Labour market concentration and gender gaps

Johanne Bacheron Sylvie Blasco Eva Moreno - Galbis Jeremy Tanguy

Abstract

This paper analyses how labour market concentration affects gender inequalities in wages, hirings, and working conditions. While theoretical models predict that firms facing low labour market competition will be able to extract a monopsony rent from workers who have lower geographical mobility, very specific skills, or specific working conditions' requirements, there is limited empirical evidence on this topic. Using French matched employer-employee data together with data on working conditions and a new definition of commuting zones that takes into account gender differences in mobility, we find that concentration in a given commuting zone and occupation increases the gender wage gap and decreases the share of women among new hires. Concentration is also associated with less job security on average and increases the gender gap in terms of job flexibility. Women with children and women of childbearing age are particularly affected by the increase in firms' monopsonistic power.

Keywords: geographical mobility; gender gap; working conditions

JEL: J31; J42; L13

1 Introduction

Gender gap in the labour market has attracted much attention for decades (Bertrand, 2011; Blau and Kahn, 2017; Goldin, 2014; Olivetti and Petrongolo, 2016) and is still of great concern. In developed countries, the convergence process between men's and women's labour market outcomes has slowed in recent years, keeping gender disparities in wages and job characteristics at a significant level.[1] Part of this gender gap remains unexplained despite the extensive research that highlights the role played by occupational and sectoral segregation, differences in working time and unbalanced sharing of housework and childcare between men and women. This paper builds on evidence of gender differences in job search behaviour, commute preferences and willingness-to-pay for certain job attributes (Gimenez-Nadal and Molina, 2016; Le Barbanchon et al., 2021; Maestas et al., 2023; Mas and Pallais, 2017; Petrongolo and Ronchi, 2020; Wiswall and Zafar, 2017) to investigate the contribution of monopsony power, a possible factor that has not been much or fully explored yet to explain gender gaps in wage but also in hirings and working conditions.

In a strict sense, monopsony on the labour market describes a market structure with a single employer facing many workers (see Robinson, 1969), giving the firm wage-setting power. However, firms may be facing an upward sloping labour supply curve in other contexts. Monopsony power may originate from some (not necessary full) employer concentration. It may also result from frictions on the labour market, or from workers' preferences for certain characteristics of the employer or job (Card et al., 2018; Manning, 2003; Robinson, 1933)), which de facto reduces the number of employers actually competing with the firm. As the number of competitors in its operating market falls, the firm increases its bargaining position when negotiating wages with potential employees, allowing the firm to extract rents from the employment relationship. This can translate not only into lower wages but also into worse non-pecuniary working conditions.

Workers with less employment opportunities or with stronger preferences for a specific set of job attributes are expected to be more exposed to monopsony power than others. As already posited by Robinson (1933), women are likely to be such vulnerable workers. The literature indeed shows that women are less geographically mobile than men: when employed, they have on average shorter commutes and are more likely to quit their job over a long commute, and when looking for a job, they have on average shorter maximum acceptable commutes and are willing to accept lower wages in exchange for a reduced commuting time (Crane, 2007; Gimenez-Nadal and Molina, 2016; Le Barbanchon et al., 2021; Petrongolo and Ronchi, 2020). Childcare and house production are important determinants of these differences (Gimenez-Nadal and Molina, 2016). Women then implicitly have a smaller local labour market than men, offering them fewer outside employment opportunities and giving firms a stronger monopsony power over them.

A growing body of literature shows that monopsony power is pervasive and has significant impact

[1] In the EU27, the gender pay gap was of 13% in 2020, only 2.8pp lower than in 2010.

on wage inequalities. But the evidence is mixed when it comes to the effect of monopsony on women's wages and the gender wage gap. The strand of literature that relies on estimating the own-firm labour supply elasticity to measure monopsony power overall supports the hypothesis that monopsony on the labour market contributes to the gender wage gap: separation elasticities are estimated to be significantly lower for women than for men in a most papers (Hirsch et al., 2010; Manning, 2011; Sharma, 2023; Sokolova and Sorensen, 2021; Webber, 2016), though not all (Caldwell and Oehlsen, 2022; Card et al., 2018). On the contrary, studies that compare local labour market concentration to evaluate the effect of monopsony show limited heterogeneity of effects with respect to gender, and even a negative impact of concentration on the gender wage gap (Rinz, 2022).

One limitation of the latter literature on local labour markets is the definition of the workforce as a homogeneous entity. The literature generally defines local labour markets as commuting zones or the intersection between the commuting zone and the industry/occupation. Indeed, it has been shown that job search behaviour is very local, often within the commuting zone, and the number of applications drops sharply with the distance (Manning and Petrongolo, 2017; Marinescu and Rathelot, 2018). However, this definition implicitly assumes that all workers residing in that local area have access to all the jobs proposed in that market, and have homogeneous preferences concerning both wage and non-wage characteristics of the job, such as geographical mobility.[2] The aforementioned evidence that women are less geographically mobile than men calls into question this assumption of a homogeneous workforce.

We take these gender differences in mobility and in labour market size into account by defining gender-specific commuting zones. For this we use the algorithm used by the French National Institute of Statistics and Economic Studies (INSEE) to define the most recent labour market areas in France and apply it on census data on women's and men's commuting patterns. Doing so, we have a more accurate measure of concentration for each gender and are able to assess the differential effects of concentration on men's and women's wages, working conditions, and hirings. With a same level of concentration, women may still face lower wages or worse working conditions due to firms being more selective in presence of asymmetric information on the labour market. Employers may prefer workers with more work experience (Bassanini et al., 2023) or, for a same level of experience, they may discriminate against women because they see them as less committed to work due to household-related responsibilities. This can result in hiring discrimination (Becker et al., 2019), and lower wages (Xiao, 2023), which may disproportionately impact women with children or women of childbearing age. We examine the role of parental status among the mechanisms driving our results, by creating commuting zones that depend on gender and parental status.

[2] Bhaskar and To (1999) develop a model of monopsonistic competition in which workers have heterogeneous preferences over some non-wage characteristics of potential jobs. In their particular model this preference is over a measure of distance to the job (closer is better). Workers facing equal wage offers accept the closer offer.

In a first stage, we exploit longitudinal data on a representative sample of French workers (*Panel Tous Salariés - Echantillon Démographique Permanent*) to compare the geographical mobility of men and women, and find, similar to existing studies (Le Barbanchon et al., 2021), that women commute significantly less than men, in particular when they have children. We then compute gender-specific commuting zones and show that those for women are smaller. Next, we exploit French exhaustive administrative linked employer-employee data (*Base Tous Salariés*) to define local labour markets at the intersection between gender-specific commuting zones and occupations, and compute the Herfindahl-Hirschman Index (HHI) by local labour market. We find that women are exposed to higher levels of concentration than men. We also show that concentration has a negative effect on wages on average, thus mechanically affecting women more than men.

In a second stage, we estimate the differential effect of concentration by gender. We control for establishment-level productivity and product market concentration through the inclusion of establishment-by-time fixed effects. To circumvent endogeneity issues, we instrument the HHI in each occupation-commuting zone using the employment-weighted average HHI within the same occupation across other commuting zones. We find that concentration negatively affects women's wages 30% more than men's wages using IV, and twice as much using OLS. Women thus face both higher levels of concentration and a stronger effect of concentration, which contribute to increase the gender wage gap. Moreover, we test whether labour market concentration affects hiring strategies in a context where firms are forced to adjust wages, for example due a high minimum wage like in France. We indeed show that an increase in labour market concentration decreases the share of women among new employees, and in particular that of young women.

In a third stage, we complement the literature by examining whether the lower geographical mobility of women translates, in addition to relative lower wages, into worse non-pecuniary working conditions. Using the French Working Conditions Survey (WCS), we define a range of indicators of non-pecuniary working conditions. We reproduce the previous analysis using these working conditions indicators as dependent variables. In line with Bassanini et al. (2023), we find that higher levels of concentration are associated with lower levels of job security on average. We further show that the gender gap in job flexibility increases with concentration, while the gap in psychological safety narrows. We find no evidence that other working conditions are affected by concentration in the local labour market.

Our paper contributes to an emerging literature analysing the consequences of labour market concentration on labour market outcomes (wages, employment, hirings).[3] As mentioned above,

[3]The literature has analysed other impacts of labour market concentration in the economy. Based on US data, Autor et al. (2020) and Barkai (2020) find a decline in labour shares driven by the increased concentration of the labour market with the emergence of superstar firms. Exploiting firm-level data for the US economy since 1955, De Loecker et al. (2020) document the evolution of market power, markups and profitability. They estimate that

there are two streams in the monopsony literature, each one adopting an alternative approach and relying on different mechanisms, but both being actually complementary.

The first stream of monopsony literature focuses on the elasticity of labour supply to the individual firm and considers particular labour markets (*i.e.* teachers, nurses, retail workers, etc.). When faced to own-elastic labour supply, firms need to offer higher wages to retain workers, but when faced with low labour supply elasticities, firms can exploit their monopsony power and extract rents by paying workers low wages (below their marginal productivity) without losing their applicants or employees to competing employers. This literature suggests considerable monopsony power, with very small estimates of labour supply elasticity in a variety of settings.[4] It estimates lower labour supply elasticities for women than for men, making monopsony power a source of the gender wage gap, though the magnitude of monopsony's contribution to the gender wage gap varies across studies (Hirsch and Janhn, 2015; Hirsch et al., 2010; Ransom and Oaxaca, 2010; Sharma, 2023; Webber, 2016).[5]

Our paper relates to the more recent second stream of monopsony literature, which does not focus on specific labour markets, but exploits variations in market concentration across local, sectoral or occupational labour markets, thereby providing a better view of the extent of labour market power and its impact on wage distribution. The implicit idea here is that workers do not engage in geographically wide-ranging job searches (as shown by Manning and Petrongolo (2017); Marinescu and Rathelot (2018)). They are therefore unable to push firms into competition with competitors located outside the local labour market when negotiating their wages. Firms can then pay lower wages when there are few competing firms in the local labour market. This series of papers also reveals that monopsony on the labour market lowers average earnings in the US (Azar et al., 2022; Benmelech et al., 2022; Rinz, 2022) and in European countries, including France (Arquie and Bertin, 2023; Bassanini et al., 2023, 2024; Marinescu et al., 2021; Martins and Melo, 2024). Estimated elasticities of wages to local labour market concentration all range between -0.01 and -0.04. It further shows that labour market concentration increases wage inequality, but it provides very limited evidence on gender differences in exposure or response to this concentration. Only Bassanini et al. (2024) and Rinz (2022) examine the heterogeneity of effects with respect to gender,

average markups start to rise in 1980 from 21% above marginal cost to 61% now. The average profit rate increased from 1% to 8%. Moreover, they find a reallocation of market share from low-margin to high-margin firms.

[4] 1.3 to 3.8. for nurses assigned to individual hospitals (Sullivan, 1989), 0.1 for nurses in US Veterans Administration hospitals (Staiger et al., 2010), and 1.0 to 1.9 for teachers in individual schools in Norway (Falch, 2010).

[5] Ransom and Oaxaca (2010) estimate a labour supply elasticity of teachers in public school districts in Missouri of about 3.7, suggesting a gender gap of 8%. Using US employer-employee data, Webber (2016) estimates that the labour supply elasticities are 1.09 and 0.94 for men and women, respectively, leading to 3.3% lower earnings for women. Using survival analysis and a large linked employer-employee dataset for Germany, Hirsch et al. (2010) estimate that at least one third of the gender pay gap is explained by gender differences in labour supply. Finally, using Brazilian data, Sharma (2023) estimates a 18pp gender gap due to monopsony.

finding respectively no significant difference between men or women and a decline in the gender earnings gap as concentration increases – which is not consistent with results from the own-firm labour supply literature nor with the theoretical predictions of the monopsony literature.

The contribution of our paper to this second stream of literature is twofold. First, we focus on heterogeneous effects of concentration with respect to gender and explicitly take into account differences in local labour markets between women and men, particularly due to lower geographical mobility of women, by computing gender-specific commuting zones and then gender-specific local labour markets (*i.e.* at the intersection between these commuting zones and occupations).[6] This allows us to take into account that, despite identical observable characteristics and location, a woman and a man are not exposed to the same degree of labour market concentration. When considering identical local labour markets for women and men, this difference is ignored and therefore partly captured in the estimated effect of concentration. Neutralizing this difference when defining local labour markets allows us to assess the true impact of labour market concentration on the gender wage gap. Our paper provides in this way a potential factor explaining the difference in the size of the gender gap estimated by the two existing streams of literature. While the stream focusing on the elasticity of labour supply to the individual firm finds a non-negligible size of the gender gap, the second stream of literature exploiting the concentration of local labour markets finds no impact or a small impact. We believe this is due to the implicit hypothesis of a homogenous workforce made by the second stream of literature.

Second, in contrast with most existing literature, we study the relationship between monopsony power and two additional outcomes: the gender gaps in hiring and (non-pecuniary) working conditions. To our knowledge, only Bassanini et al. (2024), Qiu and Sojourner (2023) and Meiselbach et al. (2022) focus on the impact of labour market concentration on non-wage attributes. Bassanini et al. (2024) find that higher concentration negatively affects job security, while the other two papers find a negative effect of concentration on employer-provided health in the U.S. Here we consider a wider range of job attributes.

The paper is organised as follows. Databases, variables and descriptive statistics are presented in Section 2. The econometric strategy is described in Section 3. Section 4 analyses the impact of market concentration on the gender gap in wages, working conditions and hirings. Section 6 studies the economic mechanisms behind the results. Section 7 concludes.

[6] Using German data, Caldwell and Danieli (2024) find that differences in outside options explain 20% of the gender earnings gap.

2 Data

2.1 Datasets

We combine a wide variety of datasets.[7] First, we use French exhaustive administrative linked employer-employee data (*Base Tous Salariés - Fichier Postes*) between 1995 and 2019. It provides us with individual level data on workplace location, wages, hours worked, occupation, industry, gender, and age. For multi-establishment firms, the data provides establishment identifier and location, which allows us to distinguish between workers employed in different establishments of the same firm. This administrative dataset covers all French private and public sector workers, however the worker identifier changes every year. It is thus an exhaustive repeated cross-section of workers that allows us to identify individual workers and their primary source of income (*i.e.* the job providing them with the most income during a given year). We use this dataset to measure the level of concentration by local labour market, *i.e.* by commuting zone and occupation.

We also use the longitudinal dimension of this data for a representative sample of French workers, coupled with data from population census (*Panel Tous Salariés - Echantillon Démographique Permanent*). This sample is based on the date of birth and covers 4% of the working population. As it is not exhaustive, this dataset cannot be used to construct concentration indices. However, its longitudinal dimension allows us to include individual fixed effects when studying the relationship between labour market concentration and wages. The census part of this dataset allows us to exploit information about the individuals' children (*e.g.* number, age).

To construct the gendered commuting zones, we use data from the 2019 census data – professional mobility detail file (*Recensement de la population 2019, fichier détail - Mobilités professionnelles*), provided by INSEE. This dataset contains information on individuals' socio-demographics characteristics, and on their municipality of residence and their municipality of work. This allows us to distinguish between men's and women's commuting patterns, but also between parents and non-parents, which we will use to study the mechanisms behind our findings.

We also use a merge between a representative sample of the records of the public employment agency and the employer-employee panel data (*FH-DADS*), that provides information on the characteristics of job-seekers, in particular their reservation wage, their maximum commuting distance and the type of jobs they are looking for. At the beginning of each unemployment spell, when they register to the unemployment agency (*Pôle Emploi*), job-seekers must indicate the minimum gross wage they are willing to work for, and the maximum distance they are willing to commute to work each day (one way). This allows us to illustrate how the willingness to commute differs between unemployed men and women. The reservation wage can be reported on an hourly,

[7] While they are not freely accessible, any researcher can request access to them through the Secure Data Access Centre (CASD).

daily, or annual basis, and we convert it to a monthly reservation wage. The maximum commuting accepted can be expressed in minutes or kilometers. When provided in minutes, we convert it to kilometers under the assumption of an average speed of 35 kilometers per hour.

Lastly, we use the French Working Conditions Survey 2013, 2016, 2019 to study the link between concentration and the gender gap in working conditions. This survey aims to obtain a concrete description of work, its organisation and its conditions from various angles: schedules, work rhythms, physical efforts or risks incurred, hardship, work organisation, safety, cooperation, conflicts, etc. The survey has been conducted for the past 40 years: every seven years until 2005 and every three years since 2013, and allows us to analyse the evolution of working conditions.

2.2 Sample selection

We focus on the period 2009-2019, during which occupations are consistently defined. We only keep private sector employees and, in line with Marinescu et al. (2021), we exclude state-sponsored workers, apprentices, interns, workers in non-governmental organisations, the art industry, museums, sport clubs, agriculture, unions and at home. We consider individuals above 23 years old, so as to avoid student jobs, and below 62 years old, which corresponds to the average retirement age in France. Because France has a binding minimum wage (and compliance is very high), we discard for every year the 2% lowest wages and, to avoid upward outliers, we also discard the 2% highest wages.[8] Since part-time employment is more common among women, we cannot focus exclusively on full-time workers, as this would lead to selection problem in the sample of women. To avoid this problem, we focus on hourly wages.

In line with Arquie and Bertin (2023), if a firm owns several establishments in the same labour market, we consider that the jobs of all these establishments belong to one and unique entity, which we consider as a unique employer. Employees of all establishments owned by the same firm within the same labour market are therefore considered as being employed by the same entity. We keep only firms with at least two employees in a given local labour market as firms with only one employee might be very specific ones.

We define local labour markets as the intersection of commuting zones and occupations. As remarked in Bassanini et al. (2023), employees change jobs across industry borders and workers in different occupations within a given industry do not compete for the same jobs. Therefore, local labour markets should not be considered at the intersection of commuting zones and sectors. In addition, a definition of local labour markets by commuting zone and sector does not allow the inclusion of plant-by-time fixed effects to control for productivity changes. Indeed, since a given plant operates in one single sector and geographical area, these fixed effects would be collinear to

[8] Arquie and Bertin (2023) remove observations whose log annualized real earnings are more than 5 standard deviations away from a predicted wage computed using a linear model including socio-demographic controls. This procedure leads them to exclude between 3% and 5% of all observations each year.

any measure of labour market concentration defined with respect to a sector in the geographical area.

2.3 Variables

2.3.1 Gender-specific commuting zones

Due to the gendered division of responsibilities within households, women typically experience shorter commute times than men and are often willing to accept lower wages for jobs located closer to where they live. One of the contributions of our paper is to take into account these differences in mobility between women and men by constructing gender-specific commuting zones (or labour market areas) and then computing concentration measures specific to male and female labour markets.

In order to construct these gender-specific commuting zones, we exploit the algorithm used by INSEE to define the 2020 labour market areas. The algorithm LabourMarketAreas (R package) has been developed by Eurostat. It was initially presented in Coombes and Bond (2008) and is an evolution of the classical methodology of the "Travel-To-Work Areas" (TTWA), defined in Coombes et al. (1986). These labour market areas (LMA) are geographical areas where most of the individuals work and live, and where firms can expect to find the main part of the workforce needed to occupy the available jobs. Each LMA must have minimum characteristics in terms of size and self-containment, *i.e.* the ratio between the number of workers who live and work in the area and the number of workers living in the area (supply side self-containment) or the number of workers working in the area (demand side self-containment).

The algorithm starts by checking if each municipality has the right characteristics to be considered a LMA. At each iteration, municipalities are aggregated or disaggregated and attached to other clusters, depending on if the conditions of the LMA are met or not. This algorithm led in France to the definition of 306 different LMAs in 2020. More details about the algorithm and the definition of gender-specific commuting zones can be found in Appendix A. We apply this algorithm separately on women's and men's commuting patterns using the 2019 census data, and distinguish also between parents and non-parents in a second stage.

2.3.2 Definition of the labour market Herfindahl-Hirschman Index (HHI)

Labour market concentration is measured through the employment Herfindahl-Hirschman Index (HHI). The HHI is defined as the sum of the shares of employment in a given market. We have defined each local labour market at the intersection of a 4-digit occupation and a gender-specific commuting zone. A firm's f labour market share in occupation o and commuting zone c in year t

will be equal to:

$$s^e_{o,c,f,t} = \frac{N_{o,c,f,t}}{\sum_f N_{o,c,f,t}} \tag{1}$$

where $N_{o,c,f,t}$ represents the number of workers employed by firm f in occupation o, commuting zone c in year t. The employment-based HHI in the corresponding local labour market defined by occupation o and commuting zone c in year t is then:

$$HHI^e_{o,c,t} = \sum_f (s^e_{o,c,f,t})^2 \times 100 \tag{2}$$

By definition the HHI is always between 0 and 100. When it is equal to 100, that means that a single employer employs all workers in the labour market. A HHI between 15 and 25 is indicative of a moderately concentrated market and above 25 of a highly concentrated market (see guidelines of the American Department of Justice and Federal Trade Commission).

An employment-based HHI is a reasonable approximation of the labour market concentration index that is relevant for wage determination in a stationary search and matching model with granular search, where concentration affects wages by changing workers' outside options (see Jarosch et al., 2024). In a non-stationary environment, downsizing of firms may have a positive share in the stock of employment in a local labour market, whereas their hirings are zero, so that they do not contribute to creating outside options for workers in that labour market. This argument is used by Bassanini et al. (2023), Bassanini et al. (2024) or Marinescu et al. (2021) to justify using new hires to compute the HHI index. In any case, since firm dynamics is likely to affect almost symmetrically both men and women, our results should not be strongly modified by focusing on employment or new hires when computing the HHI.[9]

2.3.3 Working conditions

We define 11 non-pecuniary working conditions indicators using variables from the Working Conditions Surveys. The composition of each indicator is detailed in Table 1. The value of each indicator is obtained by adding its components. As for variables composing each indicator, the higher the value of the indicator, the better the working conditions. For the regressions we use the normalised version of each indicator that takes values between 0 and 1. Lastly, we construct a Non-Pecuniary Index (NPI) that is equal to the average of these eleven indicators (normalised).

2.4 Descriptive statistics

Tables 2 and 3 show descriptive statistics on labour market outcomes and working conditions respectively. We can see that labour markets are not very concentrated in France, with an average

[9]In the presence of downsizing/upsizing firms in a local market, both men and women will see their outside employment opportunities decrease/increase.

Table 1: Non-pecuniary working conditions indicators

Indicator	Variable	Type
(*i*) Learning new things	Learning new skills on the job	Dummy
	Access to sufficient and appropriate training	Dummy
	Prospects for career advancement	Discrete
	Opportunities for professional skill development	Discrete
(*ii*) Autonomy	Ability to choose methods to accomplish work objectives	Dummy
	Adherence to orders	Discrete
	Influence of external client demands on work rhythm	Discrete
	Independence from colleagues' work	Dummy
(*iii*) Support	Support from colleagues	Dummy
	Support from manager	Dummy
	Opportunity to cooperate with other	Dummy
(*iv*) *Stability*	Unlimited duration contract	Dummy
	Weak probability of loosing one's job in the next six months	Dummy
	Highest seniority (normalized between 0 and 1 across individuals)	Continuous
(*v*) Ergonomics	Not working in painful positions	Dummy
	Not standing up a lot	Dummy
	Not walking a lot	Dummy
	Not moving loads	Dummy
	Not performing painful or tiring movements	Dummy
	Not repeating continuously the same series of gestures or operation	Dummy
(*vi*) Physical safety	Exposure to vibrations	Discrete
	Exposure to smoke	Discrete
	Exposure to chemical products	Discrete
	Exposure to traffic accidents	Discrete
(*vii*) Psychological safety	Doing things one disapproves of	Discrete
	Working under pressure all the time	Discrete
	Not experiencing tense situations with clients	Dummy
	Not experiencing tense situations with managers	Dummy
	Not experiencing tense situations with colleagues	Dummy
(*viii*) Scheduling	Not working on the evenings	Dummy
	Not working at night	Dummy
	Not working on Saturdays	Dummy
	Not working on Sundays	Dummy
	Not working early in the morning	Dummy
(*ix*) Work-life balance	Not contacted by colleagues outside of work hours in the last year	Dummy
	Necessity of working overtime	Discrete
	Necessity of bringing work home	Discrete
	Necessity of thinking about work outside of work hours	Discrete
	Work hours are compatible with family and social activities	Discrete
(*x*) Flexibility	Possibility of freely taking a break during the day	Discrete
	No monitoring of working time	Dummy
	Possibility of freely organizing working time	Dummy
	Ability to take easily 1-2 hours off during the day	Dummy
(*xi*) Intensity	Enough time to do the job	Dummy
	Not required to work at high speed	Discrete
	No deadlines	Discrete
	Not required to do an excessive amount of work	Discrete
	Enough time to do the work	Discrete

Notes: All variables, whatever their type, are between 0 and 1. For all variables, the higher the value, the better the working conditions. For 2016, the variable "traffic accidents" is not available. Since all working conditions categories are normalized every year between 0 and 1, the absence of one component in the "Physical safety" indicator for 2016 should not be an issue.

HHI of 13 when taking the individual-level data, while the median HHI is equal to 6, meaning that half of the individuals in the sample face a concentration index that is below 6. This table also shows that unemployed women that are present in the FH-DADS have a monthly reservation wage which is almost 300 euros lower than their male counterparts, and that they are willing to commute on average 7km less.[10] Using the *Panel Tous Salariés-EDP*, we estimate that employed women have an average commuting distance which is 40% lower than men.[11]

We also present in Table B.1 in Appendix the results of a linear regression of the average commuting time of employed individuals by gender and parental status, which is also an important determinant of mobility. We can see that even after controlling for the commuting zone and year, women commute on average 11km less than men. On average, parents commute less than non-parents, and this is true for both genders, but the difference is slightly higher for men. However, adding individual fixed effects shows that men commute on average 0.5km less after the first child, whereas women commute 2km less. Regarding job-seekers (Table B.2 in Appendix), we observe the same phenomenon, with a maximum commuting distance accepted which is lower for women on average, and which decreases with the first child, in particular for women. These results are consistent with the assumption that women are less geographically mobile than men. Based on this descriptive evidence, we will also use the parental status to investigate the mechanisms behind our findings in Section 6.

[10] This trade-off between commuting and wages in the French context has been studied by Le Barbanchon et al. (2021), who find that the differences in the willingness to commute account for 14% of the residual wage gap.

[11] We use the distance between the centroid of the municipality of residence and the centroid of the municipality of work to compute the commuting distance for employed individuals.

Table 2: Summary statistics - labour outcomes

	Min	Max	Median	Mean	SD	N
Panel Tous Salariés - EDP						
HHI	0.107	100	6.079	13.160	18.795	65,061,400
Male	0	1	1	0.560	0.496	6,529,444
Born in France	0	1	1	0.877	0.329	6,529,444
Age	24	61	40	40.811	10.300	6,529,444
Experience	0	49	11	11.628	6.345	6,529,444
Hourly wage	6.594	40.051	11.701	13.585	5.798	6,529,444
Number of children	0	12	0	0.628	0.899	6,529,444
No diploma	0	1	0	0.131	0.337	5,757,641
Lower secondary education	0	1	0	0.376	0.484	5,757,641
Upper secondary education	0	1	0	0.214	0.410	5,757,641
Short-cycle tertiary education	0	1	0	0.161	0.367	5,757,641
University diploma	0	1	0	0.118	0.323	5,757,641
Commuting distance - women	0	417.744	7.866	15.933	36.552	2,742,301
Commuting distance - men	0	541.690	10.478	26.404	61.954	3,502,971
FH-DADS						
Reservation wage - women	0	4983.876	1398.397	1562.490	476.308	499,691
Reservation wage - men	0	6666	1500	1780.376	693.386	541,523
Maximum commuting distance - women	0	200	20	23.037	15.337	467,601
Maximum commuting distance - men	0	200	30	30.328	21.232	495,455

In terms of working conditions, Table 3 illustrates the scores of employed men and women across the 11 indicators and the non-pecuniary index, where higher scores denote better working conditions. We can see that there is only a small difference on average between men's and women's working conditions as defined by our non-pecuniary index. However this masks some underlying differences. Men tend to have greater opportunities for learning new skills, receive more support, experience greater job stability and flexibility, and face fewer psychological risks compared to women. Conversely, women exhibit higher levels of autonomy in their roles, are notably less exposed to physical risks and non-standard working hours. Regarding ergonomics, work-life balance, and job intensity, the two genders tend to score similarly on average.

Table 3: Summary statistics - non pecuniary working conditions

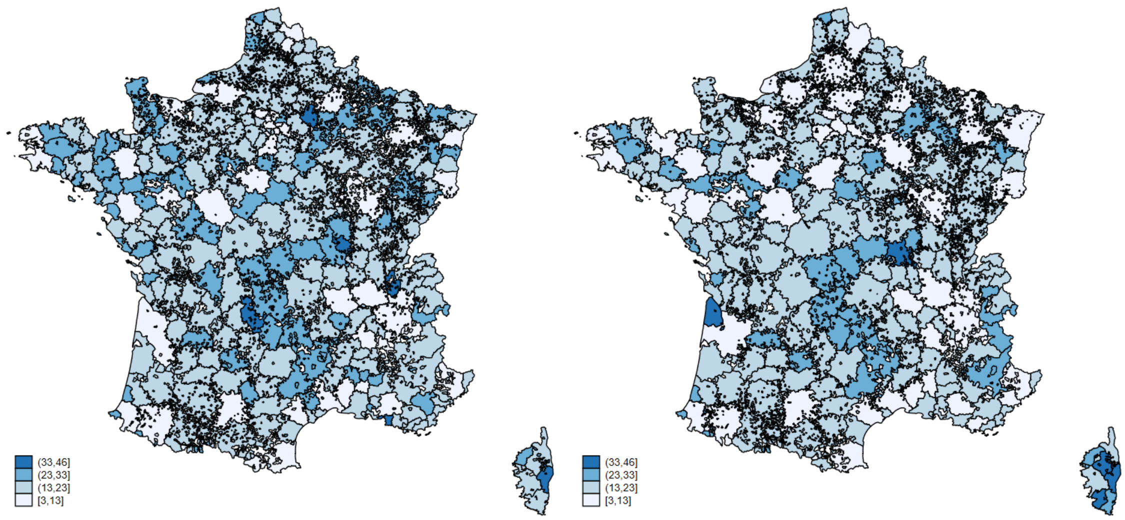
	Women				Men			
	Min	Max	Mean	N	Min	Max	Mean	N
Learning new things	0	1	0.562	19,122	0	1	0.619	15,151
Autonomy	0	1	0.592	20,001	0	1	0.572	16,126
Support	0	1	0.755	20,280	0	1	0.801	16,276
Stability	0	1	0.590	19,979	0	1	0.601	15,902
Ergonomics	0	1	0.589	20,382	0	1	0.579	16,326
Physical safety	0	1	0.819	20,393	0	1	0.62	16,318
Scheduling	0	1	0.781	20,435	0	1	0.750	16,365
Work-life balance	0	1	0.526	19,068	0	1	0.527	14,823
Flexibility	0	1	0.641	19,270	0	1	0.703	15,235
Intensity	0	1	0.615	19,270	0	1	0.622	15,198
Psychological safety	0	1	0.663	19,400	0	1	0.694	15,293
Non-Pecuniary Index	0.165	0.923	0.651	17,319	0.158	0.932	0.646	13,681

Source: Working Conditions Survey. Notes: Survey weights are used.

Since women are less mobile than men, their commuting zones are smaller. Table B.3 in Appendix shows some statistics on the gender-specific commuting zones that we computed. Women's commuting zones are smaller than men's in terms of size and in terms of population, and are less likely to include large cities. In total for Metropolitan France, we estimate that there are 271 different commuting zones for women, and only 217 for men. However, we can see that the density of population is higher for women.

These smaller commuting zones for women do not necessarily mean that they face more labour market concentration. Indeed, in the case where jobs are uniformly distributed on the territory, the size of the commuting zone does not matter. Also, if women tend to locate more in big cities, their smaller commuting zones would not translate into higher levels of concentration because the labour market is less concentrated in urban areas. However, we can see in Figure 1 that concentration varies significantly across areas in France, and that it is higher for women than for men. In Table B.4 in Appendix, we also show that there is a negative relationship between the (log) concentration and the (log) size, population, and density of the commuting zones. Higher levels of concentration can be observed also in low populated areas, particularly along the "empty diagonal" stretching from the North-East to the South-West of the country (Figure 1). A potential endogeneity issue may arise from the fact that low density areas can be both those with high concentration and higher wage gaps. The literature has shown that the gender wage gap decreases with the urban size (Nisic, 2017). Phimister (2005) finds that the urban wage premium is higher for women, and in particular for married or cohabiting women. However, we address this concern in the next section by incorporating a set of fixed effects that should capture these variations.

Figure 1: Labour market concentration by gender-specific commuting zone



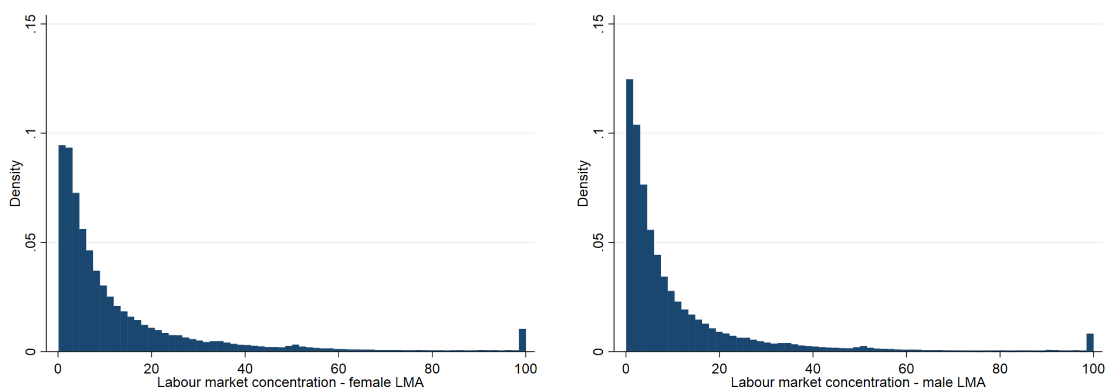
(a) Female-specific commuting zones

(b) Male-specific commuting zones

Source: Panel Tous Salariés - EDP

The difference in labour market concentration between genders can also be seen in Figure 2, which presents the distribution of the HHI for female and male local labour markets. We can see that men are more likely to face levels of concentration very close to zero. The average HHI for women in the sample is equal to 14, whereas for men it is equal to 12, while the median of the index is equal to 6.8 and 5.4, respectively.

Figure 2: Distribution of labour market concentration by gender



(a) HHI for women

(b) HHI for men

Source: Panel Tous Salariés - EDP

Figures B.1, B.2 and B.3 in Appendix show the correlation between the hourly wages or the different working conditions and the labour market concentration, separately by gender and without any controls. Each point on the graph corresponds to a commuting zone. We can see a clear decreasing relationship between the log hourly wages and the HHI for both men and women. Regarding working conditions, we can see a slightly decreasing relationship between the labour market concentration and the non-pecuniary index. The HHI seems to affect negatively the likelihood to feel supported in the workplace for both men and women, decreases the job stability, the psychological safety, and makes work-life balance more difficult for women. For men, more concentration is associated with less physical safety, but this is not the case for women. Lastly, we can see that concentration is associated with an increasing possibility to learn new skills for women. The other working conditions do not seem correlated with labour market concentration.

Finally, one might be concerned about the role of occupational segregation in the level of concentration. As shown in Figure B.4 in Appendix, women are represented in a smaller variety of occupations than men. This figure also shows that in more than 20% of the cases, the share of women within a commuting zone / occupation / year is close or equal to zero, whereas the share of men is close to zero for only 5% of the cases. We can see in Figure B.5 that there is a U-shaped relationship between the share of women in a labour market and concentration, such that the labour markets that are the most segregated are also those with the highest levels of HHI. In any case, our index of concentration is measured at the most detailed occupational level, and we include in our regressions occupational fixed effects. We thus estimate whether the same level of concentration has a greater effect on women than on men. In addition to this differential effect, women are exposed to higher levels of concentration, due to their lower mobility (as discussed earlier). Whether occupational segregation explains the differences in terms of concentration levels is out of the scope of this paper.

3 Econometric Strategy

We use the gender-specific labour market areas and the corresponding HHI that we computed based on women's and men's commuting patterns and estimate:

$$\begin{aligned} Y_{i,f,o,c,t} =& \alpha \log(HHI_{o,c,t}) + \beta \log(HHI_{o,c,t}) * Female_i + \mathbf{X}'_{i,f,o,c,t}\,\gamma \\ &+ \mu_i + \mu_{oc} + \mu_{ft} + \mu_t^M + \mu_t^F + \varepsilon_{i,f,o,c,t} \end{aligned} \tag{3}$$

where $Y_{i,j,o,c,t}$ is the outcome of interest, such as the log hourly wage or a working conditions indicator, for individual i, in establishment f, in occupation o, in commuting zone c, and in year t. The commuting zone here differs between women and men and sometimes overlaps. Therefore, we cannot include gender-specific commuting zone-occupation fixed effects. We try the specification by either including the female commuting zone-occupation or the male commuting zone-occupation fixed effects (μ_{oc}) and make sure that the results do not depend on the geographical area chosen. $\mathbf{X}$ is a vector of individual time-varying controls. μ_{ft} are establishment-by-time fixed effects. In the more demanding specification, we include individual fixed effects (μ_i) and gender-year fixed effects (μ_t^M and μ_t^F). Given the nature of the data and the information available, when studying working conditions we only include commuting zone-occupation and individual fixed effects.

A threat to identification is the existence of time-varying market-specific variables that are correlated with concentration and affect wages and working conditions. For example, a decline in market dynamism is likely to lead to a reduction in the number of jobs and to an outward migration of young workers towards more dynamic labour markets. Moreover, bargained wages are influenced by productivity, labour market tightness, outside employment opportunities and the share of acceptable geographical locations. To take into account these time-varying market-specific variables, we control for establishment-level productivity and product market concentration by including establishment-by-time-fixed effects.

In spite of our efforts to control for observable and unobservable confounders through the introduction of control variables and fixed effects, endogeneity issues remain a concern. More specifically, a biased productivity shock benefiting relatively larger firms could affect both concentration and the growth in the gender wage gap. Typically, if the gender wage gap is larger in large firms, a biased productivity shock pushing small firms out of the market and pushing up the size of large firms will drive an increase in concentration and in the gender wage gap. To circumvent endogeneity issues, we propose an instrumental variable (IV thereafter) strategy similar to that used in Azar et al. (2022), Rinz (2022) and Arquie and Bertin (2023). We instrument the HHI in each local labour market (*i.e.* occupation-commuting zone), using the employment-weighted average HHI within the same occupation across other commuting zones, excluding the one considered. This instrument provides variation in market concentration driven by national-level changes in the occupation, rather than local changes in that particular local labour market. This approach helps to mitigate endogeneity concerns in cases of asymmetric productivity shocks across commuting zones.

The instrument for labour market concentration in occupation o, commuting zone c, in period t equals:

$$HHI_{-c,o,t} = \frac{\sum_v (N_{o,v,t} \cdot HHI_{o,v,t})}{\sum_v N_{o,v,t}} \tag{4}$$

where v represents all commuting zones except c. $N_{o,v,t}$ denotes employment in occupation o, in all commuting zones except c, in period t.

Alternatively, we also instrument the HHI with the average of $\log(1/F)$ in other commuting zones for the same occupation and time period, where F refers to the number of firms in the market.

Log$(1/F)$ is less likely to be endogenous than the first instrument, based on the HHI of other labour markets, because it does not depend on market shares. In line with the first instrument, $\log(1/F)$ provides us with variation in market concentration that is driven by national-level changes in the occupation, and not by changes in that particular local labour market. In particular, $\log(1/F)$ should be independent from productivity shocks in the local labour market, which is the main confounding factor in the baseline OLS regression.

4 Results

4.1 Hourly wages

We first estimate Equation 3 excluding the interaction between HHI and the Female dummy variable to obtain the average effect of concentration on wages. We can see in Table C.1 in Appendix that an increase of 10% in the HHI decreases hourly wages by 0.06 to 0.08% (see Panel B and C with instrumented HHI). Given that women face higher levels of HHI, they are more affected by this negative relationship between concentration and wages. We now investigate whether there is a differential effect of concentration on men's and women's wages by estimating Equation 3.

We first present estimates of the effect of labour market concentration on the gender gap in hourly wages using the OLS method (Table 4), and then the IV approach with the two different instruments (Tables 5 and 6). All columns include control variables at the individual level and establishment-by-year fixed effects. Because male and female commuting zones can overlap, we cannot include gender-specific commuting zone fixed effects. We thus control successively for female commuting zone-occupation fixed effects (see columns (1)-(2)) and male commuting zone-occupation fixed effects (see columns (3)-(4)), and then check that the choice of the geographical area does not affect our results. We then further control for individual and gender-year fixed effects.

We find from Table 4 that a 10% increase in HHI is associated with an average hourly wage lower by 0.013% to 0.016% for men. Our main coefficient of interest, that on the interaction between HHI and the Female dummy variable, is negative, implying a larger negative effect of concentration on the average hourly wage of women. The magnitude of the coefficient suggests that the negative effect of labour market concentration is almost twice as high for women as it is for men.

To deal with potential endogeneity issues, we replicate the estimations using IV. We first instrument the HHI with the employment-weighted average HHI across other commuting zones (see Table 5), and then with the average of $\log(1/F)$ in other commuting zones (see Table 6), F being the number of firms in the market. The results are consistent with what we found with OLS but the magnitude of the coefficients is larger. Indeed, these IV estimates suggest that a 10% increase in the HHI decreases the average hourly wage of men by about 0.06-0.07%. Women's wages are affected even more negatively than men's by such an increase in concentration of around 30-35%. These results are consistent with our hypothesis that the wage penalty is higher for women with the same level of labour market concentration.

These results may be affected by the positive selection of women into employment. As we will see in Section 4.3, labour market concentration not only affects the gender wage gap, but also the gender gap in hiring. In commuting zones with higher concentration, women who are employed might be those with the highest potential wages, because the others do not participate or cannot find a job. Observed hourly wages for women in highly concentrated labour markets would then be biased upwards, in which case the estimated impact of concentration on the gender wage gap would be biased downwards. Our results would thus provide a lower bound of the effect of the HHI on the gender wage gap.

Table 4: Effect of HHI on hourly wages - OLS

	(1)	(2)	(3)	(4)
	Log(wage)	Log(wage)	Log(wage)	Log(wage)
Log(HHI)	-0.00130***	-0.00132***	-0.00161***	-0.00163***
	(0.000364)	(0.000364)	(0.000361)	(0.00036)
Female × Log(HHI)	-0.000956***	-0.000978***	-0.000960***	-0.000986***
	(0.000334)	(0.000334)	(0.000329)	(0.000329)
N	4,074,212	4,074,212	4,078,472	4,078,472
Controls	Yes	Yes	Yes	Yes
Establishment-year FE	Yes	Yes	Yes	Yes
Female CZ × occupation FE	Yes	Yes	No	No
Male CZ × occupation FE	No	No	Yes	Yes
Individual FE	Yes	Yes	Yes	Yes
Gender-year FE	No	Yes	No	Yes

Notes: Standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. The table reports results from a linear regression using the logarithm of hourly wage as a dependent variable. Log(HHI) corresponds to the logarithm of the concentration index computed at the intersection between a commuting zone and an occupation (with the HHI ranging between 0 and 100). Control variables include the number of children, the educational level, the work experience, the age, and a dummy variable indicating whether the individual was born in France. When individual fixed effects are included, we keep only the number of children. Since men and women have different commuting zones which overlap, we first control for female commuting zones-occupation fixed effects in columns (1)-(2), and then for male commuting zones-occupation fixed effects in columns (3)-(4).

Table 5: Effect of HHI on hourly wages - IV HHI instrument

	(1) Log(wage)	(2) Log(wage)	(3) Log(wage)	(4) Log(wage)
Log(HHI)	-0.00582***	-0.00609***	-0.00572***	-0.00597***
	(0.000997)	(0.000997)	(0.000994)	(0.000995)
Female × Log(HHI)	-0.00198***	-0.00194***	-0.00174***	-0.00170***
	(0.000477)	(0.000477)	(0.000473)	(0.000473)
N	4,074,211	4,074,211	4,078,471	4,078,471
F-test	163655.708	163495.738	155476.994	155293.142
Controls	Yes	Yes	Yes	Yes
Establishment-year FE	Yes	Yes	Yes	Yes
Female CZ × occupation FE	Yes	Yes	No	No
Male CZ × occupation FE	No	No	Yes	Yes
Individual FE	Yes	Yes	Yes	Yes
Gender-year FE	No	Yes	No	Yes

Notes: Standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. The table reports results from a linear regression using the logarithm of hourly wage as a dependent variable. Log(HHI) corresponds to the logarithm of the concentration index computed at the intersection between a commuting zone and an occupation (with the HHI ranging between 0 and 100). Control variables include the number of children, the educational level, the work experience, the age, and a dummy variable indicating whether the individual was born in France. When individual fixed effects are included, we keep only the number of children. Since men and women have different commuting zones which overlap, we first control for female commuting zones-occupation fixed effects in columns (1)-(2), and then for male commuting zones-occupation fixed effects in columns (3)-(4).

Table 6: Effect of HHI on hourly wages - IV log(1/F)

	(1) Log(wage)	(2) Log(wage)	(3) Log(wage)	(4) Log(wage)
Log(HHI)	-0.00643***	-0.00699***	-0.00668***	-0.00722***
	(0.00122)	(0.00122)	(0.00121)	(0.00121)
Female × Log(HHI)	-0.00266***	-0.00275***	-0.00236***	-0.00245***
	(0.000528)	(0.000528)	(0.000521)	(0.000521)
N	4,074,211	4,074,211	4,078,471	4,078,471
F-test	107317.175	107089.413	105255.202	105003.792
Controls	Yes	Yes	Yes	Yes
Establishment-year FE	Yes	Yes	Yes	Yes
Female CZ × occupation FE	Yes	Yes	No	No
Male CZ × occupation FE	No	No	Yes	Yes
Individual FE	Yes	Yes	Yes	Yes
Gender-year FE	No	Yes	No	Yes

Notes: Standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. The table reports results from a linear regression using the logarithm of hourly wage as a dependent variable. Log(HHI) corresponds to the logarithm of the concentration index computed at the intersection between a commuting zone and an occupation (with the HHI ranging between 0 and 100). Control variables include the number of children, the educational level, the work experience, the age, and a dummy variable indicating whether the individual was born in France. When individual fixed effects are included, we keep only the number of children. Since men and women have different commuting zones which overlap, we first control for female commuting zones-occupation fixed effects in columns (1)-(2), and then for male commuting zones-occupation fixed effects in columns (3)-(4).

We replicate these estimations using a measure of HHI based on new hires to check whether our results hold when we change the definition of concentration. These estimates are reported in Tables C.2 to C.4 in Appendix. The coefficient associated with the concentration index loses its significance, but the gender wage gap still increases with concentration.

4.2 Working conditions

If we assume that workers and firms negotiate not only over wages, but also over other working conditions, we easily deduce that the narrower the range of acceptable geographical locations, the lower the outside options and therefore the lower the bargaining position of the worker to negotiate good working conditions, including wages. Therefore, reduced geographical mobility decreases both bargained wages and working conditions, since workers with reduced geographical mobility cannot bring into competition as many employers as workers with high geographical mobility. Alternatively, we can argue that, if workers consider reduced geographical mobility as an important working condition, they may be willing to sacrifice other working conditions, pecuniary and/or non pecuniary, in order to keep this reduced geographical mobility. Therefore, reduced wages may simply denote that workers sacrifice pecuniary working conditions in exchange of reduced geographical mobility. These worse pecuniary working conditions may be associated with worse non-pecuniary conditions, depending on how much workers are willing to sacrifice in order to have a low commuting time.

To test this hypothesis we estimate Equation 3 using as a dependent variable each of the working conditions indicators defined in Section 2.3.3. We keep only local labour markets (defined by commuting zone-occupation) including at least 10 individuals. Given the small number of observations in the Working Conditions Survey, we consider occupations defined at the two-digit level to ensure a sufficient number of local labour markets. Tables 7 to 9 present the results of weighted OLS and IV estimations for each working conditions indicator. The weights are defined so that the age and gender composition within each local labour market remains constant over time. Additionally, since occupations capture the skills of the workers, we also force the local labour market to remain the same over time. This estimation strategy ensures that our results are not driven by potential changes in the socio-demographic composition of the sample induced by the fact that we only keep local labour markets including at least 10 individuals.

OLS estimates from Table 7 suggest that, in average, women benefit from more support, better ergonomics, physical safety and scheduling than men. In contrast, they have less autonomy, stability, flexibility and intensity. Larger concentration is associated with lower levels of ergonomics, work-life balance and intensity for women than for men. As shown in Appendix D, results remain consistent when replacing female commuting zone-occupation FE with male commuting zone-occupation FE.

IV estimates in Tables 8 and 9 reveal that women have in average less stability and flexibility than men. In contrast, they benefit from better ergonomics and physical safety. Labour market concentration has a stronger negative effect on ergonomics and physical safety for women than for men. Again, these findings hold when controlling for male commuting zone-occupation FE (see Appendix D).

All in all, estimates in Tables 7 to 9 tend to suggest that labour market concentration results in a deterioration of the physical working conditions of women compared to those of men.

Table 7: Effect of HHI on working conditions - OLS

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	Skills	Autonomy	Support	Stability	Ergonomics	Physical safety	Psy safety	Scheduling	Work-life balance	Flexibility	Intensity	NPI
Female	-0.010	-0.019**	0.028***	-0.026***	0.035***	0.076***	-0.009	0.036***	0.005	-0.032***	-0.051***	0.002
	(0.009)	(0.009)	(0.010)	(0.008)	(0.010)	(0.010)	(0.010)	(0.010)	(0.008)	(0.009)	(0.011)	(0.005)
Log(HHI)	0.004	0.025*	-0.002	0.019	-0.012	0.007	-0.006	-0.004	-0.009	-0.010	0.029	0.001
	(0.018)	(0.015)	(0.020)	(0.013)	(0.018)	(0.018)	(0.019)	(0.018)	(0.016)	(0.016)	(0.019)	(0.009)
Female × Log(HHI)	0.001	0.000	0.002	0.002	-0.010*	-0.004	0.005	-0.008	-0.011**	-0.002	-0.015**	-0.003
	(0.006)	(0.005)	(0.006)	(0.005)	(0.006)	(0.006)	(0.006)	(0.005)	(0.005)	(0.005)	(0.007)	(0.003)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Female CZ × occupation FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sector FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.215	0.239	0.201	0.287	0.546	0.383	0.177	0.420	0.199	0.333	0.194	0.453
Observations	4,871	5,066	5,124	5,083	5,140	5,140	4,919	5,147	4,633	4,879	4,882	4,313

Notes: Standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. The table reports results from a linear regression using as a dependent variable each of the eleven working conditions indicators and the non-pecuniary index (NPI), as described in Section 2.3.3. Log(HHI) corresponds to the logarithm of the concentration index computed at the intersection between a commuting zone and an occupation (with the HHI ranging between 0 and 100). All columns include individual fixed effects, female commuting zone-occupation fixed effects, and controls for the number of children. Counterfactual weights are used.

Table 8: Effect of HHI on working conditions - IV HHI instrument

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	Skills	Autonomy	Support	Stability	Ergonomics	Physical safety	Psy safety	Scheduling	Work-life balance	Flexibility	Intensity	NPI
Female	0.012	0.009	0.040	-0.058***	0.072***	0.087***	-0.009	0.034	-0.002	-0.060**	-0.041	0.011
	(0.022)	(0.022)	(0.027)	(0.020)	(0.023)	(0.024)	(0.024)	(0.024)	(0.024)	(0.023)	(0.028)	(0.011)
Log(HHI)	-0.086	-0.108	-0.052	0.147*	-0.178**	0.011	-0.003	-0.008	0.015	0.090	-0.028	-0.039
	(0.092)	(0.091)	(0.108)	(0.079)	(0.090)	(0.095)	(0.102)	(0.099)	(0.098)	(0.099)	(0.116)	(0.045)
Female × Log(HHI)	-0.004	0.002	-0.000	0.007	-0.012*	-0.021***	0.005	-0.004	-0.008	0.009	-0.011	-0.004
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.006)	(0.007)	(0.006)	(0.007)	(0.007)	(0.008)	(0.003)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Female CZ × occupation FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sector FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
F-test weak instrument	36.165	39.531	39.668	39.204	39.98	40.234	36.329	40.316	34.929	36.867	36.147	31.041
Observations	4,871	5,066	5,124	5,083	5,140	5,140	4,919	5,147	4,633	4,879	4,882	4,313

Notes: Standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. The table reports results from a linear regression using as a dependent variable each of the eleven working conditions indicators and the non-pecuniary index (NPI), as described in Section 2.3.3. Log(HHI) corresponds to the logarithm of the concentration index computed at the intersection between a commuting zone and an occupation (with the HHI ranging between 0 and 100). To instrument Log(HHI), we use the employment-weighted average of the HHI for the same occupation in the other commuting zones. All columns include individual fixed effects, female commuting zone-occupation fixed effects, and controls for the number of children. Counterfactual weights are used.

Table 9: Effect of HHI on working conditions - IV log(1/F)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	Skills	Autonomy	Support	Stability	Ergonomics	Physical safety	Psy safety	Scheduling	Work-life balance	Flexibility	Intensity	NPI
Female	0.009	-0.009	0.057*	-0.026	0.072***	0.081***	-0.037	0.038	0.005	0.005	-0.045	0.017
	(0.026)	(0.027)	(0.030)	(0.024)	(0.025)	(0.025)	(0.029)	(0.026)	(0.028)	(0.024)	(0.031)	(0.012)
Log(HHI)	-0.071	-0.035	-0.133	-0.000	-0.169	0.035	0.129	-0.034	-0.014	-0.219**	-0.023	-0.064
	(0.113)	(0.115)	(0.129)	(0.104)	(0.106)	(0.105)	(0.126)	(0.111)	(0.118)	(0.104)	(0.133)	(0.052)
Female × Log(HHI)	-0.003	0.005	0.001	0.007	-0.014**	-0.021***	0.005	-0.002	-0.010	0.011	-0.008	-0.005
	(0.008)	(0.007)	(0.008)	(0.007)	(0.007)	(0.007)	(0.008)	(0.007)	(0.008)	(0.007)	(0.008)	(0.003)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Female CZ × occupation FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sector FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
F-test weak instrument	41.191	40.371	40.2	40.141	40.494	40.757	43.049	40.717	36.765	47.112	41.065	36.712
Observations	4,871	5,066	5,124	5,083	5,140	5,140	4,919	5,147	4,633	4,879	4,882	4,313

Notes: Standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. The table reports results from a linear regression using as a dependent variable each of the eleven working conditions indicators and the non-pecuniary index (NPI), as described in Section 2.3.3. Log(HHI) corresponds to the logarithm of the concentration index computed at the intersection between a commuting zone and an occupation (with the HHI ranging between 0 and 100). To instrument Log(HHI), we use the unweighted average of log(1/F) in other commuting zones, with F being the number of firms in the market. All columns include individual fixed effects, female commuting zone-occupation fixed effects, and controls for the number of children. Counterfactual weights are used.

4.3 Hirings

We now consider the effect of labour market concentration on the share of women among new hires. It has been shown in Marinescu et al. (2021) that concentration negatively affects the number of new hires. Indeed, if firms with higher bargaining power cannot lower wages, *e.g.* because of a high minimum wage like it is the case in France, their increased bargaining power can translate into a decrease in the number of new employees. As shown in Section 4.1, this higher monopsonistic power can affect women more than men. Firms that become more selective because they have less competitors in the labour market may prioritise men, perceiving women as more likely to interrupt their career or reduce their labour supply due to family responsibilities. To test this hypothesis, we compute a measure of HHI for new hires, *i.e.* we only keep individuals who did not work in an establishment of their current firm the year before. We also compute the share of women newly employed in each firm and each year. Tables 10 to 12 present the effect of this newly computed HHI on the share of women hired, controlling for establishment-year fixed effects, gender-specific commuting zone fixed effects and commuting zone-occupation fixed effects. Using OLS (Table 10), we find a negative relationship between concentration and the share of women newly employed, which becomes positive and significant when including female-specific occupation fixed effects but does not hold when considering male-specific commuting zones. However, as mentioned earlier, a possible endogeneity of the concentration index may bias the results, justifying to use an IV approach. Both IV approaches (see Tables 11 and 12) suggest a negative relationship between labour market concentration and the share of women among new hires. According to these estimates, a 10% increase in the concentration index would decrease the share of women by 0.04-0.1 percentage point. On the demand side, employers' market power seems to translate into a preference for men on the labour market. This hiring discrimination based on gender has been documented in the literature and this particularly affects women of childbearing age (Becker et al., 2019). Also, when employers are unable to adjust wages, they may opt to limit the number of job opportunities available, a decision that could disproportionately impact women. It has been shown that prohibiting gender pay discrimination reduces women's employment (Neumark and Stock, 2006). This hypothesis is also consistent with our findings indicating that concentration has a a more pronounced negative effect on women's wages. In addition, women living in highly concentrated commuting zones might be discouraged to participate in the labour market, first because of the high level of competition for available job opportunities, and second because of the lower wages that are associated with more concentrated labour markets.

Table 10: Effect of HHI on the share of women hired - OLS

	(1) Share of women	(2) Share of women	(3) Share of women	(4) Share of women
Log(HHI)	-4.782***	0.147**	-4.813***	0.0923
	(0.0335)	(0.0519)	(0.0329)	(0.0516)
N	1,718,149	1,701,697	1,690,105	1,677,958
Establishment-year FE	Yes	Yes	Yes	Yes
Female CZ	Yes	No	No	No
Male CZ	No	No	Yes	No
Female CZ × occupation FE	Yes	Yes	No	No
Male CZ × occupation FE	No	No	Yes	Yes

Notes : Standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. The table reports results from a linear regression using as a dependent variable the share of women among the new hires, with a share ranging between 0 and 100. Log(HHI) corresponds to the logarithm of the concentration index computed at the intersection between a commuting zone and an occupation (with the HHI ranging between 0 and 100). All columns include establishment-by-year fixed effects.

Table 11: Effect of HHI on the share of women hired - IV HHI instrument

	(1) Share of women	(2) Share of women	(3) Share of women	(4) Share of women
Log(HHI)	-7.722***	-0.636**	-7.391***	-0.403*
	(0.0463)	(0.216)	(0.0449)	(0.202)
N	1,718,088	1,701,648	1,690,042	1,677,908
F-test	1537806.47	80503.73	1601066.31	90834.73
Establishment-year FE	Yes	Yes	Yes	Yes
Female CZ	Yes	No	No	No
Male CZ	No	No	Yes	No
Female CZ × occupation FE	Yes	Yes	No	No
Male CZ × occupation FE	No	No	Yes	Yes

Notes: Standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. The table reports results from a linear IV regression using as a dependent variable the share of women among the new hires, with a share ranging between 0 and 100. Log(HHI) corresponds to the logarithm of the concentration index computed at the intersection between a commuting zone and an occupation (with the HHI ranging between 0 and 100). To instrument Log(HHI), we use the employment-weighted average of the HHI for the same occupation in the other commuting zones. All columns include establishment-by-year fixed effects.

Table 12: Effect of HHI on the share of women hired - IV log(1/F)

	(1) Share of women	(2) Share of women	(3) Share of women	(4) Share of women
Log(HHI)	-5.560***	-1.297***	-5.507***	-1.158***
	(0.0470)	(0.257)	(0.0458)	(0.252)
N	1,718,088	1,701,648	1,690,042	1,677,908
F-test	1431686.01	55870.82	1450830.87	56764.47
Establishment-year FE	Yes	Yes	Yes	Yes
Female CZ	Yes	No	No	No
Male CZ	No	No	Yes	No
Female CZ × occupation FE	Yes	Yes	No	No
Male CZ × occupation FE	No	No	Yes	Yes

Notes: Standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. The table reports results from a linear IV regression using as a dependent variable the share of women among the new hires, with a share ranging between 0 and 100. Log(HHI) corresponds to the logarithm of the concentration index computed at the intersection between a commuting zone and an occupation (with the HHI ranging between 0 and 100). To instrument Log(HHI), we use the unweighted average of log(1/F) in other commuting zones, with F being the number of firms in the market. All columns include establishment-by-year fixed effects.

5 Economic mechanisms

In this section we investigate a mechanism through which labour market concentration can affect more women than men. Women have traditionally been less geographically mobile than men because they tend to bear most of the housework and childcare-related responsibilities. In our data, we cannot distinguish between women who are single and those in a relationship, but we have information on the number and date of birth of their children. As shown in Section 2.4, having children decreases the geographical mobility for both men and women, but with a more pronounced impact on women. We therefore decide to define new commuting zones by gender and by parental status again using the algorithm LabourMarketAreas developed by Eurostat (see Section 2.3.1).

We estimate an augmented version of Equation 3 using new local labour markets based on these parent-gender-specific commuting zones and including an interaction term between Log(HHI) and a Parent dummy variable, to see whether the concentration effect increases the gender wage gap more among parents than among non-parents. The results are presented in Table E.1 in Appendix. Columns (1)-(2) show that parents earn in average higher wages. The coefficient associated with the interaction term "Female × Parent" is negative but not significant. Labour market concentration has a negative impact on wages. Fathers are more negatively affected than non-fathers, while there is no difference between mothers and non-mothers (the sum of the coefficient associated to Parent × Log(HHI) and the coefficient associated with the triple interaction gives a result very close to zero). This would mean that the gender wage gap increases more with concentration among non-parents than among parents. However, when using the IV approach (columns (3)-(6)), the coefficient associated with the triple interaction becomes negative (not significant with the first instrument in columns (3)-(4) but significant with the second instrument in columns (5)-(6)), suggesting that concentration increases the gender wage gap more between mothers and fathers than among childless individuals.

The stratified approach by gender allows to obtain clearer conclusions. IV estimates reported in Table E.2 suggest that labour market concentration significantly increases the wage gap between mothers and non-mothers, the formers earning a lower wage (see columns (3) and (5)). The results are more mixed among men. Concentration is found to increase significantly the wage gap between fathers and non-fathers only with the first instrument; there is no significant effect with the second instrument (see columns (4) and (6)).

Note that employer discrimination may not only concern women who already have children, but also women who are seen "at risk" of having children in the near future. In particular, childless women of childbearing age may be discriminated against on the labour market because employers anticipate that they will have children and believe that they are more likely than comparable men to take parental leave and reduce their labour supply because of family responsibilities. These women are particularly likely to be discriminated against when the employer has high bargaining power. Also, the exhaustive employer-employee data that we use in this paper do not allow us to distinguish between individuals with or without children (only the panel sub-sample has this information).

We thus replicate the analysis on new hires by computing the share of women of childbearing age (below 41 years old) among new hires in each firm. We present the results in Table E.3 in Appendix. Considering the most demanding specification, a 10% increase in the concentration index decreases the share of women among new hires by 0.016 percentage point in the OLS estimates, but by up to 0.3 - 0.7 percentage point in the IV estimates. These results suggest that women of childbearing age are particularly impacted by labour market concentration, and confirm that parental status is a key mechanism in the differentiated impact of concentration by gender.

6 Robustness checks

6.1 Full-time workers

We focus in this paper on hourly wages because many more women than men work part-time in France. However, due to the nature of the work, some part-time jobs may be particularly underpaid. To ensure that our results are not driven by women in part-time positions, we now consider only workers who report working full-time. Results are displayed in Tables F.1- F.3 of Appendix F. Among full-time workers, we find that a 10% increase in labour market concentration decreases the average hourly wage by almost 0.02% in the OLS estimates and by more than 0.1%

in the IV estimates. These effects are much larger than those obtained when considering both full-time and part-time workers (see Tables 4-6), suggesting that the negative impact of concentration is increased for full-time workers. These effects are even larger for full-time women, for whom a 10% increase in concentration results in a wage decrease 0.02% higher than the average decrease observed for all women. These results confirm that our conclusions still hold when considering only full-time workers. Our benchmark results are therefore not driven by part-time workers.

6.2 Stayers

Our estimates could also be affected by worker mobility across local labour markets. In particular, our estimates may reflect differences in the composition of the workforce across local labour markets. Such compositional effects would be particularly important if, for a given occupation, the most efficient workers (*i.e.* better paid) moved towards less concentrated commuting zones while the less efficient workers (*i.e.* less paid) remained in the more concentrated commuting zones. To address this issue, we now focus on individuals who have remained in the same commuting zone during the whole considered period (see Tables F.4-F.6 in Appendix F). IV estimates from Tables F.5-F.6 confirm our main findings: the coefficient associated with the interaction between gender and the log of the concentration index remains significantly negative and is of the same order of magnitude as in our main specification, when we restrict the analysis to stayers.

6.3 Larger occupations

We check that our results are not specific to the narrow definition of local labour markets that we have chosen by now defining occupations at the 2-digit level instead of the 4-digit level, leading to a widening of the boundaries of each local labour market. By doing so, we automatically increase the number of employers in each market and also allow workers in a market to have greater mobility across occupations, since there is a wide variety of 4-digit occupations within a 2-digit occupation. We therefore expect the effect of concentration on wages to be strongly reduced, since workers can put more firms into competition for both reasons. Tables F.7-F.9 in Appendix F present the estimates obtained with local labour markets defined at the intersection between gender-specific commuting zones and 2-digit occupations. Among IV estimates (Tables F.8-F.9), our preferred specifications in columns (2) and (4) confirm that a 10% increase in labour market concentration reduces average wages between 0.047% and 0.054%. The relative effect of a 10% increase in concentration on female wages with respect to the average impact varies depending on the instrument chosen. The negative effect of concentration on women's wages is lower than average with the first instrument (see Table F.8), while it is 0.018% higher with the second instrument (see Table F.9). All in all, even when considering a large definition of occupations, we still find a negative impact of concentration on wages.

6.4 Public sector

When women struggle to find a job in the private sector or fail to obtain appropriate wages and working conditions in this sector, they may turn towards the public sector. Since our sample only considers private sector workers, we may face a sample composition bias if our sample only includes women who failed to find a job in the public sector and are then stuck with the poor working conditions in the private sector. To explore this possibility, Tables F.10-F.12 in Appendix F examine the effect of labour market concentration on the share of women among new hires in the public sector. Our preferred specifications in columns (2) and (4) confirm that, whether we consider the OLS or IV estimates, a 10% increase in concentration does not significantly increase the share of women among new hires in the public sector. We can thus rule out the possibility that our benchmark estimates in Tables 4-6 are driven by composition effects created by women moving to the public sector to avoid the pecuniary and non-pecuniary conditions offered in the private sector.

To test the robustness of our results, Tables F.13-F.15 replicate our benchmark estimations but considering a HHI computed using both public and private employees. This allows us to capture the fact that in some local labour markets the public sector may be very present and may, at least partially, compensate for the lack of employers in the private sector. Reassuringly, coefficient estimates remain very close to the benchmark results. When considering the OLS estimates, a 10% increase in HHI decreases the average wage by 0.012%-0.015%, while the decrease in the IV estimates is in the range 0.062%-0.083%. As in Tables 4-6, a 10% increase in concentration has a larger negative impact on women's wages with respect to the average. Again, the range of this impact remains very close to the one in the benchmark result, 0.015%-0.029%.

Overall, it does not seem that women are fleeing the private sector for the public sector, and the presence of the public sector in the local labour markets does not appear to smooth the effect of concentration on hourly wages.

7 Conclusion

Monopsony power can have detrimental effects on workers, in particular through the worsening of pecuniary and non-pecuniary working conditions and decreasing demand for labour. Workers who are less geographically mobile, in particular women, may be even more affected because they can put less employers into competition. In this paper, we use a new definition of commuting zones that are gender-specific and take into account these differences in mobility, to study how labour market concentration affects gender inequalities. We find that an increase in labour market concentration increases the gender gaps in hourly wages and deteriorates physical working conditions of female (*i.e.* physical safety and ergonomics). The negative impact on hourly wages is significant for both genders, but is between 30% and 100% higher for women than it is for men. In addition to that, women's labour markets are more concentrated on average. We also find that concentration decreases the share of women among new hires, suggesting that employers who cannot act on wages instead decrease the demand for female workers. Women of childbearing age seem to be the main driver of our results. Finally, we show that this effect is not driven by part-time workers or worker mobility across commuting zones, and the public sector does not seem to be hosting women fleeing the private sector when concentration increases.

Policy interventions that limit labour market concentration, such as anti-trust regulations, are likely to improve not only overall labour market outcomes but also mitigate gender inequalities. With regard to differences in geographical mobility, the growing availability of remote work may offer a solution for certain types of occupations. Finally, if, as our estimations suggest, these results are driven by discrimination against women of childbearing age, the provision of accessible and affordable childcare options, or a more equal sharing of family responsibilities within households (*e.g.* through more equal parental leave uptake) may potentially change employers' perceptions of the risks associated with hiring women over men, even if not immediately. This could also have an impact on the differences in mobility among women (mothers) and men (fathers).
An interesting avenue for future research would be to focus on job seekers and see how the duration of unemployment is affected by labour market concentration depending on characteristics such as gender, parental status and/or age group. One could also look at heterogeneous effects according to sectors/occupations, typically those that are more male-dominated or female-dominated, or those that may offer more flexibility in terms of place of work or working hours.

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A Definition of gender-specific local labour markets areas

A.1 The algorithm used to define labour market areas

The algorithm implemented in the R package *LabourMarketAreas* is an iterative agglomerative algorithm, based on Coombes and Bond (2008), that depends on a set of parameters. These parameters set the level of desired size and self-containment of the labour market areas (LMA thereafter). Self-containment can be imagined in terms of commuters who remain in the area. For example, a self-containment value of 0.75 means that the workforce who lives and works in the area is more than 75% of the commuters who only live in the area and more than 75% of those who only work in the area. The concept of self-containment of incoming and outgoing flows allows to quantify the most distinctive characteristic of a LMA, which is the ability to maximize the relationships inside its borders and minimize them across borders (Franconi et al., 2016). Let f_{hk} be the flow between municipality h and municipality k, *i.e.* the number of commuters living in h and working in k. Then, $R_i = \sum_k f_{ik}$ is the number of workers living in area i, $W_i = \sum_h f_{hi}$ is the number of workers working in area i and $RW_i = f_{ii}$ is the number of workers living and working in area i. There are two types of self-containment:

- the supply side self-containment: $SS\_SC = RW_i/R_i$
- the demand side self-containment: $DS\_SC = RW_i/W_i$

These two quantities measure the level of internal cohesion or integration of the areas with respect to the commuting flows (Franconi et al., 2016).

To be considered a LMA, a cluster of municipalities must have some minimum characteristics in terms of size and self-containment. The minimum size and minimum level of self-containment of a LMA may vary from country to another, but also from one region to another within a country, depending on the density of the population, the territorial morphology and the structure of commuting.

The algorithm allows the level of self-containment to change according to the size of the cluster so that it can be considered a LMA. This trade-off between size and self-containment is expressed by four parameters, defined by Coombes and Bond (2008), corresponding to target and minimum values of these characteristics:

- minSZ: minimum size of a cluster to be considered a LMA,
- tarSC: level of self-containment which is necessary for a cluster with minimum size to be considered a LMA,

- tarSZ: size of a cluster for which the minimum level of self-containment (minSC) is adequate for the cluster to be considered a LMA,
- minSC: minimum level of self-containment for a cluster that has size of at least tarSZ to be considered a LMA

The algorithm starts by considering each municipality as a cluster that is checked against a set of conditions to see whether it can be considered a LMA. At each stage, municipalities (or groups of municipalities aggregated previously) are aggregated according to the intensity of home-work exchanges. At each iteration clusters that are not fit for the purpose are disaggregated and a single municipality inside the cluster is chosen to be attached to a new cluster, improving the set of given conditions. The final solution is obtained when the whole set of clusters satisfies the given conditions (Franconi et al., 2016).
A validity condition, based on the parameter values, establishes the criteria that should be met by a cluster to be considered a LMA and quantifies whether the identified cluster is a valid LMA. This condition is operatively defined through a function that expresses the trade-off between the dimension (SZ), in terms of workers, and the self-containment (SC) of the cluster. This validity function, f_ν, depends also on the selected parameters and takes the following form:

$$f_\nu(SZ, SC) = \left[1 - \left(1 - \frac{minSC}{tarSC}\right) \cdot \max\left(\frac{tarSZ - SZ}{tarSZ - minSZ}, 0\right)\right] \cdot \left[\frac{\min(SC, tarSC)}{tarSC}\right] \tag{5}$$

The validity condition states that a cluster with size SZ_c and self-containment SC_c (minimum between SS_SC_c and DS_SC_c) is a proper LMA if:

$$f_\nu(SZ_c, SC_c) \geqslant \frac{minSC}{tarSC} \tag{6}$$

This condition is evaluated at each iteration to check whether all the clusters are indeed proper LMAs.

A.2 Implementation of the algorithm

In France, the values of these parameters have been defined at the national level, except for Corsica, Ile-de-France and the overseas departments, for which specific values have been defined. National parameter values in France are: minSZ=15 000, tarSZ=25 000, minSC=0.6, tarSC=0.7. The self-containment parameters are lower in Ile-de-France. In the case of Ile-de-France, a final choice was made to deviate slightly from the results of the algorithm, to respect the current limits of public establishments for inter-municipal cooperation (EPCI). Paris exerts a strong attraction on the surrounding areas, so that the other employment areas in Ile-de-France generally have a lower level of self-containment than that generally observed at the national level. Some LMAs in Ile-de-France have a self-containment level of less than 40% (*e.g.* Meaux, Etampes, Rambouillet). For the others, the self-containment level remains relatively low, between 41% and 57%, except for Paris (89%). Even outside Paris, the size contrasts between labour market areas are significant, from 15 300 jobs for Provins to 336 000 for Roissy.

The analysis of the output of the package could reveal clusters which do not reach the minimum size required to define a cluster as a proper LMA or municipalities belonging to the reserve list (see Franconi et al., 2016), that were not assigned by the algorithms. All these cases can be classified under the heading of "self-contained cluster", *i.e.* a cluster which is completely self-contained (no flows inward and/or outward). This could be the case of a small island or groups of islands that does not reach the given threshold on the size or of remote municipalities. A manual assignment resolves this type of situations (*e.g.* islands are assigned to the labour market area where the connection with the mainland exists).

The zero list contains municipalities that could not be processed by the algorithm for various reasons: either the number of residents is 0 or the number of workers/jobs is 0 or the municipality has no interaction with any other municipality. In such cases, the algorithm eliminates the municipalities from the initial list (and let the user the choice to allocate them at a later stage). For mainland France outside Ile-de-France and Corsica, the zero list is composed of 1 041 municipalities, among which:

- 868 municipalities have a non-zero number of residents but zero workers
- 63 municipalities have a non-zero number of workers but zero residents
- 110 municipalities have (presumably) no interaction with any other municipality (non-zero number of residents and workers)

The algorithm of Coombes and Bond (2008) does not take into account in its production process any territorial contiguity principle. Therefore, areas that are non-contiguous might belong to the same labour market area. These need to be treated in order to create proper areas. This treatment, called fine-tuning, treats the non-contiguity by assigning part of the territory chosen by the user to one of the other nearby labour market area based on the function of cohesion used (see Franconi et al., 2016). There are different causes that may create non-contiguities, but some of them cannot be treated as they present structural characteristics of the territory and cannot be solved via algorithms/fine-tuning of the result (Franconi et al., 2017).

A.3 Parent-specific local labour market areas

We are able to define local labour market areas which are specific for parents (mothers and fathers) using the 2019 census data - professional mobility detail file. We identify parents using information on the structure of the household. Individuals who are parents in the data may belong to the following household structures: households whose main family is single-parent, households whose main family is a couple (two working persons, one working person and one inactive person, two inactive persons). Individuals who are not parents may be persons living alone or with other people without family ties (*e.g.* roommates). Unfortunately, we do not have precise information on the age of children living in the household. We only know the number of people in school in the household (including students) and the number of pupils, students or trainees aged 14 or over in the household. Therefore, we are not able to identify precisely the households with young children, where the labour supply is most constrained and women are likely to have a smaller job search area.

B Descriptive statistics

Table B.1: Average commuting distance between the municipality of residence and the municipality of work by gender and parental status

	(1)	(2)	(3)
	distance	distance	distance
Female	-11.24***	-11.06***	
	(0.0829)	(0.0823)	
Parent	-1.877***	-2.353***	-0.502***
	(0.0867)	(0.0865)	(0.140)
Female × Parent	0.397**	0.325*	-1.548***
	(0.131)	(0.130)	(0.214)
Intercept	33.456***	33.586***	28.115***
	(0.0553)	(0.0550)	(0.0482)
N	6,308,358	6,302,649	6,187,189
Year FE	No	Yes	Yes
Female CZ FE	No	Yes	Yes
Individual FE	No	No	Yes

Source: Panel Tous Salariés - EDP. Notes : Standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. The dependant variable is the distance between the municipality of residence and the municipality of work of the individuals in kilometers. It is computed by taking the distance between the centroids of the two municipalities.

Table B.2: Maximum commuting distance accepted by job seekers, by gender and parental status

	(1)	(2)	(3)
	max distance	max distance	max distance
Female	-4.566***	-4.538***	
	(0.0544)	(0.0539)	
Parent	-1.735***	-1.580***	0.0798
	(0.0543)	(0.0538)	(0.0880)
Female × Parent	-5.181***	-5.102***	-0.598***
	(0.0776)	(0.0768)	(0.129)
Intercept	29.670***	29.710***	26.934***
	(0.0335)	(0.0331)	(0.0337)
N	963,056	963,056	676,296
Year FE	No	Yes	Yes
Female CZ FE	No	Yes	No
Individual FE	No	No	Yes

Source : FH-DADS. Notes: Standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. The dependent variable is the maximum distance that job-seekers are willing to commute in order to accept a job. It is given in kilometers. As there is only one observation per unemployment spell, the inclusion of individual fixed effects deletes individuals for which we observe only one unemployment spell. In this case, we exploit the difference in the willingness to commute of a given individual before and after she/he as a child.

Table B.3: Characteristics of gender-specific commuting zones

	Min	Max	Median	Mean	SD	N
Female commuting zones						
Area (km^2)	4.15	6494.8	1586.8	1826	1264.3	271
Population	196	4648052	145032	231308	346450	271
Density	16.88	11880	93.83	295.58	962.20	271
Cities with at least 10,000 inhabitants	0	74	2	3.49	6.14	271
Cities with at least 50,000 inhabitants	0	31	0	.506	2.044	271
Cities with at least 100,000 inhabitants	0	13	0	.170	.848	271
Male commuting zones						
Area (km^2)	.57	6633.2	2072.8	2353.7	1430.3	217
Population	51	7227657	163688	289946	557231	217
Density	4.38	7699.97	81.35	165.78	538.94	217
Cities with at least 10,000 inhabitants	0	150	2	4.36	11.37	217
Cities with at least 50,000 inhabitants	0	45	0	.631	3.152	217
Cities with at least 100,000 inhabitants	0	14	0	.212	1.010	217

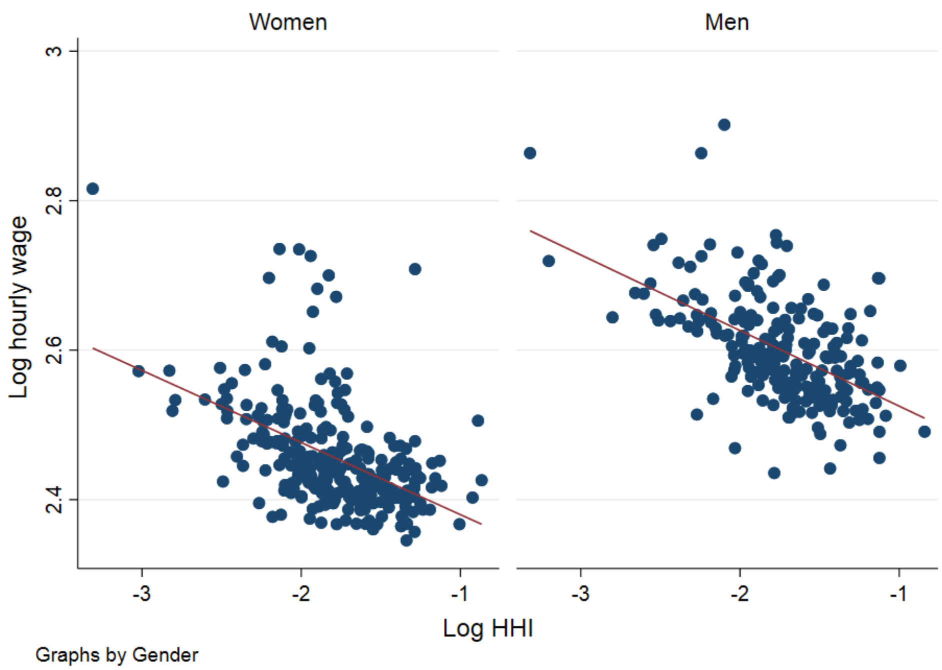
Source: IGN, census data.

Table B.4: Correlation between commuting zone size and concentration

	(1)	(2)	(3)
	Log(HHI)	Log(HHI)	Log(HHI)
Log(Density)	-0.280***		
	(0.000510)		
Log(Area)		-0.105***	
		(0.000568)	
Log(Population)			-0.319***
			(0.000448)
N	1,852,936	1,852,936	1,852,936
Year FE	Yes	Yes	Yes
Occupation FE	Yes	Yes	Yes

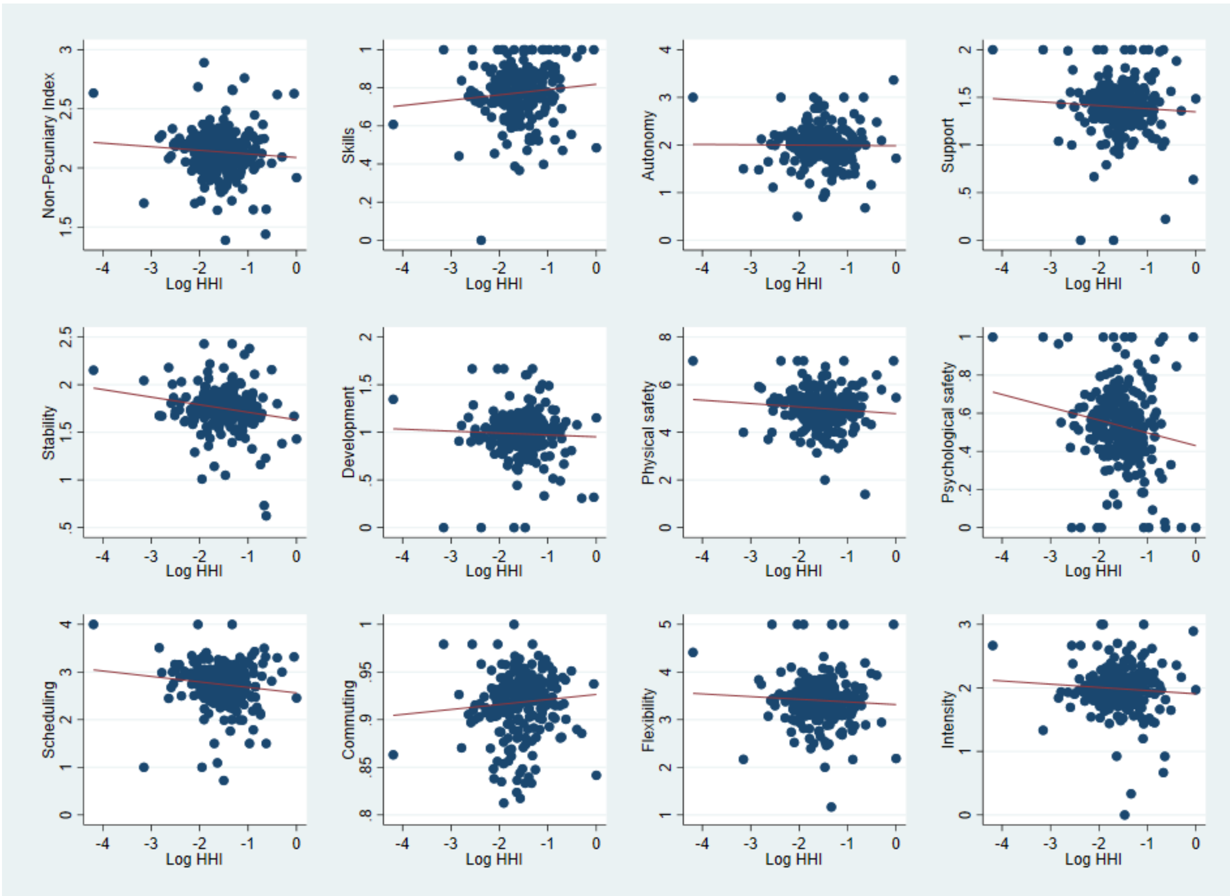
Notes: Standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Figure B.1: Relationship between log hourly wage and concentration by gender



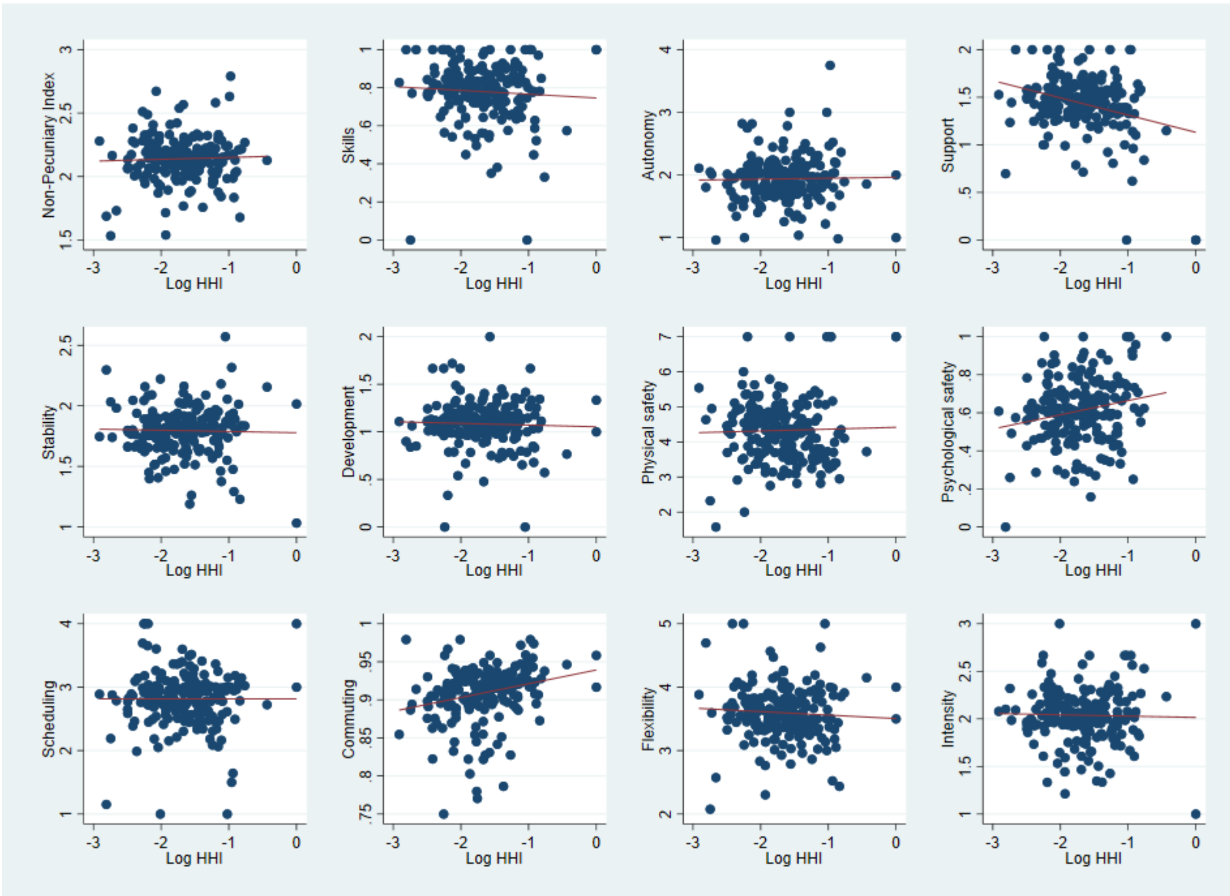
Source : Panel Tous Salariés - EDP.

Figure B.2: Relationship between working conditions and concentration among women



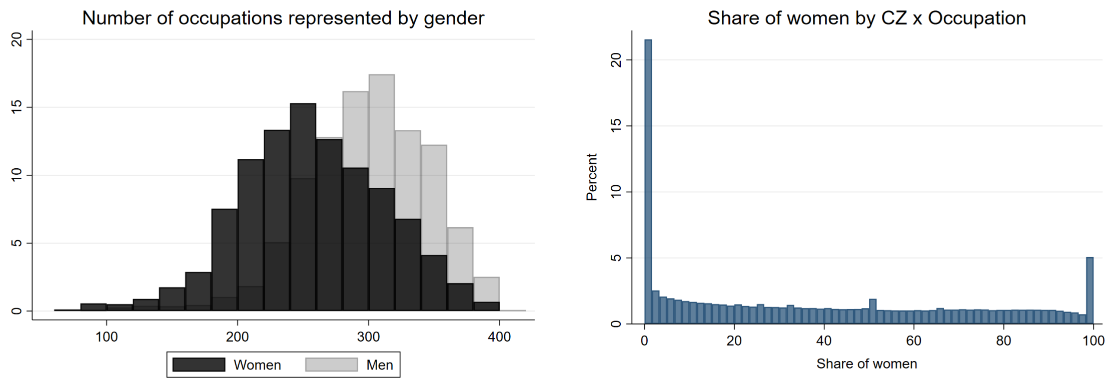
Source: Working Conditions Survey. Note : Survey weights are used.

Figure B.3: Relationship between working conditions and concentration among men



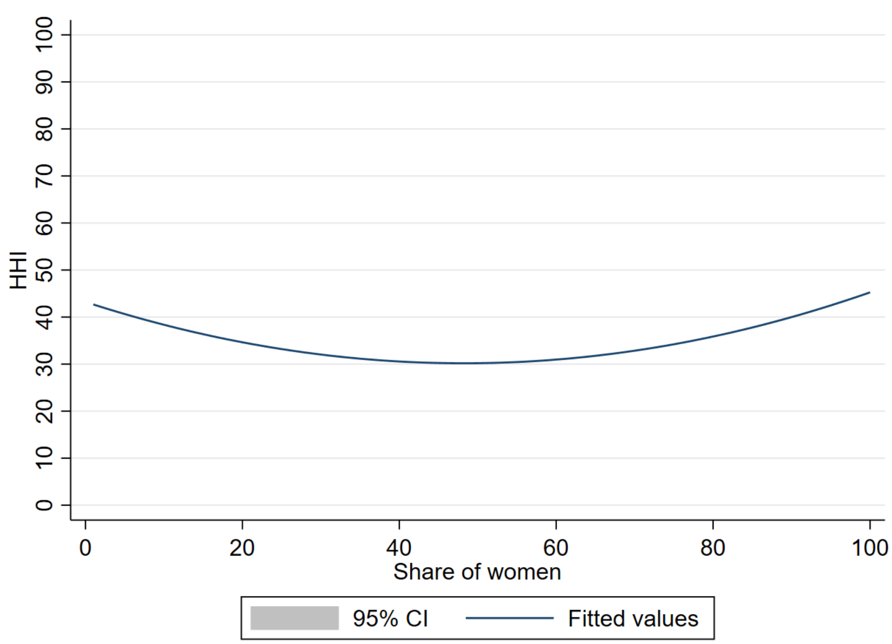
Source: Working Conditions Survey. Note : Survey weights are used.

Figure B.4: Representation of women within occupations



Notes: The left-hand side panel shows the distribution of the number of distinct occupations by gender, commuting zone and year. For example, a number equal to 200 for women means that in a given commuting zone and year, women are working in 200 different occupations. The right-hand side panel shows the distribution of the share of women in each commuting zone - occupation. It ranges from 0 (no women) to 100 (only women).

Figure B.5: Correlation between the share of women in an occupation and the level of concentration



Source: DADS Postes. Notes: The figure represents the results of a quadratic regression of the relationship between concentration and the share of women in an occupation / commuting zone / year.

C Additional results on hourly wages

C.1 Average effect of the HHI on wages

Table C.1: Average effect of HHI on hourly wages

	(1)	(2)
	Log(wage)	Log(wage)
Panel A : OLS		
Log(HHI)	-0.00231***	-0.00234***
	(0.000381)	(0.000381)
N	4,076,184	4,076,184
Panel B : IV - HHI instrument		
Log(HHI)	-0.00626***	-0.00647***
	(0.000962)	(0.000963)
N	4,076,183	4,076,183
F-test	456239.284	455638.836
Panel C : IV - log(1/F)		
Log(HHI)	-0.00813***	-0.00862***
	(0.00121)	(0.00122)
N	4,076,183	4,076,183
F-test	267920.389	267249.288
Controls	Yes	Yes
Establishment-year FE	Yes	Yes
CZ $\times$ occupation FE	Yes	Yes
Individual FE	Yes	Yes
Gender-year FE	No	Yes

Notes: Standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. The table reports results from an OLS regression (Panel A), and two instrumental variable (IV) regressions (Panels B and C) using the logarithm of hourly wage as a dependent variable. In the OLS regression, Log(HHI) corresponds to the logarithm of the concentration index computed at the intersection between a commuting zone and an occupation (with the HHI ranging between 0 and 100). In Panel B, it is instrumented with the employment-weighted average of the HHI for the same occupation in the other commuting zones. In Panel C, it is instrumented with the unweighted average of log(1/F) in other commuting zones, F being the number of firms in the market. Control variables include the number of children, the educational level, the work experience, the age, and a dummy variable indicating whether the individual was born in France. When individual fixed effects are included, we keep only the number of children.

C.2 Effect of HHI among new hires on wages

Table C.2: Effect of HHI among new hires on hourly wages - OLS

	(1)	(2)	(3)	(4)
	Log(wage)	Log(wage)	Log(wage)	Log(wage)
Log(HHI)	0.000264	0.000175	0.000345	0.000255
	(0.000312)	(0.000313)	(0.000301)	(0.000302)
Female × Log(HHI)	-0.00108**	-0.000988**	-0.00156***	-0.00146***
	(0.000365)	(0.000366)	(0.000351)	(0.000352)
N	2,972,126	2,972,126	3,044,077	3,044,077
Controls	Yes	Yes	Yes	Yes
Establishment-year FE	Yes	Yes	Yes	Yes
Female CZ × occupation FE	Yes	Yes	No	No
Male CZ × occupation FE	No	No	Yes	Yes
Individual FE	Yes	Yes	Yes	Yes
Gender-year FE	No	Yes	No	Yes

Notes: Standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. The table reports results from an OLS regression using the logarithm of hourly wage as a dependent variable. Log(HHI) corresponds to the logarithm of the concentration index computed at the intersection between a commuting zone and an occupation (with the HHI ranging between 0 and 100). It is computed on new hires only. Control variables include the number of children, the educational level, the work experience, the age, and a dummy variable indicating whether the individual was born in France. When individual fixed effects are included, we keep only the number of children.

Table C.3: Effect of HHI among new hires on hourly wages - IV HHI instrument

	(1)	(2)	(3)	(4)
	Log(wage)	Log(wage)	Log(wage)	Log(wage)
Log(HHI)	-0.00126	-0.00220	-0.00137	-0.00219
	(0.00144)	(0.00145)	(0.00128)	(0.00129)
Female × Log(HHI)	-0.00439***	-0.00329***	-0.00391***	-0.00292***
	(0.000790)	(0.000791)	(0.000733)	(0.000734)
N	2,972,077	2,972,077	3,044,019	3,044,019
F-test	33936.098	33678.636	41395.618	41119.556
Controls	Yes	Yes	Yes	Yes
Establishment-year FE	Yes	Yes	Yes	Yes
Female CZ × occupation FE	Yes	Yes	No	No
Male CZ × occupation FE	No	No	Yes	Yes
Individual FE	Yes	Yes	Yes	Yes
Gender-year FE	No	Yes	No	Yes

Notes: Standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. The table reports results from an instrumental variable regression using the logarithm of hourly wage as a dependent variable. Log(HHI) corresponds to the logarithm of the concentration index computed at the intersection between a commuting zone and an occupation (with the HHI ranging between 0 and 100). It is computed on new hires only. To instrument Log(HHI), we use the employment-weighted average of the HHI for the same occupation in the other commuting zones. Control variables include the number of children, the educational level, the work experience, the age, and a dummy variable indicating whether the individual was born in France. When individual fixed effects are included, we keep only the number of children.

Table C.4: Effect of HHI among new hires on hourly wages - IV log(1/F)

	(1) Log(wage)	(2) Log(wage)	(3) Log(wage)	(4) Log(wage)
Log(HHI)	0.00113	-0.000803	-0.00240	-0.00425*
	(0.00195)	(0.00197)	(0.00189)	(0.00192)
Female × Log(HHI)	-0.00422***	-0.00412***	-0.00421***	-0.00410***
	(0.000810)	(0.000814)	(0.000758)	(0.000763)
N	2,972,077	2,972,077	3,044,019	3,044,019
F-test	18054.259	17721.489	18441.679	18102.16
Controls	Yes	Yes	Yes	Yes
Establishment-year FE	Yes	Yes	Yes	Yes
Female CZ × occupation FE	Yes	Yes	No	No
Male CZ × occupation FE	No	No	Yes	Yes
Individual FE	Yes	Yes	Yes	Yes
Gender-year FE	No	Yes	No	Yes

Notes: Standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. The table reports results from an instrumental variable regression using the logarithm of hourly wage as a dependent variable. Log(HHI) corresponds to the logarithm of the concentration index computed at the intersection between a commuting zone and an occupation (with the HHI ranging between 0 and 100). It is computed on new hires only. To instrument Log(HHI), we use the unweighted average of log(1/F) in other commuting zones, F being the number of firms in the market. Control variables include the number of children, the educational level, the work experience, the age, and a dummy variable indicating whether the individual was born in France. When individual fixed effects are included, we keep only the number of children.

D Additional results on working conditions

D.1 Male local labour markets

Table D.1: Effect of HHI on working conditions - OLS

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	Skills	Autonomy	Support	Stability	Ergonomics	Physical safety	Psy safety	Scheduling	Work-life balance	Flexibility	Intensity	NPI
Female	-0.011	-0.023***	0.031***	-0.024***	0.033***	0.075***	-0.010	0.031***	0.000	-0.034***	-0.054***	0.000
	(0.009)	(0.008)	(0.009)	(0.008)	(0.010)	(0.010)	(0.010)	(0.010)	(0.008)	(0.009)	(0.010)	(0.005)
Log(HHI)	0.009	0.016	-0.011	0.010	-0.034*	-0.000	-0.012	-0.005	-0.001	-0.013	0.035*	-0.001
	(0.019)	(0.015)	(0.019)	(0.013)	(0.019)	(0.018)	(0.018)	(0.018)	(0.015)	(0.016)	(0.018)	(0.009)
Female × Log(HHI)	0.002	0.001	0.002	0.001	-0.010*	-0.005	0.004	-0.009	-0.011**	-0.002	-0.015**	-0.004
	(0.006)	(0.005)	(0.006)	(0.005)	(0.006)	(0.005)	(0.006)	(0.005)	(0.005)	(0.005)	(0.007)	(0.003)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Male CZ × occupation FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sector FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.209	0.233	0.198	0.280	0.545	0.381	0.174	0.422	0.195	0.333	0.189	0.448
Observations	4,860	5,053	5,113	5,074	5,127	5,128	4,909	5,134	4,623	4,869	4,873	4,307

Notes: Standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. The table reports results from a linear regression using as a dependent variable each of the eleven working condition indicators and the non-pecuniary index (NPI), as described in Section 2.3.3. Log(HHI) corresponds to the logarithm of the concentration index computed at the intersection between a commuting zone and an occupation (with the HHI ranging between 0 and 100). All columns include individual fixed effects, male commuting zone-occupation fixed effects, and controls for the number of children. Counterfactual weights are used.

Table D.2: Effect of HHI on working conditions - IV HHI instrument

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	Skills	Autonomy	Support	Stability	Ergonomics	Physical safety	Psy safety	Scheduling	Work-life balance	Flexibility	Intensity	NPI
Female	0.007	-0.001	0.037	-0.056***	0.053**	0.090***	-0.012	0.020	-0.002	-0.066***	-0.053**	0.005
	(0.021)	(0.020)	(0.025)	(0.019)	(0.021)	(0.022)	(0.023)	(0.021)	(0.022)	(0.022)	(0.025)	(0.010)
Log(HHI)	-0.063	-0.087	-0.034	0.145*	-0.128	-0.017	0.002	0.023	0.000	0.100	0.018	-0.022
	(0.087)	(0.083)	(0.101)	(0.077)	(0.083)	(0.090)	(0.096)	(0.092)	(0.093)	(0.092)	(0.105)	(0.042)
Female × Log(HHI)	-0.003	0.001	0.000	0.006	-0.010	-0.022***	0.003	-0.002	-0.007	0.010	-0.011	-0.004
	(0.007)	(0.006)	(0.007)	(0.007)	(0.006)	(0.006)	(0.007)	(0.006)	(0.007)	(0.006)	(0.008)	(0.003)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Male CZ × occupation FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sector FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
F-test weak instrument	51.539	53.207	54.463	53.873	54.81	55.179	52.28	55.455	45.108	52.426	52.009	39.071
Observations	4860	5053	5113	5074	5127	5128	4909	5134	4623	4869	4873	4307

Notes: Standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. The table reports results from an instrumental variable regression using as a dependent variable each of the eleven working conditions indicators and the non-pecuniary index (NPI), as described in Section 2.3.3. Log(HHI) corresponds to the logarithm of the concentration index computed at the intersection between a commuting zone and an occupation (with the HHI ranging between 0 and 100). To instrument Log(HHI), we use the employment-weighted average of the HHI for the same occupation in the other commuting zones. All columns include individual fixed effects, male commuting zone-occupation fixed effects, and controls for the number of children. Counterfactual weights are used.

Table D.3: Effect of HHI on working conditions - IV log(1/F)

	(1) Skills	(2) Autonomy	(3) Support	(4) Stability	(5) Ergonomics	(6) Physical safety	(7) Psy safety	(8) Scheduling	(9) Work-life balance	(10) Flexibility	(11) Intensity	(12) NPI
Female	0.008	-0.010	0.063**	-0.019	0.064**	0.078***	-0.039	0.036	0.001	0.001	-0.047	0.016
	(0.027)	(0.027)	(0.031)	(0.025)	(0.025)	(0.026)	(0.030)	(0.027)	(0.028)	(0.025)	(0.032)	(0.013)
Log(HHI)	-0.071	-0.057	-0.157	-0.031	-0.171	0.037	0.133	-0.059	-0.012	-0.223**	-0.027	-0.073
	(0.120)	(0.116)	(0.137)	(0.109)	(0.111)	(0.115)	(0.134)	(0.120)	(0.125)	(0.111)	(0.143)	(0.056)
Female × Log(HHI)	-0.002	0.004	0.001	0.005	-0.012*	-0.021***	0.003	-0.000	-0.008	0.011*	-0.007	-0.005
	(0.008)	(0.007)	(0.008)	(0.007)	(0.007)	(0.007)	(0.008)	(0.007)	(0.008)	(0.007)	(0.008)	(0.003)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Male CZ × occupation	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sector FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
F-test weak instrument	39.775	40.122	39.825	39.449	39.812	40.132	41.7	40.048	36.03	43.917	39.919	34.716
Observations	4860	5053	5113	5074	5127	5128	4909	5134	4623	4869	4873	4307

Notes: Standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. The table reports results from an instrumental variable regression using as a dependent variable each of the eleven working conditions indicators and the non-pecuniary index (NPI), as described in Section 2.3.3. Log(HHI) corresponds to the logarithm of the concentration index computed at the intersection between a commuting zone and an occupation (with the HHI ranging between 0 and 100). To instrument Log(HHI), we use the unweighted average of log(1/F) in other commuting zones, F being the number of firms in the market. All columns include individual fixed effects, male commuting zone-occupation fixed effects, and controls for the number of children. Counterfactual weights are used.

E Economic mechanisms: parental status

E.1 Hourly wages

Table E.1: Effect of HHI on hourly wages by parental status

	OLS		IV HHI instrument		IV log($1/F$)	
	(1)	(2)	(3)	(4)	(5)	(6)
	Log(wage)	Log(wage)	Log(wage)	Log(wage)	Log(wage)	Log(wage)
Parent	0.0302***	0.0318***				
	(0.000757)	(0.000760)				
Log(HHI)	-0.0363***	-0.0400***	-0.00286**	-0.00316**	-0.00277	-0.00394**
	(0.00117)	(0.00119)	(0.000972)	(0.000972)	(0.00145)	(0.00145)
Female × Parent	-0.000654	-0.000681	-0.0312***	-0.0348***	-0.0268***	-0.0297***
	(0.000369)	(0.000369)	(0.00144)	(0.00145)	(0.00162)	(0.00163)
Female × Log(HHI)	-0.000580	-0.000589	-0.000732	-0.000654	-0.00124*	-0.00127*
	(0.000344)	(0.000344)	(0.000485)	(0.000486)	(0.000545)	(0.000545)
Parent × Log(HHI)	-0.00125***	-0.00128***	-0.00147***	-0.00151***	-0.000607	-0.000662
	(0.000302)	(0.000302)	(0.000408)	(0.000407)	(0.000469)	(0.000469)
Female × Parent × Log(HHI)	0.00121**	0.00128**	-0.00106	-0.00104	-0.00327***	-0.00343***
	(0.000464)	(0.000464)	(0.000611)	(0.000611)	(0.000699)	(0.000699)
N	4,052,108	4,052,108	4,052,107	4,052,107	4,052,107	4,052,107
F-test			59390.982	59288.909	25121.382	25068.489
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Establishment-year FE	Yes	Yes	Yes	Yes	Yes	Yes
Mother CZ × occupation FE	Yes	Yes	Yes	Yes	Yes	Yes
Individual FE	Yes	Yes	Yes	Yes	No	Yes
Gender-year FE	No	Yes	No	Yes	Yes	Yes

Notes: Standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Log(HHI) corresponds to the logarithm of the concentration index computed at the intersection between a commuting zone and an occupation (with the HHI ranging between 0 and 100). We instrument Log(HHI) with the employment-weighted average of the HHI for the same occupation in the other commuting zones In columns (3)-(4) and with the unweighted average of $1/F$ in other commuting zones in columns (5)-(6), F being the number of firms in the market. Control variables include the educational level, the work experience, the age, and a dummy variable indicating whether the individual was born in France, in absence of individual fixed effects. The commuting zones used are the mother-specific commuting zones.

Table E.2: Effect of HHI on hourly wages by parental status - Stratified samples

	OLS		IV HHI instrument		IV log(1/F)	
	(1)	(2)	(3)	(4)	(5)	(6)
	Log(wage)	Log(wage)	Log(wage)	Log(wage)	Log(wage)	Log(wage)
Parent	-0.0112***	0.0305***				
	(0.00118)	(0.000800)				
Log(HHI)	0.00153*	-0.00192***	0.00134	-0.00305*	-0.00780**	-0.00334
	(0.000625)	(0.000421)	(0.00205)	(0.00127)	(0.00271)	(0.00209)
Parent × Log(HHI)	-0.000370	-0.000936**	-0.00264***	-0.00115**	-0.00633***	0.0000307
	(0.000448)	(0.000317)	(0.000620)	(0.000426)	(0.000745)	(0.000493)
Sample	Females	Males	Females	Males	Females	Males
N	1,414,982	2,140,134	1,414,981	2,140,134	1,414,981	2140134
F-test			32195.526	65522.276	17540.02	22290.844
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Establishment-year FE	Yes	Yes	Yes	Yes	Yes	Yes
Mother CZ × occupation FE	Yes	Yes	Yes	Yes	Yes	Yes
Individual FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Log(HHI) corresponds to the logarithm of the concentration index computed at the intersection between a commuting zone and an occupation (with the HHI ranging between 0 and 100). We instrument Log(HHI) with the employment-weighted average of the HHI for the same occupation in the other commuting zones In columns (3)-(4) and with the unweighted average of $1/F$ in other commuting zones in columns (5)-(6), F being the number of firms in the market. Control variables include the educational level, the work experience, the age, and a dummy variable indicating whether the individual was born in France, in absence of individual fixed effects. The commuting zones used are the mother-specific commuting zones.

E.2 Hirings

Table E.3: Effect of HHI on the share of women of childbearing age hired - OLS

	OLS		IV HHI instrument		IV log(1/F)	
	(1)	(2)	(3)	(4)	(5)	(6)
	Share of women	Share of women	Share of women	Share of women	Share of women	Share of women
Log(HHI)	-2.409***	-0.164**	-3.583***	-3.275***	-2.478***	-6.719***
	(0.0290)	(0.0509)	(0.0394)	(0.210)	(0.0403)	(0.249)
N	1,718,836	1,704,586	1,718,778	1,704,542	1,718,778	1704542
F-test			1638663.45	81953.07	1491828.71	58055.69
Establishment-year FE	Yes	Yes	Yes	Yes	Yes	Yes
Female CZ	Yes	No	Yes	No	Yes	No
Female CZ × occupation FE	No	Yes	No	Yes	No	Yes

Notes: Standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Columns (1)-(2) report results from an OLS regression using as a dependent variable the share of women under 41 years old among new hires, with a share ranging between 0 and 100. Log(HHI) corresponds to the logarithm of the concentration index computed at the intersection between a commuting zone and an occupation (with the HHI ranging between 0 and 100). We instrument Log(HHI) with the employment-weighted average of the HHI for the same occupation in the other commuting zones In columns (3)-(4) and with the unweighted average of $1/F$ in other commuting zones in columns (5)-(6), F being the number of firms in the market. All columns include establishment-by-year fixed effects.

F Robustness checks

F.1 Full-time workers

Table F.1: Effect of HHI on hourly wages - OLS - Full-time workers

	(1)	(2)	(3)	(4)
	Log(wage)	Log(wage)	Log(wage)	Log(wage)
Log(HHI)	-0.00183***	-0.00185***	-0.00206***	-0.00209***
	(0.000389)	(0.000389)	(0.000387)	(0.000387)
Female × Log(HHI)	-0.00111**	-0.00112**	-0.00103**	-0.00105**
	(0.000377)	(0.000377)	(0.000370)	(0.000370)
N	3,141,340	3,141,340	3,145,638	3,145,638
Controls	Yes	Yes	Yes	Yes
Establishment-year FE	Yes	Yes	Yes	Yes
Female CZ × occupation FE	Yes	Yes	No	No
Male CZ × occupation FE	No	No	Yes	Yes
Individual FE	Yes	Yes	Yes	Yes
Gender-year FE	No	Yes	No	Yes

Notes: Standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table F.2: Effect of HHI on hourly wages - IV HHI instrument - Full-time workers

	(1) Log(wage)	(2) Log(wage)	(3) Log(wage)	(4) Log(wage)
Log(HHI)	-0.0103***	-0.0106***	-0.0103***	-0.0106***
	(0.00110)	(0.00110)	(0.00109)	(0.00109)
Female × Log(HHI)	-0.00247***	-0.00237***	-0.00213***	-0.00203***
	(0.000542)	(0.000541)	(0.000537)	(0.000536)
N	3,141,339	3,141,339	3,145,637	3,145,637
F-test				
Controls	Yes	Yes	Yes	Yes
Establishment-year FE	Yes	Yes	Yes	Yes
Female CZ × occupation FE	Yes	Yes	No	No
Male CZ × occupation FE	No	No	Yes	Yes
Individual FE	Yes	Yes	Yes	Yes
Gender-year FE	No	Yes	No	Yes

Notes: Standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table F.3: Effect of HHI on hourly wages - IV log(1/F) - Full-time workers

	(1) Log(wage)	(2) Log(wage)	(3) Log(wage)	(4) Log(wage)
Log(HHI)	-0.0143***	-0.0150***	-0.0145***	-0.0152***
	(0.00135)	(0.00135)	(0.00133)	(0.00134)
Female × Log(HHI)	-0.00256***	-0.00260***	-0.00211***	-0.00216***
	(0.000596)	(0.000596)	(0.000587)	(0.000587)
N	3,141,339	3,141,339	3,145,637	3,145,637
F-test				
Controls	Yes	Yes	Yes	Yes
Establishment-year FE	Yes	Yes	Yes	Yes
Female CZ × occupation FE	Yes	Yes	No	No
Male CZ × occupation FE	No	No	Yes	Yes
Individual FE	Yes	Yes	Yes	Yes
Gender-year FE	No	Yes	No	Yes

Notes: Standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

F.2 Stayers

Table F.4: Effect of HHI on hourly wages - OLS - Stayers

	(1)	(2)	(3)	(4)
	Log(wage)	Log(wage)	Log(wage)	Log(wage)
Log(HHI)	-0.00190***	-0.00199***	-0.00206***	-0.00215***
	(0.000467)	(0.000466)	(0.000462)	(0.000462)
Female × Log(HHI)	-0.000353	-0.000218	-0.000427	-0.000303
	(0.000470)	(0.000470)	(0.000461)	(0.000460)
N	2,649,541	2,649,541	2,653,073	2,653,073
Controls	Yes	Yes	Yes	Yes
Establishment-year FE	Yes	Yes	Yes	Yes
Female CZ × occupation FE	Yes	Yes	No	No
Male CZ × occupation FE	No	No	Yes	Yes
Individual FE	Yes	Yes	Yes	Yes
Gender-year FE	No	Yes	No	Yes

Notes: Standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table F.5: Effect of HHI on hourly wages - IV HHI instrument - Stayers

	(1)	(2)	(3)	(4)
	Log(wage)	Log(wage)	Log(wage)	Log(wage)
Log(HHI)	-0.00187	-0.00239*	-0.00192	-0.00243*
	(0.00117)	(0.00117)	(0.00116)	(0.00116)
Female × Log(HHI)	-0.00219***	-0.00194**	-0.00193**	-0.00169**
	(0.000638)	(0.000638)	(0.000628)	(0.000628)
N	2,649,540	2,649,540	2,653,072	2,653,072
F-test				
Controls	Yes	Yes	Yes	Yes
Establishment-year FE	Yes	Yes	Yes	Yes
Female CZ × occupation FE	Yes	Yes	No	No
Male CZ × occupation FE	No	No	Yes	Yes
Individual FE	Yes	Yes	Yes	Yes
Gender-year FE	No	Yes	No	Yes

Notes: Standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table F.6: Effect of HHI on hourly wages - IV log(1/F) - Stayers

	(1)	(2)	(3)	(4)
	Log(wage)	Log(wage)	Log(wage)	Log(wage)
Log(HHI)	0.000370	-0.000717	-0.000183	-0.00123
	(0.00150)	(0.00150)	(0.00147)	(0.00148)
Female × Log(HHI)	-0.00238***	-0.00225**	-0.00207**	-0.00198**
	(0.000714)	(0.000713)	(0.000700)	(0.000699)
N	2,649,540	2,649,540	2,653,072	2,653,072
F-test				
Controls	Yes	Yes	Yes	Yes
Establishment-year FE	Yes	Yes	Yes	Yes
Female CZ × occupation FE	Yes	Yes	No	No
Male CZ × occupation FE	No	No	Yes	Yes
Individual FE	Yes	Yes	Yes	Yes
Gender-year FE	No	Yes	No	Yes

Notes: Standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

F.3 Larger occupations

Table F.7: Effect of HHI on hourly wages - OLS - 2-digit occupations

	(1)	(2)	(3)	(4)
	Log(wage)	Log(wage)	Log(wage)	Log(wage)
Log(HHI)	0.000400	0.000385	0.000305	0.000297
	(0.000486)	(0.000486)	(0.000493)	(0.000493)
Female × Log(HHI)	-0.000747	-0.000884*	-0.000735	-0.000869*
	(0.000395)	(0.000396)	(0.000393)	(0.000393)
N	4,098,578	4,098,578	4,099,654	4,099,654
Controls	Yes	Yes	Yes	Yes
Establishment-year FE	Yes	Yes	Yes	Yes
Female CZ × occupation FE	Yes	Yes	No	No
Male CZ × occupation FE	No	No	Yes	Yes
Individual FE	Yes	Yes	Yes	Yes
Gender-year FE	No	Yes	No	Yes

Notes: Standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table F.8: Effect of HHI on hourly wages - IV HHI instrument - 2-digit occupations

	(1)	(2)	(3)	(4)
	Log(wage)	Log(wage)	Log(wage)	Log(wage)
Log(HHI)	-0.00704**	-0.00502*	-0.00683**	-0.00476*
	(0.00217)	(0.00218)	(0.00222)	(0.00223)
Female × Log(HHI)	0.00152*	0.00201**	0.00160*	0.00210**
	(0.000650)	(0.000648)	(0.000650)	(0.000648)
N	4,098,578	4,098,578	4,099,654	4,099,654
F-test	59044.183	58695.14	55569.037	55216.025
Controls	Yes	Yes	Yes	Yes
Establishment-year FE	Yes	Yes	Yes	Yes
Female CZ × occupation FE	Yes	Yes	No	No
Male CZ × occupation FE	No	No	Yes	Yes
Individual FE	Yes	Yes	Yes	Yes
Gender-year FE	No	Yes	No	Yes

Notes: Standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table F.9: Effect of HHI on hourly wages - IV log(1/F) - 2-digit occupations

	(1)	(2)	(3)	(4)
	Log(wage)	Log(wage)	Log(wage)	Log(wage)
Log(HHI)	-0.00250	-0.00540*	-0.00237	-0.00523*
	(0.00249)	(0.00252)	(0.00247)	(0.00250)
Female × Log(HHI)	-0.00161*	-0.00181**	-0.00155*	-0.00175**
	(0.000644)	(0.000645)	(0.000640)	(0.000641)
N	4,098,578	4,098,578	4,099,654	4,099,654
F-test	44779.419	43728.684	45073.439	44020.176
Controls	Yes	Yes	Yes	Yes
Establishment-year FE	Yes	Yes	Yes	Yes
Female CZ × occupation FE	Yes	Yes	No	No
Male CZ × occupation FE	No	No	Yes	Yes
Individual FE	Yes	Yes	Yes	Yes
Gender-year FE	No	Yes	No	Yes

Notes: Standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

F.4 Public sector

F.4.1 Share of women among new hires

Table F.10: Effect of HHI on the share of women among new hires in the public sector - OLS

	(1) Share of women	(2) Share of women	(3) Share of women	(4) Share of women
Log(HHI)	-0.959***	0.180	-0.936***	0.148
	(0.0562)	(0.134)	(0.0470)	(0.123)
N	326,762	321,191	354,913	350,116
Controls	Yes	Yes	Yes	Yes
Establishment-year FE	Yes	Yes	Yes	Yes
Female CZ	Yes	No	No	No
Male CZ	No	No	Yes	No
Female CZ × occupation FE	No	Yes	No	No
Male CZ × occupation FE	No	No	No	Yes

Notes: Standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table F.11: Effect of HHI on the share of women among new hires in the public sector - IV HHI instrument

	(1) Share of women	(2) Share of women	(3) Share of women	(4) Share of women
Log(HHI)	-1.033***	-0.261	-0.877***	-0.132
	(0.0668)	(0.359)	(0.0548)	(0.299)
N	326,510	320,941	354,325	349,533
F-test	582711.446	35565.351	750544.09	49490.97
Controls	Yes	Yes	Yes	Yes
Establishment-year FE	Yes	Yes	Yes	Yes
Female CZ	Yes	No	No	No
Male CZ	No	No	Yes	No
Female CZ × occupation FE	No	Yes	No	No
Male CZ × occupation FE	No	No	No	Yes

Notes: Standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table F.12: Effect of HHI on the share of women among new hires in the public sector - IV log(1/F)

	(1) Share of women	(2) Share of women	(3) Share of women	(4) Share of women
Log(HHI)	-1.368***	-0.753*	-1.180***	-0.466
	(0.0670)	(0.358)	(0.0550)	(0.294)
N	326,510	320,941	354,325	349,533
F-test	569277.845	35956.535	724777.328	51336.511
Controls	Yes	Yes	Yes	Yes
Establishment-year FE	Yes	Yes	Yes	Yes
Female CZ	Yes	No	No	No
Male CZ	No	No	Yes	No
Female CZ × occupation FE	No	Yes	No	No
Male CZ × occupation FE	No	No	No	Yes

Notes: Standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

F.4.2 Hourly wages when considering public and private sector workers

Table F.13: Effect of HHI, computed using public and private sector workers, on hourly wages - OLS

	(1) Log(wage)	(2) Log(wage)	(3) Log(wage)	(4) Log(wage)
Log(HHI)	-0.00115**	-0.00117**	-0.00156***	-0.00157***
	(0.000363)	(0.000363)	(0.000360)	(0.000360)
Female × Log(HHI)	-0.000939**	-0.000957**	-0.000953**	-0.000976**
	(0.000338)	(0.000338)	(0.000332)	(0.000332)
N	4,076,737	4,076,737	4,081,003	4,081,003
Controls	Yes	Yes	Yes	Yes
Establishment-year FE	Yes	Yes	Yes	Yes
Female CZ × occupation FE	Yes	Yes	No	No
Male CZ × occupation FE	No	No	Yes	Yes
Individual FE	Yes	Yes	Yes	Yes
Gender-year FE	No	Yes	No	Yes

Notes: Standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table F.14: Effect of HHI, computed using public and private sector workers, on hourly wages - IV HHI instrument

	(1)	(2)	(3)	(4)
	Log(wage)	Log(wage)	Log(wage)	Log(wage)
Log(HHI)	-0.00614***	-0.00643***	-0.00596***	-0.00623***
	(0.000982)	(0.000982)	(0.000978)	(0.000979)
Female × Log(HHI)	-0.00180***	-0.00177***	-0.00159***	-0.00156**
	(0.000485)	(0.000485)	(0.000481)	(0.000481)
N	4,076,737	4,076,737	4,081,003	4,081,003
F-test	169803.724	169564.141	162068.728	161807.016
Controls	Yes	Yes	Yes	Yes
Establishment-year FE	Yes	Yes	Yes	Yes
Female CZ × occupation FE	Yes	Yes	No	No
Male CZ × occupation FE	No	No	Yes	Yes
Individual FE	Yes	Yes	Yes	Yes
Gender-year FE	No	Yes	No	Yes

Notes: Standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table F.15: Effect of HHI, computed using public and private sector workers, on hourly wages - IV log(1/F)

	(1)	(2)	(3)	(4)
	Log(wage)	Log(wage)	Log(wage)	Log(wage)
Log(HHI)	-0.00740***	-0.00801***	-0.00772***	-0.00830***
	(0.00125)	(0.00125)	(0.00124)	(0.00124)
Female × Log(HHI)	-0.00278***	-0.00288***	-0.00249***	-0.00260***
	(0.000550)	(0.000550)	(0.000542)	(0.000542)
N	4,076,737	4,076,737	4,081,003	4,081,003
F-test	100536.753	100277.92	98710.895	98421.62
Controls	Yes	Yes	Yes	Yes
Establishment-year FE	Yes	Yes	Yes	Yes
Female CZ × occupation FE	Yes	Yes	No	No
Male CZ × occupation FE	No	No	Yes	Yes
Individual FE	Yes	Yes	Yes	Yes
Gender-year FE	No	Yes	No	Yes

Notes: Standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.