteristics of the previous job (full-time equivalent wage in 20 bin dummies, 3-digit occupation dummies, previous hours, type of contract and distance to home), the log of the potential benefit duration (UI generosity), and the units of declaration for the reservation wage and for the maximum commute questions. Appendix Table D1 documents how men and women differ along these control dimensions. We also control for local labor market conditions with commuting zone times industries times quarter fixed effects.[22] Columns (3) and (4) add further controls for other dimensions of reported job preferences: namely dummies for whether the desired occupation is the same

[21]The distribution is discontinuous at 1. The size of the discontinuity is lower when we restrict to non-minimum wage workers in Appendix Figure C3.

[22]There are 348 commuting zones in France. We use the standard industry classification at the 2-digit level, with 38 categories. We use the quarter of the unemployment registration date.

as the previous one, whether the person is looking for a full-time job, and whether she is willing to accept a temporary job.

Table 2 provides evidence that women are less demanding than men on the wage dimension but more demanding on the commute dimension. Women specify a 3.6% lower reservation wage than men while their stated maximum acceptable commute is 14% lower than that of comparable men. Appendix Table D2 reports gender differences in other search criteria: occupation and working hours. Women and men have almost the same propensity to search for a job in the same occupation as the one they held previously (the gender gap is less than 0.7 percentage points). Consistent with previous research, women have a higher propensity to look for a part-time job than men – by 6.5 percentage points. Hence columns (3) and (4) of Table 2 test whether the gender gaps in reservation wage and in reservation commute survive when we control for the difference in preferred working hours. We find that they are barely affected by gender differences in the preference for part-time work.

Table 3 shows that gender gaps in reemployment outcomes closely follow the gender gaps in search criteria. Even when controlling finely for the previous job characteristics, the gender wage gap amounts to 3.7% (column 1), and the gender commute gap to 11.8% (column 2). These differences survive when we control for other attributes of the new job in columns (3) and (4): part-time, type of contract, change of occupation. In columns (5) and (6), we control for the search criteria (reservation wage, maximum acceptable commute, and others). With the search-related controls, magnitudes are roughly halved: the gender wage gap amounts to 1.6% and the gender commute gap to 5.3%.[23] The parallel between Tables 2 and 3 builds confidence in the validity of the answers to the search strategy questions asked by the French PES. Moreover, it suggests that gender gaps in realized job outcomes are partly driven by labor supply. This is further hinted at in the heterogeneity analyses in Section 3.2.

By construction, the sample in Table 3 – containing only job seekers who found a job within two years – is a subset of that of Table 2. Appendix Table D3 rules out major differential selection into employment across gender. Without controlling for the type of job looked for, but controlling precisely for the previous job's characteristics, the probability of women finding a job within two years is 2.4 percentage points lower than that of men. This difference becomes insignificant when we control for all the characteristics of the job sought.

[23]For the sake of completeness, Appendix Table D4 also shows the effect of controlling for search criteria on the gender gaps in full-time work and occupational switching.

Robustness to controlling for working hours flexibility From a theoretical perspective, individuals with a high value of non-working time should value both a short commute and working hours flexibility. This raises the question of whether women state a preference for a shorter commute over and above their preference for part-time jobs. We have already confirmed that this is the case controlling for the preferred hours in the gender commute gap regressions in Table 2. To further address this question, in Panel C of Appendix Table D2 we estimate gender gaps in search criteria restricting the sample to men and women with *a priori* similar preferences for working hours flexibility, i.e. job seekers who previously held a full-time job. We find an average gender gap in maximum acceptable commute of a very similar magnitude as for the whole sample (14.4%). This shows that gender differences in commute preferences complement those in the desire for flexible working hours.[24]

Robustness to residential sorting and mobility decisions In the main analysis we introduce commuting zone fixed effects to control for local labor market conditions. This also controls for residential sorting of job seekers across commuting zones. When considering finer geographical levels, there is arguably scope for differential residential sorting across gender, especially for single people. Even among job seekers in the same industry residing in the same commuting zone, women may be over-represented in municipalities where jobs are closer. In Appendix Table D5, we further control for municipality fixed effects. This barely affects the gender gaps in the reservation wage, reemployment wage, and commute. If anything, the gender difference in reemployment commute is larger. Our results cannot be mainly attributed to differential residential sorting across gender.

Willingness to commute might also interact with *residential mobility* decisions, raising a concern that these decisions do not affect men and women similarly, which could introduce some biases in gender gaps estimates. Around 15% of job seekers change municipality between their initial registration at the PES (when they declare their search criteria) and their next job. We find no gender differences in this proportion, neither conditional on our set of controls nor unconditionally. However reemployment commute depends on residential mobility: among men, commute is 15% shorter for those who moved while among women it is 4% shorter for those who moved.[25] The gender difference in commute is thus smaller for movers, hence including movers in our analysis could attenuate the gender commute gap estimate. Appendix Table D4 compares gender gaps in reemployment

[24]We have checked the robustness of this exercise with different sample restrictions: workers previously part-time, unemployed looking for a part-time job, and unemployed looking for a full-time job. Results are available upon request.

[25]For both men and women, reemployment wage is 0.6% higher for movers.

outcomes for our main sample (panel A) and for the sample of people who did not move (panel D). While the wage gap is virtually the same in the two panels, the commute gap is indeed 1 percentage point higher in panel D, i.e. when we restrict to stayers. However this difference in the gender commute gap is not statistically significant. Thus our results are unlikely to be driven by gender differences in residential mobility.

3.2 Heterogeneity by family structure and by age

Heterogeneity by family structure. In Figure 3, we report gender differences by marital status and the presence of children. These gender gaps are obtained by interacting the gender dummy with the interaction between marital status and the presence of at least one child in specifications similar to that of Tables 2 and 3. Appendix Table D6 reports the detailed estimation results. The upper-left panel shows that the gender gap in reservation wages is larger for married job-seekers and parents: married mothers have a 5.6% lower reservation wage than married fathers. Interestingly, there is still a 2.1% gap among single individuals without children. Similarly, the bottom-left panel shows that the gender gap in reservation commute increases with family size. While single women without children are willing at most to commute 7.7% less than comparable men, the difference increases to around 18% for either married workers without children or single workers with at least one child, and to even 23.7% for married workers with at least one child.

The right-hand panels report the same heterogeneity analyses for wages and commutes in the general population. For these panels, we use a sample of the employer-employee registers (DADS) matched with vital statistics (EDP), without restricting to the data matched with unemployment registers. We also find that gender gaps increase with family size.[26]

Heterogeneity with respect to age. The left-hand panels of Figure 4 show that gender gaps in reservation wage and commute grow with age until the age of 40 and then begin to plateau, following a pattern quite similar to that documented in the right-hand panels for the gender wage and commute gaps in the overall working population.[27]

[26] We perform the same heterogeneity analyses for the reemployment wage and commute in our main sample of job-seekers. We also find that gender gaps increase with family size, though at a slower pace than for attributes of the job searched for. Appendix Table D7 reports the detailed estimation results.

[27] The right-hand panels of Figure 4 are compiled using the same sample as the one used in the right-hand panels of Figure 3 spanning from 2003 to 2010. The underlying dataset starts before 2003, which allows us to tease out cohort effects from age effects. Appendix Figure C4a reports the same plot 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. Moreover, with a different notion of the wage (daily wage), we can go back until 1976, with breaks in the data in 1993 and 2002. Appendix Figure C4b through C4d report gender gaps in

3.3 External validity

Evidence from other countries. Appendix Table A1 reports estimates of the gender gap in reservation wages found in other studies, for the US, the UK and Germany. While the majority of these studies are not focused on the gender gap, they report coefficients of a gender dummy in Mincerian regressions of reservation wages. Women in the US, in the UK, and in Germany also state lower reservation wages than comparable men. The order of magnitude of these gaps is comparable to our findings for France but our administrative data on both labor market outcomes and reservation wages yield us estimates that are much more precise than in previous literature. To the best of our knowledge, no comparable studies report gender gaps in other dimensions of job search, albeit the survey of Krueger and Mueller (2016) asks workers about their willingness to commute.[28] We use these data made publicly available by the authors to compute the gender gap in desired commute time in the US (which, to our knowledge, has not been analyzed so far). Table 4 shows that US women search for jobs that can be reached with 25% less commuting time. The average desired commute is 47 minutes for men and 35 minutes for women.

Job-to-job transitions So far we have provided evidence on gender differences in unemployed's preferences and in job characteristics after a period of unemployment, but do we observe similar patterns for job-to-job transitions? The evidence below suggests that the gender differentials in employment outcomes after a labor market transition are strikingly similar whether the transition is from unemployment to employment or from one job to another. We construct a sample of job-to-job transitions from our matched unemployment-employment dataset. From the employment registers, we select all job-to-job transitions between 2004 and 2012. We then exclude transitions where workers register as unemployment between the separation date of the previous job and the hiring date of the next job, and transitions over which workers remain non-employed for more than 6 months. The resulting sample comprises 973,000 job-to-job transitions. We follow the regression specification of Table 3 with the same controls, except family status that is not available in the matched unemployment-employment dataset for workers who do not register as unemployed. Table 5 reports the results. The gender gap in reemployment wage after a job-to-job

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 4 really reflect age effects, rather than cohort effects.

[28]The survey questions are: 1/ Suppose someone offered you a job today. What is the lowest wage or salary you would accept (before deductions) for the type of work you are looking for? 2/ How many minutes a day would you be willing to commute if you were offered a job at that salary? Note that the survey specifically asks for a bundle of job characteristics.

transition is 4%, and the gender gap in commute is 12%. This suggests that focusing on unemployed workers is informative for gender differences in job preferences of the whole working population.

Overall, this section has provided evidence of wide gender gaps in reservation wage and reservation commute, as well as similar gaps in accepted commute and wage. All gaps grow wider with age and family size, suggesting that labor supply adjust differently for men and women over their working life cycle. We hypothesize that these gender gaps are partly driven by gender differences in commute valuation. Women have a higher willingness to pay for a shorter commute than men, which translates into both lower reservation wage and commute and ultimately in lower wage and commute. In the next section, we provide estimates of the gender differences in commute valuation.

4 Gender difference in commute valuation

The aim of this section is to quantify the gender gap in willingness to pay for a shorter commute. We show that commute valuation is identified from the joint distribution of reservation wage and commute and of accepted wage and commute. This is not straightforward as it requires assumptions about what job seekers understand when they declare their reservation wage and maximum acceptable commute. We first introduce a job search model that allows us to explicit and formalize these choices.

4.1 A search model where commuting matters

We consider a random job search model where commuting matters (van den Berg and Gorter, 1997). The instantaneous utility of being employed in a job with log-wage $w = \log W$ and commute τ is given by $u(W, \tau) = \log W - \alpha\tau$. The α parameter measures the distaste for commute and may differ between men and women. This is the key preference parameter we want to identify. From α, we directly obtain the commute valuation or willingness to pay for a shorter commute. The commute distaste α can be thought of as an individual preference/cost parameter or as a reduced-form parameter that is the outcome of household bargaining on gender task specialization.

Job matches are destroyed at the exogenous rate q. After match destruction, workers become unemployed and receive flow utility b. Unemployed workers draw job offers from the cumulative distribution function of log-wage and commute H. Job offers arrive at the rate λ. The job search model admits a standard solution, that is summarized in the following

Bellman equation for the unemployment value U:

$$rU = b + \frac{\lambda}{r+q} \int_0^\infty \int_0^\infty \mathbf{1}_{\{w - \alpha\tau > rU\}} (w - \alpha\tau - rU) dH(w, \tau)$$

where r is the discount rate.

Job seekers accept all jobs that are such that $w - \alpha\tau > rU$. For a job next door, i.e. when $\tau = 0$, the reservation log-wage is $\phi(0) = rU$. For a commute τ, the reservation log-wage is: $\phi(\tau) = rU + \alpha\tau$. This allows us to define a reservation log-wage curve:

$$\phi(\tau) = \phi(0) + \alpha\tau$$

The reservation log-wage curve follows the indifference curve in the log-wage/commute plane with utility level rU. Note that the slope of the reservation log-wage curve is the commute distaste parameter α, so that identifying the reservation curve yields the willingness to pay for a shorter commute.

Replacing rU by $\phi(0)$ in the Bellman equation, we obtain the solution for the intercept of the reservation log-wage curve:

$$\phi(0) = b + \frac{\lambda}{r+q} \int_0^\infty \int_{\phi(0)+\alpha\tau}^\infty (w - \phi(0) - \alpha\tau) dH(w, \tau) \tag{1}$$

This solves the model. For the sake of completeness, we express below the average commute and log-wage in the next job, τ^n and w^n:

$$\tau^n = \frac{1}{p} \int_0^\infty \int_{\phi(0)+\alpha\tau}^\infty \tau dH(w, \tau) \tag{2}$$

$$w^n = \frac{1}{p} \int_0^\infty \int_{\phi(0)+\alpha\tau}^\infty w dH(w, \tau) \tag{3}$$

where $p = \int_0^\infty \int_{\phi(0)+\alpha\tau}^\infty dH(w, \tau)$ is a normalizer and amounts to the probability of accepting a job offer.

4.2 Identifying the commute valuation

To identify the commute distaste model parameter α, we need to relate the search criteria measures to variables in the model. The PES question about the reservation wage does not explicitly anchor the commute dimension. Symmetrically, the question about the maximum acceptable commute does not specify the wage to consider. Without further information, we may consider two interpretations:

- Interpretation 1: Job seekers answer a pair (τ^*, ϕ^*) of job attributes which define one point on their reservation wage curve, so that $\phi^* = \phi(0) + \alpha\tau^*$.

- Interpretation 2: Job seekers report the reservation wage $\phi(0)$ corresponding to the minimum possible commute (zero) and the reservation commute $\phi^{-1}(\bar{w})$ corresponding to the largest wage they could get, $\bar{w}$.

Interpretation 2 differs from Interpretation 1 in that it predicts that workers do not accept jobs that are both close to their reservation wage and close to their maximum acceptable commute (see Appendix Figure C5 for an illustration). Figure 5 shows the joint density of reemployment wage and commute, relative to the reservation wage and commute. By construction, the plot is restricted to workers finding jobs.[29] Consistent with the job search model, most of the density mass is in the upper left quadrant: workers accept jobs paying more than their reservation wage and closer than their reservation commute. Importantly, we do not observe the missing mass predicted by Interpretation 2 in the bottom right corner of the upper left quadrant, where the accepted jobs are both just above the reservation wage and just below the maximum acceptable commute. Figure 5 thus provides suggestive evidence in favor of Interpretation 1. We adopt Interpretation 1 in our main analysis, and we provide a robustness analysis under Interpretation 2 in Appendix B.

To identify the reservation log-wage curve, we leverage the theoretical insight that accepted job bundles are above the reservation wage curve in the commute/wage plane. As a consequence, the frontier of the convex hull of accepted jobs draws the indifference curve delivering the reservation utility. This result holds under regularity conditions for the job offer distribution. Namely, the job offer density must be bounded from below, so that there is no region of the commute/wage plane where the acceptance strategy is degenerate and thus less informative.

The identification strategy of the commute distaste α then proceeds in two steps. First, under Interpretation 1 reservation curves pass through the point where the job bundle equals the declared reservation wage and maximum acceptable commute. This yields one first point of the reservation wage curve. Second, we identify the average slope of the reservation curve by minimizing the sum of squared distance to the reservation curve of accepted bundles that are below the reservation curve. This second step amounts to rotating potential reservation wage curves around the declared reservation job bundle and to choosing the reservation line consistent with the acceptance strategy of the job search model.

[29]We convert the maximum commuting time for those who declared in minutes into kilometers, assuming that average commuting speed is 35 km/hour.

Figure 6 illustrates this identification strategy. In the log-wage-commute plane, we plot the jobs accepted by workers with reported reservation wage ϕ^* and reservation commute τ^*. Under Interpretation 1, the reservation wage curve goes through (τ^*,ϕ^*). We draw two potential reservation wage curves: the solid and dashed lines. There are three accepted jobs below the dashed line, while there are only two jobs below the solid line. Moreover, jobs below the dashed line are further away from the dashed line than jobs below the solid line are distant from the solid line. The estimation strategy picks up the solid line. Note that the identification strategy does not require any assumptions on the exact position of the declared reservation job bundle on the reservation curve: it can be anywhere on the curve.

We now define the estimator in formal terms. We denote (τ_i, w_i) the pair of commute and wage accepted by individual i, (τ_i^*, ϕ_i^*) her declared reservation strategy and $d_{\alpha,\tau_i^*,\phi_i^*}(\tau_i, w_i)$ the distance of the job bundle (τ_i, w_i) to the reservation curve of slope α passing through (τ_i^*, ϕ_i^*). We use as a norm the Euclidean distance between the job bundle and its projection on the reservation line. We further denote $\mathcal{B}_\alpha$ the set of workers with accepted job bundles below the reservation curve.[30] We define the following estimator of the slope α:

$$\hat{\alpha} = argmin_\alpha \sum_{i \in \mathcal{B}_\alpha} p_i \left(d_{\alpha,\tau_i^*,\phi_i^*}(\tau_i, w_i) \right)^2 \tag{4}$$

We run the estimation separately for women and men. We use inverse probability weighting to make sure that the distribution of covariates in the sample of men matches that of women (Hirano et al., 2003), and define p_i as follows. In a first step, we estimate a logit model of being a woman using as covariates the controls X_i from the main gender gap regressions. These include worker characteristics (age, education, family status, work experience), previous job characteristics (past wage, past commute, part-time, labor contract, occupation) and fixed effects for past industry, commuting zone and separation year. The logit model allows us to predict the probability to be a female $\hat{p}(X_i)$. In a second step, we define the weights for men as $p_i = \hat{p}(X_i)/(1 - \hat{p}(X_i))$.

Last, we restrict the estimation to non-minimum wage workers. The job acceptance strategy of minimum wage workers is degenerate, as there exists a commute threshold such that minimum wage jobs with commute below this threshold yield more than the reservation utility.[31] We select all job seekers declaring a reservation wage 5% above the minimum wage. This represents 45.8% of our sample. We verify that our main results from Section

[30] Formally, this writes $\mathcal{B}_\alpha = \{i | w_i < \phi_i^* + \alpha(\tau_i - \tau_i^*)\}$

[31] In other words, the convex hull of accepted job has an horizontal border for low commute jobs. It cannot identify α.

3 hold in the non-minimum wage workers sample (see Appendix Tables D2, D4, and D8). Appendix Table D2 shows that the gender gaps in search criteria are similar in this sample, with the gap in reservation wage is one percentage point greater, as expected. We verify the robustness of our results to alternative definition of the non-minimum-wage worker sample.

4.3 Commute valuation estimates

Consistent with Figure 5, we take the log of wages and commutes before running the estimation. Consequently, we estimate the elasticity along the indifference curve rather than the parameter α directly. Table 6 presents our elasticity estimates for women in the first row, and for men in the second row. The third row shows the gender gap. In column (1), we pool all non-minimum wage workers. The elasticity of wages with respect to commute distance is 0.15 for women and 0.12 for men. The gender gap is positive and statistically significant at the 1% level. This confirms that the disutility associated with commute is larger for women than for men. In columns (2) to (5), we split the sample by marriage status and family size. We find that the elasticity increases slightly with household size, but the gender difference remains around the same level (without any statistically significant differences across subgroups).

Interpreting the magnitude of the commute distaste Table 6 shows that gross monthly wages (FTE) must be increased by 12% to compensate men for a doubling in the commuting distance. At the commuting average, doubling the commute increases commuting distance by 18.6 km, and this has to be compensated by 242 euros (=0.12*2,018). In other words, the monthly compensating differential for one extra kilometer is about 13 euros. Assuming that full-time employees commute 22 days per month on average (excluding week-ends), the daily compensating differential amounts to 59 cents (=13/22). How does it compare with the opportunity cost of the extra-time spent commuting? For an increase of 1 km in the home-work distance, workers spend 3.4 minutes more per day commuting (assuming an average commuting speed of 35km/hour). Workers in our sample have an hourly rate of 13.2 euros, which translates into 22 cents per minute. Consequently, the compensating differential is 0.8 times the hourly wage (=59/(3.4*22)). With an elasticity of 14.8%, we obtain a compensating differential of 0.98 times the hourly wage for women.

These estimates of compensating differential belong to the range of estimates in the literature. Mulalic et al. (2014) report that estimates of the value of travel time ranges from 20%

to 100% of hourly gross wages (Small, 1992; Small et al., 2005; Small and Verhoef, 2007; Small, 2012).

Robustness Appendix Table D9 shows the robustness of our elasticity estimates. Column 1 does not use inverse probability weighting to balance the male and female sample on covariates. Column 2 restricts the sample to workers who declare their maximum commute in kilometers. Column 3 shows robustness to another definition of non-minimum wage workers, based not on an individual's stated reservation wage, but rather on her occupation and past wage. In each occupation, we split workers according to the within-occupation median past wage. We obtain occupation-past-wage cells. In each cell, we compute the share of workers who report a reservation wage 5% above the minimum wage. We tag those cells with a corresponding share above the median as non-minimum-wage cells. Results are robust to this alternative sample selection. In column 4, we adopt another minimization criteria, namely the number of accepted bundles below the indifference curve. Again our results are robust. In column 5, we restrict the estimation sample to individuals who worked full time in their previous job. The gender difference in elasticity is smaller when we hold constant the past hours worked, but still significant. This suggests that gender differences in commute valuation come on top of potential gender differences in hours flexibility.

In this section, we have showed that women have a 22% higher willingness to pay for a shorter commute (0.027/0.121=0.223, see column 1 of Table 6). This result comes from a new – to the best of our knowledge – identification strategy that leverages unique data on job search criteria available from the French institutions. The identification strategy mostly relies on the form of the utility function when employed and on the reservation strategy embedded in standard job search models. Namely, the commute distaste parameter is separately identified from the other model parameters, as long as the job offer distributions are not degenerate. This is worth noting as an alternative hypothesis supporting the gender gaps documented in Section 3 could be that men and women do not draw job offers from the same distributions when unemployed (even if they had similar jobs before unemployment). Even in this case, our result on gender differences in willingness to pay for a shorter commute still holds. We next draw the implications of the gender differences in commute valuation for the gender wage gap.

5 Implications for the gender wage gap

As women must be compensated more than men to accept far-away jobs, they are more likely to work close to home in jobs that pay relatively less. To what extent do gender differences in commute valuation contribute to the gender wage gap? To quantify this, we first calibrate the job search model above, using the previous estimate of the commute distaste parameter. Second, we perform counterfactual simulations where we shock the commute distaste parameter only.

5.1 Calibration of the job search model

We calibrate the model for four categories of job seekers: single women without children, married women without children, single women with children, and married women with children. For each category, we proceed as follows.

First, we calibrate r such that the yearly discount rate is 12% and the match destruction rate q is equal to the inverse of the length of jobs in the subsample of interest (for the median job seeker, a job spell lasts 12 months). Second, we observe in the data (τ^*, ϕ^*), which is a point on the reservation curve, and the previous section yields an estimate of the commute distaste α. We can build the full reservation curve; in particular we can deduce $\phi(0) = \phi^* - \alpha\tau^*$.

Knowing the reservation curve, we use the empirical measures of the expectation and variance of the residualized log of the reemployment wage w^n and commute τ^n together with Equations (2) and (3) to pin down the job offer distributions. We residualize the next wage and commute with the same covariates as in the main gender gap regressions. This aims at focusing on wage and commute variations arising from random search. We assume that log-wage and commute are drawn independently respectively from the distributions F and G. The distribution of the log-wage is a Gamma distribution and we estimate its shape k_F and scale θ_F. For G, we assume the following pdf, defined over the support 0 to 100 km:

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

The distribution G is a mixture of a Gamma distribution with shape k_G and scale θ_G and of a linear distribution. The functional form of G is consistent with the distribution of distances between job seekers' residence and workplaces of vacancies posted on the French PES website (see Appendix Figure C6). Intuitively, the linear term accounts for the increase in further-away jobs when the disk of radius τ centered on the worker's residence expands over a two-dimensional uniform density of jobs.[32] For F and G, there are four moments to pin down four parameters.[33]

We use the observed job finding rate to determine the job offer arrival rate λ. Namely, we use the fact that the job finding rate should be equal to:

$$\lambda \int_0^\infty \int_{\phi(0)+\alpha\tau}^\infty dF(w)dG(\tau)$$

The flow unemployment utility b is finally obtained as a solution of Equation (1). The quantities involved in the calibration are summarized in Table 7. Table D10 provides the values of estimated/calibrated parameters for all groups.

5.2 Decomposition of the gender wage gap

The counterfactuals are obtained as follows. Keeping all other structural parameters unchanged, we replace the commute distaste α we have estimated for women by those estimated for men. In practice, we reduce α by 18.2%, the average difference between men and women as estimated in the previous section (0.027/0.148=0.182, see column 1 of Table 6). We perform the same exercise for the four groups defined by marital status and presence of children.

Reducing α in the job search model increases accepted wages and commute through two channels, related to the rotation and the shift of the reservation curve respectively. The rotation of the reservation wage curve – holding reservation utility constant – implies that the fraction of jobs accepted further away from home increases. As further-away jobs pay more, the rotation implies both an increase in wage and commute. In addition, lowering α increases the utility when employed and thus the reservation utility.[34] This induces an upward shift in the reservation wage curve, which further increases accepted wages.

Results are shown in Table 8. The last column shows the magnitude of the shock in commute valuation applied to each group. The first column reports the share of the gender gap in the residualized wage of the next job that is explained by the reduction in α.[35] The second column does the same exercise for the commute. We find that gender differences

[32] If jobs were uniformly distributed over space, the density of jobs within a disk of radius τ around the worker's residence would be proportional to the disk area: $\pi\tau^2$. When τ increases, the marginal number of jobs is proportional to $2\pi\tau$.

[33] In practice, we follow a GMM estimation with appropriate weights for the four moments.

[34] This derives from standard comparative statics of the job search model.

[35] The denominator of this ratio comes from the estimation of gender gaps in reemployment outcomes in the non-minimum wage sample, see Appendix Table D8.

in commute valuation (i.e. in α as estimated in Section 4) explain between 8.5% and 15.8% of the wage gap, depending on the group but with no clear pattern as a function of family size, and overall close to 100% of the differences in commute. Note that this is not a mechanical result, and it did not need to be the case. Men and women are likely to differ along other dimensions than α (e.g., the job offer distributions F, G) and differences in the other dimensions may trigger differences in commute as well.

This ranks gender differences in commute distaste as an important driver of the gender wage gap. Mas and Pallais (2017) finds that "with a 20 percent compensating differential for both work at home and working a fixed schedule instead of an irregular one, the differences by gender in the prevalence of these arrangements would only lead to a 1.7 percent raw gender wage gap or a 2.0 percent gap with controls." Wiswall and Zafar (2017) finds that accounting for gender differences in students preferences for future earnings growth, probability of dismissal, and working hours flexibility, account for one quarter of the gender earnings gap. Bertrand et al. (2010) finds that for MBA graduates, 30% of the gender wage gap is accounted for by gender differences in hours of work per week.

Robustness In Appendix Table D11, we simulate the effects of a reduction in commute distaste that is such that the explained share of the gender gap in commute of the next job is equal to 100%. The resulting explained shares of observed wage gaps are slightly lower, but results are fairly similar to those in Table 8. Finally, Appendix B shows a decomposition exercise under an alternative interpretation of the reported reservation job (ϕ^*, τ^*) (Interpretation 2 above). In Appendix Table B2, the share of gender wage gap explained by gender differences in commute distaste is lower, between 1.4% and 7.8%. Overall, our decomposition exercise delivers robust results, suggesting that a meaningful share of the gender wage gap can be explained by gender differences in commute valuation.

6 Further insights from application data

In this section we present further insights using application data. We leverage a rich administrative dataset that records applications of job seekers to vacancies posted at the French PES and their hiring outcomes. We first show that the elasticity of posted wages with respect to the commute distance between the vacancy workplace and the applicants' residence is larger for women than for men. This is in line with the gender gap in commute valuation estimated in Section 4. Second, we study labor demand. We find that firms do not specifically lower their hiring of women compared to men when applicants live further away.

6.1 Application data

French employers typically post vacancies on the PES website and advertise them through local agencies (in 2010, around 60% of all vacancies were posted through the PES). Workers registered as job seekers may apply through the PES website or local agencies. This generates entries into an application dataset at the vacancy $\times$ worker identifier level. We can thus analyze the attributes of the vacancies to which workers apply. Furthermore, caseworkers record the application outcome: hired or not. This allows us to analyze the hiring outcome within the pool of applicants, and to get closer to labor demand.[36] We observe over 3 millions applications from the same random subsample of workers as above.[37] We restrict the sample to applications from 2010 to 2012, because we do not observe the vacancy workplace before 2010.

Table 9 reports summary statistics for applications, vacancies and applicants. Panel A reports statistics at the application level. Around 5% of applications lead to hiring. The average commute between the vacancy workplace and the applicant's home is 19km, very similar to the average commute reported in Table 1. The posted wage is on average 1,539 euros. This is 25% lower than the average previous wage of the main sample of job-seekers in Table 1, and close to the legal minimum wage of around 1,400 euros in 2010-2012. Indeed 44% of vacancies report the minimum wage as their posted wage. All vacancies report an occupation and a required qualification (low- or high-skilled blue collar work, low- or high-skilled employee and managers). For almost half of the applications, the applicant meets the required qualification. Similarly, in almost half of the cases, the applicant selects a job in their preferred occupation.

Almost one applicant out of four is hired from a vacancy posted by the PES (see Panel C of Table 9). This builds confidence in the relevance of PES postings and applications for labor market clearing. Conditional on applying at least once, applicants apply on average for six vacancies. From the employer's side of the market (see Panel B), 94% of vacancies are filled by an applicant applying through the PES, and job ads receive 21 applications on average. Overall, firms and applicants have a high probability of finding a match through the PES marketplace conditional on posting and applying. However, there is still selection into PES posting for firms and into PES applying for workers. This is certainly an issue when measuring the number of applicants for a given vacancy or the overall search intensity of a

[36] In general, hiring is an equilibrium outcome resulting from the interaction of labor supply and labor demand. In our setting, we analyze hirings of workers applying to detailed job ads (including wages). We thus argue that if employers offer the job to an applicant, it is very likely that she accepts the offer. Consequently, hirings in our setting are rather informative of employers' choice among applicants.

[37] The sample of applicants is larger than the main sample described in Section 2. To maximize statistical power, we also include workers who do not claim unemployment benefits.

given job seeker. For example, some applicants directly apply through company websites. It is unclear though why this selection into application should be differential by gender. We argue that this selection margin leads to second-order bias when documenting gender differences in the job attributes of the applied vacancies, or when analyzing the gender hiring gap as a function of applicants characteristics.

6.2 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 distance between the vacancy workplace and the job seeker's residence.[38] 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.[39] Our main parameter of interest is the gender gap in elasticity (δ). We include 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 10 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

[38] For the sake of comparison with section 3, Appendix Table D12 shows the gender gaps in vacancy characteristics, broken down by family status.

[39] When applicants reside in the same municipality as the vacancy, we compute the average distance between any two random locations of the municipality using its area.

insignificant. However, as in the main estimation of the slope of the indifference curve in Section 4, 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 4. 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.

6.3 What about labor demand?

We have shown in Section 3 that, when newly unemployed, women and men set different search criteria: women search closer and not-so-well-paid jobs compared to men. Our main interpretation is that these differentials are due to differences in the utility function of men and women, and how they weigh commuting distances vs. wages. Another interpretation may be that gender differentials in search criteria reflect differences in the labor demand for male and female workers, in which case women would report seeking a job closer to home than men because they expect fewer job offers from distant workplaces. In other words, they would be internalizing a lower labor demand from far-away employers. Below we test this alternative explanation and find that differentials in labor demand are unlikely to explain gender gaps in search strategy.

Figure 7 plots the hiring rate of applicants as a function of the distance between the worker's home and the vacancy's location, within the pool of applicants to the same vacancy. On top of vacancy fixed effects, we also control for the applicants' age, education level and experience. The reduction in hiring rate with distance looks similar for men and women.

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 specified 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 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 11 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 and is not statistically significant at the 5% level in our preferred specification of column 4.

7 Conclusion

Our paper documents gender differentials in job seekers' search criteria, controlling finely for the characteristics of their previous job. Even single women without children have a 2.1% lower reservation wage and are willing to accept at most a commute 7.7% shorter than comparable men. These figures increase respectively to 5.6% and 23.7% for married women with children. The gaps also grow with age, following a similar pattern to that observed for wages and commutes in the overall working population.

We then use the joint distribution of reservation wages and reservation commutes together with reemployment outcomes to estimate the slope of reservation wage curves. We find that the value of commute time amounts to 80% of the gross hourly wage for men and 98% for women, a difference that is statistically significant. We build a job search model where commuting matters and show that our estimated gender differences in commute valuation can account for around 10% of the observed gender wage gap upon reemployment. We also provide evidence that the gender differences in search criteria are *not* driven by labor demand.

By highlighting the importance of gender differences in willingness to commute and linking it to the gender wage gap, we shed light on possible ways to further reduce gender wage inequality. Technological progress that lowers the firms' cost of remote work has the potential to further decrease the gender wage gap (Bloom et al., 2014). More generally, public policies on urban planning and transportation have the potential to change commuting patterns differently for men and women and may have differential effects on their relative wages (e.g. Redding and Turner, 2015). On a related note, offering financial subsidies to job seekers who apply for or accept more distant jobs may affect differently men and women, and thus the gender wage gap (Glover and Roulet, 2018).

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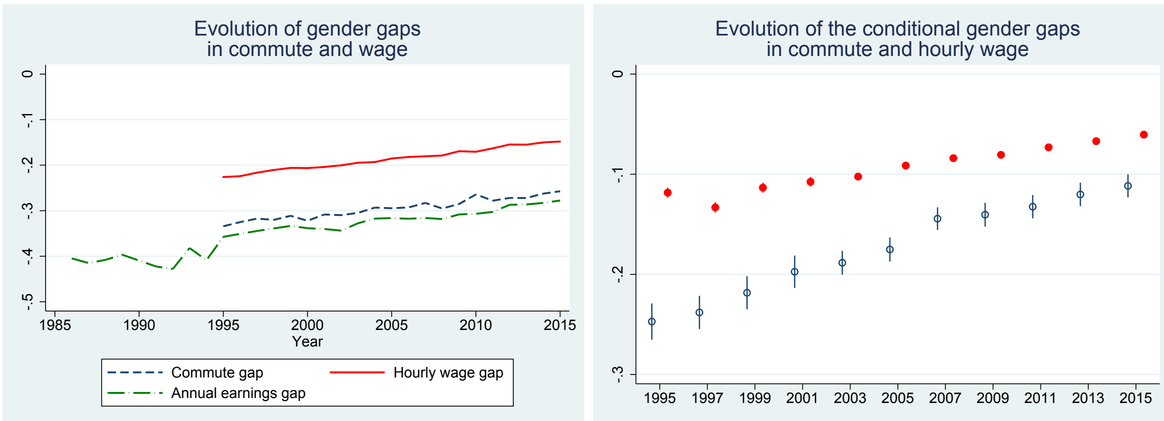
Figures

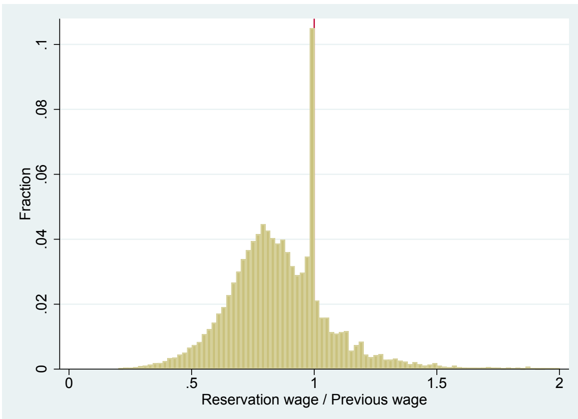
Figure 1: Gender gaps in wages and commuting distances over time



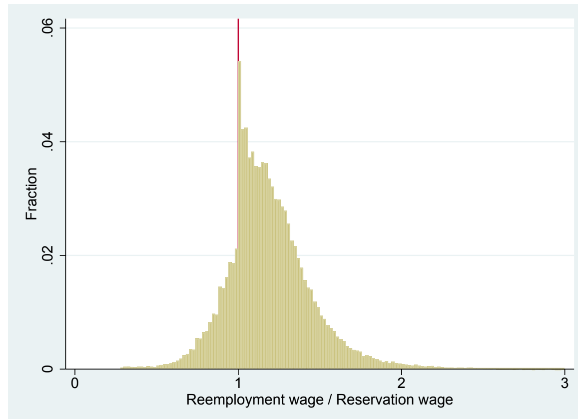
Note: These figures plot the evolution of gender gaps over time. The left panel plots the raw log-difference of the annual earnings, of the hourly wage rate and of the commuting distance between women and men. Reliable data on commuting and hours are available since 1995. The right panel plots the adjusted gender gaps in hourly wage (red dots), and in commuting distance (blue circles). We run separate regressions of both commuting and hourly wage every year. We include as controls age, occupation, experience, part-time dummy, industry and commuting zone fixed effects.
Sample: 1/60th sample of all private sector employment spells in France (DADS data).

Figure 2: Distribution of search criteria, relative to previous and next jobs

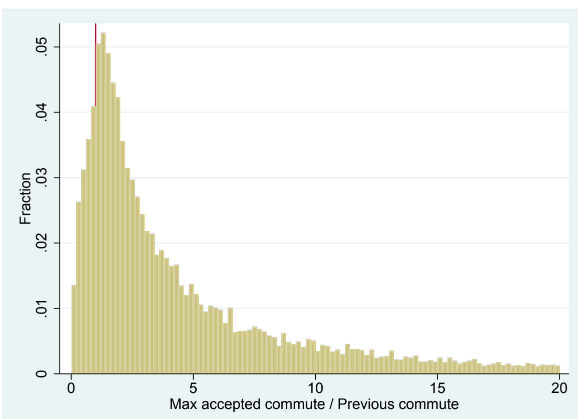
(a) Reservation wage over previous wage



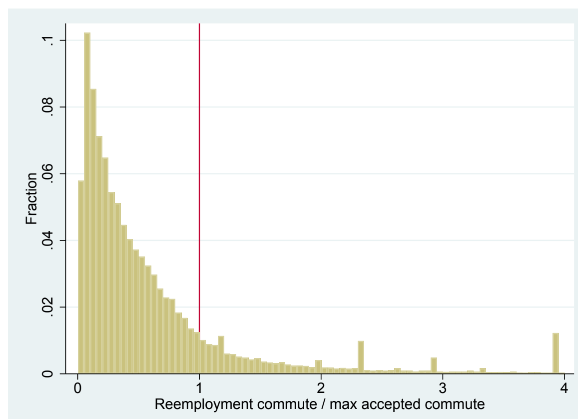
(b) Reemployment wage over reservation wage



(c) Maximum acceptable commute over previous commute



(d) Reemployment commute over maximum acceptable commute

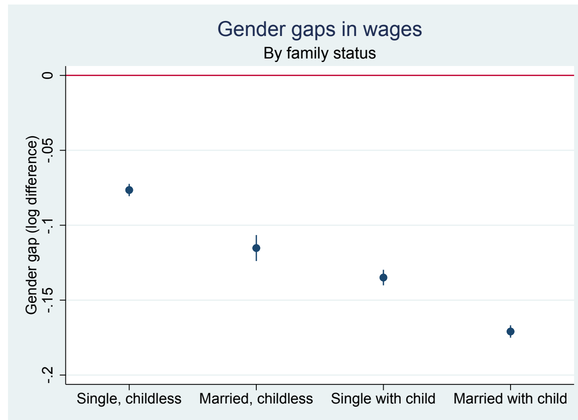


Note: These figures plot the distributions of search criteria and employment outcomes for our main sample of unemployed people restricted to those who find jobs within two years. Panel (a) plots the distribution of the ratio of the unemployed's reservation wage over the wage in her previous job (both FTE gross monthly). Panel (b) plots the ratio of the reemployment wage (also FTE gross monthly) over the reservation wage. Panel (c) plots the ratio of the maximum acceptable commute (in km) over the commuting distance in her previous job. Panel (d) plots the ratio of the reemployment commuting distance over the maximum acceptable commute (in km). The sample in Panel (c) and (d) is further restricted to workers stating their maximum acceptable commute in kilometers when they answer the public employment service questions.

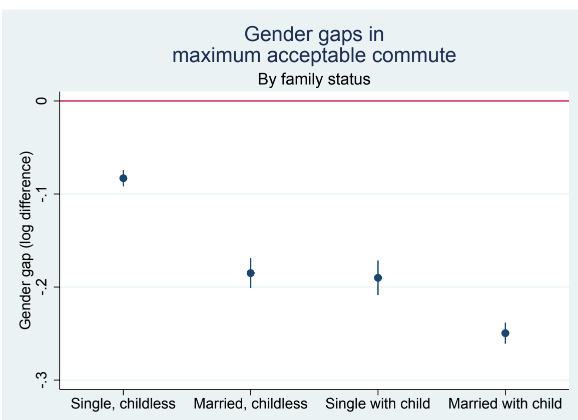
Figure 3: Gender gaps grow with family size

(a) Reservation wage

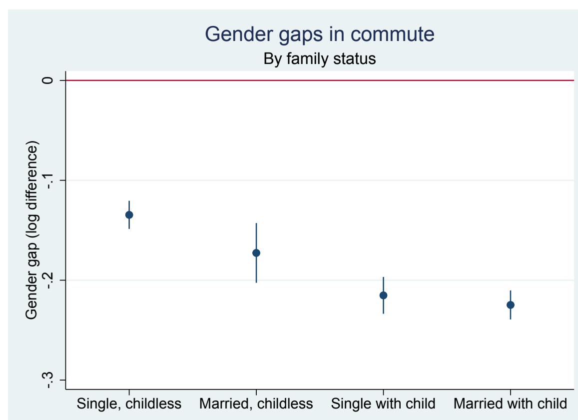
(b) Reemployment wage



(c) Maximum acceptable commute



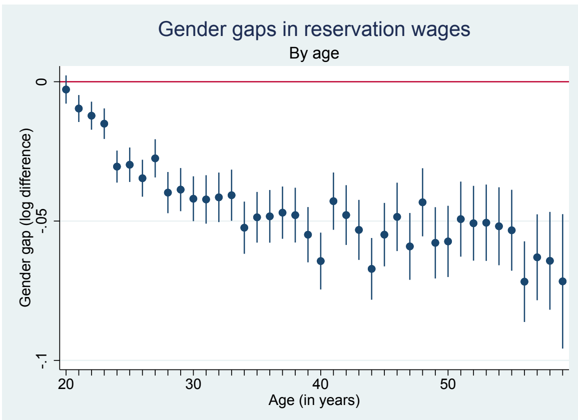
(d) Reemployment commute



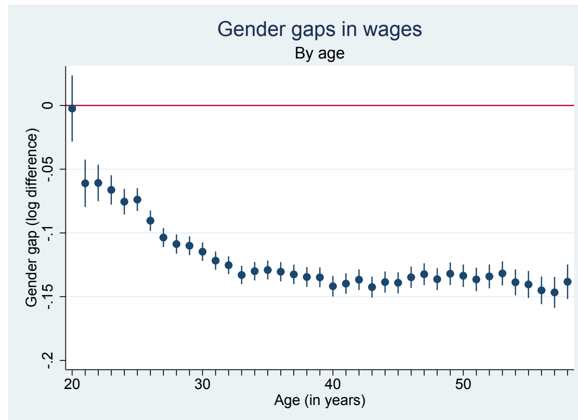
Note: These figures plot regression coefficients of a female dummy interacted with different household structure dummies, on the log of the FTE gross monthly reservation wage (panel a), the log of FTE gross monthly wages (panel b), the log of the maximum acceptable commute (panel c) and the log of commute (panel d). 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 employment spells in France between 2003 and 2010 (DADS-EDP data). We control for education, age, marital status, children, experience, 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.

Figure 4: Gender gaps grow with age

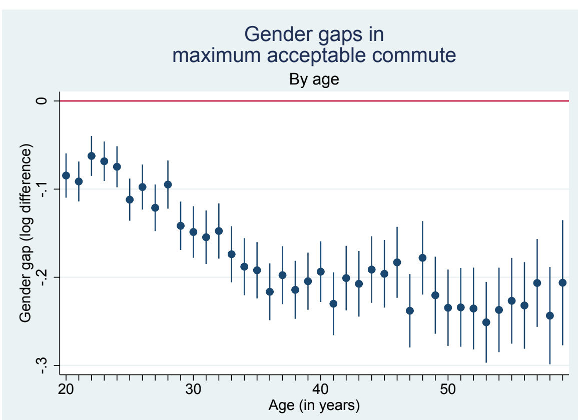
(a) Reservation wage



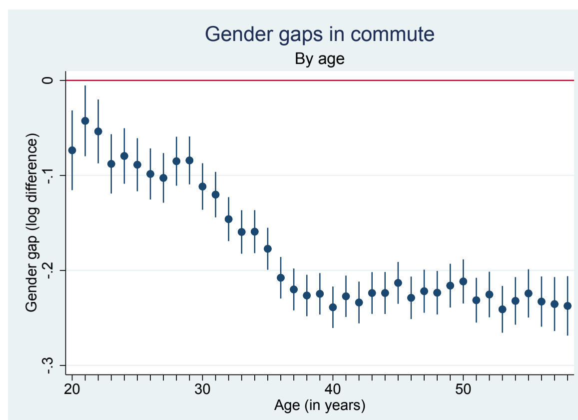
(b) Reemployment wage



(c) Maximum acceptable commute

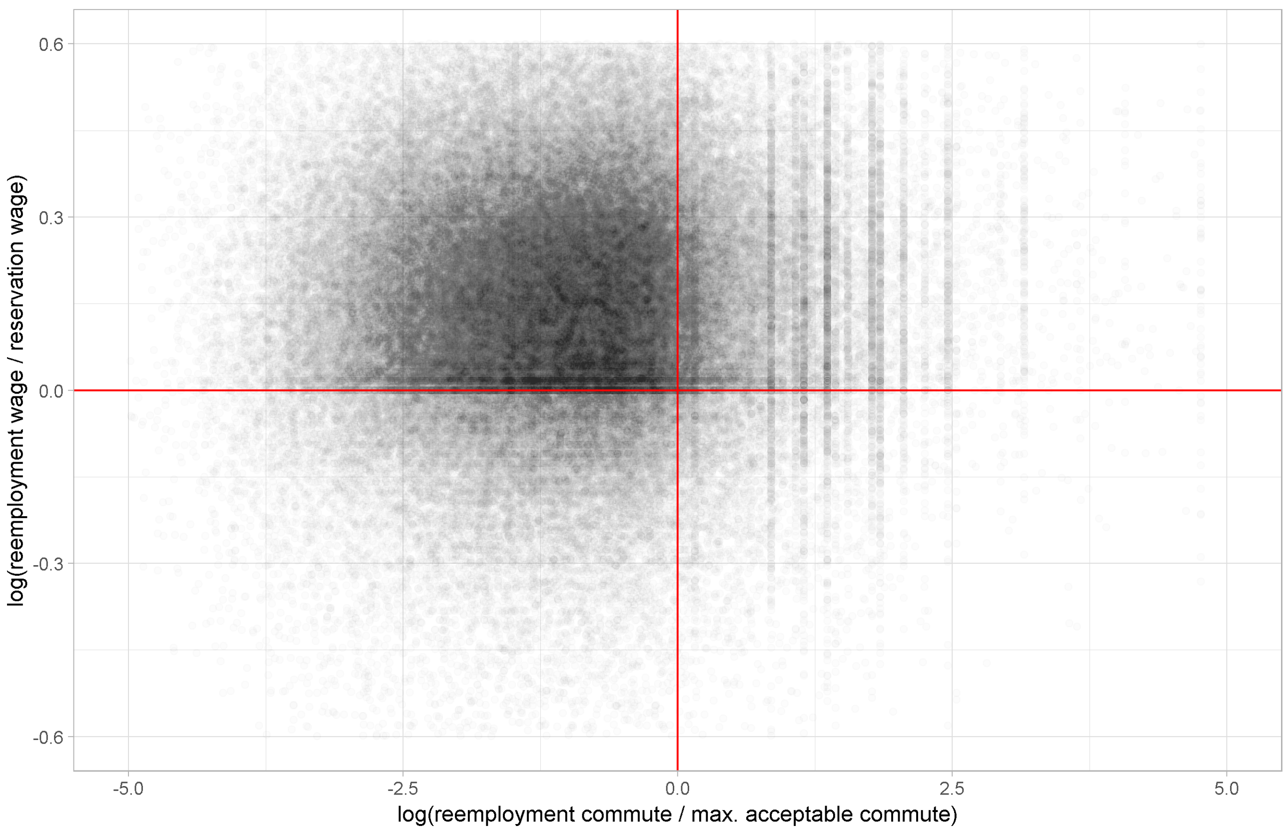


(d) Reemployment commute



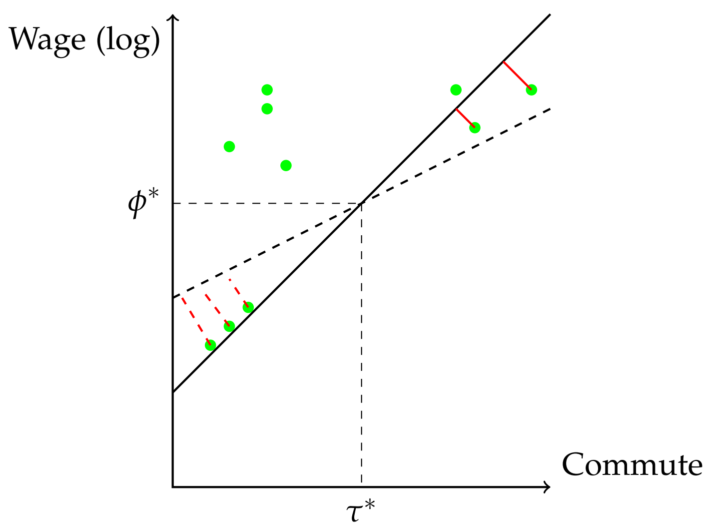
Note: These figures plot regression coefficients of a female dummy interacted with age dummies, on the log of the FTE gross monthly reservation wage (panel a), the log of FTE gross monthly wages (panel b), the log of the maximum acceptable commute (panel c) and the log of commute distances (panel d). 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 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.

Figure 5: Characteristics of next job relative to search criteria



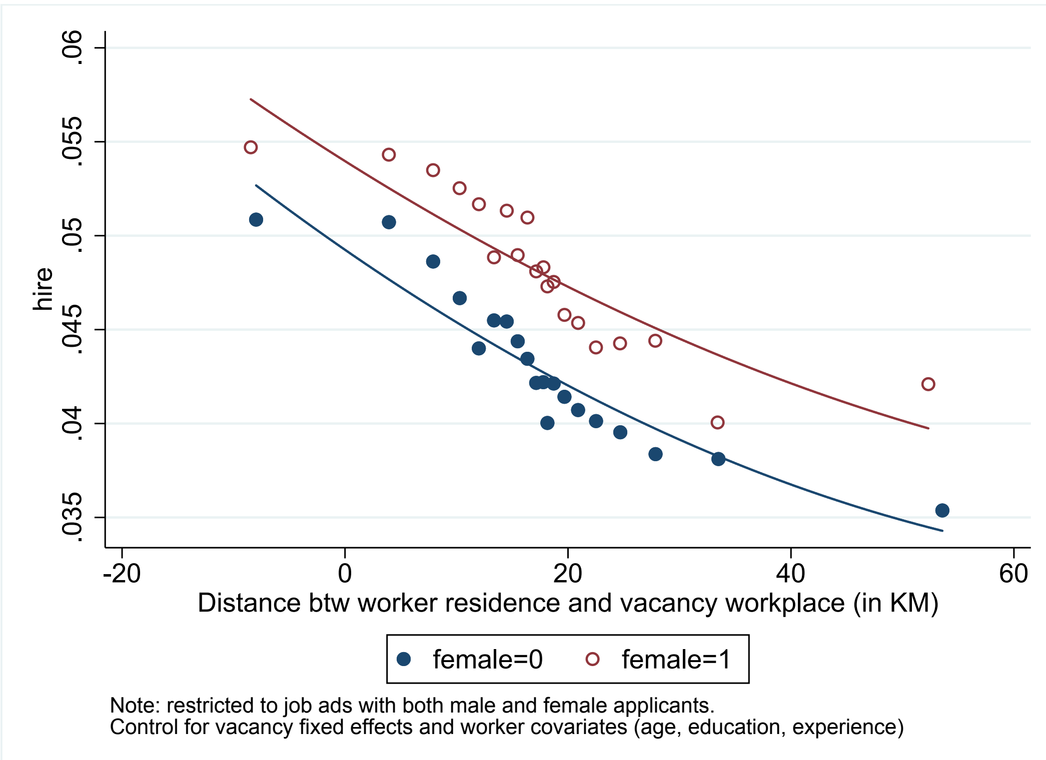
Note: The figure plots the joint density of the log reemployment wage and commute in deviation from the reservation wage and commute. The vertical red line shows where the reemployment commute equals the maximum acceptable commute. On the horizontal red line, the reemployment wage equals the reservation wage. When job seekers report their reservation commute in minutes, we convert their answers in kilometers using a speed equal to 35 kilometer/hour.

Figure 6: Estimation strategy for the slope of the reservation log-wage curve in the log-wage-commute plane



Note: The figure illustrates the estimation strategy for the slope of the indifference curve in the log-wage-commute plane. We draw as green dots jobs accepted by workers with reported reservation wage ϕ^* and reservation commute τ^*. Under Interpretation 1, reservation wage curves go through the (τ^*, ϕ^*) job. We draw two potential reservation wage curves: the solid and the dashed lines. There are three accepted jobs below the dashed line, while there are only two below the solid line. Moreover, jobs below the dashed line are further away from the dashed line (distances in red and dashed) than jobs below the solid line are distant from the solid line (distances in red and solid). Our estimation strategy chooses the solid line as the reservation wage curve.

Figure 7: Applicants' hiring rate as a function of their commute to the vacancy's workplace, by gender



Note: The figure presents a binned scatterplot of the hiring rate vs. the distance between the worker's residence and the vacancy's workplace, for men (blue dots) and for women (red circles). The sample consists in applications of workers for jobs posted on the public employment service website (from 2010 to 2012). The sample is restricted to job ads receiving applications from both women and men. The hiring rate and the commute distance are residualized using vacancy/ad fixed effects and worker characteristics (age, education and experience).

Tables

Table 1: Summary statistics

Variable	Mean	Std. dev.	Obs.
Age	33.384	11.367	319,902
Married	0.389	0.487	319,902
Child	0.370	0.483	319,902
Education (in years)	11.525	3.279	319,902
Experience (in years)	6.183	7.708	319,902
Past wage (gross, euros)	2018.207	937.286	319,902
Reservation wage (gross, euros)	1664.680	595.552	319,902
Next-job wage (gross, euros)	1884.512	607.325	185,185
Past commuting distance (km)	18.653	28.969	319,528
Max. acceptable commute dist. (km)	29.260	22.855	213,976
Max. acceptable commute time (min)	42.713	19.485	105,926
Next-job commuting distance (km)	18.893	27.799	184,965
Past job is full-time	0.745	0.436	319,902
Looking for a full-time job	0.917	0.276	319,902
Next job is full-time	0.752	0.432	185,185
Past contract is open-ended	0.422	0.494	319,902
Looking for a open-ended contract	0.920	0.272	319,902
Next-job contract is open-ended	0.377	0.485	178,082
Looking for same occupation (3-digit)	0.196	0.397	319,902
Finding in same occupation as prev. job	0.258	0.437	185,037
Found a job within 2 years	0.469	0.499	319,902
Non-employment duration (in days)	428.216	360.156	185,184

Note: The sample consists in workers 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 2: Gender effect on reservation wage and on maximum acceptable commute

	(1) Log ResW	(2) Log max. commute	(3) Log ResW	(4) Log max. commute
Female	-0.0356***	-0.140***	-0.0346***	-0.130***
	(0.000927)	(0.00351)	(0.000931)	(0.00352)
Other search criteria (hours, occ., contract)			X	X
Mean: males	1,741 €	32 km	1,741 €	32 km
Observations	319,902	319,902	319,902	319,902
R-squared	0.730	0.434	0.730	0.437

Note: The table reports regression coefficients of a female dummy on the log of the FTE gross monthly reservation wage (columns 1 and 3) and on the log of the maximum acceptable commute (columns 2 and 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 presence of children. In columns (3) and (4), we control for the other attributes of the job searched for: full-time dummy, dummy for whether the searched occupation is the same as the previous one, and type of contract. The estimation drops singleton observations within commuting zone x quarter x industry cells, so that the effective sample size is 270,934.

Table 3: Gender effect on reemployment outcomes

	(1) Log wage	(2) Log commute	(3) Log wage	(4) Log commute	(5) Log wage	(6) Log commute
Female	-0.0367***	-0.118***	-0.0409***	-0.108***	-0.0162***	-0.0526***
	(0.00190)	(0.00975)	(0.00190)	(0.00977)	(0.00212)	(0.0113)
Other new job charac. (hours, occ., contract)			X	X		
Search criteria					X	X
Mean: males	1,948 €	21.3 km	1,948 €	21.3 km	1,948 €	21.3 km
Observations	149,952	149,952	149,952	149,952	149,952	149,952
R-squared	0.543	0.346	0.549	0.347	0.579	0.359

Note: The table reports regression coefficients of a female dummy on the log of the reemployment FTE gross monthly wage (columns 1, 3 and 5) and on the log of the reemployment commuting distance (columns 2, 4 and 6). 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. In columns (3) and (4), we control for the other attributes of the new job: full-time dummy, dummy for whether the new occupation is the same as the previous one, and type of contract. In columns (5) and (6), we control for the attributes of the job searched for: reservation wage, maximum acceptable commute, desired occupation, full-time dummy, and type of labor contract. The effective estimation sample size, dropping singletons, is 114,394.

Table 4: Gender effect on the reservation wage and maximum acceptable commute in the U.S.

	(1) Log ResW	(2) Log max commute
Female	-0.0889***	-0.258***
	(0.0168)	(0.0365)
Mean: males	20.13 $	46.8 min
Observations	3,662	3,918
R-squared	0.625	0.186

Sample: Survey of Unemployed Workers in New Jersey (see Krueger and Mueller 2016).
Note: The table reports regression coefficients of a female dummy on the log of the hourly reservation wage (column 1) and on the log of the maximum acceptable commute (column 2). For the sake of comparability to Table 1 in Krueger and Mueller (2016), the sample is restricted to the first interview of each worker. Controls are the same as in Column (3) of Table 1 in Krueger and Mueller (2016) (except for non-publicly available administrative data on UI and past wage levels). Controls include age groups, education groups, potential experience and its square, marital and couple status, # of children, ethnicity and race, previous household income, spouse employment, savings, liquidity access, previous job characteristics (full-time, tenure and its square), unemployment duration, severance payments received, stated risk preferences, patience proxy and declaration unit for reservation wages. Survey weights are used. Standard errors are robust.
Column (1) replicates Krueger and Mueller (2016). Column (2) is not available in Krueger and Mueller (2016).

Table 5: Gender effect on employment outcomes in job-to-job transitions

	(1) Log wage	(2) Log commute
Female	-0.0417***	-0.121***
	(0.0007)	(0.0030)
Observations	973,762	973,337
R-squared	0.672	0.259

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 (column 1) and on the log of the commuting distance (column 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.

Table 6: Elasticity of wage with respect to commute along the reservation wage curve

	(1)	(2)	(3)	(4)	(5)
	All	Without children		With children	
		Single	Married	Single	Married
Women	0.148***	0.141***	0.165***	0.148***	0.156***
	(.0045)	(.0061)	(.015)	(.013)	(.010)
Men	0.121***	0.111***	0.126***	0.114***	0.141***
	(.0046)	(.0053)	(.014)	(.013)	(.010)
Gender gap	0.027***	0.031***	0.039*	0.034*	0.015
	(.0073)	(.0072)	(.020)	(.018)	(.015)
Obs.	75,071	38,593	8,670	6,756	21,074

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 singles without children; in column (3), to married individuals without children; in column (4), to single parents; and in column (5), to married parents. We use inverse probability weighting to balance the covariates of women and men. Bootstrapped standard errors in parenthesis.

Table 7: Calibration of the model

Parameter	Comment	Value
r	Annual discount rate 12%	0.011
q	Inverse of job spell duration, from data	0.15
ϕ^*	Log reservation wage, from data (ratio to min wage)	0.23
τ^*	Maximum acceptable commute, from data (in x00 km)	0.3
α	Estimation of α, see supra	-1.6
ϕ_0	From (ϕ^*, τ^*) and α	-0.24
w^n	Log wage in new job, from data (ratio to min. wage)	0.34
τ^n	Commute in new job, from data (in 100 km)	0.087
F: k_F	Matches the distribution of next wage w^n	3.1
F: θ_F	(id.)	0.1
G: k_G	Matches the distribution of next commute τ^n	3.5
G: θ_G	(id.)	0.017
jfr	Job-finding rate, from data	0.12
λ	Matches the job-finding rate	0.22
b	Solution of Equation (1)	-0.57

Note: The table reports the values of the model parameters, when calibrated for the sample of single women without children. In column (2), we provide a short comment on how we pin down the parameter. 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.

Table 8: Contribution of gender differences in commute valuation to gender gaps in wage and commute

	Contribution to the observed gender gaps in		Commute distaste
	Wage	Commute	shock
Single, no kids	15.8%	193.4%	-18.2%
Married, no kids	12.3%	119%	-18.2%
Single, with kids	8.5%	131.2%	-18.2%
Married, with kids	12.4%	101.4%	-18.2%

Note: The table reports the share of the empirical gender gaps in wage and commute of the next job explained by gender differences in commute distaste. The decomposition is based on the job search model in Section 4. We shock the commute distaste parameter of women by the difference in α estimated in Table 6. We simulate the job search model to predict the gender gap in wage and commute of the next job; we report in the first two columns how much it explains of the observed reemployment wage and commute gaps.

Table 9: Summary statistics of application dataset

	(1) Mean	(2) Std. dev.	(3) Obs.
Panel A: application level			3,103,522
Hiring	0.052	0.221	
Female applicant	0.489	0.5	
Posted wages (gross, FTE, euros)	1,539	336	2,923,929[(2)]
Commute (km)	18.8	21.3	
Same 3-digit occupation[(1)]	0.481	0.5	
Applicant has:			
Required qualification[(1b)]	0.414	0.49	
Required education	0.448	0.497	1,413,928[(2)]
Required experience	0.855	0.352	2,132,700[(2)]
Panel B: vacancy level			1,802,276
Hiring[(3)]	0.948	0.22	
# applicants per vacancy[(3)]	20.7	16.5	
Full-time position	0.73	0.444	
Open-ended contract	0.39	0.488	
Requires education level	0.473	0.499	
Required education level (years)	12.09	2.60	
Requires experience	0.699	0.459	
Required experience level (month)	6.89	12.88	
Panel C: applicant level			488,578
Hiring	0.238	0.426	
# applications per job-seeker	6.35	8.93	
Women	0.501	0.5	
Education (years)	11.41	3.35	
Experience (month)	63.6	77.9	
Foreigner	0.119	0.324	

Note: The table reports summary statistics on workers' applications for job ads posted on the French public employment service online job board from 2010 to 2012. In Panel A, we report statistics at the application level. In Panel B, we collapse the dataset at the vacancy level; in Panel B, we collapse the dataset at the applicant/worker level.

[(1)]: The vacancy occupation is the same as the applicant preferred occupation (3 digit level).

[(1b)]: low- or high-skilled blue collar workers, low- or high-skilled employees, or managers.

[(2)]: not all vacancies post wages or require explicitly education/experience levels. Consequently we report separately the number of observations for these dimensions.

[(3)]: as we observe 1/12th of job seekers, we multiply the sample means by 12 to obtain the population means.

Table 10: Elasticity of posted wages with respect to the commute distance between the vacancy's workplace and the jobseeker's residence, by gender

	(1)	(2)	(3)
	Log vacancy wage		
Log commute	0.00526***	0.007***	0.00319***
	(0.00017)	(0.00023)	(0.00022)
Female $\times$ log Commute	-0.00007	0.00391***	0.00202***
	(0.00024)	(0.00042)	(0.00039)
Worker Fixed Effects	X	X	X
Vacancy Controls			X
Sample		$>$min W	$>$min W
Observations	2,765,311	1,329,862	1,329,862
R-squared	0.356	0.377	0.439

Sample: applications to vacancy/job ads posted at the PES.

Note: In this table, we regress the log of the vacancy wage on the log of the commute and on its interaction with a female dummy. Vacancy wages are posted on the job ad. Commute is the distance between the applicant's residence and the vacancy's workplace. Baseline controls include dummies for the month when the vacancy was posted and worker's unemployment duration at the time of the application. Vacancy controls are occupation, temporary contracts, required hours worked, qualification, education and work experience. Standard errors are clustered at both the applicant and vacancy levels. In columns (2) and (3), the estimation sample is restricted to applicants whose preferred occupation has a share of vacancies posted at the minimum wage below 37%.

Table 11: 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 × 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 × 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.

Online Appendix

A Comparison with previous estimates in the literature

Table A1: 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 et. al. (2017)	-.052	(.013)	1,974	GER
Caliendo et al (2011)	-.103	na		GER
Brown et al (2011)	-.068	na	12,921	UK
Koenig et al (2018)	-.102	(.011)	14,847	UK
Koenig et al (2018)	-.188	(.018)	11,221	GER (west)
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 et al. (2017) and Brown et al. (2011) rather control for past wages. Koenig et al. (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 et al. (2017): Column (8) Table 4
Caliendo et al. (2011): Colmun (2) Table AV
Brown et al. (2011): Column (1) Table 1
Koenig et al. (2018): Column (2) and (4) of Table A2

B Robustness to an alternative interpretation of our declared reservation wage and reservation commute measures

In this section, we provide a robustness analysis where we adopt Interpretation 2 of the main text for jobseekers' answers to the reservation wage and maximum commute questions. 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: $\alpha = (\bar{w} - \phi(0)) / \bar{\tau}$. Under Interpretation 2, we observe $\phi^* = \phi(0)$ and $\tau^* = \bar{\tau}$. Then, with an estimate of $\bar{w}$, the data directly identify the slope of the job seeker's indifference curve (see Panel (b) of Appendix Figure C5 for an illustration).

Values of α. To provide estimates of α under this interpretation, we proceed as follows:

1. We estimate a quantile regression of entry wages on job seekers' characteristics (female, age, education, experience, occupation and year), which delivers a mapping between a vector X_i of individual characteristics and the predicted 90th percentile of the distribution of individuals with characteristics X_i: $\hat{w}_{90}(X_i)$.

2. We compute the overall slope of the indifference curve for a worker with reservation wage $\phi_i(0)$, maximum commute $\bar{h}_i$ and characteristics X_i:

$$\hat{\alpha}_i = \frac{\hat{w}^{90}(X_i) - \phi_i(0)}{\bar{\tau}_i}$$

Table B1 presents the result of a regression of the slope α on gender interacted with family characteristics. 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 female job seekers' declared job-search strategy is overall steeper than that of similar males and that the difference in slopes increases with marriage and children.

Model calibration and decomposition of the gender wage gap. We proceed as in section 5 and calibrate the model under these modified interpretation of the reservation wage and commute. Assume that we observe in the data: $\bar{\tau}, \phi(0)$. If we knew $\bar{w}$, we could infer α and hence the acceptance curve. $\bar{w}$ depends on the distribution F which is unknown. We assume that the distribution of the log-wage is a gamma distribution and estimate the shape k_F and the scale θ_F of this distribution, for each group. For 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 together with equations (2) and (3) to pin down the four parameters F and G. The moments from these equations depend on α, but α is well defined for given values of (k_F, θ_F). At the end of this step, we get the four parameters of distributions F and G, as well as α. The final steps from section 5 apply: we obtain λ and b.

The decomposition exercise is the same as above. 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 Table B1, i.e. 17.6% (0.0037/0.021=0.176). 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 B2 and are qualitatively close to those in Table 8. We perform the decomposition on the same four subgroups.

Table B1: Gender differentials in commute valuation by family situation: Alternative interpretation of the reservation wage and the maximum acceptable commute measures

	(1)	(2)	(3)	(4)
	Slope of the log-reservation wage curve ($\bar{w}$-Log ResW) / Max. commute			
Female	0.00256***	0.00270***	0.00368***	
	(0.000360)	(0.000368)	(0.000292)	
F. × single, no children				0.00153***
				(0.000295)
F. × married, no children				0.00565***
				(0.000470)
F. × single, with children				0.00575***
				(0.000470)
F. × married, with children				0.00692***
				(0.000353)
Control w_i^{90}		X	X	X
Control indiv. worker			X	X
Observations	139,884	139,884	139,884	139,884
R-squared	0.058	0.058	0.180	0.183

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.
The average outcome for men is .021. For male singles without children: .023. For male married workers without children: .021. For male singles with children: .019. For male married workers with children: .019.

Table B2: Contribution of gender differences in commute valuation to gender gaps in wage and commute: Alternative interpretation of the reservation wage and reservation commute measures

	Contribution to the observed gender gaps in		Commute distaste
	Wage	Commute	shock
Single, no kids	7.1%	165.5%	-17.6%
Married, no kids	5.9%	114.8%	-17.6%
Single, with kids	7.8%	162.6%	-17.6%
Married, with kids	1.4%	72.1%	-17.6%

Note: This table computes the share of the empirical gender gaps in reemployment wage and commute explained by gender differences in commute distaste, under the alternative interpretation of our reservation wage and maximum acceptable commute measures. We shock the commute distaste parameter of women by the difference in α estimated in Table B1 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 of the observed gaps in reemployment wage and commute.

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

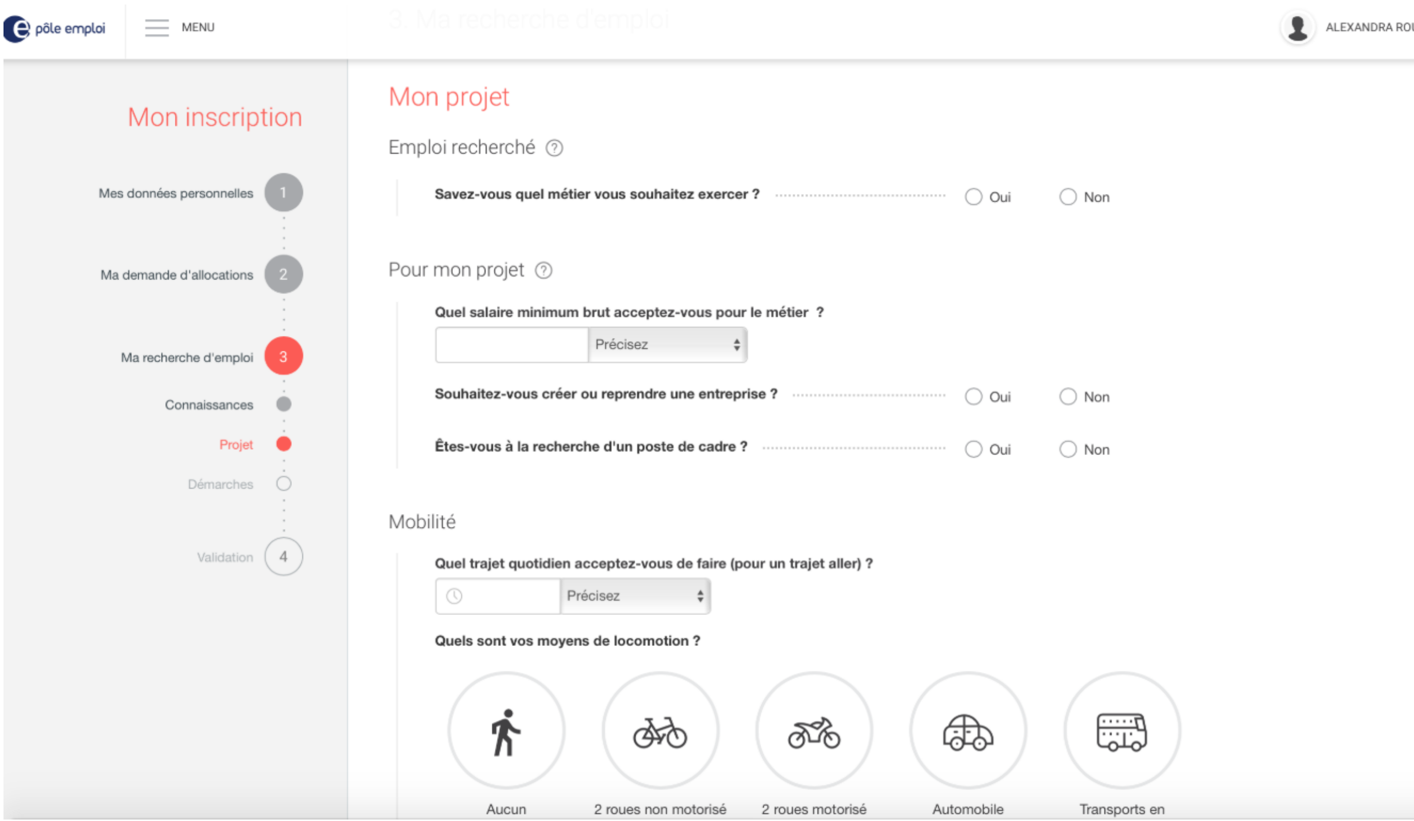


Figure C2: Screenshot of the section dedicated to desired hours worked and type of labor contract on the public employment service website at registration

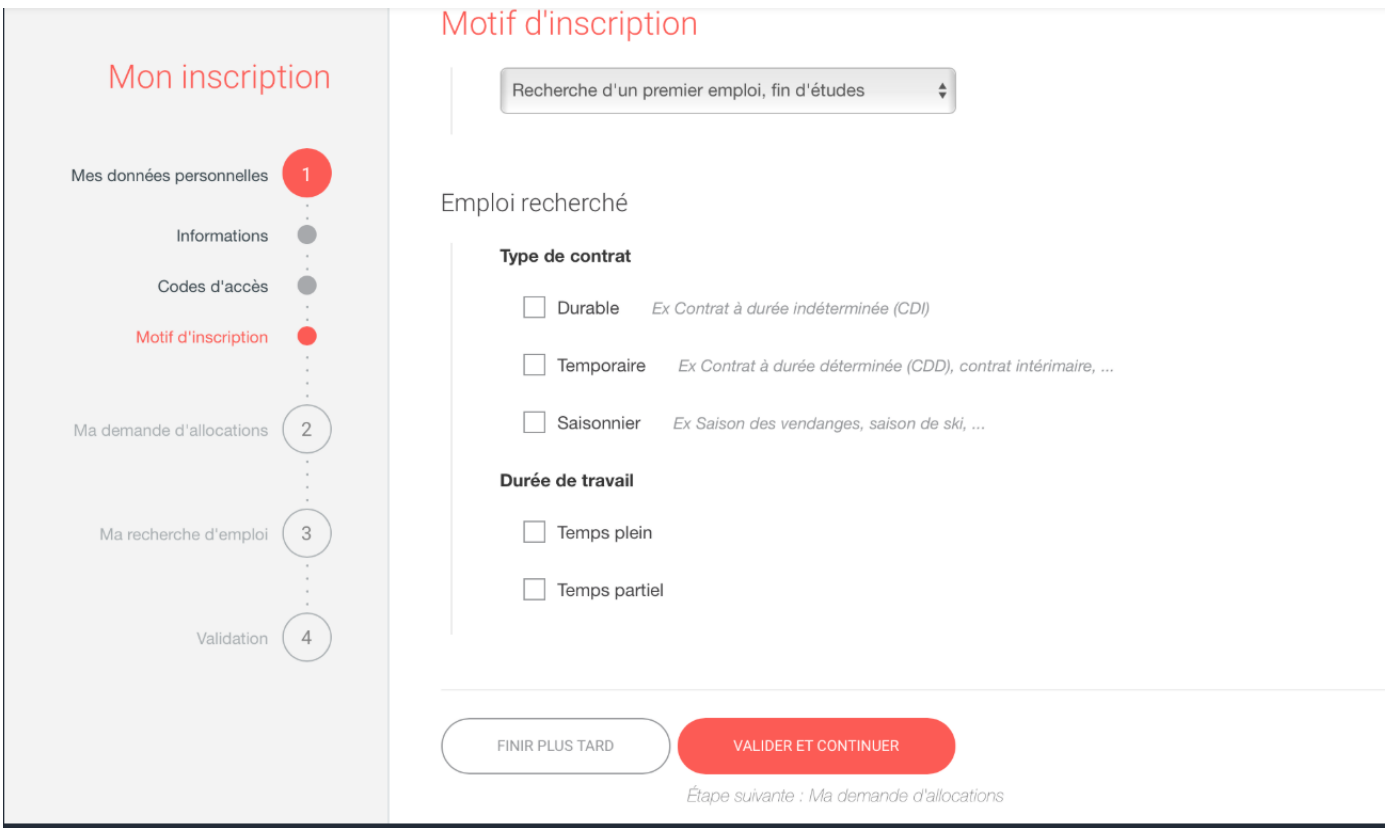
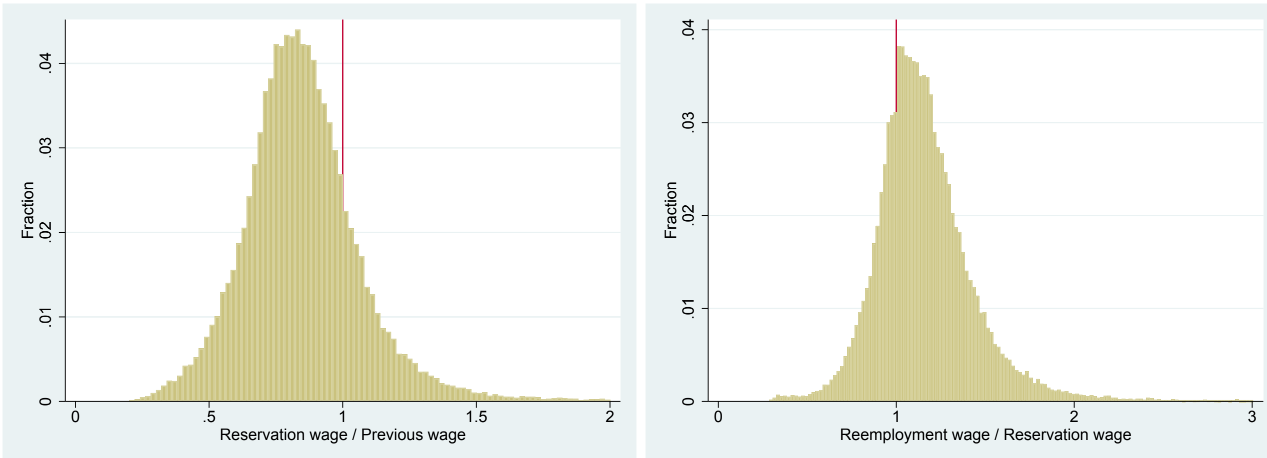


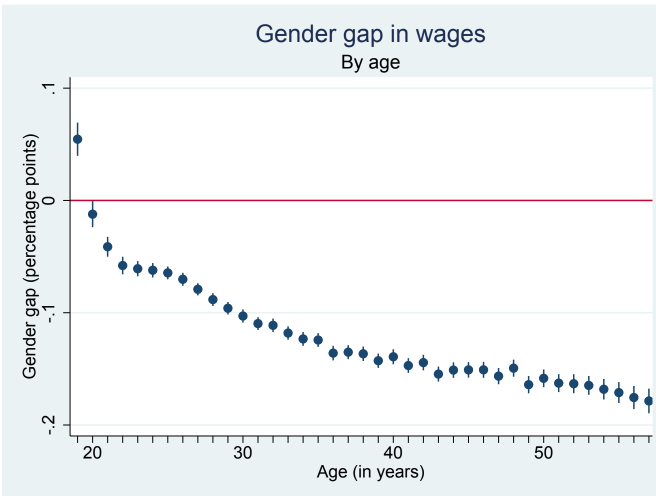
Figure C3: Reservation wage over previous wage and reemployment wage over reservation wage, excluding minimum wage workers



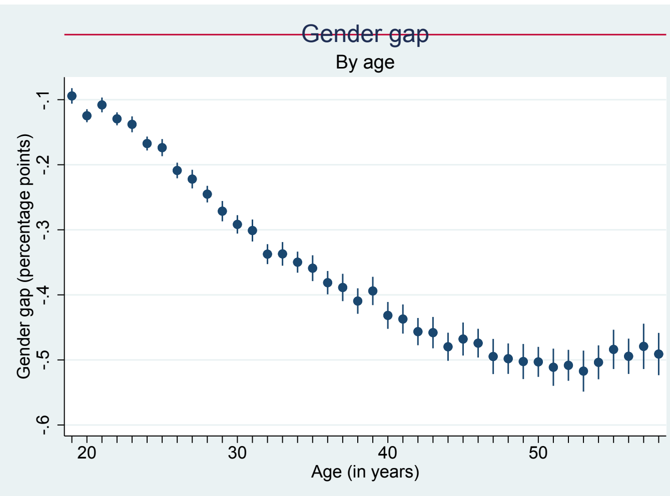
Note: The figure plots the distributions of search criteria and employment outcomes for our main sample of unemployed people restricted to those who find jobs within two years. Compared to Figure 2, we exclude minimum-wage workers. The left-hand panel plots the distribution of the ratio of the unemployed's 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: Age effects in gender wage gaps, over different periods

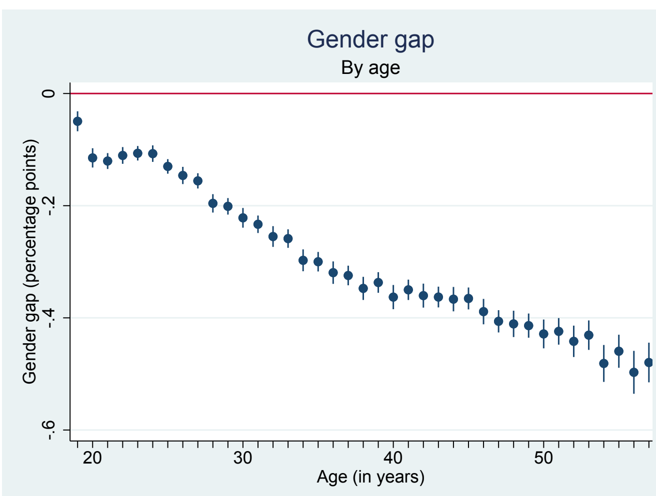
(a) FTE monthly wages, 1993-2010



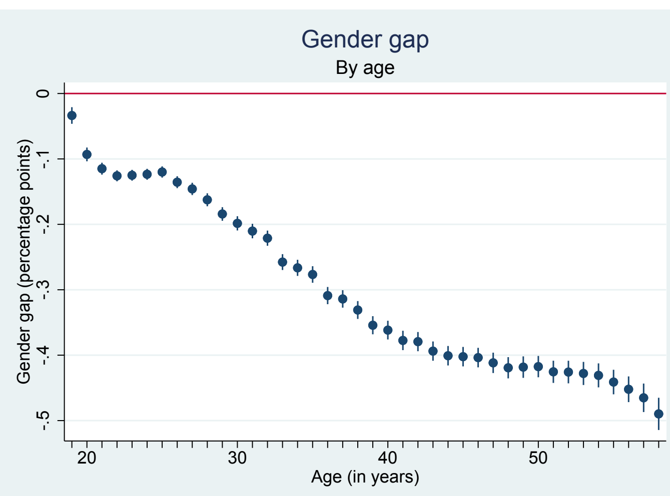
(b) Daily wages, 1976-1992



(c) Daily wages, 1993-2001



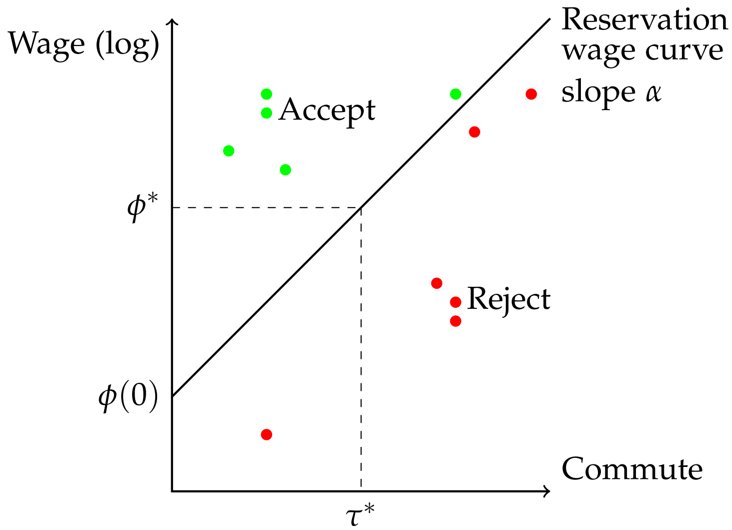
(d) Daily wages, 2002-2010



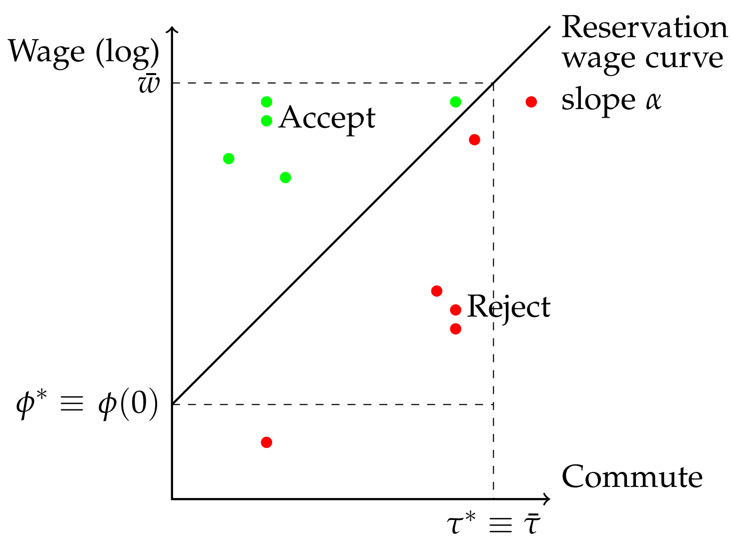
Note: We regress log-wages on a female dummy interacted with age. The figures plot the corresponding regression coefficients. Realized wages come from a random subsample of all private sector employment spells in France (DADS data). We control for education, age, marital status, children, and year $\times$ industry $\times$ CZ fixed effects. We include a part-time dummy and occupation dummies. 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, only daily wages are 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.

Figure C5: Interpretation of the reported reservation wage ϕ^* and maximum acceptable commute τ^*

(a) Interpretation 1

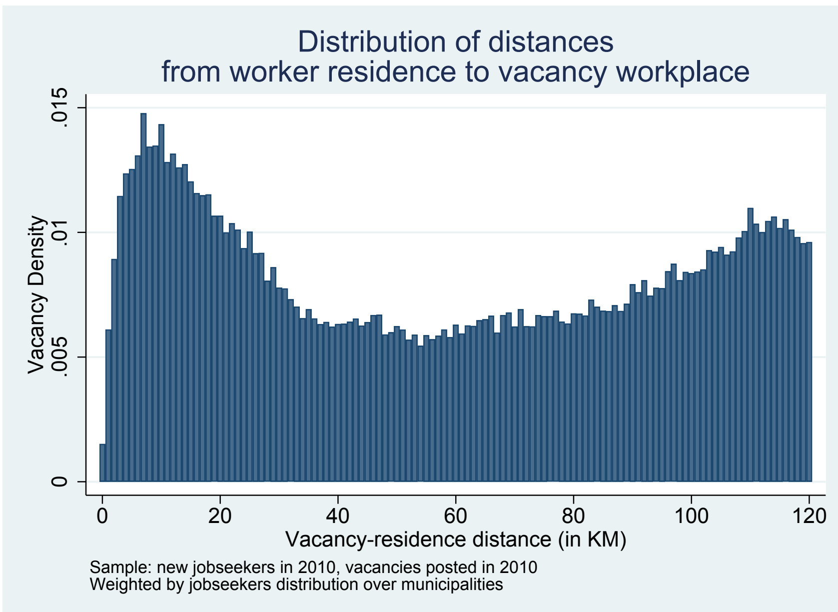


(b) Interpretation 2



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 4.2. 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 C6: 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: Summary statistics of pre-unemployment characteristics, by gender and job finding

	All		Job finders	
Variable	Men	Women	Men	Women
Age	33.4	33.4	30.8	30.9
Married	0.370	0.409	0.334	0.356
Child	0.318	0.427	0.290	0.375
Education (in years)	11.3	11.8	11.5	12.1
Experience (in years)	6.68	5.62	5.7	4.8
Past wage (gross, euros)	2,087	1,941	2,020	1,908
Past commuting distance (km)	20.6	16.4	21.4	17.2
Past job is full-time	0.825	0.656	0.86	0.72
Past contract is open-ended	0.467	0.372	0.391	0.277
Observations	168,903	151,230	81,162	68,744

Table D2: 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.
The sample in Panel A is the whole sample used in Table 2. Panel B restricts the analysis to the sample used for section 4.2, 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 D3: 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***	-0.00147
	(0.00245)	(0.00281)	(0.00303)	(0.00350)
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.

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 D4: 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.

Panel A replicates estimation results of Table 3 columns (1) and (2). Panel B adds search criteria as controls as in columns (5) and (6) of Table 3. 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 D5: 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 2 and 3.

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 municiaplity fixed effects. 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 D6: 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. 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 3.

Table D7: 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	-0.0203***	-0.0721***	-0.0445***	-6.18e-05
	(0.00247)	(0.0131)	(0.00454)	(0.00417)
Male × Married, no child	-0.00348	0.00233	0.00482	-0.000690
	(0.00377)	(0.0191)	(0.00598)	(0.00601)
Female × Married, no child	-0.0305***	-0.0744***	-0.0392***	0.00497
	(0.00372)	(0.0192)	(0.00715)	(0.00670)
Male × Single, with child	0.0102**	-0.0206	-0.00342	0.00288
	(0.00515)	(0.0253)	(0.00783)	(0.00816)
Female × Single, with child	-0.0283***	-0.106***	-0.0750***	-0.0228***
	(0.00370)	(0.0191)	(0.00729)	(0.00644)
Male × Married, with child	0.00643**	0.0302**	0.00418	-0.00581
	(0.00288)	(0.0143)	(0.00461)	(0.00470)
Female × Married, with child	-0.0261***	-0.0895***	-0.0849***	-0.00454
	(0.00321)	(0.0165)	(0.00610)	(0.00566)
R-squared	0.557	0.351	0.315	0.423
	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. The effective estimation sample size, dropping singletons, is 114,394.

Table D8: 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 D7 panel A, except that the sample is restricted to non-minimum wage workers (sample used for estimation in section 4.2, 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 D9: Wage elasticity with respect to commute along the reservation curve - Robustness

	(1) All	(2) Max commute in km	(3) Selection on occ. X pastW	(4) Min absolute distance to resW curve	(5) Previously full-time
Women	0.148***	0.119***	0.139***	0.163***	0.139***
	(.0045)	(.0061)	(.0037)	(.0039)	(.0044)
Men	0.120***	0.095***	0.12***	0.148***	0.121***
	(.0023)	(.0055)	(.0027)	(.0045)	(.0049)
Gender gap	.028***	0.024***	0.019***	0.015**	0.018***
	(.0073)	(.0080)	(.0052)	(.0063)	(.0061)
IPW		X	X	X	X
Obs.	75,071	46,900	74,635	75,071	118,794

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, except in column (3). In column (3), 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 (2), we restrict the sample to job seekers who declare their maximum acceptable commute in kilometers (rather than minutes). In column (5), we restrict to job seekers, whose previous job is full-time. We use inverse probability weighting to balance the covariates of women and men, except in column (1). Bootstrapped standard errors are in parenthesis.

Table D10: Calibration of the model: values for all subgroups

	(1)	(2)	(3)	(4)
Married	0	1	0	1
Children	0	0	1	1
q	0.15	0.15	0.12	0.12
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	3.1	3.7
F: θ_F	0.1	0.096	0.1	0.094
G: k_G	3.5	3.6	3.5	3.6
G: θ_G	0.017	0.018	0.016	0.019
λ	0.22	0.2	0.2	0.15
b	-0.57	-0.63	-0.79	-0.52

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 7.

Table D11: 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 distaste $\frac{\Delta\alpha}{\alpha}$
Single, no kids	-0.036	8.7%	-10.9%
Married, no kids	-0.039	10.5%	-16.1%
Single, with kids	-0.055	6.7%	-14.9%
Married, with kids	-0.042	12.2%	-18.1%

Note: This table computes the share of the empirical gender gap in reemployment wages explained by gender differences in commute distaste. Column (1) reports the empirical gender gap in residualized wages to be explained. The decomposition is based on the job search model in Section 4. First, gender differences in commute distastes α are estimated to match the empirical gender gap in commute. The estimated gender gap in commute distaste 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.

Table D12: Gender effects on attributes of the vacancy applied for

	(1) Log Wage	(2) Log Commute	(3) Full-time
	Panel A: Average gender gap		
Female	-0.0167***	-0.0693***	-0.169***
	(0.000760)	(0.00587)	(0.00225)
R-squared	0.214	0.154	0.202
	Panel B: heterogeneity by family size		
Female	-0.0153***	-0.0712***	-0.145***
	(0.000906)	(0.00731)	(0.00272)
Female × Married	-0.000339	0.0647***	-0.0220***
	(0.000897)	(0.00752)	(0.00313)
Male × Married	0.00294***	0.0236***	0.00435*
	(0.00111)	(0.00830)	(0.00251)
Female × Children	0.00169*	-0.00257	-0.0259***
	(0.000935)	(0.00788)	(0.00324)
Male × Children	0.00202*	0.0319***	0.0114***
	(0.00115)	(0.00850)	(0.00260)
R-squared	0.214	0.154	0.203
Observations	583,798	583,798	583,798

Note: in this table, we regress the characteristics of the vacancy for which job seekers apply on a female dummy (panel A) and on a female dummy interacted with household characteristics (panel B). This yield the gender gap in the log of posted wages in column (1), in the log of the commuting distances in column (2) and in full-time work in column (3). The regression sample consists of applications to jobs posted on the public employment service online job board in 2010-2012. 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 industry fixed effects, months when vacancy is posted, age dummies, experience and education dummies. In Panel A we also control for the presence of children and marital status.