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Motherhood and Constraints during Job Search

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Abstract

Why do women's labor earnings drop upon motherhood? We shed new light on this question by analyzing the changes in job search behavior associated with motherhood. We exploit data on the job applications sent on a popular online platform linked with administrative registers for 350,000 involuntarily unemployed workers in France. After losing their job, mothers have a 11.7% lower probability to find a job than similar women without children and send 12.2% fewer job applications. To explore the underlying mechanisms, we analyze the *timing* of job applications. Unlike other women, mothers' rate of applications decreases by about 20.5% in the hours when there is no school. Moreover, the French reform that introduced school on Wednesday in 2014 led mothers to send more applications on Wednesdays. Our results highlight that childcare creates constraints on the timing of job search activities for mothers. We finally provide suggestive evidence that these constraints decrease their return-to-search, and thereby contribute to their lower application and job finding rates.

Keywords: Gender inequality, Motherhood, Time allocation, Job search

JEL codes: J16, J22, J64

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“Eileen is job searching, but she fits this around her domestic activities, which usually center on her two children, a daughter and a fourteen-year-old son. Eileen’s job search is fragmented. Even though she spends a considerable amount of time on her search, especially before any interviews, the hours she spends tend to be patched together.”

Crunch Time: How Married Couples Confront Unemployment, by Aliya Hamid Rao

1 Introduction

Motherhood is associated with a decrease in women’s labor market earnings: mothers are more likely to be jobless, work fewer hours, and receive lower hourly wages when employed. Understanding the causes of this child penalty is crucial, as it accounts for 80% of the total gender earnings gap in recent years (Kleven et al., 2019). A popular explanation is that time constraints associated with childcare affect mothers’ work capacity, reducing their desired labor supply and shifting their preferences toward more flexible jobs. This paper explores a complementary mechanism: time constraints may also affect job search, exposing mothers to greater search frictions that hinder them from reaching their desired work outcomes.

We analyze how children affect the job search behavior of workers who lost their jobs involuntarily in France. We use data on job applications of French unemployed workers stemming from the Public Employment Service (PES) online search platform. We measure the quantity of job applications sent as in Marinescu and Skandalis (2021) and exploit for the first time information about the exact *timing* of job applications. We link job applications with administrative datasets containing rich information on workers’ labor market and demographic status at the time of job loss, in particular the parental status.¹ We track re-employment using employers’ mandatory hiring reports. The linked dataset covers about 350,000 unemployed workers who involuntarily lost their jobs in 2013-2016.

We first measure “motherhood gaps” (resp. “fatherhood gaps”) in various outcomes by estimating the differences between unemployed women (resp. men) with and without children who had similar labor market characteristics up to the point of job loss. We control for very detailed information on workers’ demographic characteristics and past labor market history. We find that mothers have a 11.7% lower probability to find a new job within 6 months than similar women with no children (we call them non-mothers henceforth). Strikingly, we find a commensurable motherhood gap in the rate of job applications: mothers send 12.2% fewer job applications than non-mothers. In contrast, fathers exhibit the same job finding rate and application rate as non-fathers.

We then investigate the potential constraints during the search process by exploiting data on the *timing* of search activities. We estimate the motherhood gaps in the counts of applications sent in every 10-minute intervals throughout the day and compare them with

¹We focus on persistent differences associated with parenthood rather than on those that might exist just in the immediate aftermath of childbirth. In particular, workers on maternity or parental leave are not included in our analysis since they are not regular unemployed workers.

the activities reported by unemployed mothers in the French Time Use Survey. Mothers exhibit the largest drops in their applications precisely during the hours when children are typically with them, which closely align to school schedules: the hours without school are associated with a 20.5% decrease in the rate of applications of mothers. Fathers also reallocate their search activities around school schedule, but about half less than mothers. Our analysis hence highlights that parents are constrained by childcare in the timing of their search activities and that these constraints are larger for mothers.

Our rich administrative data allow us to explore the heterogeneity of these parenthood gaps. We show that younger women are more likely to adjust the timing of their search activities to school schedule, consistent with prior findings of a larger child penalty just after the birth of the first child (e.g., [Kleven et al. \(2019\)](#)). But apart from these age differences, the motherhood gaps in search timing appear strikingly homogeneous. We observe large reallocations of search activities even among women who had selected into relatively demanding careers: those who were working full-time, in jobs with relatively high hourly wages, or in male-dominated occupations.

To confirm the *causal* link between children’s schedule and mothers’ search timing, we then evaluate the impact of a reform of school schedule. While kindergarten and primary school children historically had no school on Wednesday in France, school time was introduced on Wednesday mornings in 2013-14. The reform both increased the overall school time and spread it more evenly across weekdays. Though it was not its primary objective, the reform was found to boost mothers’ propensity to work full-time ([Duchini and Effen-terre, 2023](#)). We estimate the effect of the reform on job search, in differences-in-differences where unemployed workers with no children serve as a control group. We show that the reform had a positive effect on the rate of job applications of mothers overall, driven by a large effect on Wednesdays. It had no effect on fathers’ job applications.

We finally discuss the potential mechanisms through which child-related search constraints may contribute to motherhood gaps in applications and unemployment. We focus on one mechanism we can test with our data: childcare responsibilities prevent mothers from timing their job search optimally and thus reduce their application returns. When mothers cannot flexibly allocate time to job search—devoting more time when particularly relevant vacancies appear and less otherwise—they may miss high-return application opportunities. Consistent with this mechanism, we find that mothers’ applications are about 6% less likely to lead to a hire than those of other women. Moreover, mothers’ applications sent in the periods with no school (e.g., weekends or holidays) have a 14% higher probability to lead to a hire than those sent in other periods. This suggests that when mothers’ search time is limited, they only apply to the most relevant vacancies and forego other good opportunities at the margin. Relaxing timing constraints and allowing mothers to search more during no-school periods could therefore enable them to apply to these marginal opportunities with relatively high returns.

We make two main contributions to the literature. First, we add to a growing literature on gender differences in job search by providing a novel analysis of differences associated with parenthood (Faberman et al. (2025), Le Barbanchon et al. (2021), Cortés et al. (2023), Fluchtmann et al. (2024), Mas and Pallais (2017), Reuben et al. (2017), Wiswall and Zafar (2018)). While the literature focuses on differences in search selectivity, we highlight gaps in the number and timing of job applications. Closely related, Ivandić and Lassen (2023), Illing et al. (2024) show that women experience larger earnings losses than men displaced from similar jobs. Illing et al. (2024) find that earnings losses are particularly large for mothers and provide survey evidence that mothers might search less, which they attribute to mothers’ higher opportunity cost of market work. Our paper confirms these findings and suggests an additional mechanism: mothers also face greater constraints during job search.

Second, we contribute to a growing literature on child-related time constraints, which have been posited as the key driver of gender inequality in today’s labor market (Goldin (2014), Goldin and Katz (2015)). We connect to articles analyzing the consequences for women of changes in public school schedules (Duchini and Effenterre (2023), Price and Wasserman (2024)) or in the availability of cheap private childcare services (Cortés and Pan, 2019). While these papers focus on employment outcomes, we also analyze individual search behavior. We further connect to articles using high-frequency data on work schedule to show that women in jobs with flexible schedules choose to work at times associated with a lower pay than men (Adams-Prassl et al. (2023), Cook et al. (2021), Bolotnyy and Emanuel (2021)). Whereas these studies are limited to specific worker populations (e.g., gig platform workers), our sample spans a broad range of sectors and skill levels. The ability to merge our high-frequency application data with rich background information, particularly parental status, lets us pinpoint how children shape these patterns.

The paper is organized as follows. Section 2 presents the data. In Section 3, we estimate motherhood gaps in job search. In Section 4, we estimate the impact of the reform of school schedule on the timing of search activities. Section 5 discusses the potential mechanisms and Section 6 concludes.

2 Data and study samples

2.1 Data

Job applications data: We match various administrative datasets from the French Public Employment Service (PES), Pôle Emploi. First, we exploit data on the job applications sent on the PES online search platform, following Marinescu and Skandalis (2021). The French PES administers a popular search platform. In 2013, in an effort to support recruiting, employers were offered the possibility to include a link in their job ad to a standardized application procedure. In that case, job seekers could only apply by filing a detailed online form, and these online applications are tracked on the information system (“Télécandida-

tures”). To analyze search behavior *at the start of the unemployment spell*, we focus on applications sent during the first quarter of unemployment or up to re-employment (for job seekers leaving before the end of the first quarter). We exploit a novel aspect of these data: the high-frequency information about the application timing.²

One concern is that the online search platform is only one out of several possible search channels: it does not capture all the applications sent by a jobseeker. However, we show that both among women and men, parents send a similar fraction of their applications via the platform than non parents (Appendix A.2). We nonetheless address this concern further in robustness checks in Section 3.2.

Vacancy and hire data: We match job applications with data on the vacancy characteristics, in particular the date when a vacancy was posted: it allows us to measure how long after a new vacancy was posted each application was sent. We link these data with employers’ mandatory declaration of new hires (“Declarations préalables à l’embauche”, DPAE) to know whether the applicant was subsequently hired by the applied-to firm.

Individual data: We also link this data to administrative data on individuals’ background at the time of unemployment registration and on their search selectivity, collected during a mandatory survey at unemployment registration (“Fichier historique”). They contain four dimensions of selectivity: the reservation wage (converted into full-time equivalent monthly wages), the maximum commute distance (converted in kilometers³), whether people want a part-time or a full-time job and whether people want an open-ended or a finite-duration contract. Finally, our main individual employment outcome is the time before re-employment measured using the DPAE.

French Time Use Survey: Last, we use the French Time Use Survey (FTUS) from 2009-2010, which asks respondents to report all their activities during two days—a weekday and a weekend day—in intervals of 10 minutes. We focus on the 282 respondents below age 55 who are unemployed and have children, and identify the time intervals when they declare being in presence of their children.

2.2 Study samples

We study workers between 20 and 55 years old who become unemployed between September 2013 and September 2016. Following [Le Barbanchon et al. \(2021\)](#), we restrict our sample to those who become unemployed after an involuntary job loss (i.e firing from open-ended contracts or expiration of temporary fixed-term contracts) and who are eligible for unemployment insurance. We further restrict our sample to individuals who have sent at least

²We present descriptive statistics about the timing of applications in Appendix A.1.

³When respondents provide their maximum commute in time units instead of distance, we assume an average commuting speed of 35 km/hour following [Le Barbanchon et al. \(2021\)](#)

one application on the platform.⁴ That leaves us with a sample of 345,382 unemployment spells and 333,312 applications sent in the first quarter of unemployment.⁵ We describe our main sample in Table 1. Note that we further exclude the individuals who live in cities where we could not find a public school or kindergarten when we analyze the effect of the reform of school schedule (3% of our main study sample).

3 The parenthood gaps in search behavior

We highlight large motherhood gaps in job-finding and application rates and show these applications gaps are concentrated in the times when children are out of school.

3.1 Empirical strategy to estimate parenthood gaps

The parenthood gaps We start by estimating parenthood gaps in search outcomes at the start of the unemployment spell, separately for men and women (in what follows, we focus on women for simplicity). The motherhood gaps capture the persistent differences associated with motherhood rather than the differences arising immediately after the birth of the first child since motherhood is defined as having children below 18 years old. Our objective is to shed light on the factors that affect mothers specifically at the time when they search, rather than on those that have affected them up to that time: we hence control for a wide range of observable labor market characteristics. We estimate the following model at the spell level:

$$Y_{i,t} = \alpha_0 + \alpha_1 Child_{i,t} + X_{i,t}\beta + \varepsilon_{i,t} \quad (1)$$

Where $Y_{i,t}$ is the outcome for an unemployment spell that began at the calendar date t for individual i . $Child_{i,t}$ is a dummy equal to one if individual i has at least one child below age 18 when becoming unemployed. $X_{i,t}$ is a vector of time-varying and fixed characteristics for individual i at time t . It includes: job seekers' age (a dummy for each age in years), marital status, education (5 diploma levels), labor market experience (5 experience levels), type of skills (5 skill categories), past cumulated unemployment duration, count of past unemployment spells, potential UI benefits duration (a dummy for each duration integer in months), prior wage, prior work hours (a continuous ratio of hours relative to full-time). We also include fixed effects for occupation searched⁶ (about 500 occupation codes, "code rome") and city of residence. We are interested in coefficients α , which measure

⁴There were 6,788,601 unemployment spells between September 2013 and September 2016 among people between the ages of 20 and 55. We keep about 38% of them (2,579,254 spells), when we restrict to individuals who lost their job involuntarily and are eligible to unemployment insurance. We then keep about 13% of these spells (345,382 spells), when we restrict to individuals who have sent at least one application.

⁵The sample includes 341,802 individuals, i.e. almost the same number as spells, since the vast majority of individuals only have one spell in our study period.

⁶We use this variable as a proxy for prior occupation as 89% workers report having prior experience in their occupation searched. One may worry that the occupation searched captures some of the effect of parenthood on job search, however our results are virtually identical when excluding this control.

the motherhood gaps. We cluster standard errors at the city level to take into account correlations in employment prospects across people in the same labor market.

We successively consider several outcomes: a dummy for whether the individual finds a job within 6 months, the count of job applications sent at the start of the unemployment spell, the search selectivity reported in the mandatory survey at the start of the unemployment spell. Throughout the paper, when we take the count of applications, or dummies as outcomes, we present the estimates obtained from Poisson regressions which are better suited for outcome variables with a mass point at zero (all our conclusions are robust to estimating OLS regressions instead).⁷ We report the incidence rate ratios minus one, which can be interpreted as semi-elasticities.

The magnitude of reallocation To quantify the reallocation of search across periods, we create separate observations for applications sent during school and no-school periods (the sample size is hence twice larger). We estimate the following model, where τ denotes school/no-school periods:

$$Y_{i,t,\tau} = \alpha_0 + \alpha_1 Child_{i,t} + \alpha_2 Child_{i,t} \cdot NoSchool_{\tau} + \alpha_3 NoSchool_{\tau} + X_{i,t}\beta + \varepsilon_{i,t,\tau} \quad (2)$$

In our heterogeneity analysis, we estimate the same empirical model except that we fully interact $Child$, $Child \cdot NoSchool$ and $NoSchool$ with all the categories of the heterogeneity dimension considered (see exact specification in Appendix A.3).

3.2 Parenthood gaps in applications and job finding rate

We first document that motherhood is associated with differences in re-employment and search behavior. Table 2 presents estimates for the gaps in the probability to find a job within 6 months in col (1): mothers are 11.7% less likely to find a job than similar women without children. In contrast, fathers do not differ from other men in their job finding rate. These results are in line with the finding that mothers experience especially large earnings losses after being displaced in Denmark and Germany (Ivandić and Lassen (2023), Illing et al. (2024)). We turn to the analysis of job applications in col (2): mothers send 12.2% fewer job applications than similar women with no children. The motherhood gap in job finding rate is hence associated with a commensurable gap in job applications. In contrast, the rate of applications of fathers is identical to that of similar men with no children.

To consolidate this first set of results, we conduct various additional analyses. Since the count of applications sent might reflect both the intensity of search effort and the selectivity in search, we re-estimate the motherhood gap in applications controlling for our measures of workers' search selectivity. The estimated motherhood gaps are only slightly attenuated, which suggests that mothers both have a lower search intensity and a higher selectivity (Table B.1, col (2)-(3)). We also directly confirm that mothers are more selective than

⁷In order to allow for misspecification of the Poisson distribution, we present coefficients estimated using a quasi-maximum likelihood method (Wooldridge, 2010).

non-mothers by estimating parenthood gaps in various dimensions of search selectivity (Table B.1, col (4)-(7)). We then note that our estimates of parenthood gaps in the rate of applications sent on the PES search platform should provide a good measure of gaps in the rate of applications *overall* since parenthood is not associated with a difference in the proportion of applications sent in the search platform (see Appendix A.2). To confirm this, we show that mothers send fewer applications than non-mothers for all types of jobs considered, including those over-represented and those under-represented on the PES search platform (Figure B.1). We also note that we capture *all jobs* when we estimate the motherhood gaps in job finding (i.e. not only those found through the PES platform) and that our estimates for the gaps in job finding and in job applications closely align.

It is not obvious which set of control variables should be included when we estimate motherhood gaps to make an adequate comparison between mothers and non-mothers: e.g., we might leave out some of the relevant effects of motherhood on search when we control for prior labor market variables. However, we show that our estimates for the parenthood gaps remain similar when we vary the set of controls (Table B.2). Additionally, we analyze within individual variation in search behavior, for the subsample of individuals who have several unemployment spells during our study period with different numbers of children. When we estimate the effect of children in this subsample and include individual fixed effects, the estimates are imprecise but in line with our main results (Table B.3). Finally, we show that our conclusions remain unchanged when we vary the measure of the re-employment rate (Table B.4) or of the application rate (Table B.5).

3.3 Child-related constraints in the *timing* of job search

Graphical analysis We then analyze the parenthood gaps in search timing. In Figure 1, we break down the total number of applications analyzed in Table 2 into applications sent during 10-minute intervals during school days. We superimpose the proportion of unemployed parents declaring that a child was present during the same 10-minute interval in the FTUS. The light gray areas indicate children’s typical school time and sleeping time. We see that mothers strongly deviate from the typical timing of search of non-mothers: their rate of applications is 50% higher than that of non-mothers around 9:30am, while it is 40% lower around 5pm. Moreover, the granularity of the data allows us to detect that mothers search less than non-mothers precisely during the school lunch break and after school. Conversely, they often search more during the periods when children are at school or sleeping. Finally, Figure 1 highlights that the reallocation of job search around children’s schedule is much larger for mothers than fathers.

Overall, parents adjust the timing of their search activities to the typical schedule of children, but with large gender differences. These results are important: they show that childcare responsibilities do not only interfere with the schedule of work, they also affect the schedule of job search. While the trade-off between work and childcare is commonly taken

into account when discussing the causes of the motherhood penalty, the trade-off between search and childcare is typically not. We provide various additional graphical analyses to strengthen our interpretation. First, we show that our conclusions remain unchanged when we estimate parenthood gaps using OLS regressions instead of Poisson (Figure B.2). We also analyze parenthood gaps in search timing during weekends and school holidays: there is no variation around typical school times, but there is a negative motherhood gap in applications continuously between 9am and 10pm and no fatherhood gap. This confirms that the presence of children drives the differences in search timing between parents and non-parents and that mothers react more than fathers (Figure B.3).

The magnitude of reallocation We quantify the magnitude of the reallocation of search activities around children’s schedule in col (3)-(5) of Table 2. Mothers have a 24.1% lower rate of applications than non-mothers in the hours when children are neither at school nor sleeping (col (3a)). In contrast, mothers’ application rate is similar to that of non-mothers during children’s school or sleep hours (col (3b)). Therefore, beyond the variation that all women experience through the day, mothers experience a 23.2% drop in search in the hours when children are typically under parents’ responsibility (col (3c)). We see similar patterns but much attenuated for fathers: having children under parents’ responsibility is associated with a 13.2% drop in fathers’ rate of applications (col (3c)).

We also examine the allocation of job search *across days* in Table 2, col (4).⁸ We find that mothers send 17.5% fewer applications than non-mothers in the days with no school versus 11.3% fewer applications during school days: for mothers, days with no school are associated with a 7.1% decrease in the application rate. For men, we see no evidence of any reallocation of search activities across days associated with parenthood.⁹ Finally, col (5) summarizes the overall amount of reallocation around school schedule: not having children at school is associated with a 20.6% decrease in job applications for mothers and a 9.4% decrease in job applications for fathers.¹⁰ Overall, mothers reallocate their search activities around children’s schedule more than fathers by a large amount, i.e. roughly twice more.

Heterogeneity We then analyze heterogeneity in the magnitude of this reallocation. Since all individuals operate within the same flexible environment of unemployed job search, any differences we observe should reflect variation in childcare involvement rather than in environmental constraints. As expected, we find that mothers reallocate more around school schedules when they are younger, especially between 25-35—when their children are

⁸French school years go from September to June and include four two-week long holidays. We exclude the break of July-August since the job vacancies posted in the summer might be very different.

⁹Note that the coefficient associated with *Child* in col (4b) gives the average across all hours of those in col (3a) and (3b), since there are both hours with and without school during school days. Therefore, it is unsurprising that the motherhood gaps are less different across days than across hours (i.e. that the coefficient associated with *Child* \times *NoSchool* is smaller in col (4c) than in col (3c)).

¹⁰We also present the results using re-weighting to make women more comparable to men in their observable characteristics: their baseline rates of application are then closer to those of men, but all results remain unchanged (Table B.6).

most likely to be of school age (Figure B.4, Panel (1)). Consistently, the largest motherhood gaps in applications and re-employment are found among younger women (Figures B.5 and B.6). Strikingly, however, we find similar reallocation magnitudes regardless of mothers’ marital status, education level, or prior career characteristics—including wage level, full-versus part-time status, and the gender composition of their occupation (Figure B.4, Panels (2)-(6)).¹¹ Motherhood gaps in the rate of applications overall and in re-employment are also relatively homogeneous along these dimensions (Figures B.5 and B.6, Panels (2)-(6)). This suggests that mothers in different careers have a similar value for childcare relative to job search. In our setting, the value for providing childcare encompasses various elements (see framework in Cortés and Pan (2024)): how productive mothers are in rearing children relative to job search, how costly alternative childcare arrangements are, and how much utility they derive from childcare itself or from having “high-quality” children. There are probably differences across mothers in some dimensions, but our results suggest they roughly cancel each other out.¹²

4 The effect of the school schedule reform on job search

We analyze the reform of school schedule to confirm the *causal* link between children’s schedule and parents’ search and test if parents respond in the short-run to policy changes.

4.1 Empirical strategy to estimate the effects of the reform

Before 2013, kindergarten and primary school children (i.e. most children between 3 and 11 years old) went to school for four days a week, excluding Wednesday.¹³ On school days, they had six hours of teaching time (generally from 8:30am to 11:30am and from 1:30pm to 4:30pm) and two hours of lunch break in the middle. In 2013-2014, school schedules were reformed: Teaching time was added on Wednesday mornings in most schools, generally from 8:30am to 11:30am. On other weekdays, the teaching time was shortened by about 45 minutes and replaced by free non-compulsory extracurricular activities. Overall, the reform both increased the free public childcare provision at school and spread it more evenly across weekdays. About 20% of French municipalities adopted the new schedule in September 2013; the rest did so in September 2014.

To evaluate the effect of the reform, we estimate the following differences-in-differences model comparing parents to non-parents, separately for men and women:

$$Y_{i,t} = \gamma_0 + \gamma_1 Child_{i,t} + \gamma_2 Reform_{i,t} + \gamma_3 Child_{i,t} \cdot Reform_{i,t} + X_{i,t}\beta + \eta_{i,t} \quad (3)$$

¹¹These conclusions hold when we control for age interacted with *Child*, *Child·NoSchool* and *NoSchool*.

¹²We note also that women in these different groups may have different household characteristics, which could affect how they value time spent on childcare versus job search. For instance, mothers partnered with higher earners may have weaker financial incentives to search for work.

¹³In France, 95% of children aged 3-5 attend kindergarten (Goux and Maurin (2010)). Children then attend compulsory primary school from age 6 to age 11.

Where $Reform_{i,t}$ is a dummy equal to one if the reform was implemented in the city of individual i at the date t . All the other variables are similar to those in model (1), and we also cluster standard errors at the city level. Our main outcomes are the count of applications sent during various weekdays, in the morning or the afternoon.

The coefficient γ_3 gives the causal effect of the change in school schedule on the outcome, under our identifying assumptions. The identification mainly relies on two assumptions. First, parents and people with no children would have had similar changes in search behavior after September 2014 in the absence of the reform. Second, people with no children should not be affected by the reform. In particular, they should not be indirectly affected through the increased competition with non-parents. It is unlikely that there are such spillovers for search behavior, which is our main focus.¹⁴ Note that the reform only concerned children in age 3-11, but we consider as treated all parents with children below age 18, so our estimate γ_3 will have an attenuation bias.

4.2 The effect of the school schedule reform on search timing

We present in Figure 2 the estimates for the effect of the reform of school schedule on the amount of applications sent each day of the week, in the morning and the afternoon. The reform significantly increased by about 15% the application rate of mothers on Wednesday morning, i.e. precisely at the moment when school time was added for children (Panel A). On other periods, it had a generally positive but smaller and mostly non-significant impact on their applications. Interestingly, we find that the reform also slightly increased the rate of applications on Thursday, suggesting that mothers might finalize some of the extra search activities that they started on Wednesday the next day.¹⁵ In contrast, the reform did not affect the application rate of fathers at any of the considered times (Panel B). We report the corresponding magnitude of the effects of the reform in Appendix Table B.7: the reform increased by 8.8% the rate of applications sent by mothers on Wednesday, did not significantly affect their applications on other days, and increased their overall rate of applications by 4.0%. We also see from Table B.7 that before the reform, mothers were sending especially few job applications on Wednesdays: the reform hence allowed mothers to get closer to the allocation of search across weekdays of non-mothers. Overall, this analysis highlights that the reform increased mothers' search precisely in the period when school time is exogenously added: it confirms the causal effect of school schedule on the timing of job search. Moreover, we find that the reform increased mothers' overall number of job applications. Several mechanisms could explain this effect: the reform reduced the opportunity cost of working and hence strengthened mothers' incentives to search for a job ; it also reduced the timing constraints that mothers face while they search. We discuss

¹⁴There might be spillovers on re-employment since parents and non-parents may compete for the same jobs: our estimates for the effect of the reform on re-employment could then be upward biased.

¹⁵This is consistent with the persistent responses to temporary increases in expected wages found among Uber drivers by Chen et al. (forthcoming).

these mechanisms further in Section 5.

4.3 The effect on other search outcomes and robustness checks

We provide several complementary analyses of the reform. First, since the effect of the reform on the number of job applications may in principle both capture changes in search effort and changes in search selectivity, we re-estimate the effect of the reform on job applications controlling for search criteria. The results are unchanged, suggesting that the reform mostly affected mothers' search effort (Figure B.7 and Table B.8). Consistently, we find that the reform had virtually no effect on mothers' selectivity (Table B.9)—except that it increased their propensity to search for a full-time job by 0.6 percentage points, consistent with the finding by [Duchini and Effenterre \(2023\)](#) that the reform boosted mothers' full-time employment. Moreover, we show that the reform had a small positive effect on mothers' job finding rate, consistent with the effects on search behavior (Table B.10). We also analyze the heterogeneity of the effect of the reform on parents' applications on Wednesdays: consistent with our previous heterogeneity analysis, we find a quite homogeneous effect (Figure B.8).

Finally, we probe the robustness of our estimates of the reform's effect in several ways. First, we conduct differences-in-differences around the time of the late implementation of the reform in September 2014, restricting our sample to cities that implemented the reform in 2014. We confirm that mothers increased their rate of applications on Wednesday after September 2014 relative to non-mothers, while fathers kept a similar rate as non-fathers (Table B.11, Panel A). We then estimate the same empirical model in the sample of cities that implemented the reform in 2013 to provide a placebo test: the rate of applications on Wednesday evolved similarly for parents and non-parents around September 2014 (Table B.11, Panel B). Our graphical analysis shows that parents and non-parents have a similar evolution of their Wednesday applications before September 2014, consistent with the parallel trend assumption (Figure B.9). We also show that our estimates for the effects of the reform remain unchanged when we exclude individuals looking for jobs related to education or childcare for primary and kindergarten children—who might be affected by the reform through increased labor demand (Table B.12).

5 Discussion of potential mechanisms

Our analyses show that unemployed mothers face child-related time constraints during job search, and that they send fewer applications and stay unemployed longer. In this section, we provide suggestive evidence on the mechanisms underlying these patterns, examining whether time constraints causally contribute to motherhood gaps in applications and unemployment, alongside other factors.

5.1 Why may child-related time constraints matter?

Child-related constraints during job search may contribute to motherhood gaps in applications and unemployment through at least three non-exclusive mechanisms. First, mothers may lack sufficient time to exert their optimal level of search effort.¹⁶ This would mechanically force mothers to search less intensively. Second, the disutility of job search may vary across time periods, making inflexible timing costly in terms of utility. For instance, mothers who must concentrate search effort within narrow time windows may experience fatigue. By raising the utility cost of search, timing constraints may induce mothers to search less intensively. Third, job search may be more productive in some periods than others, making inflexible timing costly in terms of efficiency.¹⁷ For instance, flexibly accommodating employers' interview schedules may increase hiring probability. By reducing search returns, timing constraints may again induce mothers to search less intensively.

In the rest of our discussion, we focus on this third channel—efficiency costs from inflexible timing—where our data allow us to provide empirical validation in the specific context of online job applications. In this context, timing flexibility may allow to apply to more relevant vacancies, by devoting more time when particularly relevant vacancies appear and less otherwise. This is particularly important because online vacancies can be removed quickly (Davis and Samaniego de la Parra (2024)), meaning that jobseekers unable to search on certain days (such as holidays) may miss opportunities entirely. Moreover, applying soon after a vacancy is posted may increase hiring probability, as older vacancies are often inactive (Cheron and Decreuse (2017)) and employers may prioritize early applicants. Consistent with this, we observe that the probability of an application leading to a hire decreases with the delay between vacancy posting and application, even when controlling for vacancy characteristics, jobseeker characteristics, and match quality (Figure B.10). If this mechanism is at play, mothers should apply less quickly to new vacancies and have lower hiring returns than non-mothers—and both gaps should shrink during no-school periods, when timing constraints are relaxed.

5.2 Time constraints and application efficiency

Empirical model We test whether timing constraints decrease the efficiency of mothers' online job applications, by analyzing motherhood gaps in applications' delays and in applications' success. We estimate models similar to (1) and (2), but at the application level (see exact specification in Appendix A.3). Our sample is made of the applications sent by

¹⁶This mechanism may seem unrealistic given prior survey evidence that unemployed workers devote relatively little time to job search—well below the duration of school hours (Krueger and Mueller, 2010, 2011; Faberman et al., 2022; DellaVigna et al., 2022; Faberman et al., 2025). However, such surveys may exclude activities critical to finding employment, such as career path reflection, professional networking, and interview preparation.

¹⁷The literature on task juggling shows that timing constraints reduce productivity in various contexts (e.g., Adams-Prassl et al. (2023), Buser and Peter (2012), Coviello et al. (2014), Coviello et al. (2015)).

all unemployed individuals in our study sample (Panel A) and those below age 45 (Panel B).¹⁸ We take as outcomes a dummy for the application being sent less than two days after the vacancy was posted, and a dummy for the applicant getting hired at the firm in the year following her application. We cluster standard errors at the applicant level.

Suggestive evidence In Table 3, we first observe that mothers respond less promptly to new vacancies than non-mothers: their applications are 3.0-3.3% less likely to occur within two days of vacancy posting (col (1), Panels A-B), consistent with timing constraints affecting mothers' ability to respond quickly to new opportunities. More importantly, mothers' applications are 6.4-10.8% less likely to lead to a hire than non-mothers' applications (col (3)), suggesting that timing constraints may also decrease mothers' application efficiency. In contrast, fathers show neither delayed applications nor reduced hiring probability (col (2) and (4)). While mothers' lower success rate is consistent with timing constraints reducing application efficiency, it may also reflect factors unrelated to timing constraints, such as employer discrimination.

To further test whether timing constraints may explain mothers' lower application returns, we compare applications sent during school hours versus no-school periods. While factors such as employer discrimination should similarly affect applications sent at different times, timing constraints should generate time-specific differences.¹⁹ We find that mothers are 3.1-3.3% more likely to apply immediately after a vacancy is posted during no-school periods (Table 3, col (5)), suggesting that when time is scarce, mothers become more selective and focus on the most recent vacancies. Moreover, mothers' hiring probability is 12.6-14.1% higher for applications sent during no-school periods (col (7)), consistent with mothers applying more selectively when time-constrained, only to the highest-quality opportunities. In contrast, fathers apply with similar speed during no-school periods and their applications have similar success rates.²⁰ A concern with this comparison is that no-school periods may differ from school periods in ways unrelated to mothers' time constraints; the school reform addresses this by exogenously shifting school time. Before the reform, when child-related responsibilities limited mothers' Wednesday search time, their Wednesday applications were faster and more successful than on other weekdays—mirroring our no-school results. After the reform relaxed these Wednesday constraints, both speed and success rates on Wednesdays converged toward those of other weekdays (Table B.17).

Together, these results suggest that when search time is limited, mothers only apply to the newest and most relevant vacancies, forgoing others at the margin that are also quite new and relevant. Relaxing timing constraints and allowing mothers to allocate more search

¹⁸We estimate empirical models (A.2) in col (1)-(4) and (A.3) in col (5)-(8). See Appendix A.3.

¹⁹Employers could discriminate against mothers less when they apply during no-school periods, as this could signal timing flexibility. In that case, the discrimination would itself stem from timing constraints.

²⁰These results are robust to using OLS instead of Poisson regressions, using an alternative measure of application speed, and reweighting the sample of women's applications to make female applicants more similar to male applicants (Tables B.13, B.14, B.15, B.16).

time during no-school periods could enable them to apply to these marginal opportunities with relatively high returns. However, this evidence remains suggestive, as mothers who apply during no-school periods may differ from those who apply at other times, beyond the observable characteristics we control for.

6 Conclusion

Does motherhood change the way women search for jobs, and what are the mechanisms? We analyze uniquely rich information on search behavior for unemployed workers who lost their jobs involuntarily in France: we match job applications data with various administrative data on individuals' backgrounds and employment outcomes. We document that mothers have a 11.7% lower probability to find a job than observationally similar women with no children and send 12.2% fewer job applications. We analyze how workers modify the timing of their search activities, in order to quantify the importance of child-related time constraints during job search. We find that mothers shift their search activities around school schedule about twice more than fathers. We then confirm the causal link between children schedule and search timing by studying a reform that introduced school time on Wednesdays in France: we show that the reform increased mothers' rate of applications precisely on Wednesdays. We finally provide suggestive evidence that mothers' timing constraints during job search reduce their return-to-search, and thereby explain part of mothers' lower rate of applications and of job finding.

Our results imply that gender differences in childcare responsibilities create inequality in the labor market, even beyond the gender differences in preferred work arrangements previously analyzed in the literature (e.g. [Goldin \(2014\)](#)): They also generate gender differences in constraints during job search. It is not clear how public policies can address this, since mothers may take these responsibilities for various reasons: they may lack affordable and flexible childcare substitutes, they may have strong preferences for doing childcare themselves (possibly influenced by social norms), etc. In line with [Duchini and Effenterre \(2023\)](#) and [Price and Wasserman \(2024\)](#), our evaluation of the French school schedule reform highlights that school schedules are a powerful policy instrument since parents use school as a substitute for maternal childcare. In addition, our findings suggest there might be scope for more modest policy interventions to facilitate mothers' search during unemployment. Parents may face obstacles in getting access to childcare services specifically once they become unemployed, which should be removed: e.g., financial constraints, delays in adjustment of means-tested services to changes in income, prioritization of employed parents. Public Employment Services should make sure that their active labor market policies (e.g. job search counselling programs) account for mothers' schedule constraints.

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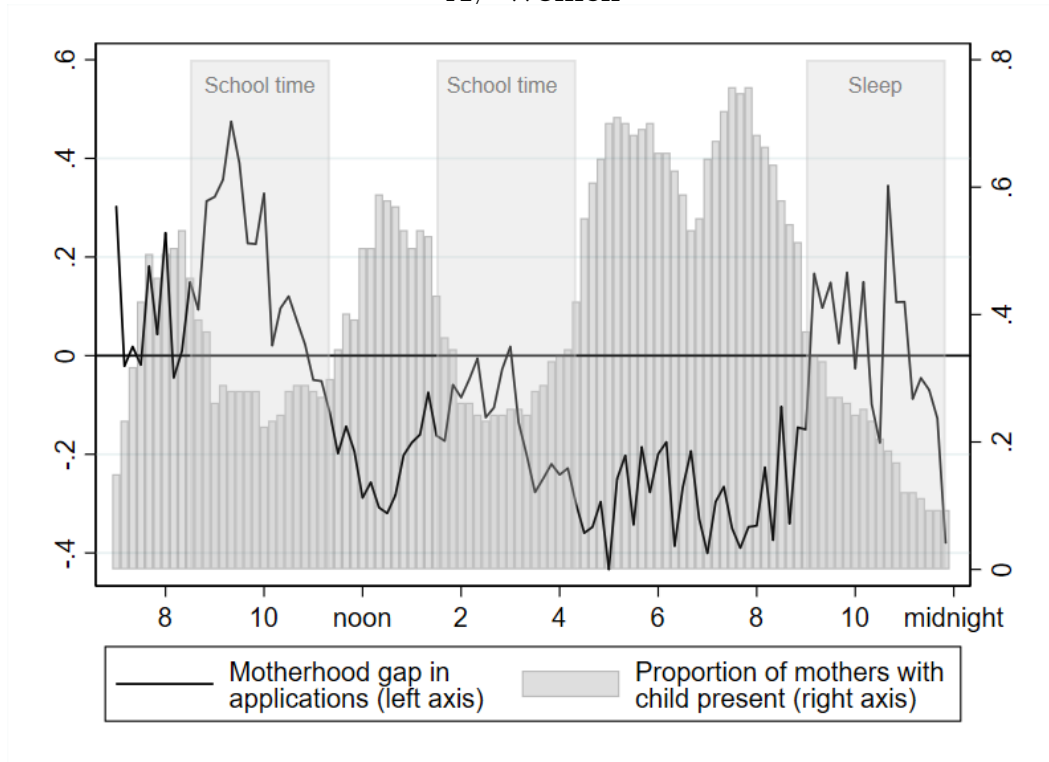
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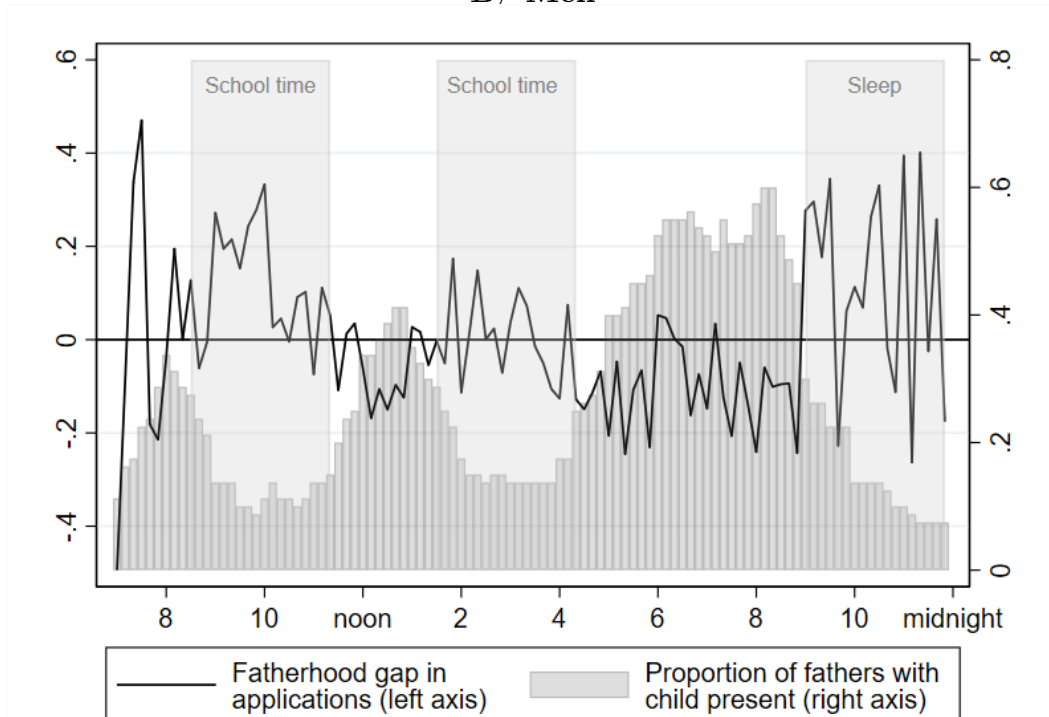
TABLES AND FIGURES

Figure 1: Parenthood gaps in job search timing

A/ Women

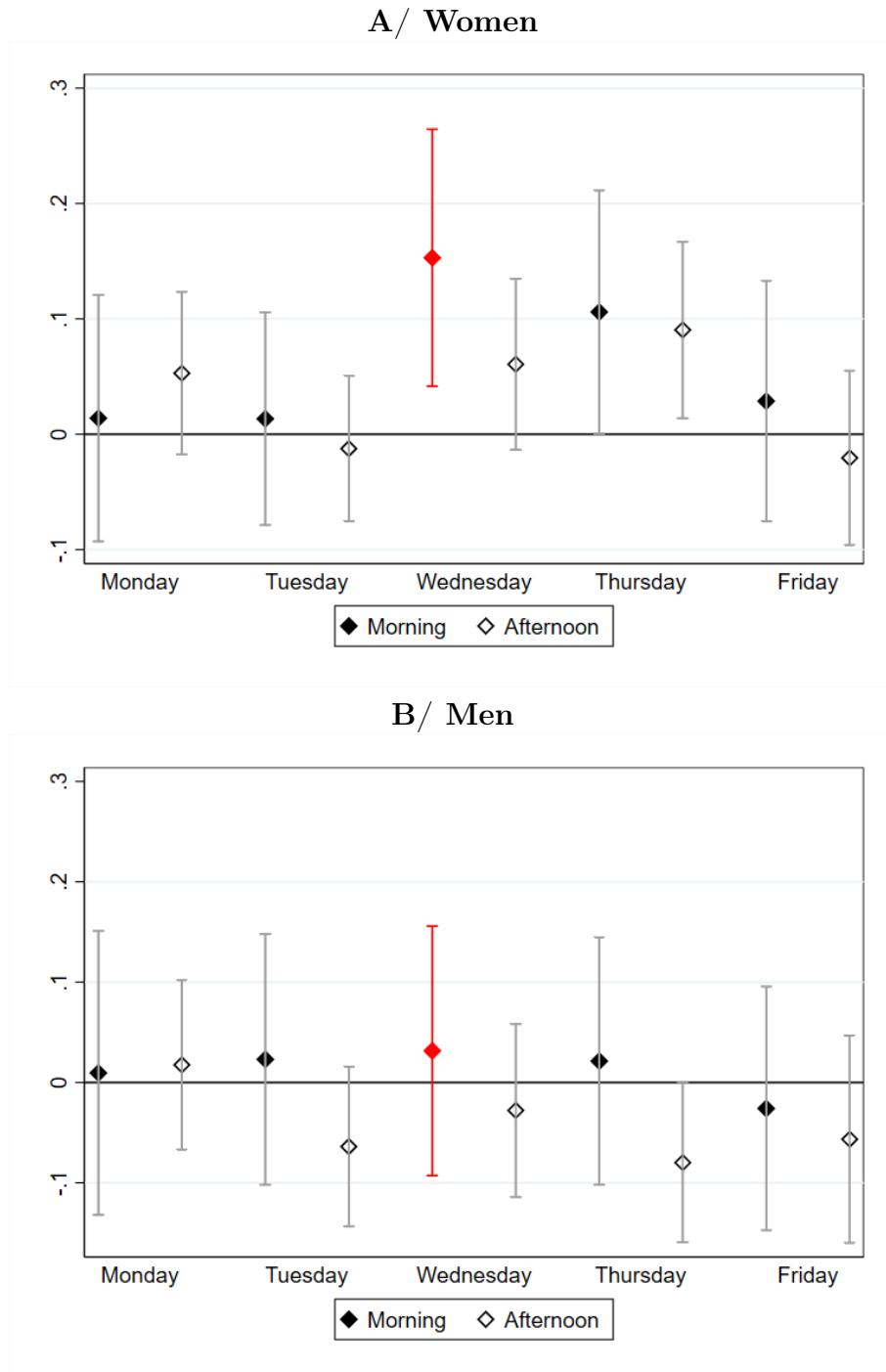


B/ Men



Notes: This Figure presents the parenthood gap in applications sent in 10-minutes intervals during school days (black line). We control for the individual characteristics listed in Section 3.1. We estimate Poisson count models and report the incidence rate ratios minus one, which can be interpreted as semi-elasticities. It also presents the fraction of unemployed parents who report being in presence of a child in the French Time Use Survey (gray bars).

Figure 2: The effect of the school schedule reform on job applications at different times



Notes: This Figure presents the effect of the reform of school schedule on the rate of applications sent at different times. It corresponds to the coefficient associated with *ChildXReform* in model (3). We control for the individual characteristics listed in Section 3.1. We estimate Poisson count models and report the incidence rate ratios minus one which can be interpreted as semi-elasticities. We present the 95% confidence intervals based on SE clustered at the city level.

Table 1: Descriptive statistics for main study sample

Variable	Women			Men		
	All	No child	Child	All	No child	Child
Demographics						
Age	33.89 (9.91)	29.78 (9.85)	37.74 (8.28)	34.11 (9.92)	31.26 (9.63)	39.20 (8.24)
Marital status: single	0.55 (0.50)	0.77 (0.42)	0.35 (0.48)	0.60 (0.49)	0.83 (0.37)	0.19 (0.39)
Highest diploma						
≤ Highschool	0.06 (0.24)	0.05 (0.21)	0.07 (0.26)	0.09 (0.28)	0.07 (0.26)	0.11 (0.31)
Vocational highschool	0.29 (0.45)	0.29 (0.45)	0.28 (0.45)	0.23 (0.42)	0.25 (0.43)	0.20 (0.40)
General highschool	0.28 (0.45)	0.24 (0.42)	0.33 (0.47)	0.40 (0.49)	0.37 (0.48)	0.45 (0.50)
Higher education	0.37 (0.48)	0.43 (0.49)	0.32 (0.47)	0.28 (0.45)	0.31 (0.46)	0.25 (0.43)
Skill level						
Blue collar, basic	0.02 (0.14)	0.02 (0.14)	0.02 (0.14)	0.08 (0.27)	0.08 (0.27)	0.08 (0.27)
Blue collar, specialized	0.02 (0.14)	0.02 (0.15)	0.02 (0.14)	0.18 (0.38)	0.16 (0.37)	0.20 (0.40)
White collar, basic	0.17 (0.38)	0.18 (0.38)	0.17 (0.38)	0.12 (0.33)	0.14 (0.34)	0.10 (0.30)
White collar, specialized	0.65 (0.48)	0.64 (0.48)	0.67 (0.47)	0.44 (0.50)	0.46 (0.50)	0.40 (0.49)
Intermediary position	0.09 (0.29)	0.10 (0.30)	0.08 (0.28)	0.12 (0.33)	0.12 (0.32)	0.13 (0.34)
Management position	0.04 (0.19)	0.04 (0.19)	0.04 (0.19)	0.06 (0.24)	0.05 (0.21)	0.09 (0.29)
Unemployment insurance						
Potential benefit duration (month)	18.05 (7.99)	17.08 (8.19)	18.96 (7.68)	17.63 (8.17)	16.75 (8.15)	19.21 (7.98)
Benefits amount (monthly)	928.77 (319.68)	921.28 (295.71)	935.80 (340.49)	1073.00 (368.68)	1010.47 (320.42)	1185.00 (419.45)
Labor market history						
Prior wage (monthly)	1820.16 (650.46)	1764.21 (617.00)	1872.67 (676.17)	1922.45 (701.24)	1813.99 (635.58)	2116.69 (768.22)
Last job was part-time (dummy)	0.40 (0.49)	0.37 (0.48)	0.44 (0.50)	0.19 (0.39)	0.21 (0.41)	0.14 (0.35)
Past unemployment spells (count)	1.90 (1.90)	1.77 (1.84)	2.03 (1.95)	1.98 (2.06)	2.07 (2.10)	1.82 (1.97)
Observations	202,971	98,263	104,708	142,411	91,386	51,025

Variable	Women			Men		
	All	No child	Child	All	No child	Child
Job searched for						
Sales	0.25 (0.43)	0.26 (0.44)	0.24 (0.43)	0.16 (0.37)	0.18 (0.38)	0.13 (0.34)
Construction	0.01 (0.08)	0.01 (0.09)	0.00 (0.07)	0.13 (0.33)	0.11 (0.32)	0.15 (0.36)
Restaurant, tourism, entertainment	0.09 (0.29)	0.12 (0.32)	0.08 (0.26)	0.12 (0.33)	0.14 (0.34)	0.10 (0.30)
Industry production	0.03 (0.16)	0.03 (0.17)	0.02 (0.15)	0.08 (0.27)	0.08 (0.26)	0.08 (0.27)
Installation and maintenance	0.00 (0.04)	0.00 (0.04)	0.00 (0.04)	0.09 (0.29)	0.09 (0.28)	0.09 (0.29)
Healthcare	0.05 (0.22)	0.05 (0.21)	0.05 (0.22)	0.01 (0.11)	0.01 (0.11)	0.01 (0.10)
Personal care and service	0.20 (0.40)	0.18 (0.38)	0.23 (0.42)	0.09 (0.28)	0.08 (0.27)	0.10 (0.30)
Office administrative support	0.29 (0.45)	0.27 (0.44)	0.31 (0.46)	0.08 (0.28)	0.09 (0.28)	0.08 (0.26)
Transportation and logistics	0.02 (0.13)	0.02 (0.13)	0.02 (0.13)	0.16 (0.37)	0.14 (0.35)	0.19 (0.39)
Application & reemployment						
Applications in first quarter (count)	1.12 (1.94)	1.27 (2.09)	0.97 (1.77)	1.02 (1.90)	1.05 (1.97)	0.98 (1.79)
Finds job within 1 year (dummy)	0.57 (0.49)	0.65 (0.48)	0.49 (0.50)	0.60 (0.49)	0.62 (0.48)	0.56 (0.50)
Search criteria						
Reservation wage (monthly)	1667.72 (446.37)	1634.98 (395.66)	1698.43 (487.20)	1800.56 (553.28)	1723.91 (472.26)	1937.83 (652.35)
Maximum commute distance (km)	26.55 (51.50)	28.81 (58.32)	24.42 (44.05)	33.67 (73.14)	33.20 (61.24)	34.53 (90.62)
Wants open-ended job (dummy)	0.94 (0.23)	0.93 (0.26)	0.96 (0.19)	0.95 (0.22)	0.94 (0.24)	0.97 (0.16)
Wants part-time job (dummy)	0.11 (0.31)	0.06 (0.24)	0.16 (0.36)	0.02 (0.14)	0.02 (0.15)	0.02 (0.14)
Observations	202,971	98,263	104,708	142,411	91,386	51,025

Notes: This table describes the unemployed workers in our main study sample. Prior and reservation wages correspond to monthly, full-time equivalent wages. The search criteria are measured at the start of the unemployment spell (cf Section 2.1).

Table 2: Parenthood gaps in job search

A/ Women											
	Re-employment	Applications	Applications across hours			Applications across days			Applications across hours and days		
	(1)	(2)	NoSchool (3a)	School (3b)	All (3c)	NoSchool (4a)	School (4b)	All (4c)	NoSchool (5a)	School (5b)	All (5c)
Child	-0.117*** (0.018)	-0.122*** (0.010)	-0.241*** (0.012)	-0.011 (0.015)	-0.011 (0.015)	-0.175*** (0.016)	-0.113*** (0.011)	-0.113*** (0.011)	-0.214*** (0.011)	-0.011 (0.015)	-0.011 (0.015)
ChildxNoSchool					-0.232*** (0.013)			-0.071*** (0.017)			-0.205*** (0.012)
NoSchool					Yes			Yes			Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Outcome mean	0.104	1.267	0.383	0.486	0.435	0.260	0.890	0.575	0.643	0.486	0.565
No. of Obs.	202,971	202,971	202,971	202,971	405,942	202,971	202,971	405,942	202,971	202,971	405,942
B/ Men											
	Re-employment	Applications	Applications across hours			Applications across days			Applications across hours and days		
	(1)	(2)	NoSchool (3a)	School (3b)	All (3c)	NoSchool (4a)	School (4b)	All (4c)	NoSchool (5a)	School (5b)	All (5c)
Child	0.031 (0.026)	-0.002 (0.015)	-0.081*** (0.023)	0.060*** (0.022)	0.060*** (0.022)	0.016 (0.026)	-0.003 (0.018)	-0.003 (0.018)	-0.040** (0.019)	0.060*** (0.022)	0.060*** (0.022)
ChildxNoSchool					-0.132*** (0.023)			0.020 (0.027)			-0.094*** (0.021)
NoSchool					Yes			Yes			Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Outcome mean	0.107	1.048	0.310	0.401	0.356	0.225	0.735	0.480	0.534	0.401	0.468
No. of Obs.	142,411	142,411	142,411	142,411	284,822	142,411	142,411	284,822	142,411	142,411	284,822

Notes: This table presents parenthood gaps in the re-employment hazard and the rate of applications for women (A/) and men (B/). The estimates are obtained using model (1), except in col (3c), (4c) and (5c), where they are obtained using model (2). In col (3), we compare children's school or sleep hours (8:30-11:30am, 1:30-4:30pm, 9pm-midnight) with other daytime hours during school days. In col (4), we compare weekdays to weekends or school holidays, excluding summer months. In col (5), we compare children's typical school or sleep hours during school days with other school days' hours or days with no school. We estimate Poisson count models and report the incidence rate ratios minus one, which can be interpreted as semi-elasticities. We control for the individual characteristics listed in Section 3.1. Robust SE clustered at the city level in parentheses. Outcome means are calculated among non-parents.

Table 3: Parenthood gap in characteristics of applications sent at different times

A/ Applications sent by all unemployed								
	Sent just after posting		Followed by hire		Sent just after posting		Followed by hire	
	Women (1)	Men (2)	Women (3)	Men (4)	Women (5)	Men (6)	Women (7)	Men (8)
Child	-0.030*** (0.009)	0.003 (0.015)	-0.064 (0.041)	0.000 (0.060)	-0.048*** (0.011)	-0.015 (0.018)	-0.135** (0.051)	-0.004 (0.079)
No-SchoolXChild					0.031*** (0.012)	0.030 (0.018)	0.141** (0.072)	0.007 (0.084)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
No-School					Yes	Yes	Yes	Yes
Outcome mean	0.393	0.330	0.024	0.024	0.393	0.330	0.024	0.024
No. of Obs.	203,400	129,912	203,400	129,912	203,400	129,912	203,400	129,912
B/ Applications sent by all unemployed below age 45								
	Sent just after posting		Followed by hire		Sent just after posting		Followed by hire	
	Women (1)	Men (2)	Women (3)	Men (4)	Women (5)	Men (6)	Women (7)	Men (8)
Child	-0.033*** (0.011)	0.006 (0.018)	-0.108** (0.046)	-0.037 (0.068)	-0.053*** (0.013)	-0.012 (0.022)	-0.169*** (0.056)	-0.023 (0.090)
No-SchoolXChild					0.033** (0.013)	0.029 (0.022)	0.126* (0.080)	-0.023 (0.094)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
No-School					Yes	Yes	Yes	Yes
Outcome mean	0.389	0.329	0.025	0.024	0.389	0.329	0.025	0.024
No. of Obs.	166,954	104,370	166,954	104,370	166,954	104,370	166,954	104,370

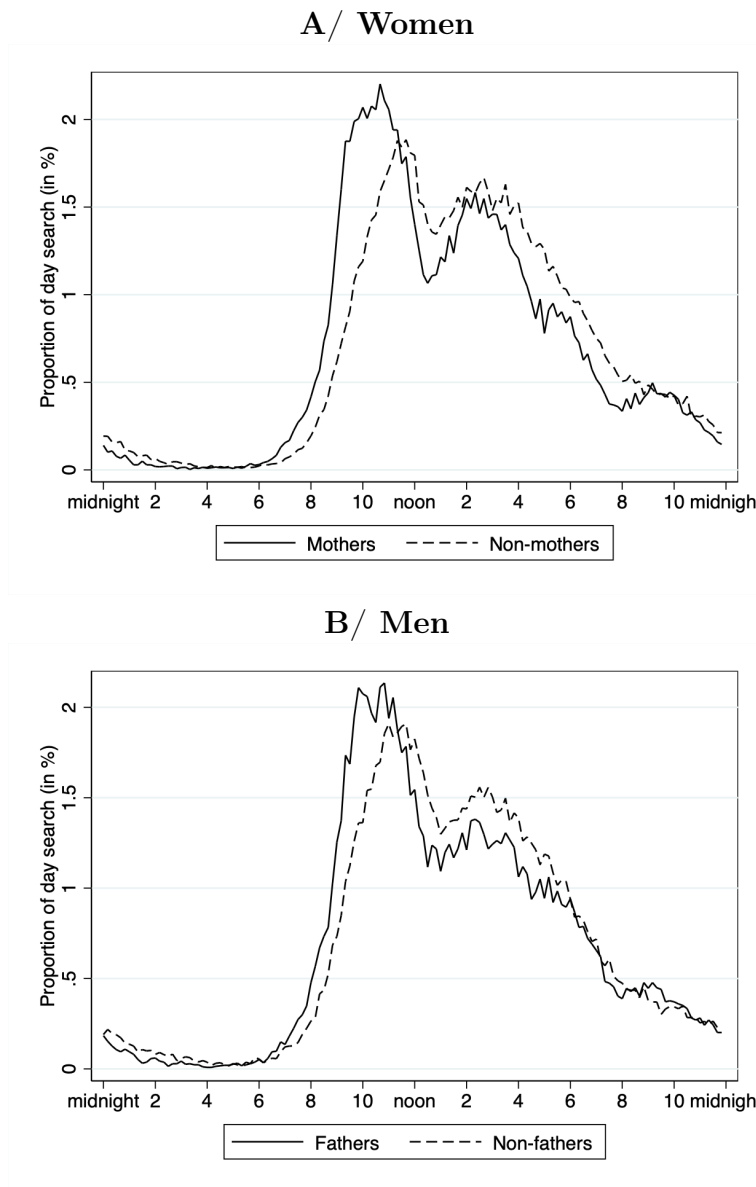
Notes: This table presents parenthood gaps in the probability that an application was sent less than two days after the vacancy was posted or followed by a hire. They are obtained by estimating model (A.2) in col (1)-(4) and model (A.3) in col (5)-(8), in the sample of *applications* from unemployed workers in our main study sample in Panel A/ and those below age 45 in Panel B/. In col (5)-(8), we distinguish between applications sent during children’s typical school or sleep hours during weekdays and those sent on other weekdays’ hours or days with no school. We run separate regressions for applications sent by men and women and control for the individual characteristics listed in Section 3.1. We estimate Poisson count models and report the incidence rate ratios minus one, which can be interpreted as semi-elasticities. Robust SE clustered at the individual level in parentheses. Outcome means are calculated among non-parents.

ONLINE APPENDIX

A Additional information on data and empirical models

A.1 Timing of job applications

Figure A.1: *Within day evolution of parents' and non-parents' applications*



Notes: This Figure presents the proportion of applications sent by women (Panel A) and men (Panel B), with (solid line) or without (dashed line) children, per 10-minute intervals during weekdays.

A.2 Selection of job applications on the PES search platform

The PES search platform only represents one search channel among others. An important question is to what extent the gaps in job applications on the platform that we can detect are representative of gaps in job applications overall. To address this question, we first compare the applied-to vacancies on the PES search platform (col (1)) to the jobs that people in our sample are hired into (all in col (2), and by gender and family status in col (3)-(6)) in Table A.1. We see that the vacancies on the online platform cover all types of contracts, firm sizes, and sectors. We notice, however, that temporary contracts are under-represented on the PES platform, while finite-duration contracts are over-represented. Small establishments (less than five employees) are slightly under-represented on the PES search platform. In terms of sectors, we note that Administrative services jobs are under-represented, but the sector composition is overall pretty balanced.

Next, we make sure that our specific results in this paper are not biased by potential differences in the fraction of applications done on the online search platform associated with motherhood. For that purpose, we detect the jobs that have been found via the search platform.²¹ In Table A.2, we show that about 7% of women without children in our sample found their job via the PES search platform, and this rate is not significantly different among mothers (col (1) and (2)). We also find that about 6% of men without children in our sample found their job via the PES search platform, and this rate is not significantly different among fathers (col (3) and (4)). This test suggests that parenthood is not associated with changes in the fraction of applications done on the online search platform for women and men. When denoting the share of applications on the PES search platform $s = \frac{N_{PES}}{N_{Tot}}$, one can see that: $\Delta \ln N_{Tot} = \Delta \ln N_{PES} - \Delta \ln s$, and therefore $\Delta \ln N_{Tot} \approx \Delta \ln N_{PES}$ if $\Delta \ln s \approx 0$. The results from Table A.2 hence tell us that we can directly interpret our estimates for motherhood gaps in the applications on the PES platform as gaps in applications overall. In robustness checks, we will also subtract the coefficients presented in Table A.2 to the estimates for motherhood gaps in the applications on the PES platform we obtain and compute the corresponding standard errors to account more directly for the selection of job applications on the PES search platform.

²¹In practice, we detect people who start working at a firm after applying to it on the PES search platform, among those who start a job in the year following their job loss.

Table A.1: Descriptive statistics on jobs advertised on the PES search platform

Variable	(1) Vacancies	(2) Hires all	(3) Hires women no child	(4) Hires women child	(5) Hires men no child	(6) Hires men child
Contract: Open-ended	0.42 (0.49)	0.55 (0.50)	0.62 (0.49)	0.61 (0.49)	0.48 (0.50)	0.43 (0.50)
Contract: Finite duration	0.51 (0.50)	0.22 (0.41)	0.20 (0.40)	0.21 (0.41)	0.23 (0.42)	0.26 (0.44)
Contract: Temporary	0.07 (0.26)	0.23 (0.42)	0.18 (0.39)	0.18 (0.38)	0.28 (0.45)	0.31 (0.46)
Size: less than 5 employees	0.38 (0.49)	0.56 (0.50)	0.52 (0.50)	0.54 (0.50)	0.58 (0.49)	0.60 (0.49)
Size: 6-19 employees	0.23 (0.42)	0.16 (0.36)	0.16 (0.37)	0.15 (0.35)	0.16 (0.37)	0.15 (0.36)
Size: 20-49 employees	0.15 (0.36)	0.10 (0.30)	0.10 (0.30)	0.10 (0.30)	0.09 (0.29)	0.09 (0.29)
Size: at least 50 employees	0.24 (0.43)	0.19 (0.39)	0.21 (0.41)	0.21 (0.41)	0.17 (0.37)	0.15 (0.36)
Sector: Manufacturing	0.07 (0.26)	0.04 (0.21)	0.04 (0.19)	0.04 (0.19)	0.05 (0.22)	0.06 (0.23)
Sector: Trade	0.18 (0.39)	0.15 (0.35)	0.17 (0.37)	0.14 (0.35)	0.14 (0.35)	0.13 (0.33)
Sector: Hostels, restaurants	0.13 (0.34)	0.09 (0.29)	0.10 (0.30)	0.07 (0.26)	0.12 (0.33)	0.08 (0.27)
Sector: Scientific services	0.05 (0.23)	0.05 (0.22)	0.06 (0.23)	0.05 (0.23)	0.05 (0.22)	0.04 (0.20)
Sector: Administrative services	0.10 (0.29)	0.31 (0.46)	0.26 (0.44)	0.26 (0.44)	0.36 (0.48)	0.39 (0.49)
Sector: Public administration	0.05 (0.23)	0.04 (0.20)	0.05 (0.22)	0.06 (0.23)	0.02 (0.15)	0.02 (0.15)
Sector: Education	0.06 (0.24)	0.03 (0.18)	0.03 (0.18)	0.06 (0.23)	0.01 (0.12)	0.02 (0.13)
Sector: Health, social assistance	0.13 (0.34)	0.11 (0.31)	0.13 (0.34)	0.17 (0.38)	0.04 (0.20)	0.05 (0.21)
Sector: Other services	0.05 (0.22)	0.03 (0.18)	0.05 (0.21)	0.04 (0.20)	0.02 (0.13)	0.02 (0.13)
Observations	645,137	345,378	98,262	104,707	91,384	51,025

Notes: In this table, we compare the characteristics of the jobs that unemployed workers in our study sample (described in Section 2.2) get re-employed into and the jobs that they can apply to on the PES online search platform: Col (1) includes all vacancies available for application for people in our study sample, col (2) includes the first job after the start of unemployment of people in our study sample, col (3) includes the first job of women with no children in our study sample, col (4) includes the first job of mothers in our study sample, col (5) includes the first job of men with no children in our study sample, col (6) includes the first job of fathers in our study sample.

Table A.2: Parenthood gaps in probability to find a job via PES search platform

	Women		Men	
	(1)	(2)	(3)	(4)
Child	0.009 (0.03)	-0.004 (0.03)	-0.063 (0.04)	-0.063 (0.04)
Ind. controls	Yes	Yes	Yes	Yes
Search criteria		Yes		Yes
Outcome mean	0.07	0.07	0.06	0.06
No. of Obs.	115,944	115,944	85,533	85,533

Notes: This table presents the parenthood gaps in the probability to have found the job via the PES search platform, conditional on starting a job in the year following job loss. We consider a job has been found via the PES search platform if we detect an application to that firm on the PES search platform in the year preceding the job start. We estimate Poisson count models and report the incidence rate ratios minus one, which can be interpreted as semi-elasticities. We control for the individual characteristics listed in Section 3.1. In columns (2) and (4), we additionally control for the reservation wage, maximum commute distance, desired type of contract, and preferred working time. We report robust SE clustered at the city level in parentheses. Outcome mean corresponds to the rate of jobs found via the PES search platform among non-parents.

A.3 Additional information on empirical model

Heterogeneity of the reallocation of job applications across periods We estimate the same empirical model as model (2) except that we fully interact $Child$, $Child \cdot NoSchool$ and $NoSchool$ with all the categories of the heterogeneity dimension considered. This corresponds to the following model, where k are the categories of heterogeneity dimension Het :

$$Y_{i,t,\tau} = \sum_{k=1}^K \mathbb{1}[Het_i = k] \cdot \left(\alpha_{0,k} + \alpha_{1,k} Child_{i,t} + \alpha_{2,k} Child_{i,t} \cdot NoSchool_{\tau} + \alpha_{3,k} NoSchool_{\tau} \right) + X_{i,t} \beta + \varepsilon_{i,t,\tau} \quad (\text{A.1})$$

Application level: Motherhood gap in application characteristics To analyze motherhood gaps in applications characteristics, we estimate similar empirical models as (1) but at the application level, such as:

$$Y_{i,t,a} = \alpha_0 + \alpha_1 Child_{i,t} + X_{i,t} \beta + \varepsilon_{i,t,a} \quad (\text{A.2})$$

$Y_{i,t,a}$ represents an outcome for application a , sent by individual i who started their unemployment spell in t .

We also analyze how the motherhood gap in application characteristics varies depending on the period when the application was sent, by estimating a version of model (2) at the application level:

$$Y_{i,t,a,\tau} = \alpha_0 + \alpha_1 Child_{i,t} + \alpha_2 Child_{i,t} \cdot NoSchool_{a,\tau} + \alpha_3 NoSchool_{a,\tau} + X_{i,t} \beta + \varepsilon_{i,t,a,\tau} \quad (\text{A.3})$$

B Additional results

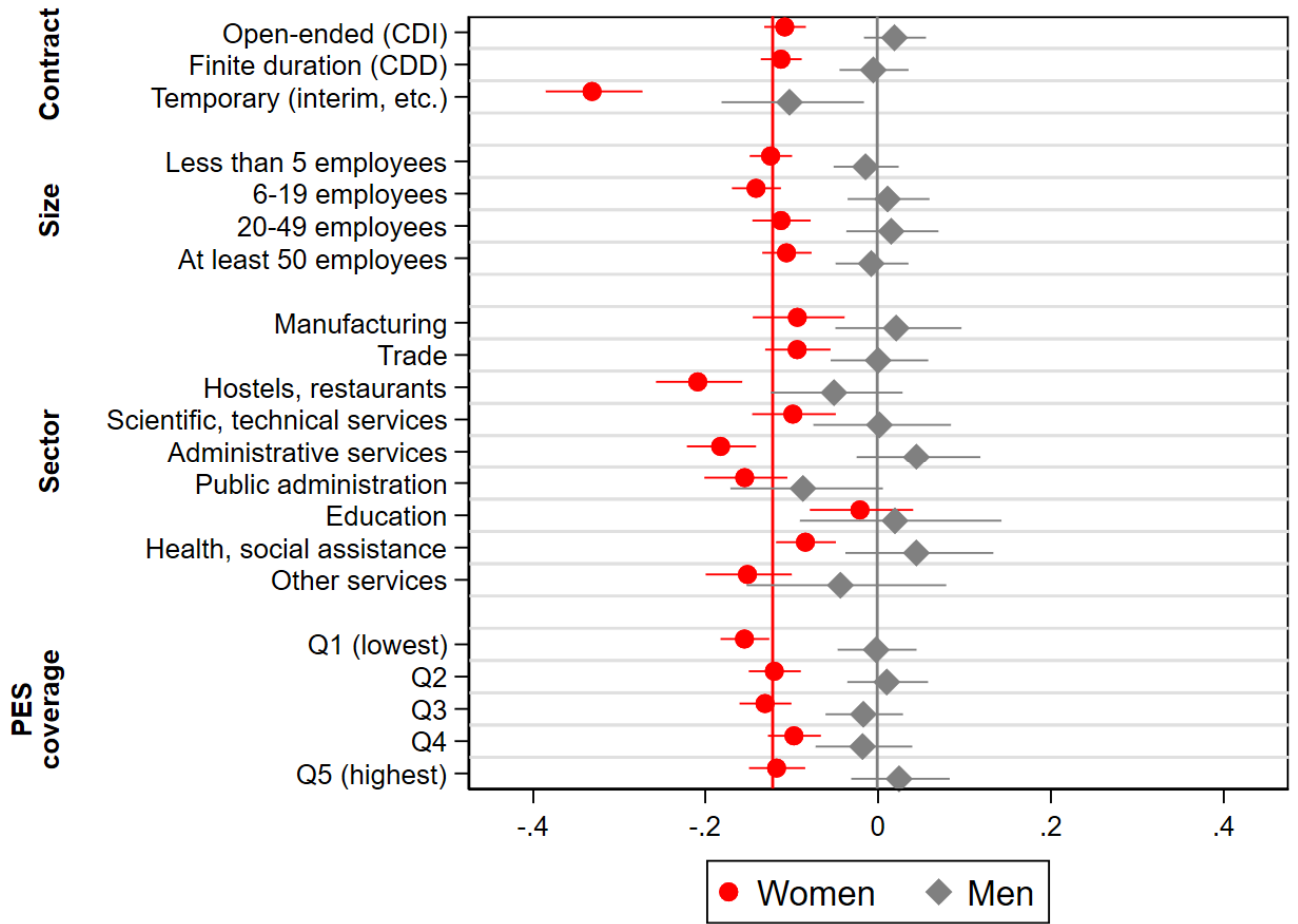
Table B.1: Parenthood gaps in search and re-employment outcomes

A/ Motherhood gaps in:	Re-employment		Job search				
	Re-employment rate	Application rate		Reservation wage, log	Max commute distance, log	Open-ended contract	Part-time job
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Child	-0.117*** (0.02)	-0.122*** (0.01)	-0.089*** (0.01)	0.006*** (0.00)	-0.078*** (0.00)	0.013*** (0.00)	0.051*** (0.00)
Ind. controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Search criteria			Yes				
Outcome mean	0.10	1.27	1.27	1634.98	28.81	0.93	0.06
No. of Obs.	202,971	202,971	202,971	202,971	202,971	202,971	202,971

B/ Fatherhood gaps in:	Re-employment		Job search				
	Re-employment rate	Application rate		Reservation wage, log	Max commute distance, log	Open-ended contract	Part-time job
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Child	0.031 (0.03)	-0.002 (0.02)	-0.003 (0.02)	0.009*** (0.00)	0.004 (0.00)	0.008*** (0.00)	-0.001 (0.00)
Ind. controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Search criteria			Yes				
Outcome mean	0.11	1.05	1.05	1723.91	33.20	0.94	0.02
No. of Obs.	142,411	142,411	142,411	142,411	142,411	142,411	142,411

Notes: This table presents the parenthood gaps for women and men in the hazard of re-employment within 6 months (col (1)), the count of job applications (col (2)-(3)), full-time equivalent monthly reservation wage (col (4)), maximum commute distance (col (5)), desired contract (open-ended vs short-term contract) (col (6)), preferred working time (part-time vs full-time) (col (7)). In col (1)-(3), we estimate Poisson count models and report the incidence rate ratios minus one, which can be interpreted as semi-elasticities ; we estimate linear models using OLS in col (4)-(7). We control for the individual characteristics listed in Section 3.1. In col (3), we additionally control for the reservation wage, maximum commute distance, desired type of contract, and preferred working time. We report robust SE clustered at the city level in parentheses. Outcome mean corresponds to the non-logged average outcome among non-parents.

Figure B.1: Parenthood gap in applications to different types of jobs



Notes: This Figure presents estimates of parenthood gaps in the count of applications (similar to Table B.1), except that we consider separately the applications to different types of jobs: we consider jobs with different types of contract, in establishments of different sizes, in different sectors (descriptive statistics of jobs in terms of those characteristics are presented in Table A.1). Finally, we use an index for whether the job has characteristics (in terms of contract, establishment size, and sector) that are highly represented on the PES search platform relative to their prevalence among hires. We divide jobs into quintiles of this index: the lowest quintile Q1 includes the jobs with characteristics that tend to be the most underrepresented on the PES search platform, while the highest quintile Q5 includes the jobs with characteristics that are the most overrepresented. Like in the rest of the analysis, we run separate regressions for men and women and control for the individual characteristics listed in Section 3.1. We estimate Poisson count models and report the incidence rate ratios minus one, which can be interpreted as semi-elasticities. We present the 95% confidence intervals based on robust SE clustered at the city level. The vertical lines indicate the parenthood gap in all applications, estimated for women in red and men in gray (they correspond to the estimates presented in col (2) of Table 2).

Table B.2: Robustness check: Parenthood gaps in application and job finding rate, with different set of covariates

		A/ Job finding rate									
		Women					Men				
		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Child		-0.190***	-0.122***	-0.119***	-0.118***	-0.117***	0.104***	0.055**	0.029	0.030	0.031
		(0.01)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.03)	(0.03)	(0.03)	(0.03)
Age	Yes		Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Marital, Educ, City			Yes	Yes	Yes	Yes		Yes	Yes	Yes	Yes
Experience, skill, occupation				Yes	Yes	Yes			Yes	Yes	Yes
Prior unemployment, UI					Yes	Yes				Yes	Yes
Prior wage, Prior hours						Yes					Yes
No. of Obs.		202,971	202,971	202,971	202,971	202,971	142,411	142,411	142,411	142,411	142,411

		B/ Applications rate									
		Women					Men				
		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Child		-0.134***	-0.106***	-0.110***	-0.122***	-0.122***	-0.021*	-0.028*	-0.016	-0.002	-0.002
		(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)	(0.02)
Age	Yes		Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Marital, Educ, City			Yes	Yes	Yes	Yes		Yes	Yes	Yes	Yes
Experience, skill, occupation				Yes	Yes	Yes			Yes	Yes	Yes
Prior unemployment, UI					Yes	Yes				Yes	Yes
Prior wage, Prior hours						Yes					Yes
No. of Obs.		202,971	202,971	202,971	202,971	202,971	142,411	142,411	142,411	142,411	142,411

Notes: This table presents the parenthood gap in the rate of re-employment within 6 months (Panel A/) and the count of online applications on the PES search platform at the start of the spell (Panel B/). We estimate the same empirical models as for col (1)-(2) of Table 2, except that we successively include the individual controls. We estimate Poisson count models and report the incidence rate ratios minus one, which can be interpreted as semi-elasticities. We report robust SE clustered at the city level in parentheses.

Table B.3: Parenthood gap in employment and search, within individual

Panel A: Women		
	Job finding rate	Application rate
	(1)	(2)
Number of children	-0.202** (0.09)	-0.616** (0.15)
Individual FE	Yes	Yes
Outcome mean	1.79	0.11
No. of Obs.	411	411
Panel B: Men		
	Job finding rate	Application rate
	(1)	(2)
Number of children	-0.139 (0.09)	0.162 (0.30)
Individual FE	Yes	Yes
Outcome mean	1.35	0.08
No. of Obs.	463	463

Notes: This Table presents estimates of parenthood gaps in re-employment and job search behavior (similar to col (1)-(2) of Table 2). We focus on individuals who have several unemployment spells during our study period, with different numbers of children, and estimate the effect of children in empirical models with individual fixed effects. We restrict consider the sample of women in Panel A, and men in Panel B. We estimate Poisson count models and report the incidence rate ratios minus one, which can be interpreted as semi-elasticities. We report robust SE clustered at the individual level in parentheses.

Table B.4: Robustness check: Parenthood gaps in re-employment rate, with alternative measures of re-employment rate

A/ Motherhood gap						
	Duration before first job		Duration before first long-term job		Duration before unemployment exit	
	≤ 6 months (1)	≤ 1 year (2)	≤ 6 months (3)	≤ 1 year (4)	≤ 6 months (5)	≤ 1 year (6)
Child	-0.152*** (0.01)	-0.088*** (0.01)	-0.117*** (0.02)	-0.061*** (0.01)	-0.142*** (0.01)	-0.082*** (0.01)
Ind controls	Yes	Yes	Yes	Yes	Yes	Yes
Outcome mean	0.37	0.62	0.11	0.22	0.18	0.43
No. of Obs.	202,971	202,971	202,971	202,971	202,220	180,988

B/ Fatherhood gap						
	Duration before first job		Duration before first long-term job		Duration before unemployment exit	
	≤ 6 months (1)	≤ 1 year (2)	≤ 6 months (3)	≤ 1 year (4)	≤ 6 months (5)	≤ 1 year (6)
Child	-0.007 (0.01)	0.009 (0.01)	0.031 (0.03)	0.040** (0.02)	-0.061*** (0.02)	-0.007 (0.01)
Ind controls	Yes	Yes	Yes	Yes	Yes	Yes
Outcome mean	0.37	0.62	0.11	0.22	0.18	0.43
No. of Obs.	142,411	142,411	142,411	142,411	142,019	128,998

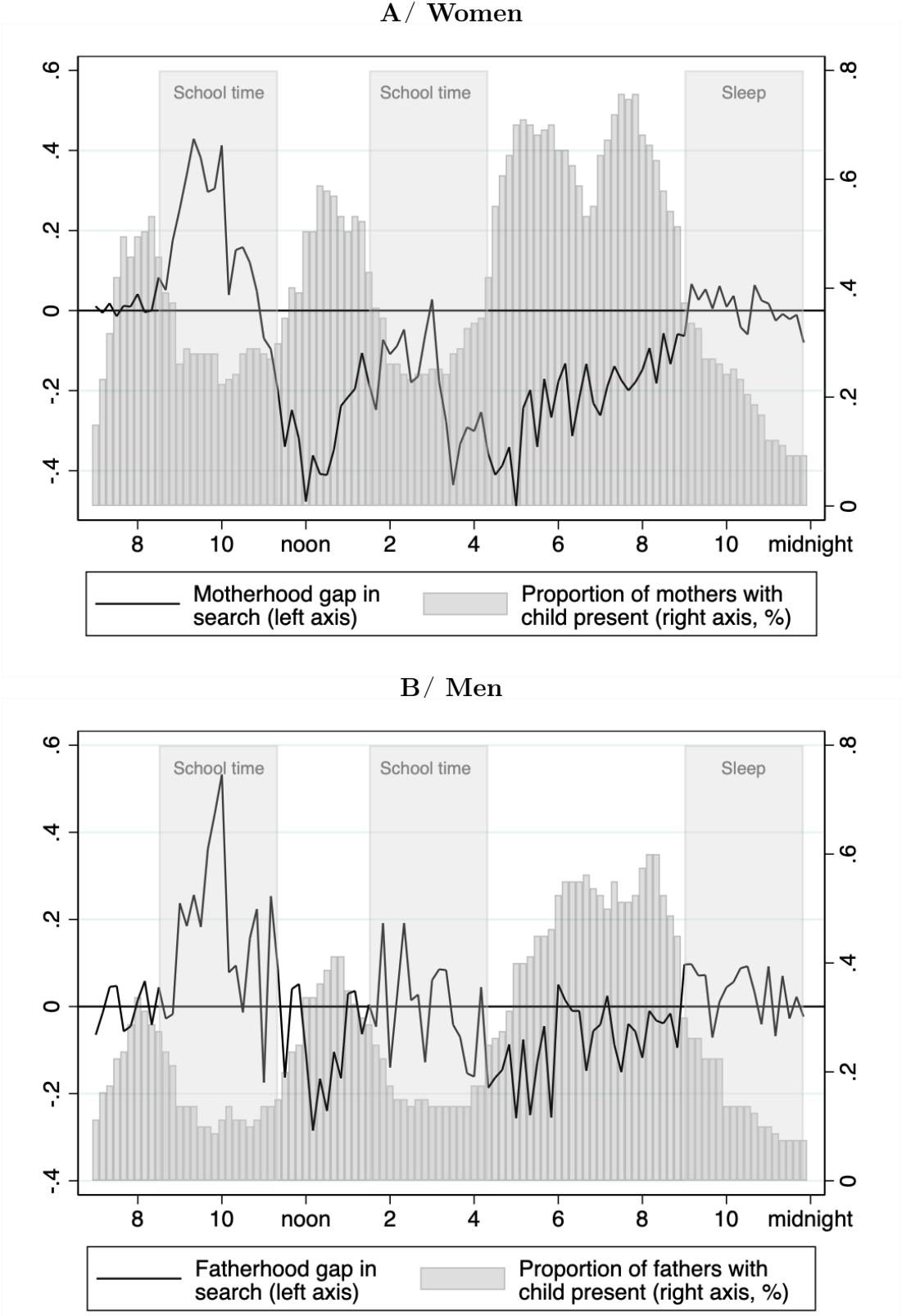
Notes: This table presents the parenthood gap in the re-employment rate among women (Panel A/), and among men (Panel B/). We estimate the same empirical models as for col (1) of Table 2, but we consider alternative outcome variables. We consider first the duration before the individual starts any job (col (1)-(2)), then the duration before the first job long-term job (col (3)-(4)), and finally the duration before the individual leaves the unemployment register (col (5)-(6)). Each time, we take as an outcome a dummy for the duration being below 6 months or 1 year. Note that our main outcome variable in the rest of the analysis corresponds to the one presented in column (2). Like in Table B.1, we estimate Poisson count models and report the incidence rate ratios minus one, which can be interpreted as semi-elasticities. We report robust SE clustered at the city level in parentheses. Outcome means are calculated among non-parents.

Table B.5: Robustness check: Parenthood gaps in application, with alternative measures of application counts

	A/ Motherhood gap					
	Sum of applications			Sum of applications over duration of search		
	2 months	3 months	6 months	2 months	3 months	6 months
	(1)	(2)	(3)	(4)	(5)	(6)
Child	-0.130***	-0.122***	-0.098***	-0.151***	-0.141***	-0.115***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Ind controls	Yes	Yes	Yes	Yes	Yes	Yes
Outcome mean	0.76	1.05	1.70	1.19	1.48	2.13
No. of Obs.	202,971	202,971	202,971	202,971	202,971	202,971
	B/ Fatherhood gap					
	Sum of applications			Sum of applications over duration of search		
	2 months	3 months	6 months	2 months	3 months	6 months
	(1)	(2)	(3)	(4)	(5)	(6)
Child	0.004	-0.002	-0.014	-0.011	-0.012	-0.018
	(0.02)	(0.02)	(0.01)	(0.02)	(0.02)	(0.01)
Ind controls	Yes	Yes	Yes	Yes	Yes	Yes
Outcome mean	0.76	1.05	1.70	1.19	1.48	2.13
No. of Obs.	142,411	142,411	142,411	142,411	142,411	142,411

Notes: This table presents the parenthood gap in the count of online applications on the PES search platform at the start of the spell among women (Panel A/) and among men (Panel B/). We estimate the same empirical models as for col (2) of Table 2, but we consider alternative outcome variables. First, we count the number of applications sent in the last 2/3/6 months or until the end of the search spell if the spell is interrupted before (col (1), (2), (3)). Second, we count the number of applications sent in the last 2/3/6 months divided by the duration of the search spell up to 2/3/6 months (col (4), (5), (6)). Note that our main outcome variable in the rest of the analysis corresponds to the one presented in column (2). Like in Table B.1, we estimate Poisson count models and report the incidence rate ratios minus one, which can be interpreted as semi-elasticities. We report robust SE clustered at the city level in parentheses. Outcome means are calculated among non-parents.

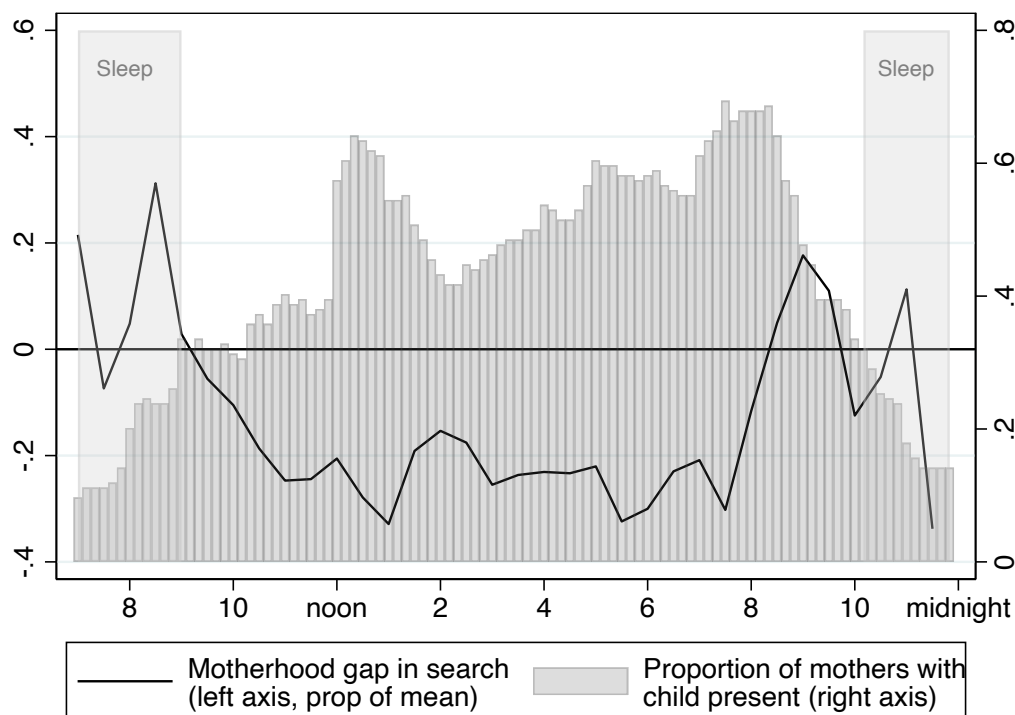
Figure B.2: Parenthood gap in applications at different times of the day, using OLS regressions



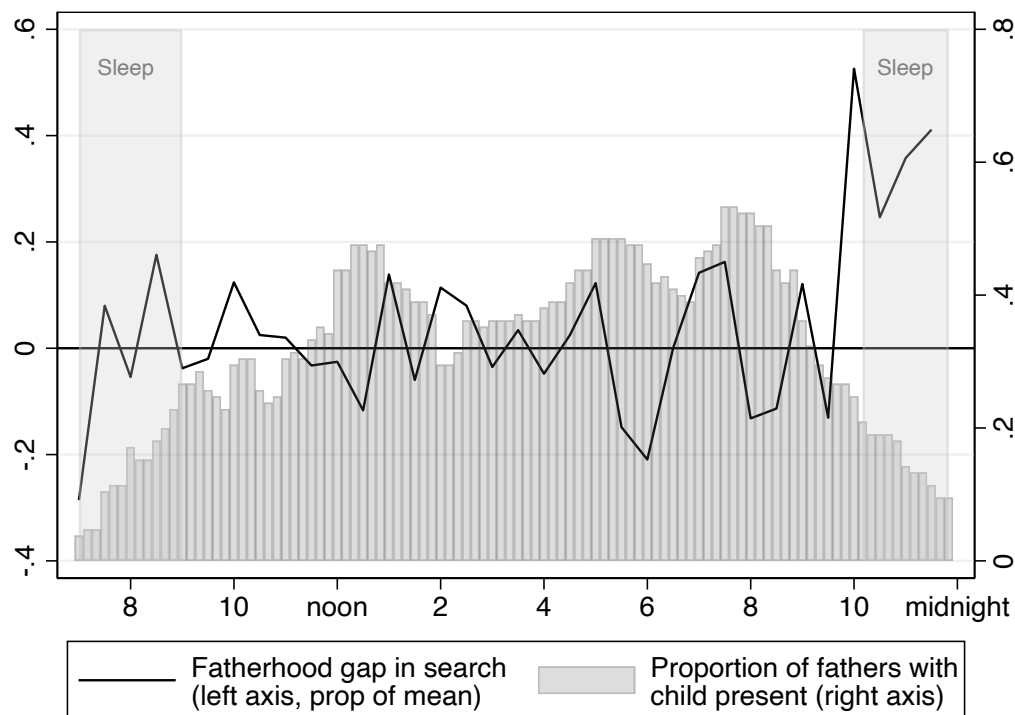
Notes: This figure is similar to Figure 1 except that we use a different method to estimate the parenthood gaps in applications. We first estimate the parenthood gaps in applications sent in all 10-minute intervals in absolute terms using OLS regressions, then we re-scale the obtained coefficients by dividing them by the number of applications sent by non-mothers (respectively non-fathers in Panel B) on average across all the in 10-minutes intervals considered (i.e. between 7am and midnight during weekdays).

Figure B.3: Parenthood gap in applications, during weekends and school holidays (30-minute intervals)

A/ Women



B/ Men



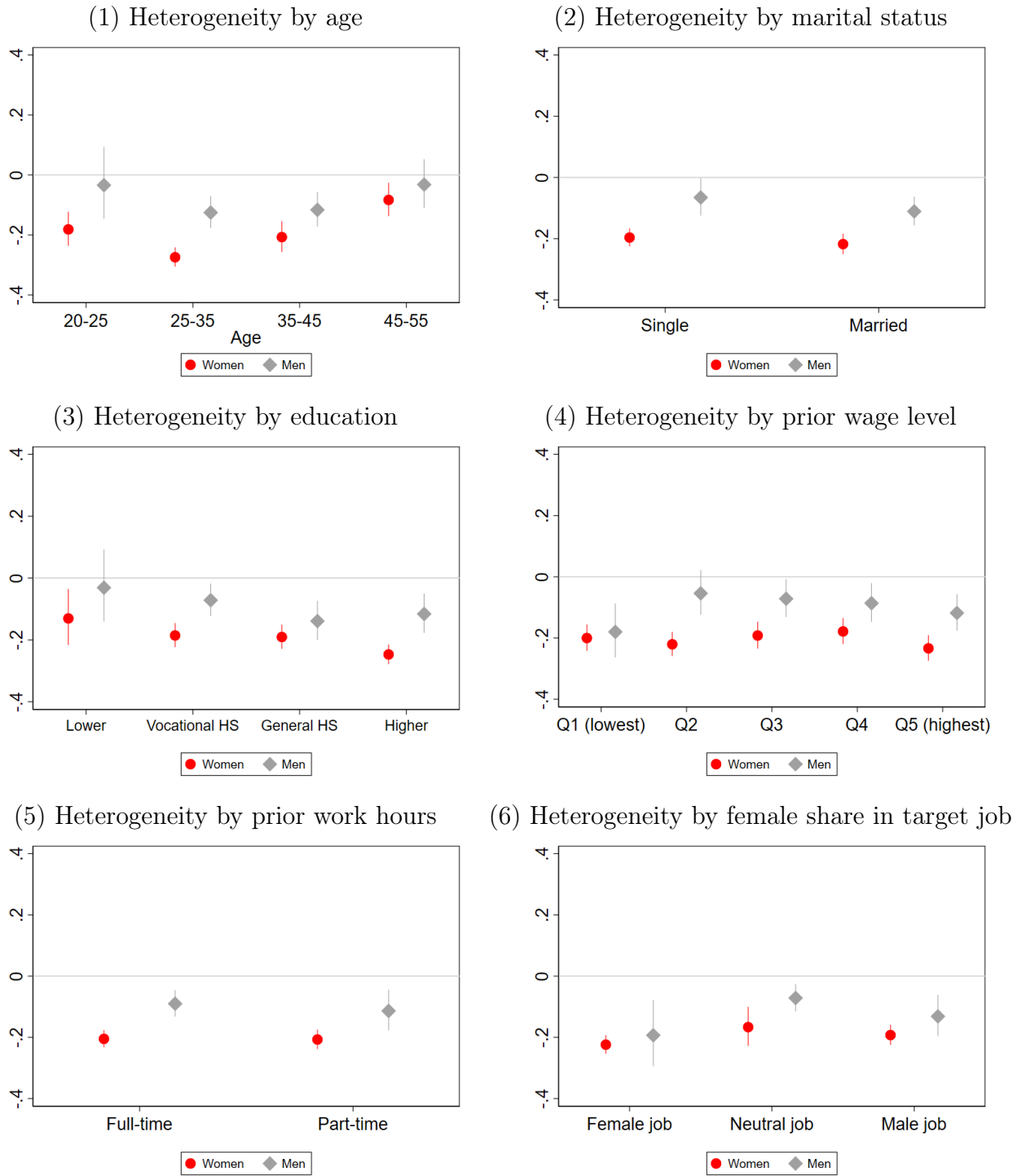
Notes: This Figure presents the estimates for the parenthood gap in the rate of applications sent in 30-minute intervals (black line), and the fraction of unemployed parents who report being in presence of at least one child during the same 10-minutes intervals in the French Time Use Survey (gray bars). These statistics are obtained during weekends or school holidays (excluding July-August), instead of during weekdays as in Figure 1.

Table B.6: Robustness checks: Parenthood gaps in job search using re-weighted sample

A/ Women											
	Re-employment	Applications	Applications across hours			Applications across days			Applications across hours and days		
			NoSchool	School	All	NoSchool	School	All	NoSchool	School	All
Child	-0.082*** (0.029)	-0.112*** (0.016)	-0.244*** (0.018)	0.012 (0.025)	0.012 (0.025)	-0.187*** (0.027)	-0.101*** (0.018)	-0.101*** (0.018)	-0.215*** (0.017)	0.012 (0.025)	0.012 (0.025)
ChildxNoSchool					-0.253*** (0.021)			-0.096*** (0.031)			-0.224*** (0.021)
NoSchool					Yes			Yes			Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Outcome mean	0.095	1.107	0.332	0.421	0.376	0.237	0.772	0.504	0.569	0.421	0.495
No. of Obs.	202,971	202,971	202,971	202,971	405,942	202,971	202,971	405,942	202,971	202,971	405,942
B/ Men											
	Re-employment	Applications	Applications across hours			Applications across days			Applications across hours and days		
			NoSchool	School	All	NoSchool	School	All	NoSchool	School	All
Child	0.031 (0.026)	-0.002 (0.015)	-0.081*** (0.023)	0.060*** (0.022)	0.060*** (0.022)	0.016 (0.026)	-0.003 (0.018)	-0.003 (0.018)	-0.040** (0.019)	0.060*** (0.022)	0.060*** (0.022)
ChildxNoSchool					-0.132*** (0.023)			0.020 (0.027)			-0.094*** (0.021)
NoSchool					Yes			Yes			Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Outcome mean	0.107	1.048	0.310	0.401	0.356	0.225	0.735	0.480	0.534	0.401	0.468
No. of Obs.	142,411	142,411	142,411	142,411	284,822	142,411	142,411	284,822	142,411	142,411	284,822

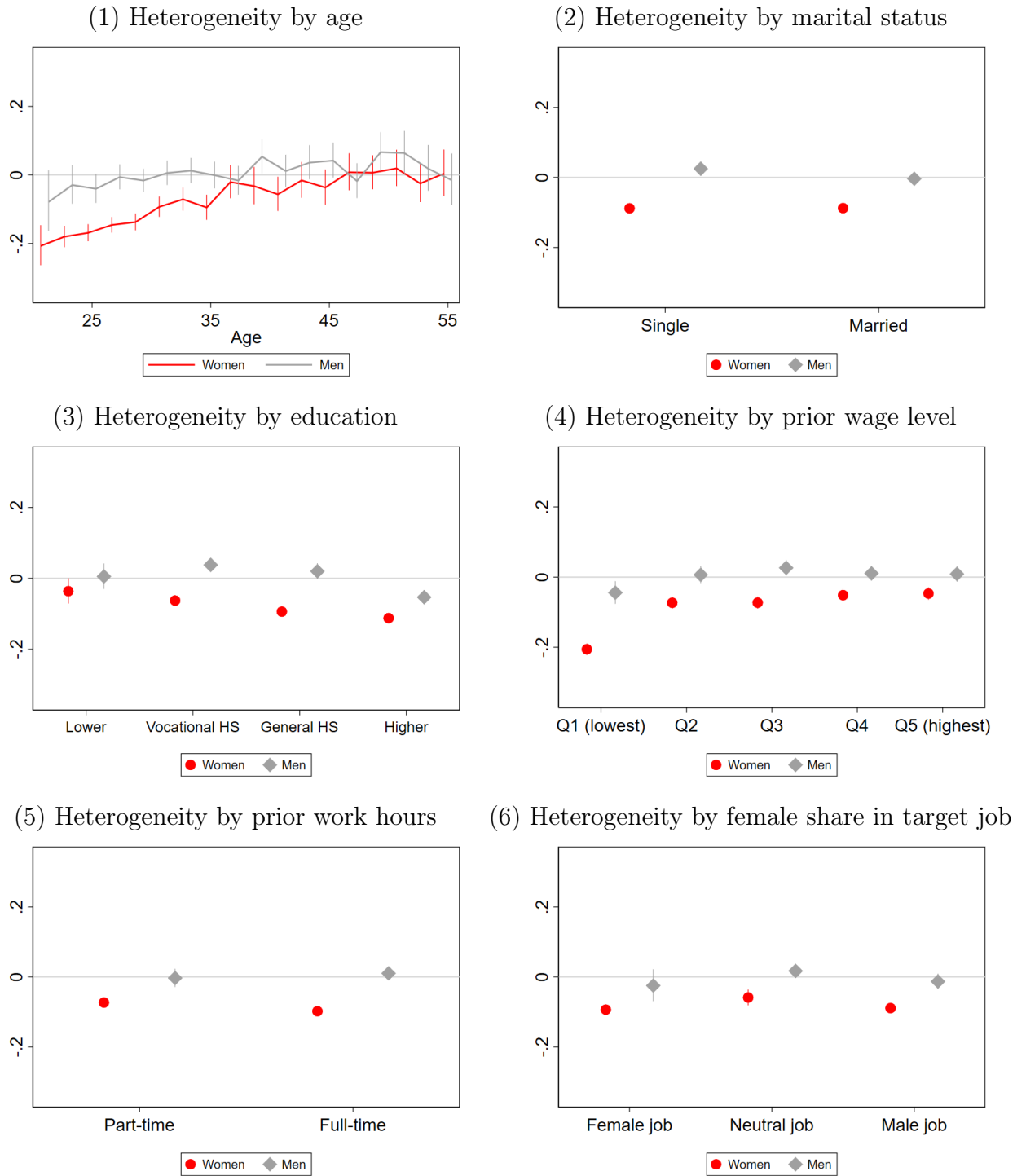
Notes: This Table presents the same results as in Table 2, except that the sample of women is re-weighted to make it more similar to the sample of men. To calculate the weights for the sample of women, we follow [Illing et al. \(2024\)](#): we compute $\frac{\hat{p}}{1-\hat{p}}$, where \hat{p} is the predicted propensity score obtained from regressing a dummy for being man on a wide set of individual variables in a probit model. Our probit regression includes the set of individual characteristics that we use as controls in our main empirical models excluding fixed effects (listed in Section 3.1)—except that we use continuous measures for age and potential benefit duration. It hence includes: job seekers' age (in years), marital status, education (5 diploma levels), labor market experience (5 experience levels), type of skills (5 skill categories), past cumulated unemployment duration, count of past unemployment spells, potential UI benefits duration (in months), prior wage, prior work hours (a continuous ratio of hours relative to full-time).

Figure B.4: Heterogeneity in the magnitude of parents' time reallocation of search activities



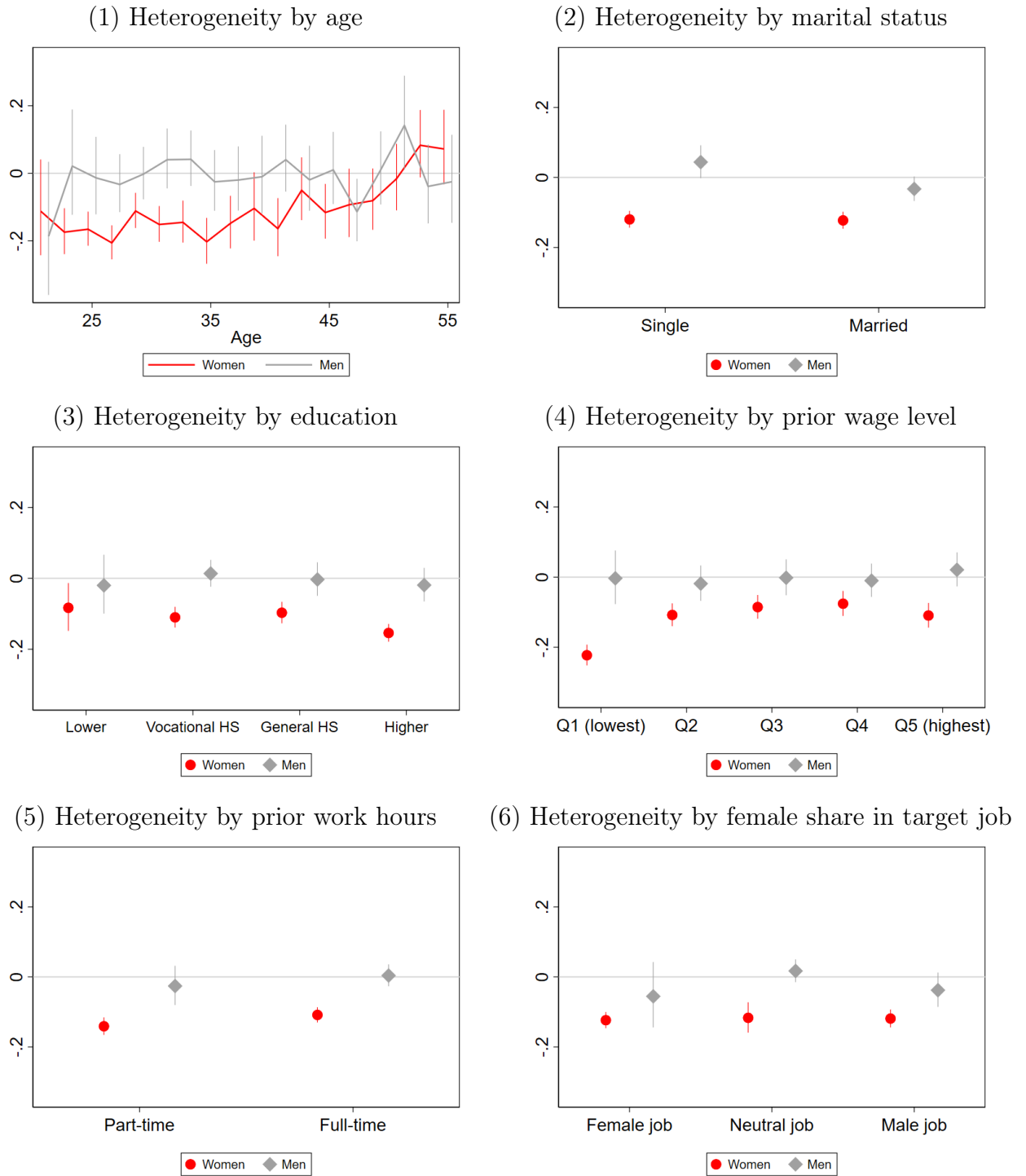
Notes: This Figure presents the heterogeneity of the effect of having children out of school on the rate of applications, corresponding to the coefficient associated with *ChildXNoSchool* in col (5c) of Table 2. We successively consider heterogeneity by age, marital status, diploma level (lower than high school, vocation high school, general high school or higher education), wage level at the prior job, hours worked at prior job and proportion of women in the occupation looked for (highest quartile, middle, lowest quartile). We present the 95% confidence intervals based on robust SE clustered at the city level.

Figure B.5: Heterogeneity of parenthood gaps in the re-employment rate



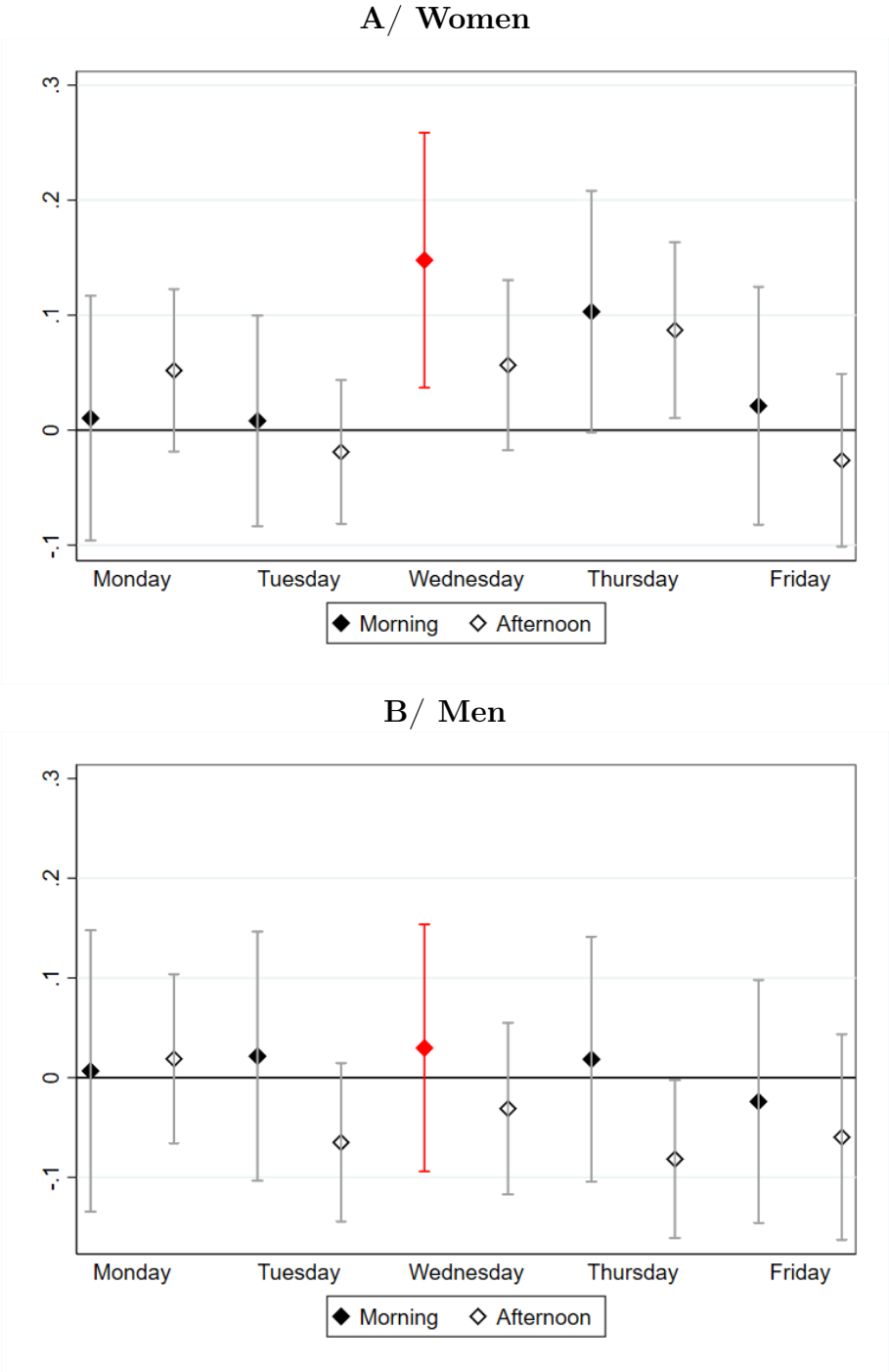
Notes: In this Figure, we analyze the heterogeneity of the parenthood gaps in the hazard of re-employment within 6 months corresponding to the coefficient associated with *Child* in col (1) of Table 2: we estimate Poisson count models and report the incidence rate ratios minus one, which can be interpreted as semi-elasticities. We successively consider heterogeneity by age (Panel (1)), by marital status (Panel (2)), by diploma level (lower than high school, vocation high school, general high school or higher education); Panel (3)), by wage level at the prior job (Panel (4)), by hours worked at prior job (Panel (5)) and by proportion of women in the occupation looked for (highest quartile, middle, lowest quartile; Panel (6)). We present the 95% confidence intervals based on robust SE clustered at the city level.

Figure B.6: Heterogeneity of parenthood gaps in the application rate



Notes: In this Figure, we analyze the heterogeneity of the parenthood gaps in the rate of applications corresponding to the coefficient associated with *Child* in col (2) of Table 2: we estimate Poisson count models and report the incidence rate ratios minus one, which can be interpreted as semi-elasticities. We successively consider heterogeneity by age (Panel (1)), by marital status (Panel (2)), by diploma level (lower than high school, vocation high school, general high school or higher education); Panel (3)), by wage level at the prior job (Panel (4)), by hours worked at prior job (Panel (5)) and by proportion of women in the occupation looked for (highest quartile, middle, lowest quartile; Panel (6)). We present the 95% confidence intervals based on robust SE clustered at the city level.

Figure B.7: Robustness check: Effect of the school schedule reform on parents' application, controlling for search criteria



Notes: This Figure presents the estimates for the effect of the reform of school schedule (i.e. adding school time on Wednesday morning) on the rate of applications sent on different days of the week. We use the same specifications as in Figure 2, except that we include search criteria as additional controls. We estimate Poisson count models and report the incidence rate ratios minus one, which can be interpreted as semi-elasticities. We present the 95% confidence intervals based on SE clustered at the city level.

Table B.7: The effect of the school schedule reform on job applications at different times

	A/ Women			B/ Men		
	Wednesday (1)	Other days (2)	Any day (3)	Wednesday (4)	Other days (5)	Any day (6)
ChildXReform	0.088*** (0.033)	0.029 (0.019)	0.040** (0.018)	-0.014 (0.037)	-0.031 (0.024)	-0.027 (0.022)
Child	-0.189*** (0.022)	-0.134*** (0.015)	-0.145*** (0.015)	-0.038 (0.034)	0.031 (0.025)	0.017 (0.023)
Reform	Yes	Yes	Yes	Yes	Yes	Yes
Individual controls	Yes	Yes	Yes	Yes	Yes	Yes
Outcome mean	0.257	1.045	1.302	0.205	0.860	1.065
No. of Obs.	195,530	195,530	195,530	138,018	138,018	138,018

Notes: This table presents the effect of the reform of school schedule on the rate of applications sent on different days (see empirical model (3)). We estimate the effect separately for women (in Panel A) and men (in Panel B) on various outcomes: In col (1)-(4), we consider the rate of applications sent on Wednesdays. In col (2)-(5), we consider the rate of applications sent on any other day. And in col (3)-(6), we consider the rate of applications sent overall. We estimate Poisson count models and report the incidence rate ratios minus one, which can be interpreted as semi-elasticities. We control for the individual characteristics listed in Section 3.1. Robust SE clustered at the city level in parentheses. Outcome means are calculated among non-parents before the reform.

Table B.8: Robustness check: Impact of the school schedule reform on the time allocation of search activities, controlling for search criteria

	A/ Women			B/ Men		
	Wednesday (1)	Other days (2)	Any day (3)	Wednesday (4)	Other days (5)	Any day (6)
ChildXReform	0.083*** (0.033)	0.025 (0.019)	0.036** (0.018)	-0.016 (0.037)	-0.032 (0.024)	-0.029 (0.022)
Child	-0.157*** (0.023)	-0.098*** (0.016)	-0.110*** (0.015)	-0.037 (0.034)	0.029 (0.025)	0.016 (0.023)
Reform	Yes	Yes	Yes	Yes	Yes	Yes
Individual controls	Yes	Yes	Yes	Yes	Yes	Yes
Other search criteria	Yes	Yes	Yes	Yes	Yes	Yes
Outcome mean	0.257	1.045	1.302	0.205	0.860	1.065
No. of Obs.	195,530	195,530	195,530	138,018	138,018	138,018

Notes: This table presents the effect of the reform of school schedule on the rate of applications sent on different days by parents. We present the same specifications as in Table B.7, except that we include search criteria as additional controls. We estimate the effect separately for women (in Panel A) and men (in Panel B). In col (1) and (4), we consider the rate of applications sent on Wednesdays. In col (2) and (5), we consider the rate of applications sent on any other day. And in col (3) and (6), we consider the rate of applications sent overall. We estimate Poisson count models and report the incidence rate ratios minus one, which can be interpreted as semi-elasticities. We control for the individual characteristics listed in Section 3.1. We additionally control for the search criteria reported at the start of the unemployment spell: the reservation wage, maximum commute distance, desired type of contract, and preferred working time. SE clustered at the city level in parentheses. Outcome means are calculated among non-parents before the reform.

Table B.9: Effect of the reform on search selectivity

A/ Women:	Search selectivity			
	Reservation wage, log	Max commute distance, log	Long contract	Part time
	(1)	(2)	(3)	(4)
ChildXReform	0.000 (0.002)	0.003 (0.005)	0.003 (0.002)	-0.006** (0.003)
Child	0.005*** (0.002)	-0.080*** (0.005)	0.011*** (0.002)	0.055*** (0.003)
Individual controls	Yes	Yes	Yes	Yes
Reform	Yes	Yes	Yes	Yes
Outcome mean	1637.512	29.576	0.932	0.054
No. of Obs.	195,530	195,530	195,530	195,530
B/ Men:	Search selectivity			
	Reservation wage, log	Max commute distance, log	Long contract	Part time
	(1)	(2)	(3)	(4)
ChildXReform	0.002 (0.002)	0.011 (0.007)	0.004* (0.002)	0.002 (0.002)
Child	0.008*** (0.002)	-0.003 (0.006)	0.005** (0.002)	-0.002 (0.002)
Individual controls	Yes	Yes	Yes	Yes
Reform	Yes	Yes	Yes	Yes
Outcome mean	1732.977	33.709	0.941	0.020
No. of Obs.	138,018	138,018	138,018	138,018

Notes: This table presents the estimates for the effect of the reform of school schedule (adding school time on Wednesday morning) on the selectivity in search reported in a mandatory survey at the start of the spell. We control for the individual characteristics listed in Section 3.1. SE in parentheses clustered at the city level. Outcome means are calculated among non-parents before the reform.

Table B.10: Effect of the reform on re-employment

A/ Women						
	Duration before first job		Duration before first long-term job		Duration before unemployment exit	
	≤ 6 months	≤ 1 year	≤ 6 months	≤ 1 year	≤ 6 months	≤ 1 year
	(1)	(2)	(3)	(4)	(5)	(6)
Child	-0.170***	-0.104***	-0.145***	-0.090***	-0.130***	-0.080***
	(0.01)	(0.01)	(0.03)	(0.02)	(0.02)	(0.01)
Ind controls	Yes	Yes	Yes	Yes	Yes	Yes
Outcome mean	0.37	0.62	0.11	0.22	0.18	0.43
No. of Obs.	195,530	195,530	195,530	195,530	194,809	174,349
B/Men						
	Duration before first job		Duration before first long-term job		Duration before unemployment exit	
	≤ 6 months	≤ 1 year	≤ 6 months	≤ 1 year	≤ 6 months	≤ 1 year
	(1)	(2)	(3)	(4)	(5)	(6)
Child	-0.029*	-0.005	0.010	0.017	-0.062**	-0.008
	(0.02)	(0.01)	(0.03)	(0.02)	(0.03)	(0.01)
Ind controls	Yes	Yes	Yes	Yes	Yes	Yes
Outcome mean	0.37	0.62	0.11	0.22	0.18	0.43
No. of Obs.	138,018	138,018	138,018	138,018	137,632	125,017

Notes: This table presents the estimates for the effect of the reform of school schedule (adding school time on Wednesday morning) on the hazard of re-employment. We estimate Poisson count models and report the incidence rate ratios minus one, which can be interpreted as semi-elasticities. We control for the individual characteristics listed in Section 3.1. SE in parentheses clustered at the city level. Outcome means are calculated among non-parents before the reform.

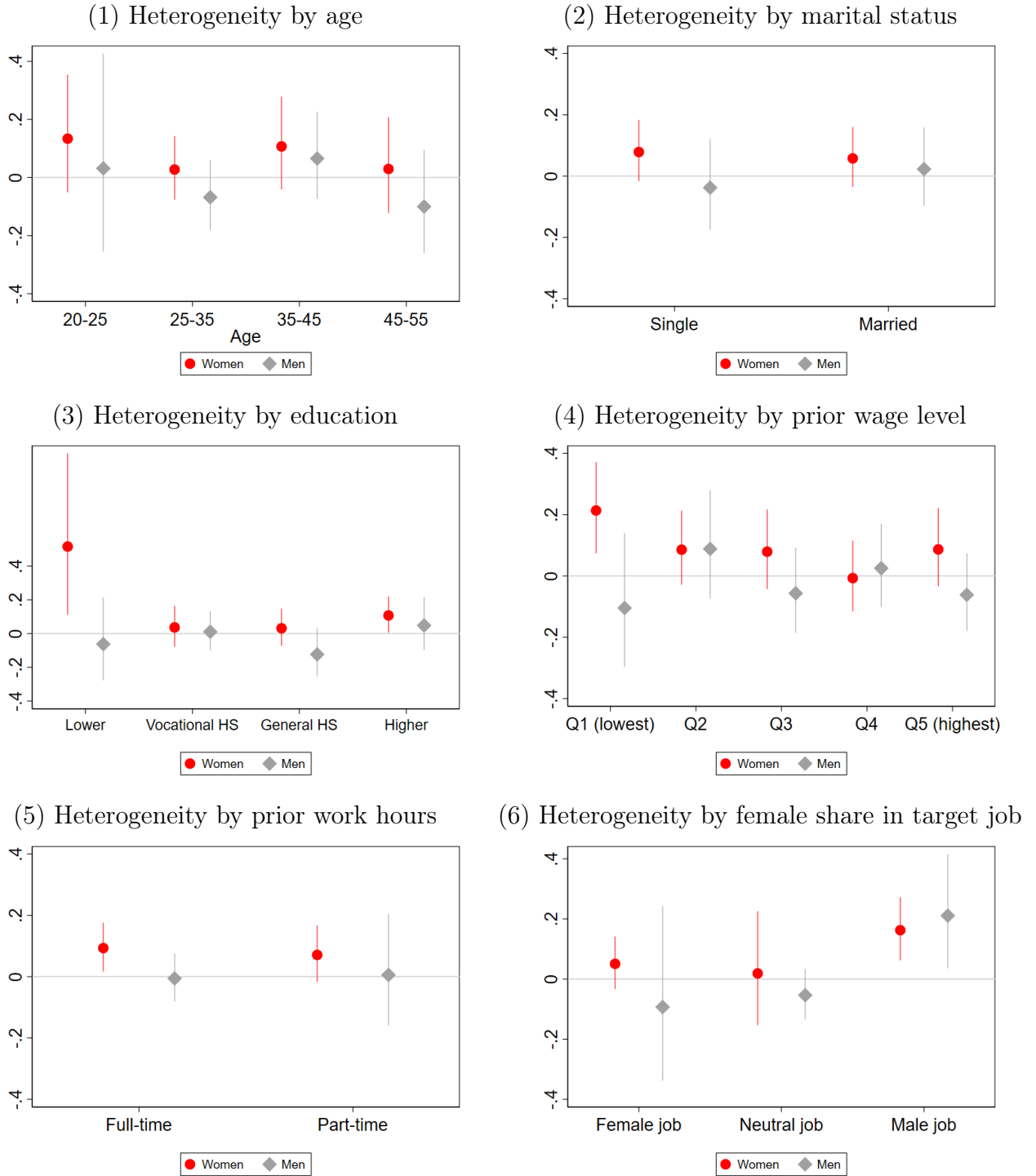
Table B.11: Effects of the 2014 reform and placebo test

A/ Effect of reform in cities which implemented the reform in 2014						
	Women			Men		
	Wednesday	Other days	Any day	Wednesday	Other days	Any day
	(1)	(2)	(3)	(4)	(5)	(6)
ChildXAfterSep2014	0.081** (0.035)	0.025 (0.020)	0.036* (0.020)	-0.015 (0.041)	-0.038 (0.026)	-0.034 (0.024)
Child	-0.181*** (0.023)	-0.132*** (0.016)	-0.141*** (0.015)	-0.023 (0.037)	0.037 (0.026)	0.025 (0.025)
AfterSep2014	Yes	Yes	Yes	Yes	Yes	Yes
Individual controls	Yes	Yes	Yes	Yes	Yes	Yes
Outcome mean	0.257	1.045	1.302	0.205	0.860	1.065
No. of Obs.	150,700	150,700	150,700	105,807	105,807	105,807

B/ Placebo test in cities which implemented the reform in 2013						
	Women			Men		
	Wednesday	Other days	Any day	Wednesday	Other days	Any day
	(1)	(2)	(3)	(4)	(5)	(6)
ChildXAfterSep2014	-0.032 (0.054)	0.045 (0.035)	0.030 (0.034)	0.029 (0.079)	0.048 (0.047)	0.044 (0.045)
Child	-0.121*** (0.043)	-0.134*** (0.026)	-0.131*** (0.026)	-0.108* (0.054)	-0.035 (0.040)	-0.049 (0.037)
AfterSep2014	Yes	Yes	Yes	Yes	Yes	Yes
Individual controls	Yes	Yes	Yes	Yes	Yes	Yes
Outcome mean	0.247	1.052	1.300	0.212	0.837	1.050
No. of Obs.	44,830	44,830	44,830	32,211	32,211	32,211

Notes: This table presents the estimates obtained when estimating an alternative differences-in-differences model than in our main specification (presented in Table B.7): instead of the dummy variable *Reform* indicating that the individual became unemployed after the reform was implemented in her city, we use the dummy *AfterSep2014* indicating that the individual became unemployed after September 2014. This allows us to estimate the effect of the reform when we restrict our sample to the cities which implemented the reform in 2014 (Panel A/), and this provides a placebo test when we restrict our sample to the cities which implemented the reform in 2013 (Panel B/). We control for the individual characteristics listed in Section 3.1. We estimate Poisson count models and report the incidence rate ratios minus one, which can be interpreted as semi-elasticities. SE clustered at the city level in parentheses. Outcome means are calculated among non-parents before September 2014.

Figure B.8: Heterogeneous effect of school schedule reform on applications on Wednesdays



Notes: In this Figure, we analyze the heterogeneity of the effect of the school reform on applications sent on Wednesday, corresponding to the coefficient associated with *ChildXReform* in col (2) and (5) of Table B.7. For each Panel and each gender, we obtain the reported coefficients in a single regression: we estimate the same empirical model as in Table B.7, except that we fully interact *Child*, *ChildXReform* and *Reform* with all the categories of the heterogeneity dimension considered. We successively consider heterogeneity by age (Panel (1)), by marital status (Panel (2)), by diploma level (lower than high school, vocation high school, general high school or diploma from higher education; Panel (3)), by wage level at the prior job (Panel (4)), by hours worked at prior job (Panel (5)) and by proportion of women in the job looked for (highest quartile, middle, lowest quartile; Panel (6)). We present the 95% confidence intervals based on SE clustered at the city level.

Figure B.9: Effect of the 2014 reform on applications sent on Wednesday and placebo test



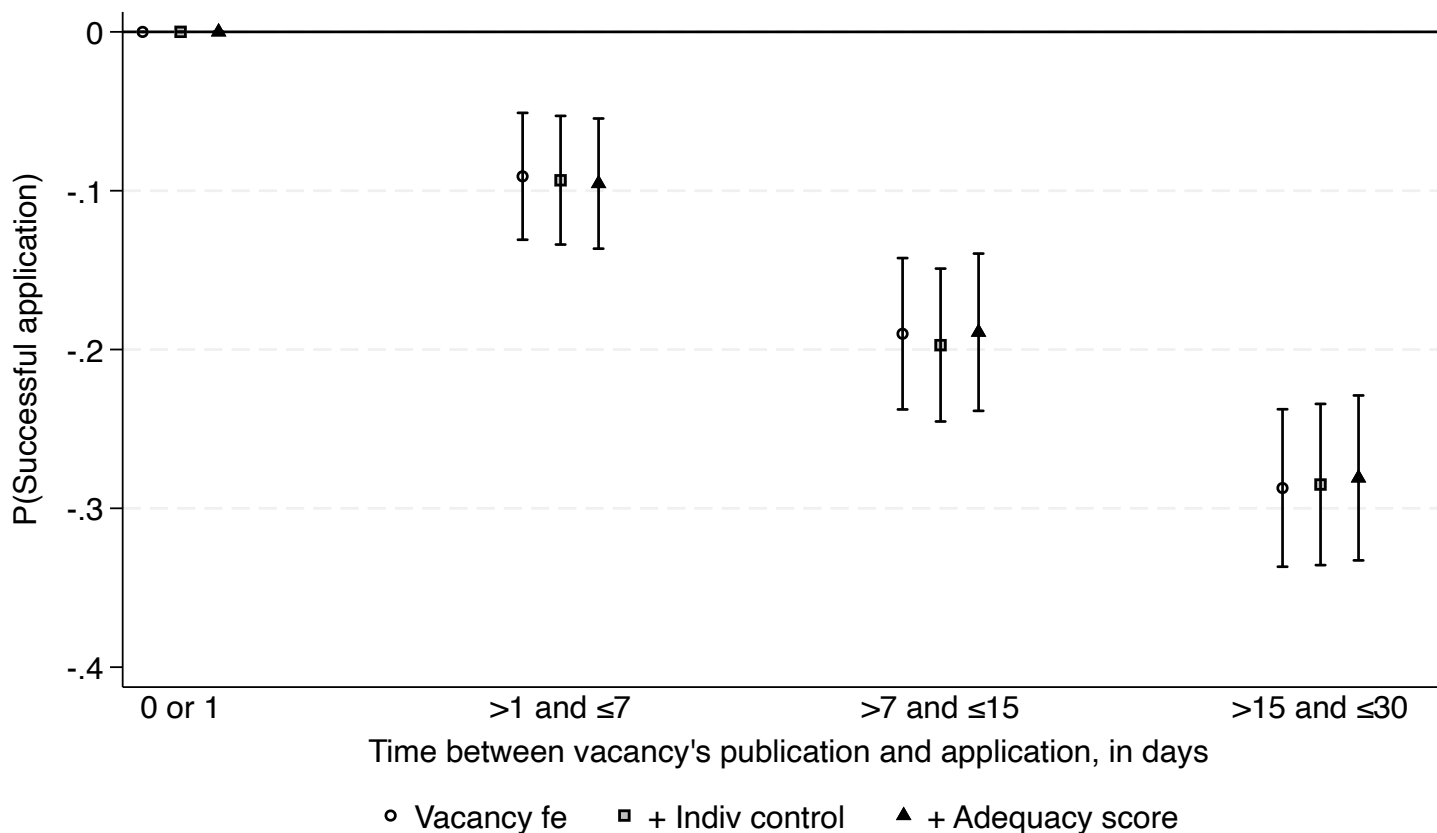
Notes: This Figure presents the estimates obtained in a similar specification as in Table B.11 col (1), except that instead of having one dummy *AfterSep2014*, we include several dummies representing 3-month periods relative to the implementation of the reform in Sept-Nov 2014: $D_\tau = \mathbb{1}[t = \text{SeptNov2014} + \tau]$. We include all 3-month periods covered in our sample, except the last period before the implementation of the 2014 reform (i.e. June-August 2014) which serves as the reference period. We report the coefficients associated with $ChildXD_\tau$. For $\tau \geq 0$, the coefficients allow us to estimate the effect of the reform on the applications sent on Wednesday when we restrict our sample to the cities which implemented the reform in 2014 (Panel A/), and this provides a placebo test when we restrict our sample to the cities which implemented the reform in 2013 (Panel B/). For $\tau < 0$, the coefficients allow us to test the parallel trend assumption when we restrict our sample to the cities which implemented the reform in 2014 (Panel A/). We estimate Poisson count models and report the incidence rate ratios minus one, which can be interpreted as semi-elasticities. We present the 95% confidence intervals based on SE clustered at the city level.

Table B.12: Robustness check: Impact of the school schedule reform on the time allocation of search activities, excluding teachers

	A/ Women			B/ Men		
	Wednesday (1)	Other days (2)	Any day (3)	Wednesday (4)	Other days (5)	Any day (6)
ChildXReform	0.080*** (0.031)	0.022 (0.019)	0.033* (0.018)	-0.011 (0.037)	-0.034 (0.023)	-0.030 (0.022)
Child	-0.187*** (0.022)	-0.129*** (0.015)	-0.141*** (0.014)	-0.039 (0.034)	0.034 (0.023)	0.020 (0.022)
Reform	Yes	Yes	Yes	Yes	Yes	Yes
Individual controls	Yes	Yes	Yes	Yes	Yes	Yes
Outcome mean	0.257	1.048	1.306	0.206	0.861	1.067
No. of Obs.	191,776	191,776	191,776	137,260	137,260	137,260

Notes: This table presents the effect of the reform of school schedule on the rate of applications sent on different days (see empirical model (3)). We estimate the effect separately for women (in Panel A) and men (in Panel B) on various outcomes: In col (1) and (4), we consider the rate of applications sent on Wednesdays. In col (2) and (5), we consider the rate of applications sent on any other day. And in col (3) and (6), we consider the rate of applications sent overall. We estimate Poisson count models and report the incidence rate ratios minus one, which can be interpreted as semi-elasticities. We control for the individual characteristics listed in Section 3.1. SE clustered at the city level in parentheses. Outcome means are calculated among non-parents before the reform.

Figure B.10: Probability that an application leads to a hire, depending on delay between application and vacancy posting times



Notes: In this Figure, we document the decrease in the probability that applicants are hired at the applied-to-firm with the delay between application and vacancy posting times. We keep all applications sent in less than 31 days by individuals in our main study sample. We build 4 categories of delays: 0 day, when the application is sent the day the vacancy was posted or the next, [1,7] days, [7,15] days, and [15,30] days. All three models include vacancy fixed effects to leverage variation in applications within vacancies rather than across vacancies. Model 2 (presented with squares) additionally controls for applicants' characteristics (all individual characteristics listed in Section 3.1 in except for city of residence fixed effects). Model 3 (triangles) also controls for the adequacy score computed by the French Public Employment Services to assess the quality of the applicant-vacancy match. We estimate Poisson count models and report the incidence rate ratios minus one, which can be interpreted as semi-elasticities.

Table B.13: Parenthood gap in probability that applications was sent within a week

Outcome: Dummy for application being sent less than a week after vacancy posting								
	Women, all (1)	Women, below 45 (2)	Men, all (3)	Men, below 45 (4)	Women, all (5)	Women, below 45 (6)	Men, all (7)	Men, below 45 (8)
Child	-0.012** (0.006)	-0.018** (0.007)	0.013 (0.010)	0.009 (0.012)	-0.024*** (0.007)	-0.029*** (0.009)	0.012 (0.013)	0.011 (0.015)
No-SchoolXChild					0.018** (0.008)	0.018** (0.009)	0.001 (0.012)	-0.004 (0.014)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
No-School					Yes	Yes	Yes	Yes
Outcome mean	0.585	0.580	0.515	0.513	0.585	0.580	0.515	0.513
No. of Obs.	203,400	166,954	129,912	104,370	203,400	166,954	129,912	104,370

Notes: This Table presents results from the same specification as in Table 3, but the outcome is a dummy for application being sent less than one week after vacancy posting, rather than a dummy for the application being sent less than two days after vacancy posting. We estimate Poisson count models and report the incidence rate ratios minus one, which can be interpreted as semi-elasticities.

Table B.14: Parenthood gap in characteristics of applications sent at different times, estimated in OLS regressions

Outcome: Dummy for application being sent less than two days after vacancy posting								
	Women, all (1)	Women, below 45 (2)	Men, all (3)	Men, below 45 (4)	Women, all (5)	Women, below 45 (6)	Men, all (7)	Men, below 45 (8)
Child	-0.012*** (0.004)	-0.013*** (0.005)	0.001 (0.005)	0.001 (0.006)	-0.020*** (0.005)	-0.022*** (0.006)	-0.006 (0.006)	-0.005 (0.008)
No-SchoolXChild					0.012** (0.005)	0.013** (0.005)	0.010 (0.006)	0.010 (0.007)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
No-School					Yes	Yes	Yes	Yes
Outcome mean	0.393	0.389	0.330	0.329	0.393	0.389	0.330	0.329
No. of Obs.	203,400	166,954	129,912	104,370	203,400	166,954	129,912	104,370
Outcome: Dummy for application leading to a hire								
	Women, all (1)	Women, below 45 (2)	Men, all (3)	Men, below 45 (4)	Women, all (5)	Women, below 45 (6)	Men, all (7)	Men, below 45 (8)
Child	-0.002 (0.001)	-0.003** (0.001)	0.000 (0.001)	-0.001 (0.002)	-0.003** (0.001)	-0.004** (0.002)	0.000 (0.002)	-0.000 (0.002)
No-SchoolXChild					0.003* (0.001)	0.002 (0.002)	0.000 (0.002)	-0.001 (0.002)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
No-School					Yes	Yes	Yes	Yes
Outcome mean	0.024	0.025	0.024	0.024	0.024	0.025	0.024	0.024
No. of Obs.	203,400	166,954	129,912	104,370	203,400	166,954	129,912	104,370

Notes: This Table presents results from the same specification as in Table 3, but estimated using OLS regressions instead of Poisson regressions.

Table B.15: Parenthood gap in application delays, estimated in OLS regressions

Outcome: ln(Number of days since vacancy was posted)								
	Women, all (1)	Women, below 45 (2)	Men, all (3)	Men, below 45 (4)	Women, all (5)	Women, below 45 (6)	Men, all (7)	Men, below 45 (8)
Child	0.031*** (0.011)	0.042*** (0.013)	-0.007 (0.016)	-0.002 (0.019)	0.054*** (0.013)	0.067*** (0.015)	0.000 (0.019)	0.003 (0.023)
No-SchoolXChild					-0.037*** (0.013)	-0.040*** (0.014)	-0.011 (0.018)	-0.007 (0.021)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
No-School					Yes	Yes	Yes	Yes
Outcome mean (no log)	11.477	11.605	15.122	15.154	11.477	11.605	15.122	15.154
No. of Obs.	203,400	166,954	129,912	104,370	203,400	166,954	129,912	104,370

Notes: This Table presents results from the same specification as in Table 3, but estimated using OLS regressions instead of Poisson regressions. We consider a different outcome: the logged number of days between the vacancy was posted and the application was sent.

Table B.16: Robustness check: Parenthood gap in characteristics of applications sent at different times, using re-weighted sample

A/ Applications sent by all unemployed								
	Sent just after posting		Followed by hire		Sent just after posting		Followed by hire	
	Women	Men	Women	Men	Women	Men	Women	Men
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Child	-0.046***	0.003	-0.121**	0.000	-0.070***	-0.015	-0.228***	-0.004
	(0.013)	(0.015)	(0.054)	(0.060)	(0.016)	(0.018)	(0.063)	(0.079)
No-SchoolXChild					0.040**	0.030	0.239**	0.007
					(0.020)	(0.018)	(0.119)	(0.084)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
No-School					Yes	Yes	Yes	Yes
Outcome mean	0.367	0.330	0.025	0.024	0.367	0.330	0.025	0.024
No. of Obs.	203,400	129,912	203,400	129,912	203,400	129,912	203,400	129,912
B/ Applications sent by all unemployed below age 45								
	Sent just after posting		Followed by hire		Sent just after posting		Followed by hire	
	Women	Men	Women	Men	Women	Men	Women	Men
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Child	-0.036**	0.006	-0.150**	-0.037	-0.061***	-0.012	-0.269***	-0.023
	(0.015)	(0.018)	(0.064)	(0.068)	(0.019)	(0.022)	(0.071)	(0.090)
No-SchoolXChild					0.040*	0.029	0.283**	-0.023
					(0.023)	(0.022)	(0.140)	(0.094)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
No-School					Yes	Yes	Yes	Yes
Outcome mean	0.365	0.329	0.025	0.024	0.365	0.329	0.025	0.024
No. of Obs.	166,954	104,370	166,954	104,370	166,954	104,370	166,954	104,370

Notes: This Table presents parenthood gaps in the probability that an application was sent less than two days after the vacancy was posted, and that an application leads to a hire. This Table presents the same results as in Table 3, except that the sample of women is re-weighted to make it more similar to the sample of men. We use the same weights as for Table B.6.

Table B.17: Motherhood gap in characteristics of applications sent at on Wednesdays versus other days, before and after the school schedule reform

	Sent just after posting		Followed by hire	
	Before (1)	After (2)	Before (3)	After (4)
Child	-0.105*** (0.029)	-0.029 (0.019)	-0.223 (0.153)	-0.154 (0.102)
WednesdayXChild	0.089** (0.041)	0.028 (0.024)	0.851** (0.572)	-0.065 (0.164)
Controls	Yes	Yes	Yes	Yes
Wednesday	Yes	Yes	Yes	Yes
Outcome mean	0.446	0.457	0.024	0.024
No. of Obs.	19,825	42,882	19,825	42,882

Notes: This table presents the motherhood gaps in the probability that application was sent the day when the vacancy was posted, and that it was followed by a hire. They are obtained in the sample of *applications* from female unemployed workers in our main study sample, that are sent on weekdays at typical school time excluding Thursdays. We control for the individual characteristics listed in Section 3.1. We estimate Poisson count models and report the incidence rate ratios minus one, which can be interpreted as semi-elasticities. Robust SE clustered at the individual level in parentheses. Outcome means are calculated among non-parents.