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Displaced or depressed? Working in automatable jobs and mental health

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Abstract
Automation may destroy jobs and change the labor demand structure, thereby potentially impacting workers' mental health. Implementing propensity score matching on French individual survey data, we find that working in an automatable job is associated with a 3 pp increase in the probability of suffering from mental disorders. Fear of automation through fear of job loss, expectation of a required change in skills, and fear of unwanted job mobility seem to be relevant channels to explain the findings.

JEL CLASSIFICATION
I10, J81

INTRODUCTION

Over the past decades, the development of new technologies has profoundly changed the labor market and working conditions. Artificial intelligence and recent technical advances—referred to as the "fourth industrial revolution" (Brynjolfsson & McAfee, 2012; DeCanio, 2016)—have revived the debate around the "end of work" or "robots versus workers," with a broader range of workers exposed to the risk of automation. Josten and Lordan (2020) estimate that 35% of jobs in the EU will be fully automatable within the next decade, while Frey and Osborne (2017) estimate that 47% of total US employment is at risk of computerization.[1] While the economic literature has extensively explored the consequences of automation on employment and labor demand (Acemoglu & Autor, 2011; Acemoglu & Restrepo, 2019; Autor et al., 2003; Frey & Osborne, 2017), new attention has

[1]According to a report from the European Commission in 2018 (Nedelkoska & Quintini, 2018), "14% of jobs in OECD countries were automatable and another 32% of jobs could face substantial change in how they are carried out." A previous estimate indicated that 9% of jobs in 21 OECD countries were automatable (Arntz et al., 2016). In France, 10% of current jobs are highly vulnerable to automation, and 50% should see their content significantly transformed within the next 15 years (COE, 2017).

been recently paid to the effects on (mental) health (Gihleb et al., 2022; Gunadi & Ryu, 2021; Lordan & Stringer, 2022; Patel et al., 2018; Venkataramani et al., 2020; Venkataramani & O'Brien, 2020). Measuring and understanding the possible health effects of a major labor market change such as automation, that is, a potential work-related mental health risk factor implying costs, is crucial to effective policymaking. According to the OECD, the total cost of mental illness amounted to 4% of GDP across EU countries in 2018 (including the costs of healthcare, social security programs, sick leave, and losses in employment and productivity). Identifying new health hazards is important to promote the design of effective prevention policies, thereby limiting the costs related to workers' mental illnesses. In this paper, we aim to assess the extent to which working in automatable jobs is associated with well-being and mental health.

The health effects of automation exposure are theoretically undetermined. On the one hand, automation risk may negatively impact workers' mental health because of increased work intensity (Antón et al., 2022; Green, 2004; Karasek, 1979), job insecurity (Abeliansky & Beulmann, 2019; Patel et al., 2018),[2] and lower wage dynamics (Acemoglu & Restrepo, 2020). On the other hand, automation could improve working conditions and health by reducing repetitive and routine tasks (Autor, 2015; Maurin & Thesmar, 2004) if the new technologies are used to support workers (so they can engage in more fulfilling tasks) and if this improves job quality prospects. Gihleb et al. (2022) show that robot exposure reduces physical job intensity and work-related injuries. Gunadi and Ryu (2021) also find that robot adoption is associated with a better health of low-skilled workers partly due to a reallocation of tasks. All of this makes the effects of automation risk on the quality of working conditions and, in turn, on workers' mental health an empirical question.

To study the association between working in an automatable job and mental health, we use the 2013 and 2016 French Working Conditions Surveys, which provide detailed information about working conditions, labor market history, and health status for about 14,000 individuals representative of the working age population employed both in 2013 and 2016. We estimate the association between various mental health indicators, including depression and anxiety, the World Health Organization-5 well-being index (WHO-5), and a self-assessed health indicator. An automatable job is defined therein as presenting three features: repetitive tasks, close monitoring, and detailed instructions. Our definition builds on an actual description of the job (rather than on a perceived risk) and basically assumes that jobs exposed to the risk of automation feature routine tasks, which is a traditional view of exposure to automation. But, contrary to previous studies based on occupational-level data (Autor & Dorn, 2013; Frey & Osborne, 2017), we exploit individual data. Therefore, we are able to account for diverse workplace practices and diverse ways of doing a job within a given occupation, as recommended by Arntz et al. (2017). As workers are not randomly exposed to working conditions nor randomly allocated to tasks and jobs, and since working in automatable jobs is correlated to other factors that also affect health, we implement propensity score matching to address selection on observables (with working in an automatable job as a binary treatment variable). The richness of our data makes the Conditional Independence Assumption (CIA) credible. In addition to the standard demographic variables (gender, age, marital status, number of children, level of education, nationality, region of residency) and usual job attributes (occupation, sector, type of contract, hours, and income), we also condition on confounding working conditions, as well as on past labor market status and past health.

Results indicate that workers who have an automatable job are more likely to report severe mental disorders, with the probability of being anxious or depressed increasing by 3.2 pp in our preferred specification. We find heterogeneous effects with respect to age and education, with

[2]There is a broader literature on the effects of job insecurity on mental health. See Caroli and Godard (2016), Reichert and Tauchmann (2017), Cottini and Ghinetti (2018), Schwabe and Castellacci (2020).

middle-aged (29–49 years old) and middle-educated workers being more affected. An analysis of intermediary outcomes indicates that workers with an automatable job are more likely to report a feeling of job insecurity. Among workers threatened by automation, a higher share also reports expecting a required change in skills within the next 3 years. Work intensity and fear of unwanted job mobility are also greater among workers whose job is at risk of automation.

This paper contributes to the literature showing how automation and new technologies change the skill content of jobs and the skill demand in the labor market (Acemoglu & Autor, 2011; Acemoglu & Restrepo, 2019, 2020; Autor et al., 2003). By looking at how these changes in working conditions may affect workers' well-being and mental health, we add to an emerging literature. Innoncenti and Golin (2022) show that not all workers are equally worried about the risk of automation and that those worried about being displaced by a machine or algorithm also intend to invest more in human capital in the form of training outside their workplace. According to Schwabe and Castellacci (2020), automation in industrial firms in recent years has led 40% of employed workers to fear that an intelligent machine might replace their work in the future. Clearly, the fear of future replacement negatively affects workers' job satisfaction at present. This negative result is driven by low-skilled workers, those carrying out routine-based tasks and therefore more exposed to the risk of automation.

Only a few studies look at the health effects of automation risk. They focus on the adoption of industrial robots and measure automation risk from occupational or industry data. Patel et al. (2018) document the detrimental effects of automation risk and robot penetration on health (both physical and mental) in the United States, using aggregate data (county level) and focusing on the job insecurity mechanism. From US aggregate data, Venkataramani and O'Brian (2020) and Venkataramani et al. (2020) also find a positive association between robot penetration and drug overdose, opioid overdose mortality, or disability. Gunadi and Ryu (2021) find that higher penetration of industrial robots is negatively related to health and disability. Using Australian survey data, Lordan and Stringer (2022) find evidence that automatable work has a small detrimental impact on workers' mental health and life satisfaction within some industries, particularly when levels of job automation risk are higher (e.g., manufacturing). Last, using European data, Antón et al. (2022) show that robotization increases work intensity and the probability of reporting work-related stress and anxiety. Unlike these studies, we use a measure of automation risk defined at a micro level, as recommended by Arntz et al. (2017). Gihleb et al. (2022) use both US occupational data and German individual data to look at the impact of industrial robots on mental health (among other outcomes). While they document a significant increase in mental health problems in US commuting zones more exposed to robot penetration, they find no evidence of a detrimental impact on German workers' mental health. Their mixed results call for further investigations, which we do using detailed data on firms' practices. In addition to the fear of job loss, we also explore alternative channels that have not been empirically tested yet, namely management practices, work intensity, and expected changes in required skills.

Unlike existing studies, our definition of automation risk is not restricted to exposure to industrial robots. Therefore, our paper contributes to the literature by covering other forms of automatability, where computers and algorithms may also replace tasks or jobs.

Finally, while most empirical studies on the effect of automation (risk) on workers' health use German or US data (except Lordan and Stringer (2022) based on Australian data), we contribute to the literature by shedding light on the association between automation and workers health using data from France. France is a good representative of other European countries in terms of the average health status of the population[3] and in terms of the adop-

[3]On average, more than one in six people in EU countries have a mental health problem, and France stands with these statistics: regarding self-assessed health, 66% of French people report being in good or very good health in 2016, compared to 68% on average in Europe. See https://health.ec.europa.eu/system/files/2020-02/2018_healthatglance_rep_en_0.pdf.

tion of automation technologies.[4] Moreover, it seems relevant to explore the link between the risk of automation and mental health in a context where automation is still ongoing, as one might expect the effects of automation to be heterogeneous with respect to the stage of the automation process.

The rest of the paper is organized as follows. Section 2 describes the data, the sample, and our measures of automation risk and mental health. Section 3 explains the empirical strategy. We present our results in Section 4 and discuss possible mechanisms in Section 5. Section 6 concludes and draws policy implications.

DATA

Sample

We use surveys of working conditions (*Conditions de travail* and *Conditions de travail-Risques Psycho-sociaux*) produced by the statistical Department of the French Ministry of Labour. These surveys have been conducted every 3 years since 2013 to create a representative panel of workers and monitor the evolution of working conditions and psycho-social risks in the workplace in France. Each wave provides information about employment status, working conditions, and health for about 28,000 individuals above 15 years old, whether employed or self-employed. Workers are interviewed mainly face to face and complete a self-administered questionnaire for more sensitive questions. All waves share a common block of core questions. The 2016 wave is the only one that provides a variety of detailed measures of mental health[5] and additional questions about psycho-social risks.

As we aim to assess the association between working in automatable jobs and mental health, we focus on the 2016 wave. We use the 2013 wave to retrieve information about workers' past labor market status and health, as required by our empirical strategy to strengthen the credibility of the unconfoundedness identifying assumption (see Section 3: Empirical strategy).

Our analysis sample consists of 13,544 wage earners in 2016 who were also interviewed in 2013.[6] We exclude self-employed workers because they can control job loss (hence job insecurity) and job changes, unlike employed workers. We build the appropriate weights to deal with non-responses and to have a sample representative of the 2016 working population. Table A1 in the appendix describes the sample as a whole. About half are women, and around one-third are aged 50 years. Over 32% of the sample have no diploma or a low education level, 49% have a university degree, and 23% are executives. The services sector is by far the most widely represented activity (about three quarters).

Measure of automation risk

Workers are defined as working in automatable jobs if they (i) execute repetitive tasks, (ii) have a job that can be easily monitored (due to a constrained pace), and (iii) have to follow detailed

[4]Looking at robot density to proxy automation (though our measure is different), Germany is the most automated European country—ranked 4th worldwide—with 371 units for 10,000 employees. In comparison, France has a robot density of 194 units (ranked 16th worldwide). While France is, like Germany, above the global average of 126 robots, it is closer to other EU countries like Spain (203 units), Austria (205 units), or the Netherlands (209 units). See https://ifr.org/ifr-press-releases/news/robot-density-nearly-doubled-globally.

[5]The 2013 and 2019 waves only give the WHO-5 score for well-being.

[6]Of the 28,000 individuals who were interviewed in 2016, only about 22,000 were also interviewed in 2013. We have excluded workers employed by a private individual (660 observations). We have deleted observations with missing values for key variables (7280 observations), and we have excluded individuals living overseas (675 observations).

instructions with no latitude in tasks performed and in the manner of performing them.[7],[8] Our definition basically assumes that jobs exposed to the risk of automation are jobs that feature routine tasks, which is the traditional view of exposure to automation. Routine tasks can be more easily automated, and workers whose job involves a higher proportion of routine tasks are more likely to be displaced by computers.

These three conditions are in many ways close to those found in papers where the O*NET data are used to identify occupations involving a higher proportion of routine tasks (Acemoglu & Autor, 2011; Frey & Osborne, 2017). However, we lack information about dexterity (a possible protection from automation), which may lead to falsely classifying workers as working in automatable jobs. Moreover, we cannot assess the routine task share of all the tasks that define a job. Ideally, we would have liked to know the share of automatable tasks to determine the salience of the risk of displacement and/or change in the job description. Our assumption, however, is that workers will answer that their job has a specific feature if they consider it is important enough or is a key aspect of the job, which should also allow us to capture jobs that are at least partially automatable.

Importantly, contrary to Autor et al. (2003) and Frey and Osborne (2017), a nice feature of our approach is that we rely on information at the individual level rather than at the occupational level. Therefore, we are able to overcome an important limitation of the occupational approach by accounting for the possibility that not all workers within a given occupation will be equally exposed to the risk of automation due to diverse workplace practices and the diverse ways of actually performing a given job. Arntz et al. (2017) highlight the importance of defining the risk of automation at the individual level (rather than at the occupational level) to account for these workplace-specific practices. Using detailed task data, they show that, when the spectrum of tasks within occupations is taken into account, the automation risk of US jobs drops from 38% to 9%. Adopting an individual approach is even more important with our data since our indicator of automation risk varies substantially within occupations: for almost 50% of occupations, about one of five workers considers that her or his occupation is at risk of automation (Appendix Figure A1).

To assess how our measure of automation risk relates to the main approaches found in the literature, we compare our measure's distribution—redefined at the occupational level—with the distribution of two alternative measures of automation risk. First, relying on Autor and Dorn (2013)'s approach, we use a crosswalk table between the international standard classification of occupations (ISCO) included in our French data and the US classification to apply the O*NET job description to jobs in France. Second, we use the probability of computerization computed by Frey and Osborne (2017). Both alternative measures rely on the assumption that job attributes are the same in France and the United States. Our measure (redefined at the occupational level) is positively correlated with both Autor and Dorn's measure and Frey and Osborne's measure (Appendix Figures A2 and A3).

Under our definition of automatability, about 19% of workers in our sample had automatable jobs in 2016. The hierarchy of occupations and of jobs seems consistent with expectations, and there are large differences in the exposure to automation across occupations (Appendix Tables A4 and A5). For instance, about 59% of checkout assistants have a job classified as

[7]Table A2 in the appendix lists the exact questions used to construct our measure of working in automatable jobs. To be classified as working in an automatable job (binary variable), workers must have answered yes to at least one question for each condition. Considering the nature of the questions, our measure actually builds on an actual description of the job rather than on a direct question on the perceived risk of automation.

[8]Table A3 in the appendix shows correlations between the three conditions that define our measure of working in automatable jobs. It is not restricted to a measure of repetitive work. Out of the individuals who report a repetitive job, only half are considered to be working in automatable jobs (i.e., meeting the three conditions), 22% have latitude regarding tasks, and 32% experience no pace constraints.

automatable versus less than 1% of teachers and psychologists. Similarly, unskilled workers are more likely to have an automatable job than executives (43% vs. 3%).

Measures of health

Our primary measure of mental health is the occurrence of a major depressive episode (MDE) or a generalized anxiety disorder (GAD), two closely related and common severe mental disorders. We rely on answers to the Mini international neuropsychiatric interview[9] included in the survey (self-administered) and follow the DSM-IV guidelines to determine whether individuals suffer from an MDE or a GAD. In particular, the DSM-IV guidelines characterize a major depressive episode as a depressed mood or loss of interest or pleasure for almost all activities and by the daily presence of several psychiatric symptoms or a neuro-vegetative state for at least 2 weeks. A generalized anxiety disorder is characterized by excessive anxiety with somatic symptoms, which is difficult to control. It may arise even in the absence of a destabilizing factor, may be continuous, or may include several events for at least 6 months.[10]

As people may experience mental problems that do not reach the threshold for diagnosis as a mental disorder, we consider as an additional proxy for poor mental health the probability of being anxious almost all the time in the past 6 months (without necessarily suffering from a GAD). We also use the World Health Organization-Five well-being index (WHO-5)—both the continuous score and a dichotomous version to look at the probability of having a WHO-5 score lower than 50 (out of 100). For comparability purposes, we also use self-assessed overall health to analyze the probability of being in very good or in good health. Self-assessed overall health is related to mental health but relies on different dimensions, including physical health.[11]

As shown in Appendix Table A1, almost 10% of workers in our sample suffered from an MDE or a GAD in 2016. Nearly 30% had a low well-being score, and 25% reported not being in good or very good health. Workers with automatable jobs have a poorer mental health status than other workers (respectively, 15% vs. 8% with an MDE or a GAD, and 35% vs. 27% with a low WHO-5).

EMPIRICAL STRATEGY

To evaluate the effect of working in an automatable job on mental health, we need to deal with endogenous issues: Workers whose job is at risk of automation may have specific attributes that may also affect their mental health and well-being, irrespective of their exposure to automation. Indeed, individuals whose job is defined as automatable are, on average, younger,

[9]The Mini International Neuropsychiatric Interview (MINI) was designed by the Harm Research Institute as a brief structured diagnostic interview for the major psychiatric disorders in DSM-III-R, DSM-IV and DSM-5 and ICD-10. See https://harmresearch.org/mini-international-neuropsychiatric-interview-mini/ for details.

[10]Considering the DSM-IV classification, individuals suffer from an MDE if they answer *yes* to the question "Have you been depressed or down, or did you feel sad, empty, or hopeless, most of the day, nearly every day, for the past 2 weeks?" OR *yes* to the question "In the past 2 weeks, were you much less interested in most things or much less able to enjoy the things you used to enjoy most of the time?" AND report at least four of seven related psychiatric symptoms. Respondents suffer from a GAD if they answer *yes* to the question "In the past 6 months, did you feel too worried about anything and everything, did you feel excessively concerned, worried, anxious for problems of everyday life, at work, at home, or about those close to you?" AND *yes* to the question "Do you have these kinds of concerns almost every day?" AND *yes* to the question "Do you find it difficult to control these concerns or do they prevent you from concentrating on what you have to do?" AND report at least three of six related psychiatric symptoms.

[11]Mental health is an important component of health, and self-assessed health is a good predictor of mortality (Jylhä, 2009). In our sample, the correlation between the indicator of (very) good self-assessed health and the indicator of reporting MDE or a GAD is significant and equal to −0.26.

have lower educational and occupational levels, have experienced more possibly damaging events in the past, and report poorer health in 2013 than workers not subject to automation risk (Appendix Table A1). Additionally, workers in automatable jobs are more likely to work in the construction industry and to report poorer working conditions (higher exposure to physical risks, atypical working hours, and changing and/or unpredictable schedules) and a work environment that underwent organizational changes in the past year. Overall, workers threatened with automation present features that may harm health.

We exploit the richness of our data to partly correct the endogeneity issue by implementing matching, that is, by comparing individuals working in automatable jobs to individuals not working in automatable jobs, but who are otherwise comparable in terms of observables.[12][13] Specifically, we combine exact matching on key attributes—gender, age (3 categories), education (3 categories), sector (private vs. public), and occupation (9 categories), with propensity score matching (Rosenbaum & Rubin, 1983) that matches individuals on their probability of being treated given their observed covariates X. The effect of the "treatment" (working in a job classified as automatable—binary variable) is measured as the difference in average outcomes between those "treated" and the matched "untreated" (matched control group). Our parameter of interest is then the average treatment on the treated (ATT) defined as:

$$\delta_{\text{ATT}} = E(Y(1) | D = 1, X) - E(Y(0) \mid D = 1, X)$$

where $Y(1)$ and $Y(0)$ are the outcomes, and D the treatment indicator taking value 1 for individuals working in jobs classified as automatable, and 0 otherwise.

The empirical counterpart of δ_{ATT} is the difference between the mean outcome of the treated and the weighted mean outcome of the controls:

$$\hat{\delta}_{\text{ATT}} = \frac{1}{N_1} \sum_{i=1}^{N_1} y_i(1) - \sum_{j=1}^{N_0} \hat{w}_j y_j(0)$$

where N_0 and N_1 are the number of treated and control individuals, respectively. Weights $\hat{w}_j$ are obtained through matching and satisfy $\hat{w}_j \geq 0$ and $\sum_{j=1}^{N_0} \hat{w}_j = 1$.

Propensity score matching relies on two main identification assumptions: unconfoundedness (or Conditional Independence Assumption, CIA) and common support (or overlap).[14] When the ATT is the parameter of interest, these assumptions write:

$$\text{(CIA)}\ Y(0) \perp\!\!\!\perp D \mid p(X) \forall X$$

$$\text{(CS)}\ p(X) = P(D = 1 | X) < 1$$

with $p(X)$ being the propensity score.

The literature shows that conditioning on past outcomes and events significantly improves matching quality and the credibility of the unconfoundedness assumption (Caliendo et al., 2017;

[12] Alternatively, we would have liked to account for unobserved heterogeneity by constructing a three-wave panel (using the 2019 wave of the surveys), and then estimating a model with fixed effects. Unfortunately, we are unable to get a consistent indicator of the risk of automation across the three waves because two important questions required to construct the indicator were not asked in 2019 and 2013 (especially questions relating to latitude, which is a crucial aspect of automation risk). Moreover, we cannot use specific mental health measures such as MDE or GAD indicators in 2013 and 2019 since questions are not asked in 2013 and 2019.

[13] Alternatively, the endogeneity issue can be solved using trade exposure or gradual diffusion of robotics as an instrument for the risk of automation (Autor et al., 2003; Gihleb et al., 2022; Gunadi & Ryu, 2021; Patel et al., 2018). We do not choose this strategy as we have rich data at the individual level.

[14] An additional identifying assumption is the stable unit treatment value assumption, SUTVA, according to which individuals are unaffected by the treatment status of others.

Lechner, 2002). Therefore, in addition to the standard demographic variables (gender, age, marital status, number of children, level of education, nationality, region) and usual job attributes (occupation (23 categories), tenure, type of contract, sector of activity (15 categories), income (14 categories), hours worked (part-time or full-time)), we also include in the propensity score variables describing the labor market history and past health. In particular, we control for having experienced family or health events in childhood or the past 3 years, for changes in the workplace that have occurred in the past year,[15] for self-assessed health in 2013, labor market status in 2013, occupation in 2013 (23 categories), working conditions in 2013, and for having an automatable job in 2013.[16] Such controls capture heterogeneity that may be important determinants of the job situation and health status, but are usually unobserved. Including those in our propensity score alleviates the concerns about selection into automatable jobs and omitted variable bias.[17]

As our treatment indicator relies on subjective answers on working conditions, controlling for past health outcomes is crucial. We use questions aimed to elicit the most factual possible description of working conditions, but there may still be some subjectivity in the answers. Differences between workers' subjective appreciation of a given situation may create an identification issue if factors that affect the perception of working conditions are also correlated with factors that affect mental health, or if mental health itself changes how workers view their working conditions. This may create a problem of reverse causality (i.e., workers with poor mental health possibly having biased perceptions of their job and thus falling into the automatable job category) that cannot be addressed by matching. However, our results hold regardless of the automation measure, including the most objective measures built by Frey and Osborne (2017) and Acemoglu and Autor (2011) (see upcoming Table 3). Moreover, matching individuals on past health limits such a bias.

We also need to consider working conditions that could be correlated both with the working conditions used to define our treatment and with the health status. This is why we control for exposure to physical risks and to means constraints, unpredictable or atypical working hours, hourly constraint, poor work–life balance, quality of management (i.e., support from colleagues and managers, effort recognition), and contact with the public.[18] By doing so, we both control for confounding factors and limit the omitted variable bias.

By matching workers exactly on nine broad occupation categories, we are able to control for the selection into occupations partly,[19] and to exploit the variation of automation risks within occupations. Following Arntz et al. (2017), we rely on the idea that, within an occupation, a given job may be done differently due to firms' and workplaces' specific practices. In our context, it means that workers with similar observed attributes, working in the same occupation and exposed to similar working conditions, could be working in an automatable job or not (and could therefore be treated or not), depending on the specific practices at the workplace. If workers select themselves into workplaces based on unobservables that are both

[15]More precisely, we control for changes in work organization, changes in location, changes in hierarchy, and other changes that are neither changes in the job description and changes in techniques, nor collective layoff. We exclude those changes because they are likely to be either a determinant or a consequence of automation.

[16]While we estimate the effect of a within-individual change in automatability over time when matching on having worked in an automatable job in 2013, measures of automation in 2013 and in 2016 are not exactly the same. The automatability measure for 2013 does not include two important questions related to latitude, which is a crucial aspect of automation risk. Missing questions are: "Do you have the opportunity to put your own ideas into practice in your job?" and "Does your job require you to take initiative?"

[17]What we use as prior outcomes need not necessarily be prior outcomes as the selection into the current workplace may have occurred at any time. Still, it seems important to control for past health outcomes to address potential selection bias on health. If it captures part of the effect, then we have a lower bound for the parameter of interest.

[18]The complete list of covariates is given in Figure 1.

[19]Matching on nine broad occupation categories is not enough to entirely solve the selection into occupations. Our sample does not allow to implement exact matching on a more detailed classification, at the risk of excluding a large number of observations. Nevertheless, we control for a more detailed classification of occupation (23 categories) in the propensity score.

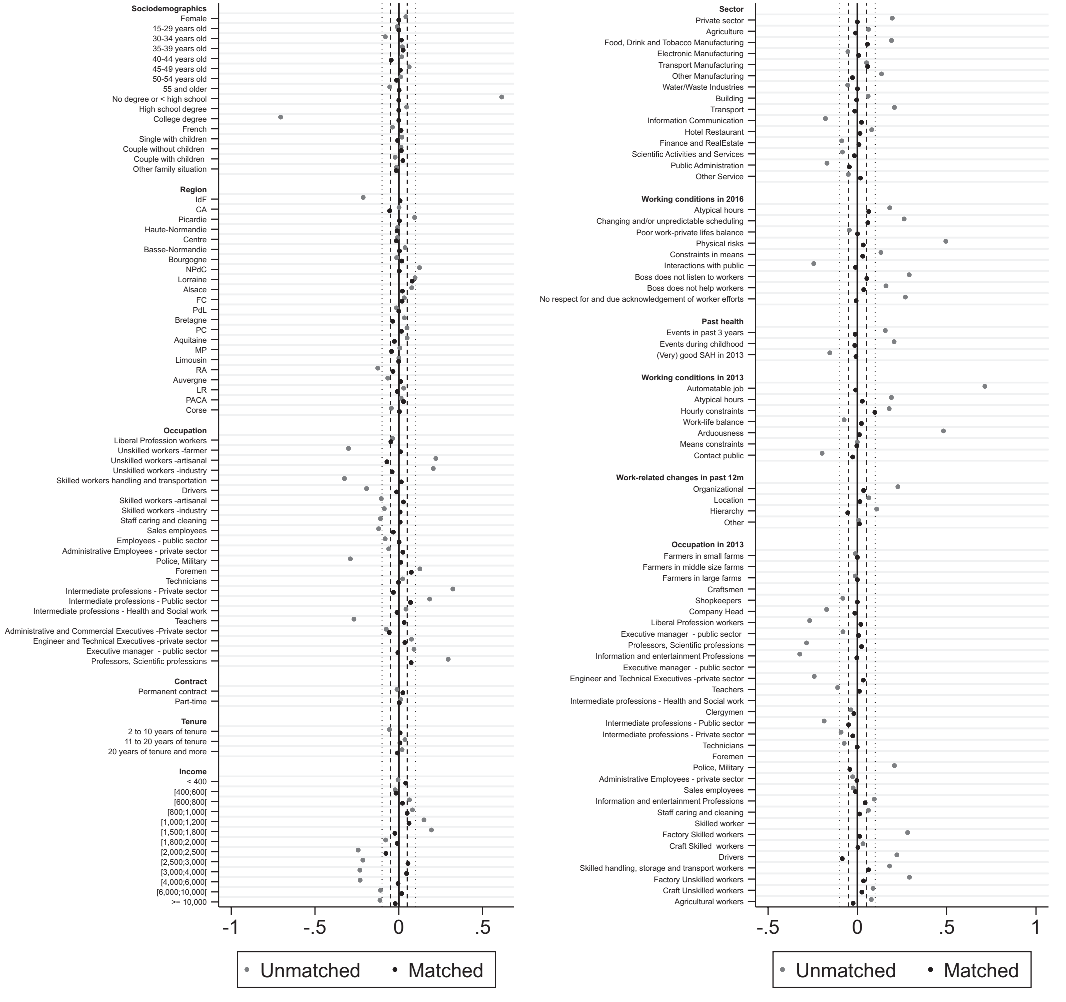

FIGURE 1 Standardized % bias across controls.

related to the degree of automation at the workplace on the one hand and on their own health on the other hand, then our estimation strategy cannot identify a causal effect. As we cannot entirely exclude such a selection into firms and jobs, we take caution in interpreting our results.

In our preferred specification, we estimate the propensity score with a logit model and match observations by combining the Epanechnikov kernel with a caliper at 0.05 and exact matching on demographic variables (gender, age, education) and job attributes (sector—private vs. public—and occupation). Figure 1 shows that covariates are well balanced in the matched sample.[20] In a sensitivity analysis, we use alternative algorithms and distances and perform inverse probability weighting (IPW) to estimate the propensity score.[21]

[20]Figure A4 in the appendix shows the good quality of the common support. Results hold when we run the estimation on a sample where the top and the bottom 5 percentiles of the distribution of the propensity score are excluded (see Column (4) in Table A6 in the appendix).

[21]We could not perform exact or coarsened exact matching since the large number of covariates in our model leads to matching on a limited number of observations.

TABLE 1 Working in an automatable job and the probability of declaring a major depression episode (MDE) or generalized anxiety disorder (GAD).

	(1)	(2)	(3)	(4)	(5)
Automatable job	0.078***	0.069***	0.069***	0.054***	0.032***
	(0.002)	(0.004)	(0.004)	(0.007)	(0.007)
Observations	13,544	13,544	13,544	13,544	13,544
Controls					
Sociodemographics	No	Yes	Yes	Yes	Yes
Job attributes	No	Yes	Yes	Yes	Yes
Health history	No	No	Yes	No	Yes
Current working conditions	No	No	No	Yes	Yes
Past working conditions	No	No	No	Yes	Yes

Note: Bootstrapped standard errors in parentheses. ***$p<0.01$. Sample: wage earners with non-missing relevant observables, interviewed both in 2013 and in 2016, and employed in 2016. Dependent variable: declaring a MDE or a GAD. Measure of automation risk defined in Section 2.2. Exact matching on gender, age (3 categories), education, sector (private or public) and occupation (9 categories), combined with propensity score-kernel matching and full list of controls (see Figure 1 for the detailed list of variables included in the estimation of the propensity score).

Source: French Working Conditions Surveys 2013 and 2016.

RESULTS

Main results

Table 1 presents the estimates of the average treatment on the treated (ATT) of working in automatable jobs on the probability of suffering from an MDE or a GAD. While Column (1) shows the raw difference between the treated and controls, Columns (2)–(5) present estimates once the endogenous exposure to the risk of automation is accounted for. The coefficient of interest slightly drops when we control for socio-demographics, job attributes, and past health outcomes[22] (0.078–0.069), showing a selection bias that would lead to overestimating the strength of the link between automation and health if ignored. Controlling for past and current working conditions strongly lowers the coefficient of interest (0.078–0.054), confirming the need to account for confounding working conditions. Results are noticeably reduced but remain significantly positive once we add the full set of controls. We find that workers whose job may be subject to automation in the future are 3.2 pp more likely at present to report symptoms of an MDE or a GAD than if not threatened with automation. Considering the baseline at 15.8% (Appendix Table A1), this actually implies a 20% increase in the probability of suffering from a mental disorder among the treated. This substantial increase can partially be explained by the fact that our outcome of interest is statistically rather infrequent.

Our negative results are in line with Patel et al. (2018) who find a negative impact of automation risk (at the county level) on mental health in the United States using a 2SLS estimation. From a linear regression with fixed effects, Lordan and Stringer (2022) also find evidence that automatable work has a small detrimental impact on Australian workers' mental health and life satisfaction within some industries (particularly manufacturing).

Replicating the analysis on subsamples, we find heterogeneity with respect to sociodemographic characteristics (Figure 2).[23] In particular, middle-aged workers (aged between 30 and

[22]We add three main covariates controlling for initial health: Health events in the past 3 years, possibly traumatic events that occurred in childhood and the self-assessed health reported in 2013.

[23]We do not match on occupations in 2013 for the subsample "15–29 years old" as past occupation is mostly missing for this age group.

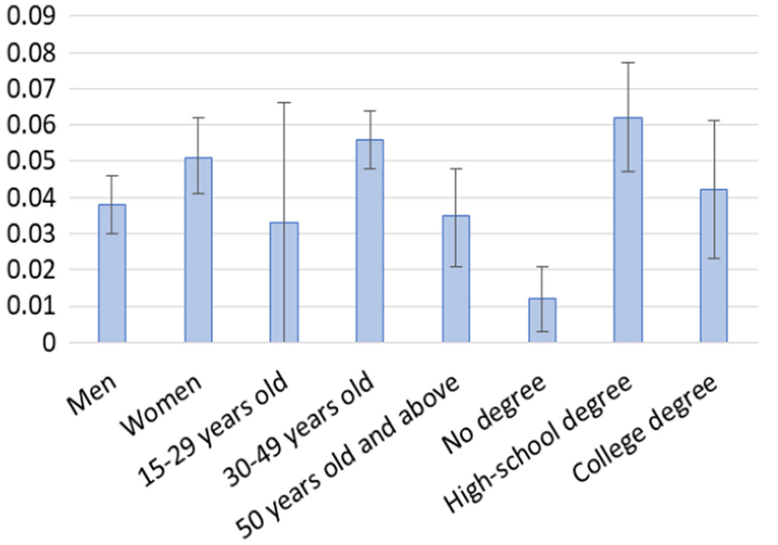

FIGURE 2 Heterogeneous effects of automation risk on the probability of declaring a MDE or GAD (ATT). *Note*: Stratified estimation of sub-samples of wage earners with non-missing relevant observables, interviewed both in 2013 and in 2016, and employed in 2016. Balancing on each sub-sample presented in Appendix Figure A6. Dependent variable: experiencing a major depression episode (MDE) or a generalized anxiety disorder (GAD). Measure of automation risk defined in Section 2.2. Exact matching on gender, age (3 categories), education (3 categories), sector (private or public) and occupation (9 categories), combined with propensity score-kernel matching and full list of controls (see Figure 1 for the detailed list of variables included in the estimation of the propensity score). Bootstrapped standard errors. Caps represent 95% confidence intervals.

TABLE 2 Working in an automatable job and alternative health outcomes.

Dependent variable	MDE or GAD	Anxiety	Low WHO-5	WHO-5 score	(Very) good health
Automatable job	0.032***	0.037***	0.026***	−0.238	−0.01
	(0.003)	(0.008)	(0.008)	(0.347)	(0.008)
Observations	13,544	13,544	13,544	13,544	13,544

Note: Bootstrapped standard errors in parentheses. ***$p < 0.01$. Sample: wage earners with non-missing relevant observables, interviewed both in 2013 and in 2016, and employed in 2016. Measure of automation risk defined in Section 2.2. Exact matching on gender, age (3 categories), education, sector (private or public) and occupation (9 categories), combined with propensity score-kernel matching and full list of controls (see Figure 1 for the detailed list of variables included in the estimation of the propensity score).

Source: French Working Conditions Surveys 2013 and 2016.

Abbreviations: GAD, generalized anxiety disorder; MDE, major depression episode.

49 years)[24] and workers with intermediate or high levels of education (high-school or college degree) are more likely to have an MDE or GAD when working in an automatable job.[25] We do not find heterogeneous effects between men and women.[26]

[24]For both middle-aged and older workers, the increase is about 50% while the likelihood of reporting a mental disorder for younger workers is roughly doubled (but not significant).

[25]Results are qualitatively unchanged but slightly larger when we exclude workers aged below 18 or 25 and workers above 59 years old (Table A6 in the appendix), which aligns with the idea that working in an automatable job is less detrimental to younger and older workers than to middle-aged workers.

[26]Balancing indicators are displayed in Figure A6 in the appendix. Matching quality is not as good for women and middle-educated workers as for the main estimates.

TABLE 3 Working in an automatable job and the probability of declaring a major depression episode (MDE) or generalized anxiety disorder (GAD)—Robustness analysis.

	Routine, pace constraints, and No latitude	Routine and pace constraints			No latitude	Main measure + Frey and Osborne's measure > 10%	Acemoglu and Autor's measure	
		All workers	Job with latitude	Job without latitude			Score > average	Score > p75
	(1)	(2a)	(2b)	(2c)	(3)	(4)	(5a)	(5b)
Automatable job	0.019**	0.060***	0.048***	0.047***	0.029***	0.017**	0.030**	0.041
	(0.008)	(0.005)	(0.017)	(0.007)	(0.003)	(0.007)	(0.010)	(0.023)

Note: Standard errors (SE) in parentheses. Bootstrapped SE in columns (1)–(4), clustered SE at the occupation category level in columns (5a) and (5b). $^{***}p<0.01$, $^{**}p<0.05$. Sample: wage earners with non-missing relevant observables, interviewed both in 2013 and in 2016, and employed in 2016. Dependent variable: declaring a MDE or a GAD. Measures of automatability used in columns (1)–(3) are different combinations of conditions (i), (ii), and (iii) described in Table A3 (i.e., Condition (i) = Routine; Condition (ii) = Pace constraints; Condition (iii) = No latitude). Column (1) uses Conditions (i) and (ii), and the first two questions of Condition (iii); columns (2a)-(2c) use Conditions (i) and (ii), and provide effect heterogeneity with respect to Condition (iii); Column (3) uses Condition (iii) only. The measure used in Column (4) takes our main indicator and additionally imposes that the individual works in an occupation for which the Frey and Osborne's probability of computerization is at least equal to 10%. Measures of automatability used in columns (5a) and (5b) rely on the Acemoglu and Autor (2011)'s score of intensity in routine tasks defined at the occupation level. Exact matching on gender, age (3 categories), education, sector (private or public), and occupation (10 categories), combined with propensity score-kernel matching and full list of controls (see Figure 1 for the detailed list of variables included in the estimation of the propensity score).

Source: French Working Conditions Surveys (2013 and 2016).

Sensitivity analysis

In addition to MDE and GAD, we consider less severe alternative health measures. Results are presented in Table 2. We find similar significant negative associations between the automatability of the job and the probability of feeling anxious almost all the time every day (3.7 pp vs. 3.2 pp for the main outcome). We find mixed evidence for the association between well-being and working in an automatable job: The association is significant when we consider the probability of having a low WHO-5 (2.6 pp vs. 3.2 pp) and is not significant when we take the continuous WHO-5 score.[27]

There is also no significant link between self-assessed health and working in an automatable job. This is not in contradiction with both Gunadi and Ryu (2021) who find that increasing robots' utilization is associated with reduced poor health reporting, and Gihleb et al. (2022) who show that robot exposure leads to a decline in disability. Since self-assessed health also captures the physical dimension of health, this result does not contradict our results on mental health. It shows that automation may differently affect mental health, well-being, and overall health.

We also compare the sensitivity of the main results to our definition of working in automatable jobs (Table 3). Results are robust to the way we proxy the lack of latitude (see Column (1) which relies on a less restrictive and more standard measure of low latitude[28]). Routine and pace constraints appear to be important features for the association between the automatability of the job and mental health, regardless of the degree of latitude (Columns (2a) to (3)).

As explained in Section 2: Data, we lack information about some job requirements (especially dexterity) that may prevent a worker from being displaced by a machine or a computer. Therefore, we restrict our measure of automation risk to jobs with at least a 10% probability of computerization, as defined by Frey and Osborne (2017). This ensures that we do not include workers whose jobs are actually not at risk of automation in the treatment group. Results are still significant but smaller when we add this condition (1.7 pp vs. 3.2 pp).

Additionally, we repeat the analysis using a measure of automatability based on Acemoglu and Autor (2011)'s measure, now defined at the occupational level. In this robustness test, we consider as treated individuals who work in an occupation whose share of routine tasks is either higher than the average or higher than the 75th percentile of the index distribution. Results are of the same order of magnitude as those obtained with our preferred specification and our preferred measure of automatability (even if the coefficient is only significant when we consider a score higher than the average of the index distribution).

Results as a whole are also unchanged when we consider alternative matching algorithms and distances, and inverse-probability weighting (Appendix Figure A5).[29]

Lastly, we investigate the credibility of the unconfoundedness assumption by calculating the Rosenbaum bounds (Becker & Caliendo, 2007; Rosenbaum, 2002). We obtain a critical value of 2.1 for Γ, which means that estimates would lose significance if unobservables caused the odds ratio of the assignment to treatment to differ by 2.1 between the treated and the controls. This high critical value indicates that our results are not sensitive to deviations from the CIA, or that such a deviation needs to be large enough for unobserved heterogeneity to reverse the inference.

[27]Having one result that is significant and the other one that is not significant does not mean that our results are not robust. Indeed, both outcomes do not measure the same thing: The increase in the score would translate into an increase in the probability of having a low WHO-5 only if the score is modified around the threshold that defines a low WHO-5.

[28]More precisely, this alternative indicator of automation risk takes the same definition of routine job and pace constraints (Conditions (i) and (ii) in Table A2), but defines the absence of latitude by only using the questions about instructions and orders (first two questions of Condition (iii) in Table A2), which tackles more directly the matter of work autonomy.

[29]We do not show results from multidimensional nearest neighbor matching, leading to poor balancing performances.

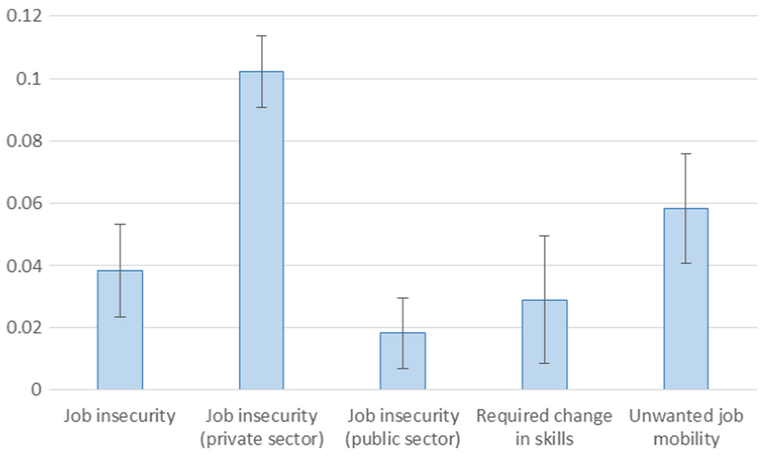

FIGURE 3 Effect of automation risk on intermediate outcomes (ATT).
Note: Bootstrapped standard errors. Caps represent 95% confidence intervals. Sample: wage earners with non-missing relevant observables, interviewed both in 2013 and in 2016, and employed in 2016. Separate estimation on each intermediate outcome. Measure of automation risk defined in Section 2.2. Exact matching on gender, age (3 categories), education, sector (private or public) and occupation (9 categories), combined with propensity score-kernel matching and full list of controls (see Figure 1 for the detailed list of variables included in the estimation of the propensity score).

MECHANISMS AND DISCUSSION

We explore different channels to explain the negative link between automatability and mental health. The first channel we highlight is the fear of automation, which includes not only the fear of job loss (as in most papers) but also the fear of unwanted job mobility within the workplace, and the expectation of a required change in skills. We also explore three alternative channels to the fear of automation: the role of management practices, the income channel, and the risk of offshoring. We end the discussion with a paragraph on the nature of the effects by discussing actual automation.

Fear of automation

Our hypothesis to explain the findings is that working in an automatable job may negatively impact mental health if workers are aware that their job is at risk of automation and that this will alter their career path. We test this mechanism by replicating the analysis using three intermediary outcomes reflecting the fear of automation (namely fear of job loss, fear of unwanted job mobility within the workplace, and expectation of a required change in skills) as dependent variables.[30] This provides indicative evidence on possible relevant channels, although without testing them directly.

Figure 3 shows that workers exposed to automation risk report fear of job loss within the year (first bar), expectation of a required change in skills within the next 3 years (fourth bar), and fear of unwanted job mobility within the workplace (fifth bar), all being significantly positive. We further confirm the relevance of the job insecurity channel by disentangling the private and public sectors, as public servants in France are at very low risk of dismissal (second

[30]All intermediary outcomes are significantly and positively correlated with the indicator of reporting an MDE or GAD (see Table A7 in the Appendix).

and third bars). The effect is indeed very small in the public sector (less than 2 pp vs. more than 10 pp in the private sector).

The fear of automation channel is also consistent with the heterogeneity of the effects of working in automatable jobs on mental health. Previous studies tend to show that new technologies are biased against older workers. Because of their lower ability to adapt and skill obsolescence, older workers may be more likely to be separated and less likely to be hired (Aubert et al., 2006). They could therefore be more worried about being displaced due to automation. Our results partially support this statement. Middle-aged workers may perceive automation as a threat to their career path (with possible job loss and unwanted job mobility) and may feel less able to adapt to such changes. By contrast, older workers may feel protected from automation by the prospect of retiring (i.e., a horizon effect).

To better link the intermediary outcomes to the final health outcome, we take the interaction term between the intermediary outcomes and the indicator of an automatable job as the treatment variable. Results are presented in Table A8 in the appendix. They are qualitatively similar when we consider job insecurity: The association between automation and health is stronger when workers fear for their job. Results are also significant when we consider the expectation of a required change in skills or the fear of unwanted job mobility.[31]

Management practices

As a first alternative to the fear of automation channel, we now discuss the role of management practices on the negative link between automatability and mental health. Jobs classified as automatable in the future actually also share attributes with jobs that, by nature, involve unsatisfactory working conditions, which may contribute to explaining the negative relation between working in automatable jobs and mental health. Indeed, automatable jobs may be more often unfulfilling or subject to poor management.

As mentioned in the sensitivity analysis (Table 3 in Section 4: Results), the combination of all three aspects of automatable jobs (routine, pace constraints, and lack of latitude) is detrimental to health. Moreover, workers in automatable jobs are more poorly managed (see Appendix Table A1). In addition to including a dummy capturing bad management,[32] we break the sample down into two groups: individuals exposed to bad management and those who are not, replicating the analysis on both subgroups. While the association is much stronger for workers subject to bad management, the estimate is also positive for workers who are not (0.077 vs. 0.012, see Appendix Table A8). We take this result as an indication that management practices also matter to explain the negative link between automatability and mental health.

[31]An alternative strategy consists in introducing the possible mediating variables into the matching process. If part of the effect goes through these intermediary outcomes, the association between our main variables of interest should be weaker. When we do so, the estimated coefficient associated with our indicator of automatable job remains significant but is reduced by 22% (going from 3.2 pp in our main specification to 2.5 pp when we match individuals on the intermediary outcomes). While the fear of automation (through these mediating variables) may be an important part of the overall effect of working in an automatable job, it does not seem to be the entire story since coefficients do not go down to zero. For two individuals being equally afraid of losing their job, automatability still increases mental health issues.

[32]The dummy takes value 1 if the individual reports at least one of three conditions: (i) The manager does not pay attention to the individual's work, (ii) the manager does not help the worker carry out her tasks, and (iii) the worker does not receive the recognition that her work deserves considering all her efforts. 51% of workers at risk of automation are exposed to bad management practices.

Income channel

Another alternative to the fear of automation as a mechanism to explain the findings could be that automatable jobs are low-paying jobs or may lead to wage drops. We verify that those two mechanisms cannot be the primary drivers.

First, workers may have poor mental health because of low income, regardless of the risk of automation. We account for this confounding factor by controlling for the net monthly income and various past and present working conditions in the estimation of the propensity score.[33] Splitting the sample between individuals receiving a net monthly income below and above 2000 euros[34] (referred to as low-income and high-income, respectively), we note that 14% of the treated group are high-income individuals,[35] which highlights that a significant share of treated workers has high-wage jobs. Additionally, when we replicate the analysis on those two subgroups, we find that the coefficient is significantly positive for both groups and fairly similar (0.038 for low-income workers vs. 0.044 for high-income workers, see Appendix Table A8).[36]

Second, we estimate the role of income variation as a transmission channel. We build an indicator of wage variation taking value 1 if the worker experiences a wage drop higher than 10% and 0 otherwise. Workers exposed to automation risks are less likely to experience a wage decrease (the correlation is equal to −0.17). To go beyond this simple raw statistic, we run the analysis separately on workers who experience a wage decrease and those who do not (and restricting to workers who stayed in the same occupation in 2013 and 2016). We find that the negative association between automatable jobs and mental health is much stronger when workers experience a wage cut than when they do not (6 pp vs. 2.3 pp, see Appendix Table A8). Note that the negative association is also significant and sizeable when workers do not experience a drop in their wage.[37] Moreover, using our indicator of wage decrease as the dependent variable, we find a significant negative association between working in an automatable job and experiencing a wage drop (−0.025, see Appendix Table A8). This counterintuitive result is in line with Aghion et al. (2019) who show that French innovative companies offer higher wages to retain the best workers among the least qualified.

Offshoring risk

Another alternative to the fear of automation channel to explain the negative link between automation risk and mental health could be the risk of offshoring. Because our measure of automation risk may also describe jobs at risk of offshoring, workers may be worse off as they fear losing their job not because of automation but because of a relocation abroad. As shown in Appendix Table A5, jobs with the highest shares of automatability (machine and forklift operators, checkout assistants, and drivers) are not likely to be relocated abroad

[33]Refer to Figure 1 for the complete list of covariates included in the estimation of the propensity score.

[34]We use the wage category [2000–2500[as the cutoff, which includes the average net monthly wage (around 2200 euros in 2016). Results are qualitatively similar when we use the median net monthly wage to distinguish low-income and high-income workers (around 1800 euros in 2016): the coefficient is also significantly positive for both groups of workers, but the split at the median wage gives a larger coefficient for high-income workers. This is because the median wage is lower than the average wage.

[35]The share equals 19% if we take the threshold at the median.

[36]By running the analysis separately on workers who experience a wage decrease and those who do not (and restricting to workers who stayed in the same occupation in 2013 and 2016), we find that the negative association between automatable jobs and mental health is much stronger when workers experience a wage cut than when they do not (6 pp vs. 2.3 pp, see Appendix Table A8). Note that the negative association is also significant and sizeable when workers do not experience a drop in their wage.

[37]We build another indicator of wage variation, taking value 1 if the worker moves to a lower wage category and 0 otherwise. The association is weaker but in the same direction when we use this second measure of wage drop (2.1 pp when moving to a lower wage category vs. 1.5 pp when no move). The first coefficient (lower category) is not significant because very few individuals move to a lower category.

due to their nature. Therefore, the risk of offshoring does not seem to be the main mechanism at play.[38]

Actual automation

Finally, we discuss the nature of the effects by considering actual automation as opposed to the fear of automation. It can be argued that jobs classified as at risk of future automation might actually already be partly automated (e.g., checkout assistants, forklift operators, and forklift drivers). The following discussion distinguishes between two cases, depending on whether automation leads to positive or negative changes. On the one hand, automation may lead to a better allocation of tasks, for example, by removing automatable tasks and leaving workers with self-fulfilling tasks only. Individuals subject to such an automation process would not be classified as treated (i.e., working in automatable jobs) and would be part of the control group. In that case, we would overestimate the negative association between automatable jobs and mental health because some people who would actually benefit from automation would not be considered part of the treatment group. On the other hand, if automation increases work intensity, individuals experiencing such an automation would report job attributes fitting our definition of automatable jobs (i.e., no latitude, repetitive tasks, and close monitoring) and would therefore be classified as treated. In this case, our results would not be biased, but we would capture the impact of both automatability and actual (partial) automation. Replicating the analysis with work intensity as the dependent variable, we find that working in automatable jobs increases the probability of reporting work intensity by 5.5 pp (Appendix Table A8). Work intensity may contribute to worsening the mental health of workers who have an automatable job: in the specification with an interaction term between work intensity and the indicator of automatable job as the treatment variable, the effect becomes larger than the baseline result (4.2 pp vs. 3.2 pp).[39]

Overall, we are fairly confident that our measure of automation risk captures the fear of automation well enough to explain the findings. Poor management practices also seem to be part of the story. While the offshoring risk and the income channel cannot be fully ruled out, they appear weaker.

CONCLUSION

This is among the first studies to measure automation risk at the individual level to examine the link between the risk of future automation and workers' present mental health. With individual data, we are able to account for diverse workplace practices and ways of performing a job within a given occupation. Using propensity score matching, we find a substantial negative association between mental health and having a job with tasks that could be (partially) displaced by machines or computers. We explore the underlying mechanisms and find evidence indicating that fear of automation through job insecurity and expectation of a required change in skills are

[38] We observe a negative correlation between the rate of relocated jobs between 1995 and 2017 (Beaurepaire & Lavialle, 2022) and the rate of automation risk at the regional level. This supports our hypothesis, but we cannot exclude that some automatable jobs are offshored, in which case offshoring and automation risk lead together to the fear of job loss. Another concern is that workers in automatable jobs may also be more confronted with competition with immigrant workers since immigrants are overrepresented in the bottom third of the skill distribution, where jobs could be more automated. This greater competition with immigrant workers could create fear of job loss and poorer job prospects, thereby reducing mental health and well-being. But we could not find evidence that immigrants are specifically in competition for automatable jobs. Instead, we observe that they are more employed in tight labour markets (Desjonquères et al., 2021).

[39] Alternatively, when we add work intensity along with the other intermediary outcomes in the propensity score, the coefficient of interest drops to 2.5 pp.

good candidates to explain our results. Poor management practices also seem to be part of the story since jobs classified as automatable in the future share attributes with jobs that, by nature, involve unsatisfactory working conditions with no latitude, and are subject to bad management.

Even without establishing causal effects of working in automatable jobs on mental health, we find a strong link between automatability and deteriorated mental health. This result has important implications for firms' management practices. Building a climate of confidence could help workers feel valuable and cope with automation, even before tasks are actually automated, which would benefit both employees and employers.

From a public policy perspective, policies aimed at helping workers be better prepared to face and cope with technological changes could have beneficial effects on their well-being. In particular, promoting support groups at the workplace and retraining seem relevant actions. Decreasing mental health hazards may enhance productivity and reduce sick leave, which will in turn reinforce the positive economic and labor market impacts of prevention policies.

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APPENDIX A

TABLE A1 Sample composition - overall and by automatability (in %).

	Automatable job		
	No	Yes	*p*-value
Individual characteristics			
Women	0.476	0.482	***
15–29 years old	0.180	0.184	*
30–49 years old	0.529	0.531	
50 years old and above	0.291	0.285	
French	0.970	0.965	***
No immigrant origins	0.854	0.823	***
No degree or < high school	0.315	0.615	***
High school degree	0.193	0.212	***
College degree	0.492	0.173	***
Job characteristics			
Private sector	0.658	0.764	***
Occupation			
CEOs, CFOs, COOs	0.060	0.007	***
Ingeneers and scientists	0.247	0.035	***
Middle managers (executives)	0.229	0.163	***
Office workers	0.105	0.126	***
Bank employees, sales representatives	0.138	0.190	***
Farmers and workers in agriculture	0.015	0.029	***
Skilled workers in industry	0.075	0.102	**
Drivers and other skilled workers	0.055	0.233	***
Unskilled workers	0.076	0.116	***
Permanent contract	0.923	0.904	**
Part-time	0.155	0.156	
Tenure in [0;5] years	0.292	0.291	
Tenure in [5;20] years	0.473	0.479	
Tenure > 20 years	0.235	0.230	
1 to 49 employees	0.342	0.269	***
50 to 499 employees	0.220	0.259	***
≥500 employees	0.438	0.472	***
Sector			
Agriculture	0.010	0.016	***
Food, drink and tobacco manufacturing	0.021	0.055	***
Electronic manufacturing	0.015	0.025	
Transport manufacturing	0.025	0.037	***
Other manufacturing	0.072	0.121	***
Water/Waste industries	0.020	0.012	

TABLE A1 (Continued)

	Automatable job		
	No	**Yes**	***p*-value**
Building	0.047	0.061	
Trade	0.107	0.115	**
Transport	0.043	0.091	***
Information communication	0.042	0.013	***
Hotel restaurant	0.024	0.037	
Finance and real estate	0.052	0.034	***
Scientific activities and services	0.091	0.061	***
Public administration	0.391	0.290	***
Other service	0.041	0.031	**
Region			
Ile-de-France	0.217	0.127	***
Champagne-Ardenne	0.020	0.021	
Picardie	0.027	0.045	***
Haute-Normandie	0.026	0.027	
Centre	0.034	0.032	**
Basse-Normandie	0.012	0.016	
Bourgogne	0.029	0.029	
Nord-Pas-de-Calais	0.078	0.113	***
Lorraine	0.048	0.072	*
Alsace	0.041	0.054	
Franche-Comté	0.017	0.021	
Pays de la Loire	0.075	0.070	
Bretagne	0.044	0.049	**
Poitou-Charentes	0.022	0.029	
Aquitaine	0.032	0.038	
Midi-Pyrénées	0.036	0.036	
Limousin	0.011	0.010	
Rhône-Alpes	0.109	0.081	***
Auvergne	0.026	0.027	
Languedoc-Roussillon	0.031	0.036	
Provence-Alpes-Côte d'Azur	0.060	0.065	
Corse	0.003	0.001	**
Changed region	0.003	0.002	
Working conditions			
Atypical hours	0.610	0.696	***
Changing and/or unpredictable scheduling	0.469	0.612	***
Poor work-private lifes balance	0.743	0.716	*
Physical risks	0.756	0.949	***
Constraints in means	0.672	0.743	***

(Continues)

TABLE A1 (Continued)

	Automatable job		
	No	**Yes**	***p*-value**
Interactions with public	0.743	0.614	***
Income < 1200 euros	0.115	0.174	***
Income in [1200; 1800[euros	0.340	0.559	***
Income in [1800; 2500[euros	0.292	0.182	***
Income ≥ 2500 euros	0.253	0.085	***
Variation in wage	0.556	0.516	
Poor quality management	0.350	0.490	***
Past working conditions (in 2013)			
Atypical hours	0.602	0.698	***
Changing and/or unpredictable scheduling	0.531	0.630	***
Poor work-private lifes balance	0.691	0.666	***
Physical risks	0.757	0.938	***
Constraints in means	0.673	0.677	**
Interactions with public	0.725	0.632	***
Experienced one or several changes in work in past year	0.438	0.506	***
Worked in an automatable job in 2013	0.102	0.387	***
Health history			
Events during childhood	0.530	0.633	***
Events in past 3 years	0.488	0.564	***
(Very) good health (SAH) in 2013	0.803	0.726	***
Variables of interest			
Mental disorder: MDE or GAD (DSM-IV)	0.080	0.158	***
Anxiety almost every day in past 6 months	0.142	0.238	***
Self-assessed health			
(Very) good health (SAH)	0.770	0.684	***
Fair	0.198	0.237	***
Poor	0.029	0.073	***
Very poor	0.003	0.007	***
Low WHO-5 score	0.273	0.352	***
Works in an automatable job (treatment)	0.000	1.000	***
N	10,904	2,640	

Note: Sample of wage earners with non-missing relevant observables, interviewed both in 2013 and 2016. Weighted statistics. ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

Source: French Working Conditions Survey 2013 and 2016.

TABLE A2 Questions used to define the measure of automation risk.

Condition (i): repetitive tasks - based on one question

Does your job consist of continually repeating the same series of gestures or operations?

(*yes or no question*)

Condition (ii): close monitoring - based on six questions

Do you work on the line?

(*yes or no question*)

Is your work pace imposed by the automatic movement of a product or a part?

(*yes or no question*)

Is your work pace imposed by the automatic pace of a machine?

(*yes or no question*)

Is your work pace imposed by other technical constraints?

(*yes or no question*)

Is your work pace imposed by permanent (or at least daily) checks or monitoring by management?

(*yes or no question*)

Is your work pace imposed by computerized control or monitoring?

(*yes or no question*)

Condition (iii): detailed instructions - based on four questions

The instructions given by your management tell you what to do. In general, do they also tell you

- How to proceed?
- Give the objective and you decide how to proceed?

You receive orders and instructions. To do your work correctly, do you

- Strictly follow instructions?
- Do as you wish in some cases?
- Do as you wish most of time?

Do you have the opportunity to put your own ideas into practice in your job?[a]

(*yes or no question*)

Does your job require you to take initiative?[a]

(*yes or no question*)

Note: To be classified as working in an automatable job, workers must have answered yes to at least one question for each condition.

Source: French Working Conditions Survey 2016.

[a]Not included in the indicator of automation risk used in Column (1) of Table 3.

TABLE A3 Components of the measure of automation risk.

	Automation risk	Routine	Pace constraints	No latitude
Routine = 1	0.496	1	0.686	0.700
Pace constraints = 1	0.331	0.457	1	0.633
No latitude = 1	0.329	0.464	0.629	1

Note: Sample of 13,554 wage earners with non missing relevant observables interviewed both in 2013 and 2016. Measure of automation risk defined in Section 2.2.

Reading: 49.6% of workers who have a routine job component are classified as being exposed to the risk of automation.

Source: French Working Conditions Survey 2013 and 2016.

TABLE A4 Automation exposure by occupation.

	Automation risk (%)	***N***
Unskilled workers	0.429	553
Skilled workers	0.359	1627
Sales employees	0.286	419
Employees - public sector	0.246	2656
Employees to private employers	0.221	383
Employees - firm administration	0.171	769
Technicians	0.143	638
Intermediate professions - firm administration and sales	0.128	832
Foremen	0.101	319
Intermediate professions - public sector	0.093	2662
Executive manager - private sector	0.035	1162
Executive manager - public sector	0.032	1357

Note: Analysis restricted to occupation categories containing at least 20 surveyed individuals. Weighted statistics.
Source: French Working Conditions Survey 2016.

TABLE A5 Automation exposure by type of job.

	Automation risk (%)	***N***
The 10 jobs with the highest shares of automation		
Machine operators for the manufacture of food items and related products	0.67	70
Packaging, bottling and labeling machine operators	0.62	81
Mechanical fitters	0.612	73
Forklift operators and drivers	0.602	60
Checkout assistants and ticket agents	0.594	45
Post service workers	0.571	44
Bus and tram drivers	0.509	48
Operators of machinery and fixed installations not elsewhere classified	0.491	80
Truck and truck drivers	0.471	132
Machine tool setters and operators	0.445	46
The 10 jobs with the lowest shares of automation		
Teachers, technical, vocational education and adult education	0.008	52
Teachers (technical and adult education)	0.008	30
Software designers	0.007	45
Pharmacist	0.003	34
Primary school teachers	0.003	328
Psychologists	0	97
Directors and executive managers	0	34
Educational directors and executives	0	45
Professors (Universities and institutions of higher education)	0	71
Specialists, technical sciences	0	45

Note: Analysis restricted to job titles containing at least 20 surveyed individuals. Weighted statistics.
Source: French Working Conditions Survey 2016.

TABLE A6 Working in an automatable job and the probability of declaring a MDE or GAD – Robustness analysis.

Subsample	(1) 18–59 years old	(2) 25–59 years old	(3) Same job in 2013 and 2016	(4) Trimmed propensity score ($p5 > ps < p95$)
Automatable job	0.034***	0.045***	0.045***	0.032***
	(0.003)	(0.004)	(0.006)	(0.004)
Socio-demographics	Yes	Yes	Yes	Yes
Job attributes	Yes	Yes	Yes	Yes
Health history	Yes	Yes	Yes	Yes
Current working conditions	Yes	Yes	Yes	Yes
Past working conditions	Yes	Yes	Yes	Yes
Observations	12,841	12,687	12,081	10,857

Note: Bootstrapped standard errors in parentheses. *** p<0.01. Sample: wage earners with non-missing relevant observables, interviewed both in 2013 and in 2016, employed in 2016, and satisfying the condition mentionned in "Subsample". Column (4): propensity score (ps) is trimmed at p5 and p95. Measure of automation risk defined in Section 2.2. Exact matching on gender, age, education, sector (private or public) and occupation (9 categories), combined with propensity score-kernel matching and full list of controls (see Figure 1 for the detailed list of variables included in the estimation of the propensity score).

Abbreviations: GAD, generalized anxiety disorder; MDE, major depression episode.

Source: French Working Conditions Surveys 2013 and 2016.

TABLE A7 Correlations between mental disorders and mediating variables.

	Share with mental disorder (MDE or GAD)	p-value (χ^2 test)
Job insecurity		
No	0.072	***
Yes	0.185	
Qualification change		
No	0.064	***
Yes	0.162	
Forced mobility		
No	0.082	***
Yes	0.141	
Intensity		
No	0.041	***
Yes	0.108	
Income drop (−10%)		
No	0.094	**
Yes	0.098	
Income drop (lower wage category)		
No	0.092	***
Yes	0.110	
Income drop		
No	0.099	***
Yes	0.909	
Bad management		
No	0.053	***
Yes	0.163	

Note: ***$p < 0.01$, **$p < 0.05$. The χ^2 test tests whether the difference between both categories is significant.
Reading: 18% of workers who fear job insecurity have a mental disorder (MDE or GAD).
Abbreviations: GAD, generalized anxiety disorder; MDE, major depression episode.
Source: French Working Conditions Survey 2016.

TABLE A8 Working in an automatable job and the probability of declaring a MDE or GAD – Testing mechanisms.

Baseline effect (for reference)	–	0.032***	(0.007)
Alternative treatment: intermediary outcomes interacted with automatibility indicator			
Job insecurity x automatibility	(1)	0.088***	(0.012)
Required change in skills x automatibility		0.06***	(0.016)
Unwanted job mobility x automatibility		0.052***	(0.017)
Work intensity x automatibility		0.042***	(0.006)
All 4 intermediary outcomes in the propensity score	(2)	0.025***	(0.008)
Heterogeneity: split by management practices			
Good management	(3)	0.012***	(0.005)
Bad management		0.077***	(0.007)
Heterogeneity: split by income level			
High	(4)	0.044***	(0.004)
Low		0.038***	(0.004)
Heterogeneity: split by income variation (first specification)			
Wage drop	(5)	0.060**	(0.024)
No wage drop		0.023***	(0.008)
Heterogeneity: split by income variation (second specification)			
Lower wage category	(6)	0.021	(0.031)
No lower wage category		0.015**	(0.007)
Experiencing a wage drop as intermediary outcome	(7)	−0.025***	(0.005)
Work intensity as intermediary outcome	(8)	0.042***	(0.004)

Note: Bootstrapped standard errors in parentheses. ***$p < 0.01$, **$p < 0.05$. Sample: wage earners with non-missing relevant observables, interviewed both in 2013 and in 2016, and employed in 2016. Measure of automation risk defined in Section 2.2 (treatment for Rows (2)–(7)). Exact matching on gender, age (3 categories), education, sector (private or public) and occupation (9 categories), combined with propensity score-kernel matching and full list of controls (see Figure 1 for the detailed list of variables included in the estimation of the propensity score). Baseline effect from Table 1 (Column (5)). Rows (1): separate estimations with each alternative treatment. Row (2): estimation with an additional control in the estimation of the propensity score. Rows (3)–(6): stratified estimations for each sub-sample. Rows (7) and (8): separate estimations on each intermediate outcome.

Source: French Working Conditions Surveys 2013 and 2016.

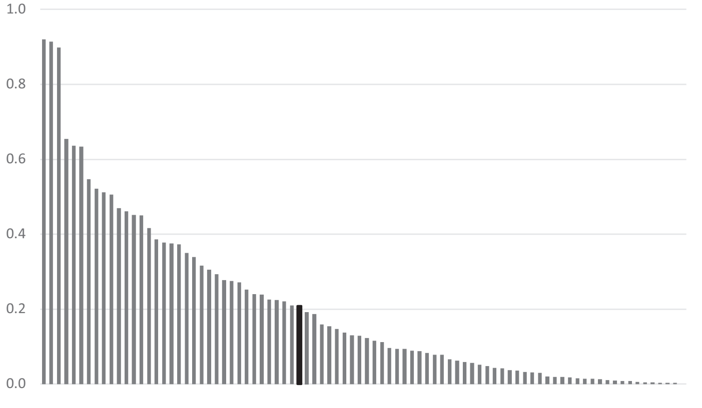


FIGURE A1 Within-occupation shares of workers considered as being at risk of automation.
Reading: for almost 50% of occupations (thicker line), one out of five workers consider that their occupation is at risk of automation.
Note : each of the 87 bars shows the share of workers within the occupation who think that their job is at risk of automation (according to our definition of automatibility). Restricted to occupations containing at least 10 surveyed individuals. Weighted statistics.
Source: French Working Conditions Survey 2016.

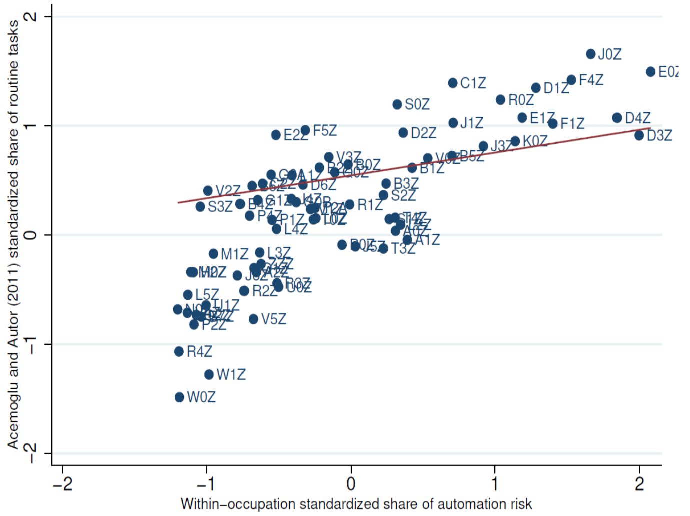


FIGURE A2 Comparison between Acemoglu and Autor (2011)'s measure of automation and ours (redefined at the occupational level). *Note*: Coefficient of correlation = 0.545***. The first letter of the label refers to the sector of activity and the first digit to the occupation level. A, agriculture and food, drink and tobacco manufacturing; B, building; C, electronic manufacturing; D, metal manufacturing; E and H, other manufacturing; F, wood and textile; G and J, maintenance and handling; K, craftmanship; L, office work; M, services to the firms; N, scientific activities and services; P, public administration; Q, banking and finance; R, trade; S, hotel restaurant; T, home help; U, information, communication and arts; V, health ans associations; W, teaching and training; Z, other.

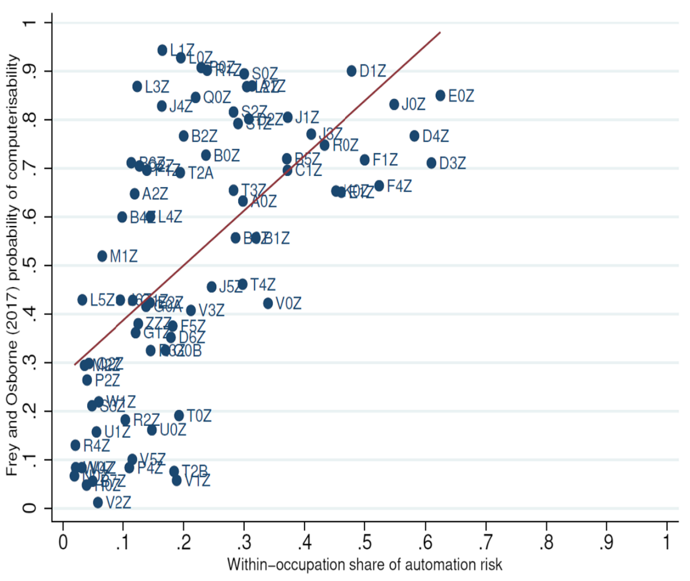


FIGURE A3 Comparison between Frey and Osborne (2017)'s measure of automation and ours (redefined at the occupational level). *Note*: Coefficient of correlation = 1.018***. The first letter of the label refers to the sector of activity and the first digit to the occupation level. A, agriculture and food, drink and tobacco manufacturing; B, building; C, electronic manufacturing; D, metal manufacturing; E and H, other manufacturing; F, wood and textile; G and J, maintenance and handling; K, craftmanship; L, office work; M, services to the firms; N, scientific activities and services; P, public administration; Q, banking and finance; R, trade; S, hotel restaurant; T, home help; U, information, communication and arts; V, health ans associations; W, teaching and training; Z, other.

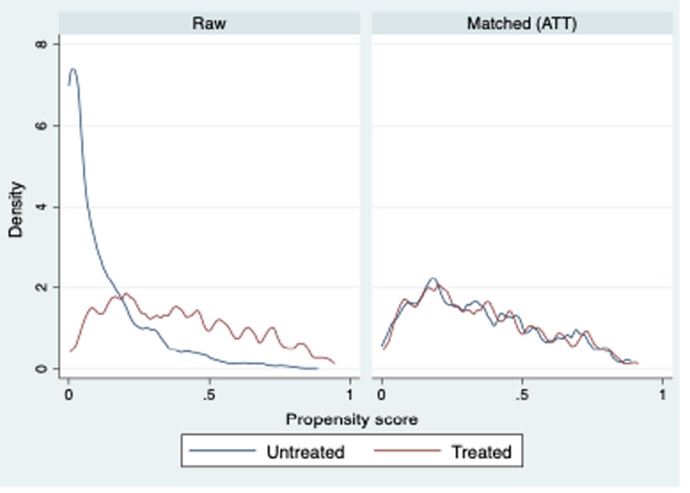


FIGURE A4 Distribution of the propensity score on the matched and unmatched samples.
Source: French Working Conditions Surveys 2013 and 2016.

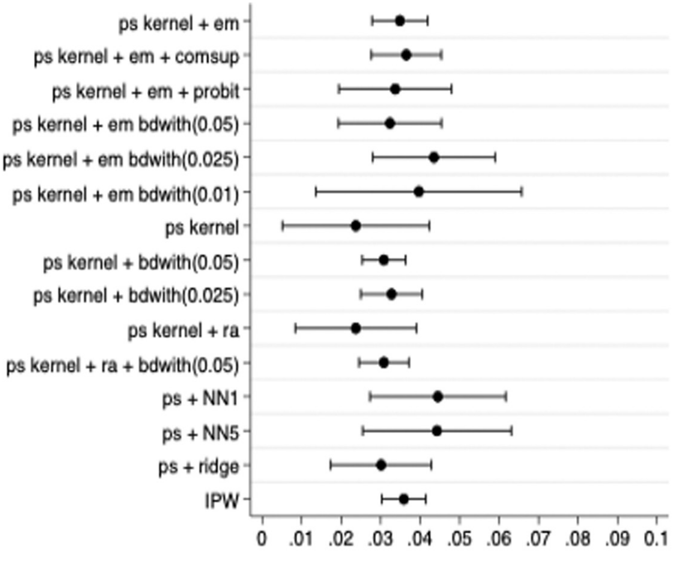


FIGURE A5 ATT estimates using alternative matching techniques.
*Note:*Separate analysis on sub-samples among wage earners with non-missing relevant observables interviewed both in 2013 and 2016. Dependent variable: having a major depression episode (MDE) or a generalized anxiety disorder (GAD). Measure of automation risk defined in Section 2.2.
Source: French Working Conditions Survey 2013 and 2016.

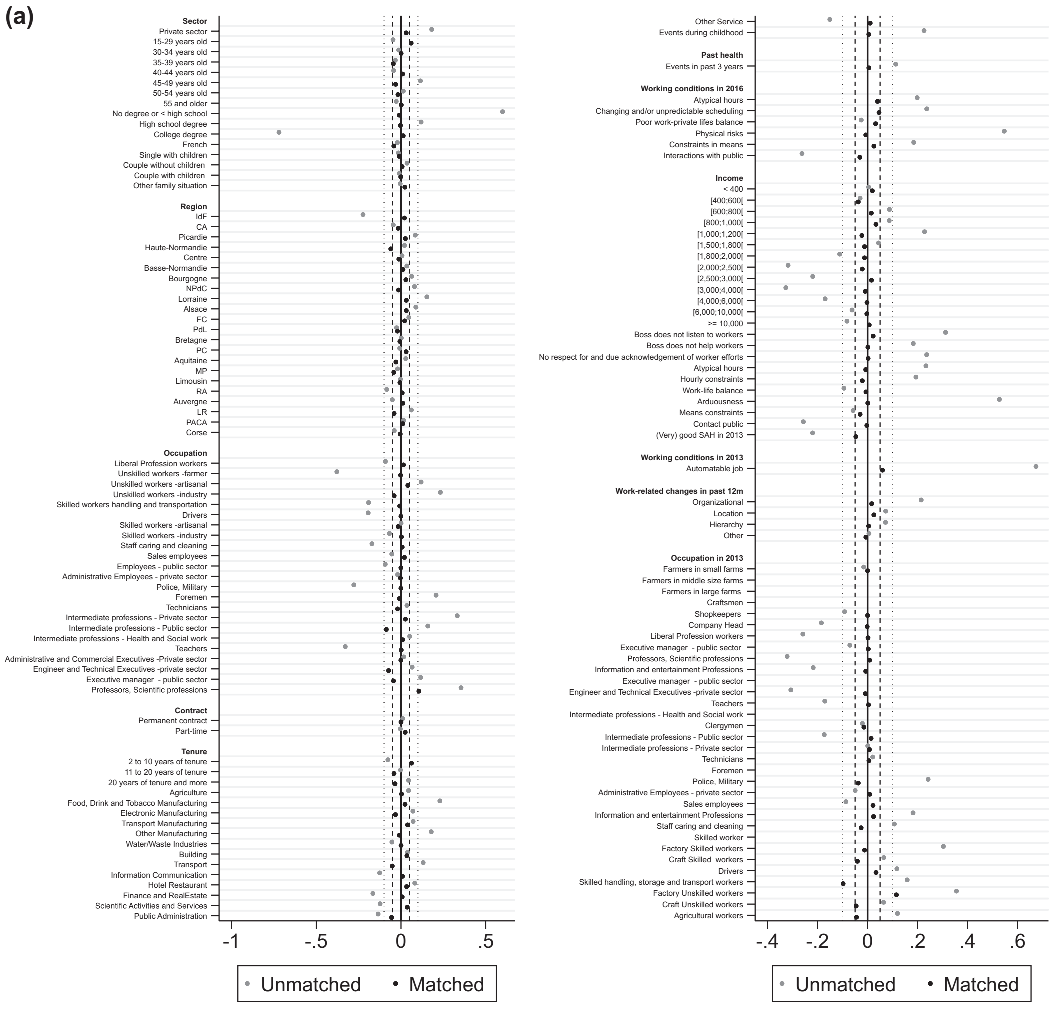


FIGURE A6 Standardized % bias across covariates for estimation by sub-populations. (a) Women. (b) Men. (c) 15–29 years. (d) 30–49 years. (e) 50 years old and above. (f) No degree. (g) High-school degree. (h) College degree. *Source*: French Working Conditions Surveys 2013 and 2016.

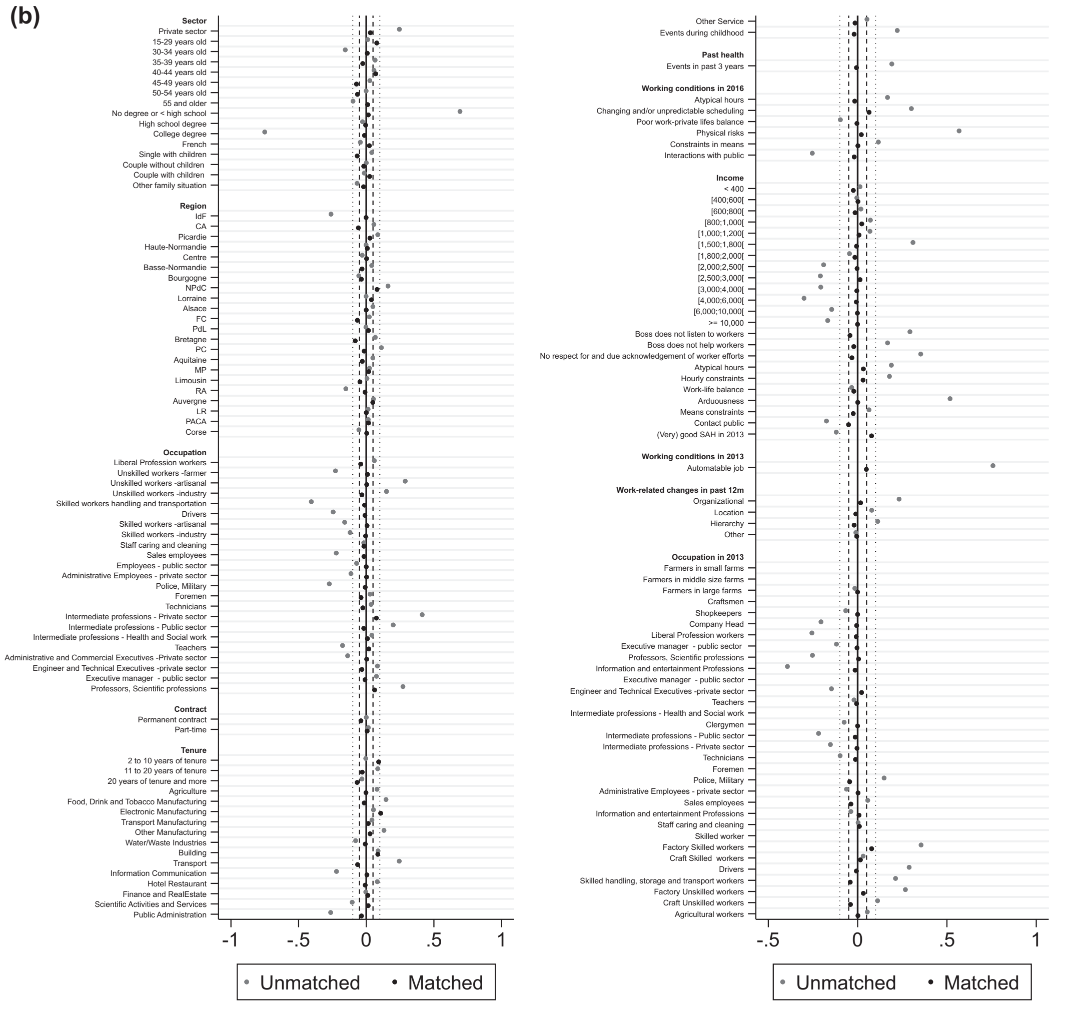


FIGURE A6 (Continued)

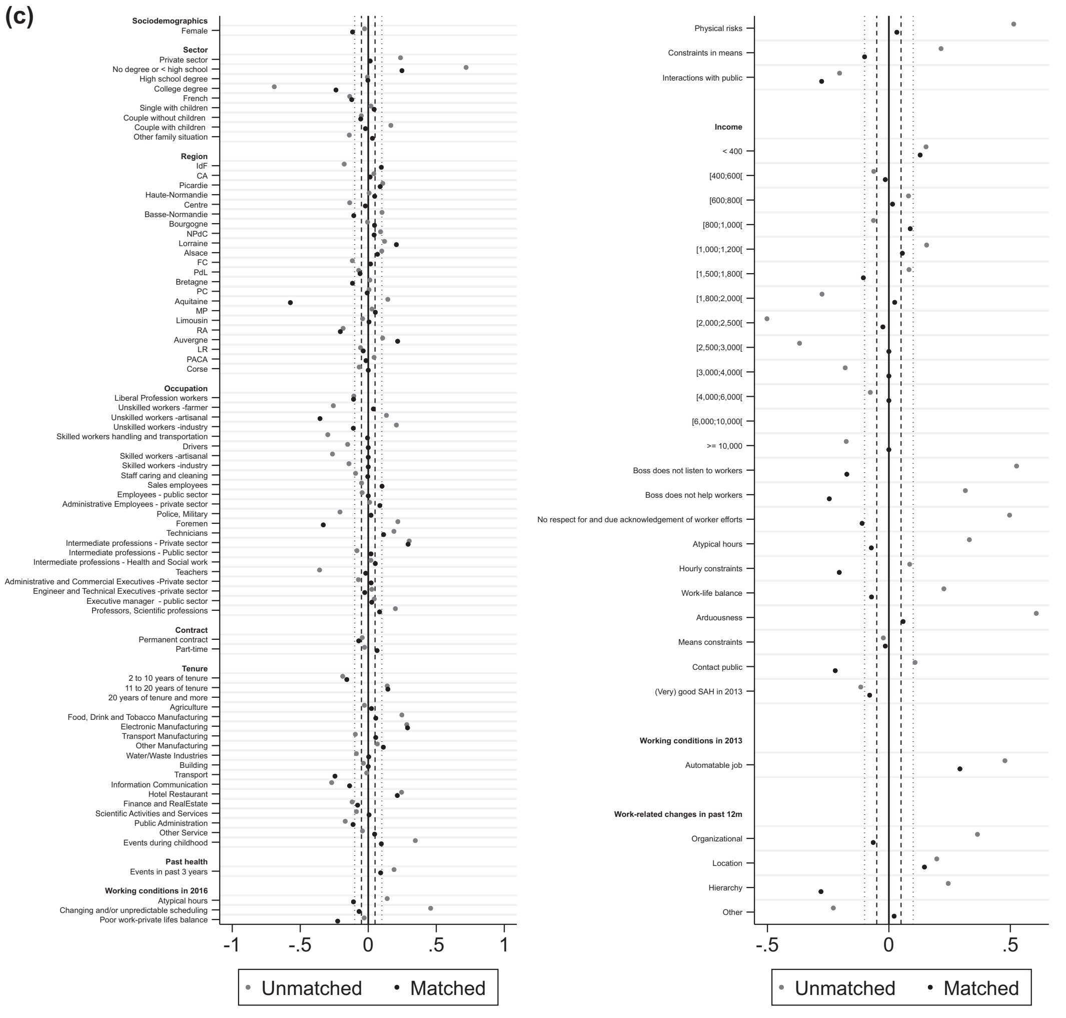


FIGURE A6 (Continued)

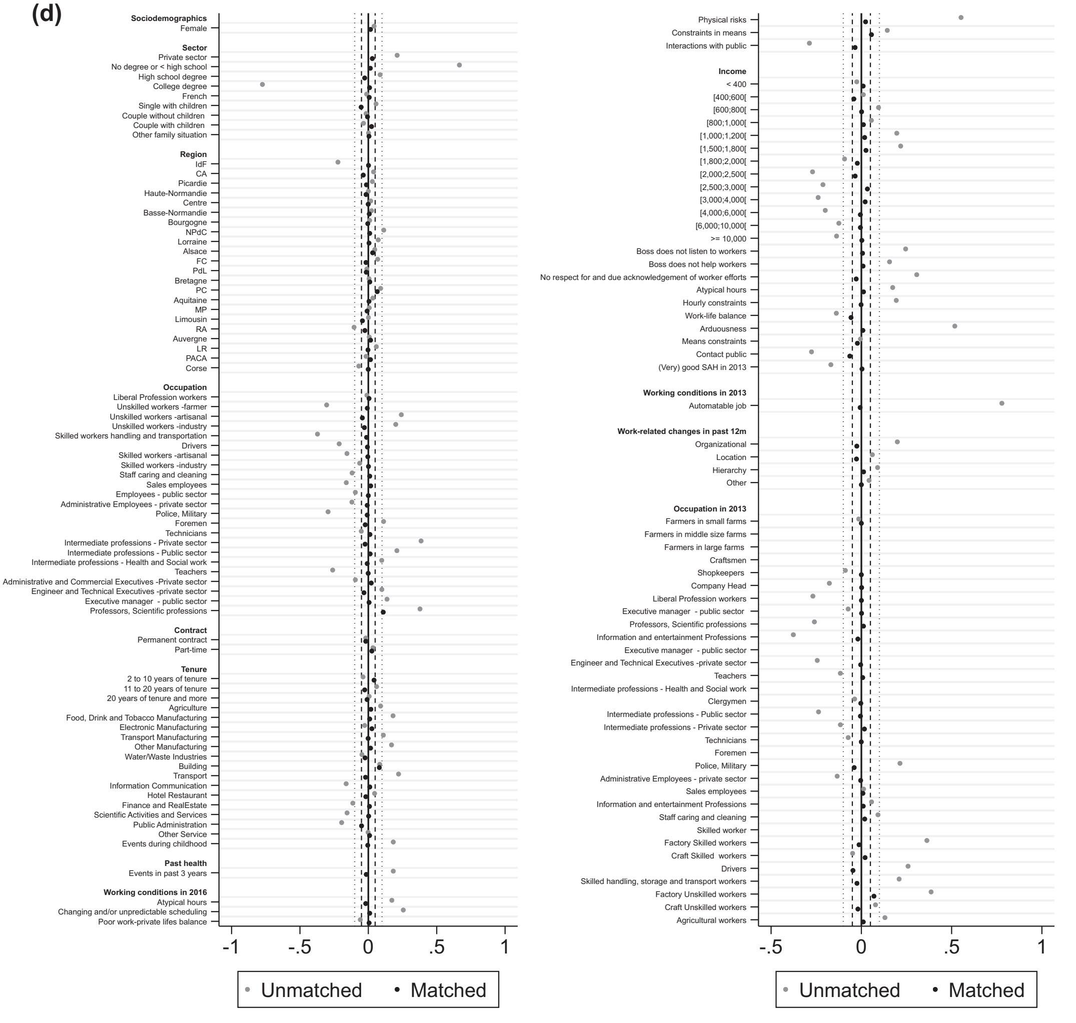


FIGURE A6 (Continued)

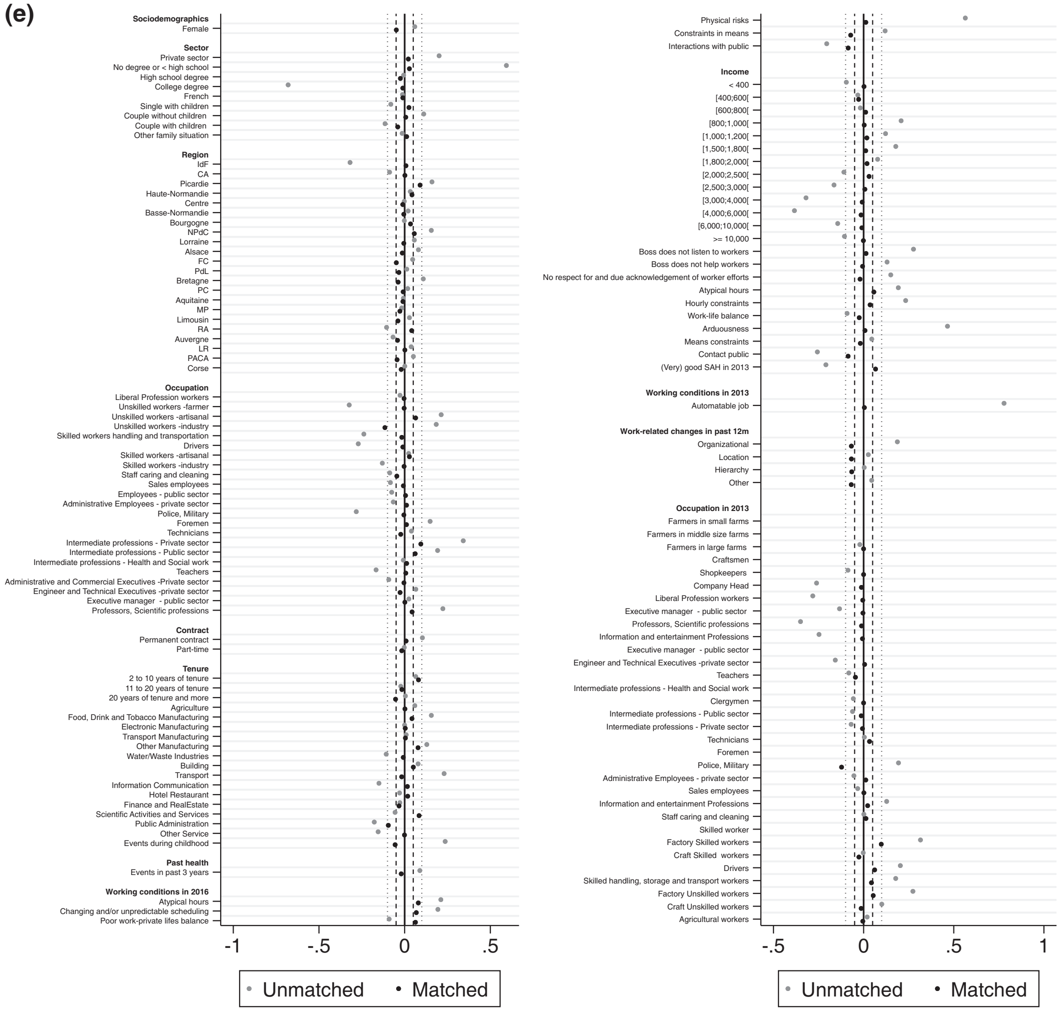


FIGURE A6 (Continued)

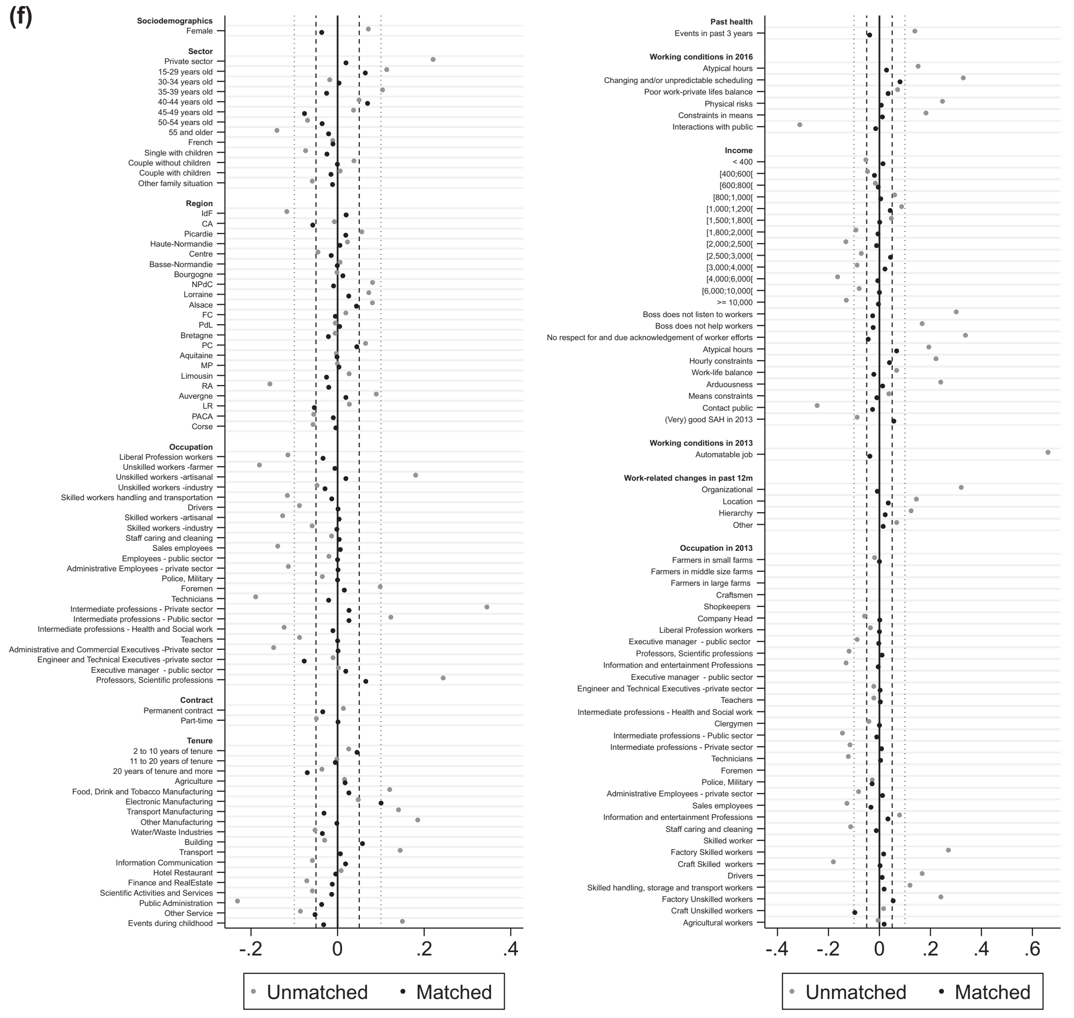
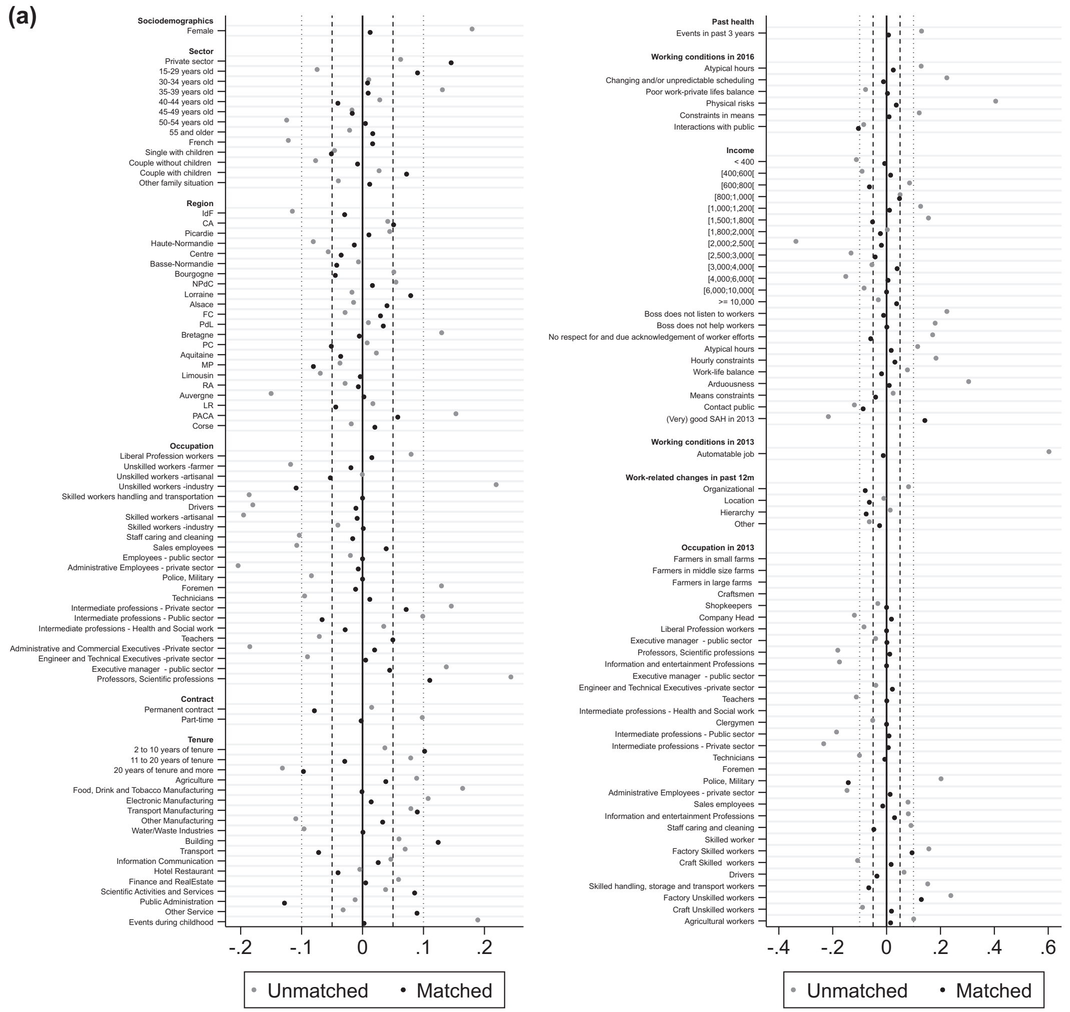


FIGURE A6 (Continued)



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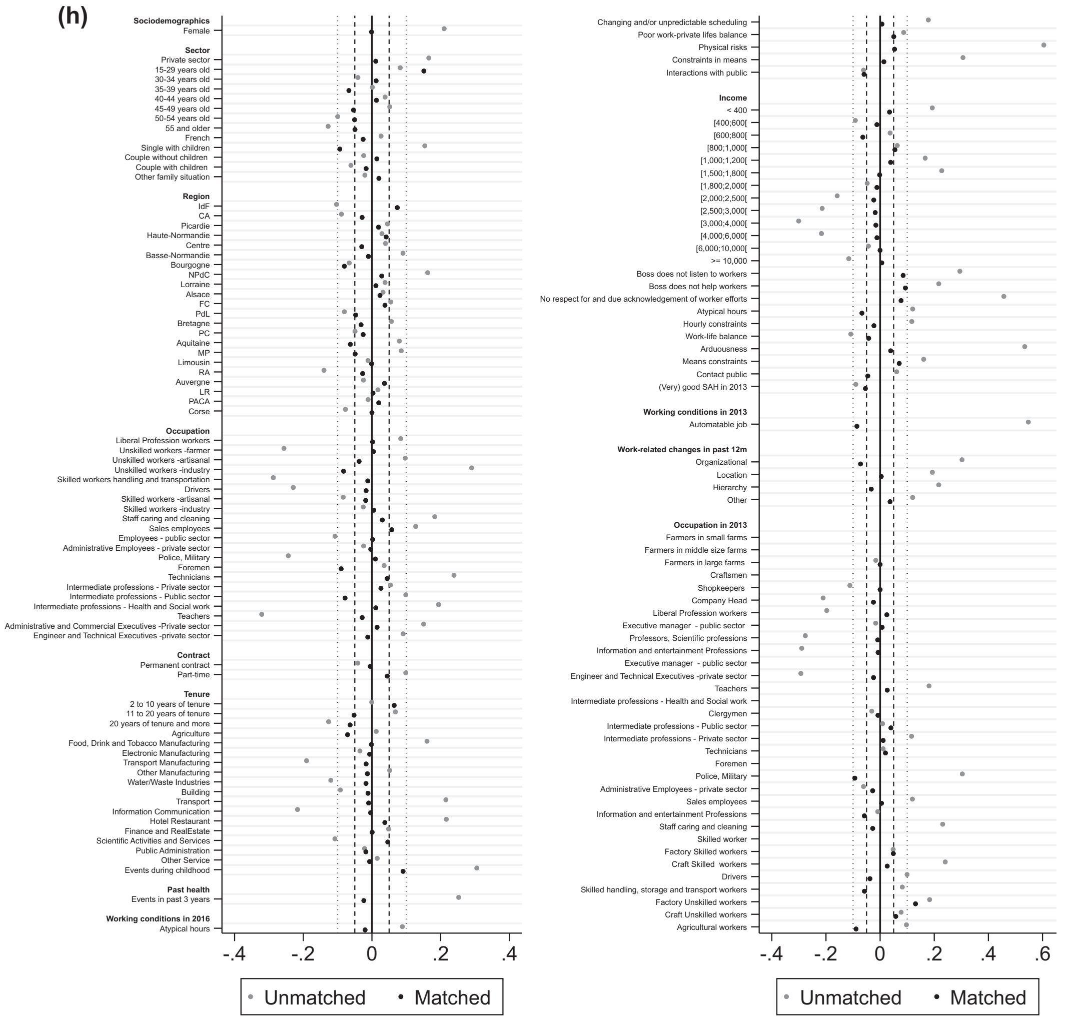

FIGURE A6 (Continued)