I Z A Institute of Labor Economics
Initiated by Deutsche Post Foundation

DISCUSSION PAPER SERIES

IZA DP No. 15434

Displaced or Depressed? The Effect of Working in Automatable Jobs on Mental Health

Sylvie Blasco
Julie Rochut
Bénédicte Rouland

JULY 2022

I Z A Institute
of Labor Economics
Initiated by Deutsche Post Foundation

DISCUSSION PAPER SERIES

IZA DP No. 15434

Displaced or Depressed? The Effect of Working in Automatable Jobs on Mental Health

Sylvie Blasco
Le Mans University, IRA and IZA

Julie Rochut
Cnav, URV

Bénédicte Rouland
University of Nantes

JULY 2022

ISSN: 2365-9793

IZA – Institute of Labor Economics

Schaumburg-Lippe-Straße 5–9
53113 Bonn, Germany
Phone: +49-228-3894-0
Email: publications@iza.org
www.iza.org

ABSTRACT

Displaced or Depressed? The Effect of Working in Automatable Jobs on Mental Health*

Automation may destroy jobs and change the labour demand structure, thereby potentially impacting workers' health and well-being. Using French individual survey data, we estimate the effects of working in automatable jobs on mental health. Implementing propensity score matching to solve the issue of endogenous exposure to automation risk, we find that workers whose job is at risk of automation in the future are about 4 pp more likely to suffer at present from severe mental disorders. Fear of job loss within the year and fear of qualification or occupational changes seem relevant channels to explain our findings.

JEL Classification: I10, J24

Keywords: mental health, automation, job insecurity, propensity score matching

Corresponding author:
Sylvie Blasco
Le Mans University
UFR DEG
Av. Olivier Messiaen
72085 Le Mans Cedex 9
France

E-mail: sylvie.blasco@univ-lemans.fr.

* We acknowledge financial support from the Dares, and helpful comments from Jose De Sousa, Xavier D'Haultfoeuille, Eva Moreno-Galbis and Yves Zenou. We are grateful to seminar participants at GAINS and conference participants at JMA 2021, LAGV 2022, ESPE 2022, EuHEA 2022 and the 2022 French Stata conference in applied econometrics for useful comments and suggestions.

1 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 and McAfee, 2012; DeCanio, 2016)—have revived the debate around the "end of work" or "robots versus workers", with a wider 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 and Autor, 2011; Acemoglu and Restrepo, 2019; Autor et al., 2003; Frey and Osborne, 2017), little attention has been paid to the effects on (mental) health, Patel et al. (2018) and Lordan and Stringer (2022) being exceptions. Yet measuring and understanding the possible health effects of a major labor market change such as automation, a potential work-related mental health risk factor entailing costs, will be crucial to effective policy making. 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 could promote the design of effective prevention policies, thereby limiting the costs entailed in workers' mental illness. In this paper, we aim to assess the extent to which working in automatable jobs impacts 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 (Green, 2004; Karasek, 1979), job insecurity (Abeliansky and Beulmann, 2019; Patel et al., 2018)[2] and lower wage dynamics (Acemoglu and Restrepo, 2020). On the other hand, automation could improve working conditions and health by reducing repetitive and routine tasks (Autor, 2015; Maurin and Thesmar, 2004), if the new technologies are used as a support for workers (thus freeing them to engage in more fulfilling tasks) and if this improves job quality prospects. All 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 effects of exposure to automation risk on mental health, we use the 2013 and 2016 French Working Conditions Surveys. These surveys provide detailed information about working conditions, labor market history and health status for about 28,000 individuals representative of the working-age population.

[1] According to a report from the European Commission in 2018 (Nedelkoska and 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 fifteen years (COE, 2017).

[2] There is a broader literature on job insecurity on mental health. See for instance Cottini and Ghinetti (2018); Reichert and Tauchmann (2017); Schwabe and Castellacci (2020).

We estimate effects on various indicators of mental health, 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 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 and Dorn, 2013; Frey and 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 as working in automatable jobs is correlated to other factors that also affect health, we implement propensity score matching to solve the selection issue. The richness of our data allows us to satisfy the Conditional Independent Assumption (CIA). Notably, in addition to the standard demographic variables (gender, age, marital status, number of children, level of education, nationality), we also condition on labor market and health previous histories.

Results indicate that workers who have an automatable job are 4 pp more likely to declare anxiety or depression. We find heterogeneous effects with respect to age and education, with middle-aged and mid-educated workers being more affected. An analysis of intermediary outcomes indicates that workers who have an automatable job are more likely to report a feeling of job insecurity. Among workers threatened by automation, higher proportions also report fear of qualification or occupational changes within the next three years. Work intensity and undesired job mobility are also greater among workers whose job is at risk of automation, though the association between automation risk and these two intermediary outcomes is weaker than the association between automation risk and job insecurity and expected qualification change.

This paper contributes to the literature that shows how automation and new technologies change the skill content of jobs and skill demand on the labor market (Acemoglu and Autor, 2011; Acemoglu and 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 extend the literature in a new direction. Recently, Innocenti and Golin (2022) have also shown that not all workers are equally worried about the risk of automation, and that those who are worried about being displaced by a machine or algorithm also intent 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 workers currently in employment to fear that their work might be replaced by a smart machine in the future. Clearly, the fear of future replacement does negatively affect workers present job satisfaction. This negative effect is driven by low-skilled workers, those carrying out routine-based tasks and therefore more exposed to the risk of automation. Only two studies have looked at the health effects of automation risk, measured from occupational data in both and using the probability of occupational automation. Patel et al. (2018) document the detrimental effects of automation risk on health (both physical and mental) in the US, using aggregate data (county-level) and focusing on the job insecurity mechanism. Lordan and Stringer (2022) explore the effect on mental health and life satisfaction of working in an automatable job, using Australian survey data. To the best of our knowledge, ours is the first paper to use a measure of automation risk defined at a micro level, as recommended by Arntz et al. (2017). To explain the findings, we explore alternative channels that have not previously been empirically tested, namely work intensity and expected changes in required qualifications.

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 4 concludes and draws policy implications.

2 Data

2.1 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 labor. These surveys have been conducted every three years since 2013 to create a representative panel of workers and to monitor the evolution of working conditions and psycho-social risks at the workplace in France. They provide information about employment status, working conditions and health for about 28,000 individuals aged above 15 and employed or self-employed. Workers are questioned mainly face-to-face, as well completing a self-administered questionnaire for more sensitive questions. All waves share a common block of core questions. The 2016 wave contains additional questions about mental health and psycho-social risks and is the only wave that provides a variety of detailed measures of mental health[3].

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

Our analysis sample consists of 14,221 wage-earners in 2016 who were also interviewed in 2013. We exclude self-employed workers and craftsmen 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. Column 1 of Table A.1 in Appendix A describes the sample as a whole. About half are men, and around one third are aged 45 years and over. 12% of the sample have no diploma, while a quarter have a university degree and 20 % are executives. The services sector is by far the most widely represented activity (about three quarters).

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

2.2 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 monitored easily (due to constrained pace) and (iii) have to follow detailed instructions, with no latitude in tasks performed and in the manner of performing them.[4],[5] 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 more easily be automated, and workers whose jobs entails 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 and Autor, 2011; Frey and 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 tasks that are automatable, so as 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 that this feature is important enough or is a key aspect of the job, which should also us to capture jobs that are at least partially automatable.

Importantly, and 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 doing 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 all the more important with our data, since our automation risk indicator can vary within occupations: for about 50% of occupations, one out of five workers disagrees with the prevailing view about automation within the occupation (Figure A.1 in Appendix A).

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 alter-

[4]Table A.2 in Appendix A lists the exact questions used to construct our measure of working in automatable jobs.

[5]Table A.3 in Appendix A shows correlations between the three conditions that define our measure of working in automatable jobs. It actually does not restrict to a measure of repetitive work. Of the individuals reporting having a repetitive job, only half are considered as working in automatable jobs (i.e., meeting the three conditions), 22% having latitude regarding tasks and 32% experiencing no pace constraints.

native measures of automation risk. First, relying on Autor and Dorn (2013)'s approach, we use a crosswalk between the international classification ISCO included on 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 in the US. Figures A.2 and A.3 in Appendix B show that our measure (redefined at occupational-level) is positively correlated with both Autor and Dorn's measure and Frey and Osborne's measure.

Under the present definition, about 19% of workers in our sample had automatable jobs in 2016. Table A.4 in Appendix A reports the rate of automation risk by occupation and Table A.5 shows the 10 jobs with the highest and lowest shares of workers in automatable jobs. While the hierarchy of occupations and that of jobs seem consistent with what was expected, both tables show that there are large differences in the exposure to automation.

2.3 Measures of health

Our main 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 self-administered Mini international neuropsychiatric interview and follow the DSM-IV guidelines to determine whether individuals suffer from a MDE or a GAD. A major depressive episode is characterized by a depressed mood or loss of interest or pleasure for almost all activities and by the daily presence of a number of psychiatric symptoms or a neuro-vegetative state for at least two 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 destabilising factor, may be continuous or may include several events over a period of at least 6 months.

As people may experience mental problems that do not reach the threshold for diagnosis as a mental disorder, we consider additional proxies for poor mental health: the probability of being anxious almost all the time in the past 6 months (without necessarily suffering from a GAD), the World Health Organization-Five well-being index (WHO-5) and self-assessed overall health. For comparability purposes, we use dichotomous versions of the continuous outcomes and look at the probability of having a WHO-5 score lower than 50 (out of 100) and at the probability of being in very good or in good health.

As shown in column 1 of Table A.1 in Appendix A, almost 10% of workers in our sample suffered from a MDE or a GAD in 2016. Almost 30% had a low well-being score and 25% reported not being in good or very good health.

3 Empirical strategy

To evaluate the impact 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, Table A.1 in Appendix A shows that individuals whose job is defined as automatable are on average younger, have lower educational and occupational levels, have experienced more possibly damaging events in the past and report poorer state of health in 2013 than workers not threatened with automation.[6] 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, changing and/or unpredictable schedule) and a work environment that has undergone technology and/or organizational changes in the past year. Overall, workers threatened with automation present features that may be detrimental to health. The challenge is to disentangle automation risk's possible causal effect on mental health both from confounding factors and from selection into jobs and careers threatened by automation.

We exploit the richness of our data to solve the endogeneity issue by implementing matching, comparing individuals working in automatable jobs to individuals not working in automatable jobs, but who are otherwise comparable in terms of observables.[7] Specifically, we use the propensity score matching method (Rosenbaum and Rubin, 1983), which 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) 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:

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

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, where weights are obtained through matching:

$$\widehat{\delta}_{ATT} = \frac{1}{N_1} \sum_{i=1}^{N_1} y_i(1) - \sum_{i=1}^{N_0} \hat{w}_i y_i(0)$$

Propensity score matching relies on two main identification assumptions: unconfoundedness (or condi-

[6] Groups do not significantly differ with respect to gender and nationality.

[7] 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; Patel et al., 2018). We do not choose this strategy as we have rich data at the individual level.

tional independence assumption, CIA) and common support (or overlap).[8] When the ATT is the focus, these assumptions write:

$$(CIA) \qquad Y(0) \perp\!\!\!\perp D \mid p(X) \forall X$$
$$(CS) \qquad p(X) = P(D = 1 \mid X) < 1$$

where $p(X)$ is 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; Lechner, 2002). Therefore, in addition to the standard demographic variables (gender, age, marital status, number of children, level of education, nationality), we also condition on labor market and health histories. In particular, we control for having experienced family or health events in childhood or in the past three years, and for health and labor market status in 2013. Controlling for past health outcomes is all the more important since our treatment indicator relies on workers' subjective reports of working conditions. We use questions aimed at eliciting 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. 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 health status. Thus, we control for sector of activity, income, type of contract, exposure to physical risks and to means constraints, unpredictable or atypical working hours, quality of management and any organizational, technology or other changes in the past twelve months.[9]

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 sector). In a sensitivity analysis, we use alternative algorithms and distances, and perform inverse probability weighting (IPW) to estimate the propensity score.[10]

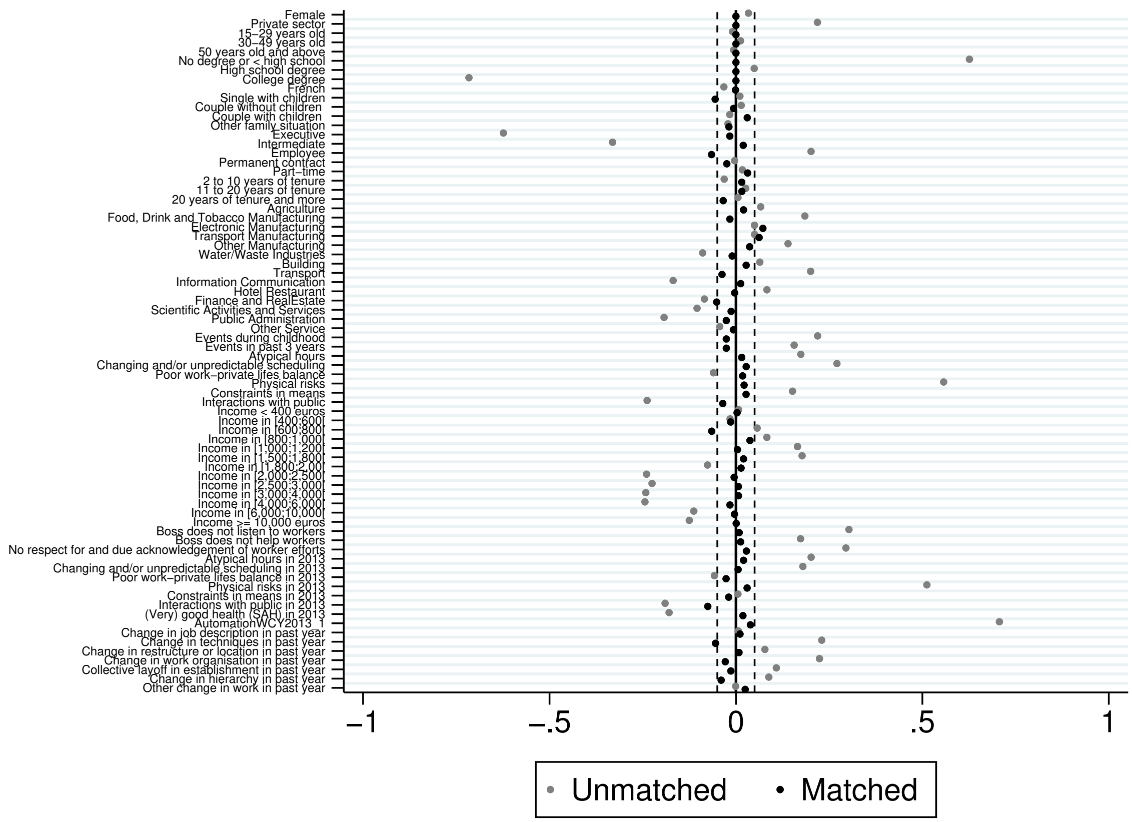
Figure 1 and figure B.1 in Appendix B show the quality of the covariate distribution and of the common support after matching. Covariates are well balanced and the matching procedure appears reliable.

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

[9] The full list of covariates is given in Table 1.

[10] We could not perform exact or coarsened exact matching, as the large number of covariates included in our model leads to matching on a limited number of observations. Results are presented in the next section.

Figure 1: Standardized % bias across covariates



4 Results

Main results. Table 1 displays the estimates of the average treatment effect on the treated (ATT) of working in automatable jobs on the probability of suffering from a MDE or a GAD. While Column (1) shows the raw difference between the treated and controls, Columns (2) to (5) present estimates once the endogenous exposure to risk of automation is accounted for. Results are noticeably reduced but remain significantly positive. When we add the whole set of controls, including past working and health conditions, we find that workers whose job may be subject to automation in the future are 3.8 pp more likely at present to report symptoms of a MDE or a GAD than if not threatened with automation. Considering the baseline at 15.7% (Table A.1 in Appendix A), this actually implies a 25% 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 income of interest is statistically rather infrequent.

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

Table 1: Effect of working in automatable jobs on the probability of declaring a MDE or GAD

	(1)	(2)	(3)	(4)	(5)
ATT	0.077***	0.072***	0.058***	0.039***	0.038***
	(0.002)	(0.002)	(0.003)	(0.004)	(0.003)
Socio-demographics	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

Source: French Working Conditions Survey 2013 and 2016.
Notes: Sample of 14,221 wage earners with non-missing relevant observables interviewed both in 2013 and 2016 and employed in the private or public sector in 2016. Dependent variable: having 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, education and sector (private/public) combined with propensity score-kernel matching (Refer to Figure 1 for the full list of covariates included in the estimation of the propensity score.). Bootstrapped standard errors.

Replicating the analysis on sub-samples, we find heterogeneity with respect to socio-demographic characteristics (Figure 2). In particular, effects are stronger for middle-aged workers and workers with intermediate or high levels of education. But we do not find heterogeneous effects between men and women.[11]

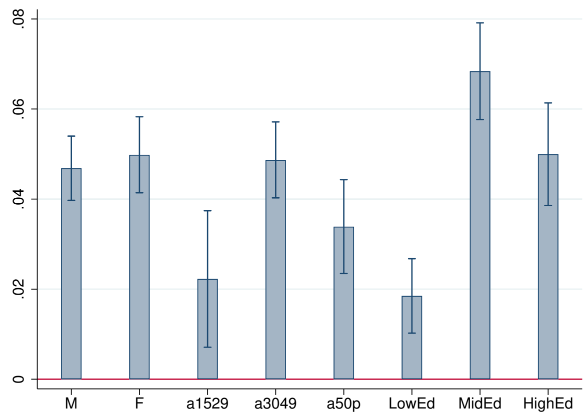
Sensitivity analysis. In addition to MDE and GAD, we consider alternative health measures, less severe ones. Results are presented in Table B.1 in Appendix B.[12] We find similar significant negative impacts of automation risk on the probability of feeling anxious almost all the time every day (4pp *vs* 3.8 pp for the main outcome) and on the WHO-5 indicator of well-being (3pp).

We also compare the sensitivity of the main results to our definition of working in automatable jobs.

[11] Balancing indicators are displayed in Figure B.3 in Appendix B. For women and mid-educated workers, matching quality is not as good as for the main estimates.

[12] Balancing indicators are displayed in Figure B.4 in Appendix B. Covariates are well balanced.

Figure 2: Heterogeneous effects of automation risk on the probability of declaring a MDE or GAD (ATT)



Source: French Working Conditions Survey 2013 and 2016.
Notes: Stratified estimation of sub-samples among wage earners with non-missing relevant observables interviewed both in 2013 and 2016 and employed in the private or public sector in 2016. Balancing on each subsample in Figure B.3 in Appendix B. Dependent variable: having 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, education and sector (private/public) combined with propensity score-kernel matching (see Figure 1 for the list of variables included in the propensity score estimation). Bootstrapped standard errors.

As explained in Section 2, we lack information about some requirements of the job (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 that also have at least a 10% probability of computerisation, as defined by Frey and Osborne (2017). This ensures that we do not include in the treatment group workers whose jobs are actually not at risk of automation. Results are unchanged when we add this condition (3.4pp).

As shown in Figure B.2 in Appendix B, results as a whole are unchanged when we consider alternative matching algorithms and distances or inverse-probability weighting.[13]

Lastly, we investigate the credibility of the unconfoundedness assumption by calculating the Rosenbaum

[13] We do not show results from multidimensional nearest neighbour matching which leads to poor balancing performances.

bounds (Becker and Caliendo, 2007; Rosenbaum, 2002).[14] We obtain a critical value for Γ of 2.1, 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 for unobserved heterogeneity to overturn the inference.

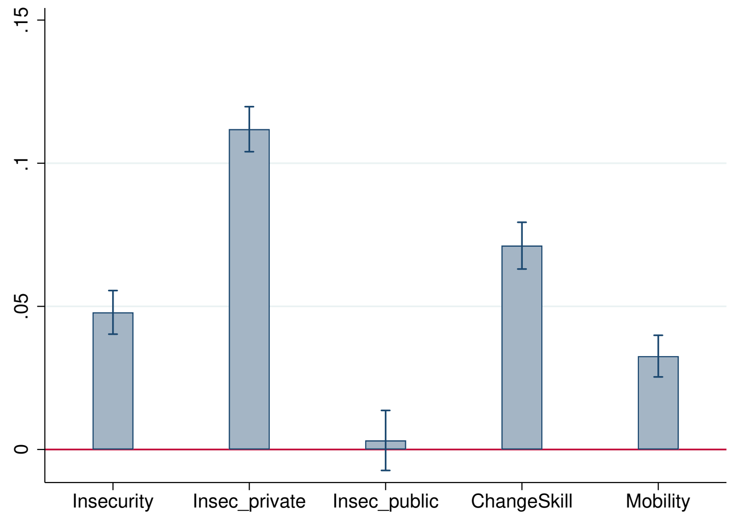
5 Mechanisms and discussion

To explain these findings, our hypothesis 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. To test this mechanism, we replicate the analysis using intermediary outcomes as dependent variables. 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), fear of qualification or occupational changes within the next three years (fourth bar) and fear of having to take a different and undesired job at 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 and third bars). The effect is very small indeed in the public sector (about 1 pp *vs.* 11 pp in the private sector). Therefore, the fear of automation in the near future appears a relevant explanation for the negative impact that working in automatable jobs has on mental health.

These channels are also consistent with the heterogeneity of the effects of working in automatable jobs on mental health. Middle-aged workers may perceive automation as threatening to disrupt their career path (with possible job loss and undesired job mobility), and may feel less able to adapt to such changes. By contrast, older workers may feel protected from automation by the horizon effect (*i.e.,* the prospect of retiring shortly).

[14] 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 none of the questions required to construct the indicator were asked in 2019, making it impossible to perform such a complementary analysis.

Figure 3: Effect of automation risk on intermediate outcomes (ATT)



Source: French Working Conditions Survey 2013 and 2016.
Notes: Separate estimation on each intermediate outcome. Measure of automation risk defined in section 2.2. Exact matching on gender, age, education and sector (private/public) combined with propensity score-kernel matching (see Figure 1 for the list of variables included in the propensity score estimation). Bootstrapped standard errors. Caps represent 95% confidence intervals.

Regarding our measure of automation risk, 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). Our measure distinguishes between two cases, depending on whether automation leads to positive or negative changes. If automation leads to a better allocation of tasks and improves working conditions, individuals in our sample subject to such automation are not classified as treated (i.e., working in automatable jobs) and are part of the control group. This implies that we are overestimating the negative effect of automation on mental health because some people who would benefit from automation are not considered part of the treatment group. However, this bias is likely to be limited since IA, sophisticated chatbots and advanced information systems were not fully developed in 2016. On the other hand, if automation worsens working conditions (e.g., increased work intensity), individuals are likely to report job attributes fitting our definition of automatable jobs (i.e., no latitude, repetitive tasks and close monitoring), and therefore be classified as treated. In this case, our results are not biased, but we would capture the impact of both automatability and actual (partial) automation. This could possibly negatively impact mental health if it induces work intensification and loss of meaning on the job. Replicating the analysis with work intensity as dependent variable, we actually find that working in automatable jobs increases the probability of feeling rushed at work by 4pp.

An alternative to the fear of automation as a mechanism to explain the findings could be bad working conditions. Jobs classified as automatable in the future actually share attributes with jobs that by nature entail bad working conditions. Therefore, regardless of the risk of automation, workers may have poor mental health because of bad working conditions. We verify, however, that this mechanism cannot be the main driver of our results. First, we control for net monthly income as well as various past and present working conditions in the estimation of the propensity score.[15] Second, splitting the sample between individuals receiving a net monthly income below and above 2000 euros (referred to as low-income and high-income respectively) and replicating the analysis on those two sub-groups, we find that the ATT is significantly positive for both groups and fairly similar (0.039 for low-income workers *vs.* 0.034 for high-income workers). We also note that 21% of the treated group are high-income individuals, so a significant share of treated workers are in good jobs.

Bad management could be another possible channel explaining the negative effect of working in automatable jobs on mental health. In particular, bad management could explain why we find a negative effect for the high-income group as well. Again, we provide evidence in favour of our first explanation (the fear of automation as main driver). In addition to including a dummy capturing bad management,[16] we break the sample down into two groups: individuals exposed to bad management and those who are not, replicating the analysis on both sub-groups. While the effect is much stronger for workers subject to bad management, the estimate is still significantly positive for workers who are not (0.073 *vs.* 0.02).

We are thus confident that our measure of automation risk captures the fear of automation well enough to explain the results. While bad working conditions and bad management cannot be fully ruled out, they do not appear to be the main mechanisms driving these findings.

6 Conclusion

This is the first study to measure automation at the individual level to examine the effects of risk of future automation on workers' present mental health. Using propensity score matching, we find a substantial negative impact of having a job whose tasks could be (partially) displaced by machines and computers. We explore the underlying mechanisms and find evidence indicating that job insecurity and fear of qualification

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

[16] 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 the treated group are exposed to good management.

or organisational changes are related to automation risk and may be good candidates to explain our results.

The impacts of automation are not restricted to employment level and the employment structure, but also affect workers' mental health. This latter effect occurs even before the tasks are actually automated. Policies aimed at helping workers be better prepared to face and overcome 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.

References

Abeliansky, A. L. and Beulmann, M. (2019). Are they coming for us? Industrial robots and the mental health of workers. *cege Discussion Papers, University of Göttingen*, 379.

Acemoglu, D. and Autor, D. (2011). Skills, Tasks and Technologies: Implications for Employment and Earnings. In Ashenfelter, O. and Card, D., editors, *Handbook of Labor Economics*, volume 4 of *Handbook of Labor Economics*, chapter 12, pages 1043–1171. Elsevier.

Acemoglu, D. and Restrepo, P. (2019). Automation and new tasks: How technology displaces and reinstates labor. *Journal of Economic Perspectives*, 33(2):3–30.

Acemoglu, D. and Restrepo, P. (2020). Robots and jobs: Evidence from US labor markets. *Journal of Political Economy*, 128(6):2188–2244.

Arntz, M., Gregory, T., and Zierahn, U. (2016). The Risk of Automation for Jobs in OECD Countries. OECD Social, Employment and Migration Working Papers No. 189, OECD Publishing, Paris.

Arntz, M., Gregory, T., and Zierahn, U. (2017). Revisiting the risk of automation. *Economics Letters*, 159.

Autor, D. and Dorn, D. (2013). The growth of low-skill service jobs and the polarization of the US labor market. *American Economic Review*, 103(5).

Autor, D., Levy, F., and Murnane, R. J. (2003). The skill content of recent technological change: An empirical exploration. *The Quarterly Journal of Economics*, 118(4):1279–1333.

Autor, D. H. (2015). Why are there still so many jobs? The history and future of workplace automation. *Journal of Economic Perspectives*, 29(3):3–30.

Becker, S. O. and Caliendo, M. (2007). Sensitivity analysis for average treatment effects. *Stata Journal*, 7(1):71–83.

Brynjolfsson, E. and McAfee, A. (2012). *Race against the machine: How the digital revolution is accelerating innovation, driving productivity, and irreversibly transforming employment and the economy.* New York, NY: Digital Frontier Press.

Caliendo, M., Mahlstedt, R., and Mitnik, O. A. (2017). Unobservable, but unimportant? The relevance of usually unobserved variables for the evaluation of labor market policies. *Labour Economics*, 46(C):14–25.

COE (2017). Automatisation, numérisation et emploi - les impacts sur le volume, la structure et la localisation de l'emploi. *rapport*, Tome 1.

Cottini, E. and Ghinetti, P. (2018). Employment insecurity and employees' health in Denmark. *Health Economics*, 27.

DeCanio, S. (2016). Robots and humans—complements or substitutes? *Journal of Macroeconomics*, 49(C):280–291.

Frey, C. B. and Osborne, M. A. (2017). The future of employment: How susceptible are jobs to computerisation? *Technological Forecasting and Social Change*, 114:254 – 280.

Green, F. (2004). Work intensification, discretion, and the decline in well-being at work. *Eastern Economic Journal*, 30(4).

Innocenti, S. and Golin, M. (2022). Human capital investment and perceived automation risks: Evidence from 16 countries. *Journal of Economic Behavior & Organization*, 195:27–41.

Josten, C. and Lordan, G. (2020). *Robots at Work: Automatable and Non-automatable Jobs*, pages 1–24. Springer International Publishing, Cham.

Karasek, R. (1979). Job demands, job decision latitude, and mental strain: Implications for job redesign. *Administrative Science Quarterly*, 24(2).

Lechner, M. (2002). Program heterogeneity and propensity score matching: An application to the evaluation of active labor market policies. *The Review of Economics and Statistics*, 84(2):205–220.

Lordan, G. and Stringer, E.-J. (2022). People versus machines: The impact of being in an automatable job on australian workers mental health and life satisfaction. *Economics & Human Biology*, 46:101144.

Maurin, E. and Thesmar, D. (2004). Changes in the functional structure of firms and the demand for skill. *Journal of Labor Economics*, 22(3).

Nedelkoska, L. and Quintini, G. (2018). Automation, skills use and training. OECD Social, Employment and Migration Working Papers, OECD Publishing, Paris.

Patel, P. C., Devaraj, S., Hicks, M. J., and Wornell, E. J. (2018). County-level job automation risk and health: Evidence from the united states. *Social Science & Medicine*, 202:54–60.

Reichert, A. and Tauchmann, H. (2017). Workforce reduction, subjective job insecurity, and mental health. *Journal of Economic Behavior & Organization*, 133(C):187–212.

Rosenbaum, P. R. (2002). *Observational Studies*. New York: Springer, 2nd edition.

Rosenbaum, P. R. and Rubin, D. B. (1983). The central role of the propensity score in observational studies for causal effects. *Biometrika*, 70(1):41–55.

Schwabe, H. and Castellacci, F. (2020). Automation, workers' skills and job satisfaction. *PLOS One*, 15(11).

Appendices

A Data

Table A.1: Sample composition - overall and by automatability (in %)

	All	Automatable job		
		No	Yes	p-value
Individual characteristics				
Female	0.477	0.476	0.484	***
15-29 years old	0.180	0.179	0.184	*
30-49 years old	0.529	0.529	0.528	
50 years old and above	0.292	0.293	0.288	
French	0.969	0.970	0.966	***
No degree or < secondary school	0.374	0.318	0.614	***
Secondary school diploma	0.196	0.192	0.213	***
University degree	0.430	0.490	0.172	***
Job characteristics				
Private sector	0.675	0.655	0.759	***
Executive	0.207	0.246	0.037	***
Intermediate	0.285	0.312	0.172	***
Employee	0.288	0.272	0.355	***
Worker	0.220	0.170	0.436	***
Permanent contract	0.918	0.922	0.902	**
Part-time	0.155	0.155	0.156	
Tenure in [0;5] years	0.291	0.291	0.291	
Tenure in]5;20] years	0.474	0.473	0.476	
Tenure > 20 years	0.235	0.236	0.233	
1 to 49 employees	0.330	0.345	0.273	***
50 to 499 employees	0.231	0.222	0.262	***
≥ 500 employees	0.440	0.433	0.465	**
Agriculture	0.011	0.010	0.017	***
Food, Drink and Tobacco Manufacturing	0.027	0.021	0.054	***
Electronic Manufacturing	0.017	0.015	0.025	
Transport Manufacturing	0.027	0.024	0.036	***
Other Manufacturing	0.079	0.070	0.116	***
Water/Waste Industries	0.019	0.020	0.010	
Building	0.050	0.047	0.062	
Trade	0.109	0.108	0.116	***
Transport	0.053	0.043	0.091	***
Information Communication	0.036	0.041	0.014	***
Hotel Restaurant	0.026	0.024	0.037	*
Finance and Real Estate	0.048	0.051	0.033	***
Scientific Activities and Services	0.085	0.091	0.062	***

(Continued on next page)

Table A.1 – continued from previous page

	All	Automatable job		*p*-value
		No	Yes	
Public Administration	0.375	0.394	0.295	***
Other Service	0.038	0.040	0.031	**
Working conditions				
Atypical hours	0.626	0.610	0.695	***
Changing and/or unpredictable scheduling	0.496	0.470	0.611	***
Poor work-private life balance	0.737	0.742	0.715	*
Physical risks	0.793	0.757	0.949	***
Constraints in means	0.684	0.671	0.741	***
Interactions with public	0.721	0.744	0.621	***
Income < 1200 euros	0.128	0.117	0.176	0.000
Income in [1,200;1,800[euros	0.380	0.339	0.555	0.000
Income in [1,800;2,500[euros	0.271	0.291	0.185	0.000
Income >= 2,500 euros	0.221	0.253	0.084	0.000
Poor quality management	0.376	0.350	0.489	0.000
Past working conditions (in 2013)				
Atypical hours	0.618	0.600	0.696	***
Changing and/or unpredictable scheduling	0.549	0.531	0.626	***
Poor work-private life balance	0.685	0.690	0.664	***
Physical risks	0.791	0.757	0.937	***
Constraints in means	0.674	0.674	0.675	*
Interactions with public	0.709	0.726	0.638	***
Experienced one or several changes in work in past year	0.450	0.437	0.507	***
Automatable job	0.157	0.103	0.385	***
Health				
Events during childhood	0.550	0.531	0.633	***
Events in past 3 years	0.504	0.489	0.566	***
(Very) good health (self-assessed) in 2013	0.787	0.802	0.725	***
Variables of interest				
Mental disorder: MDE or GAD (DSM-IV)	0.094	0.080	0.157	***
Anxiety almost every day in past 6 months	0.160	0.142	0.239	***
Self-assessed health				
(Very) good health	0.752	0.769	0.680	***
Fair	0.206	0.199	0.239	***
Poor	0.037	0.029	0.073	***
Very poor	0.004	0.003	0.007	***
Low WHO-5 score	0.288	0.273	0.353	***
N	14,221	11,397	2,824	

Source: French Working Conditions Survey 2013 and 2016.

Notes: Sample of wage earners with non-missing relevant observables, interviewed both in 2013 and 2016. Weighted statistics.

Table A.2: 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
Do you have the opportunity to put your own ideas into practice in your job?
(yes or no question)
Does your job require you to take initiative?
(yes or no question)
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?*

Source: French Working Conditions Survey 2016

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

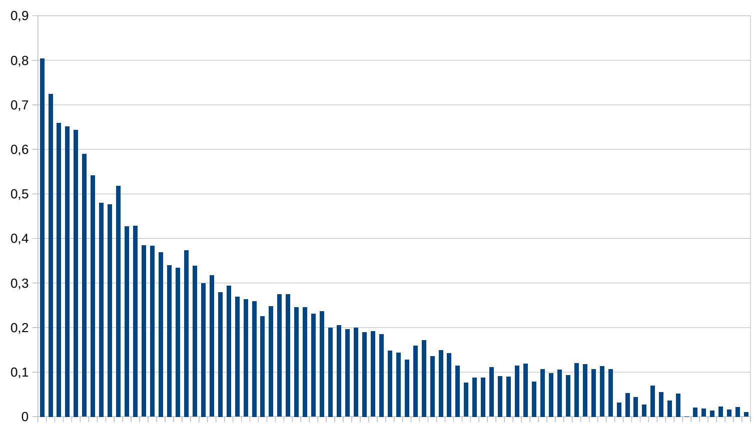
Table A.3: Components of the measure of automation risk

	Automation Risk	Routine	No Latitude	Pace Constraints
Routine=1	0.494	1	0.782	0.684
No Latitude=1	0.190	0.388	1	0.537
Pace Constraints =1	0.332	0.460	0.726	1

Source: French Working Conditions Survey 2013 and 2016.

Notes: Sample of 14,221 wage earners with non missing relevant observables interviewed both in 2013 and 2016. Measure of automation risk defined in Section 2. Reading: 49.4% of workers who declare having a routine job are classified as being exposed to the risk of automation.

Figure A.1: Within-occupation shares of workers considered as being at risk of automation



Source: French Working Conditions Survey 2016.

Notes: Each bar represents one occupation. Restricted to occupations containing at least 10 surveyed individuals. Weighted statistics.

Table A.4: Automation exposure by occupation

	Automation risk rate	N
Unskilled workers	.433	592
Skilled workers	.356	1703
Sales employees	.287	458
Employees - public sector	.249	2801
Employees - private sector	.221	421
Employees - firm administration	.174	826
Technicians	.143	659
Intermediate professions - firm administration and sales	.13	883
Foremen	.103	332
Intermediate professions - public sector	.095	2753
Executive manager - private sector	.035	1195
Executive manager - public sector	.033	1421

Source: French Working Conditions Survey 2016.

Notes: Sample: analysis restricted to occupation categories containing at least 20 surveyed individuals. Weighted statistics.

Table A.5: Automation exposure by type of job

	Automation rate	N
The 10 jobs with the highest shares of automation		
Machine operators for the manufacture of food items and related products	.672	71
Packaging, bottling and labeling machine operators	.619	84
Mechanical fitters	.612	73
Forklift operators and drivers	.601	63
Checkout assistants and ticket agents	.586	52
Post Service workers	.569	46
Bus and Tram Drivers	.515	53
Operators of machinery and fixed installations not elsewhere classified	.487	82
Truck and truck drivers	.47	136
Machine tool setters and operators	.443	48
The 10 jobs with the lowest shares of automation		
Teachers, technical, vocational education and adult education	.008	53
Teachers (technical and adult education)	.008	31
Software designers	.007	47
Pharmacist	.006	36
Primary school teachers	.003	342
Psychologists	0	45
Directors and executive managers	0	48
Educational directors and executives	0	36
Professors (Universities and institutions of higher education)	0	71
Specialists, technical sciences	0	100

Source: French Working Conditions Survey 2016.

Notes: Sample: analysis restricted to the jobs containing at least 20 surveyed individuals. Weighted statistics

Figure A.2: Comparison between Acemoglu and Dorn (2013)'s measure of automation and ours (redefined at the occupational level)

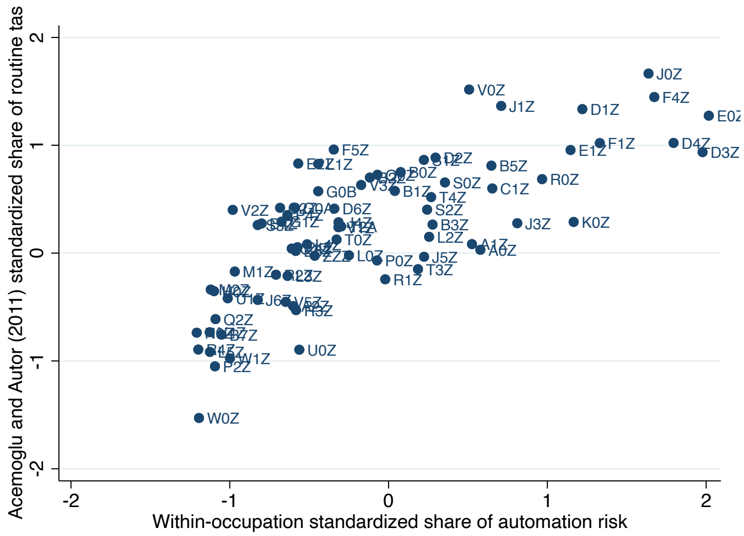
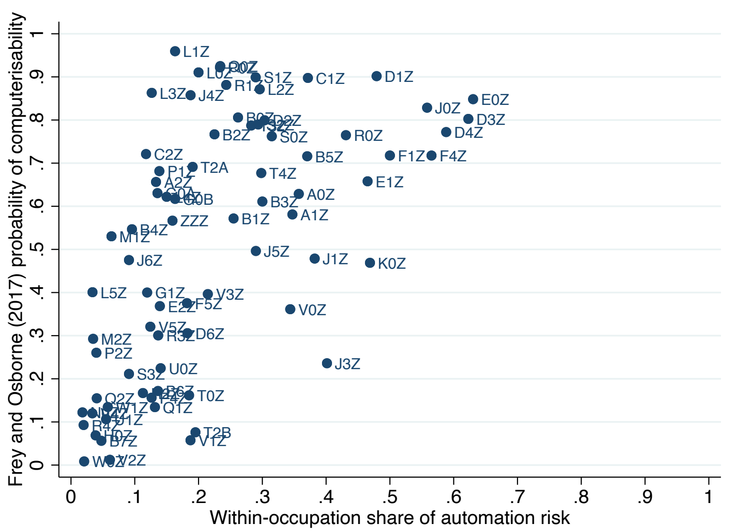


Figure A.3: Comparison between Frey and Osborne (2017)'s measure of automation and ours (redefined at the occupational level)



B Main and sensitivity analysis

Figure B.1: Distribution of the propensity score on the matched and unmatched samples

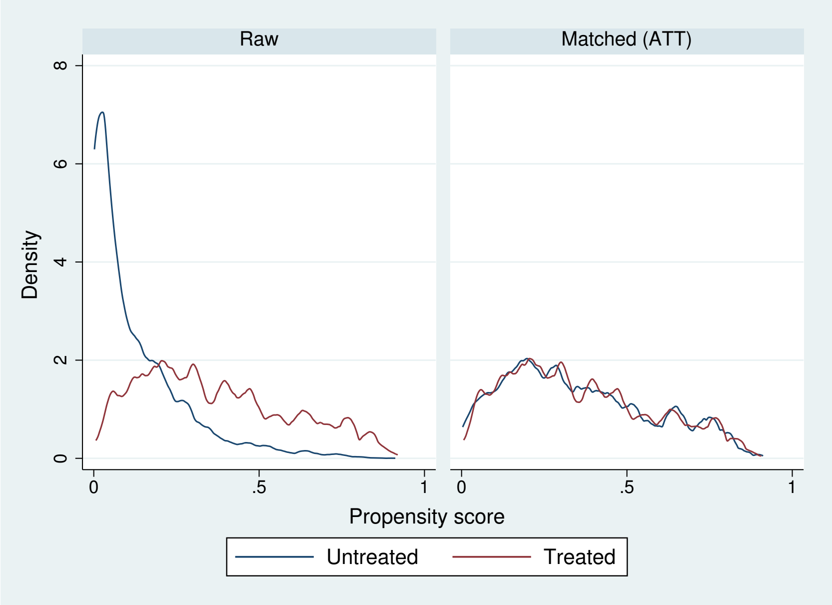
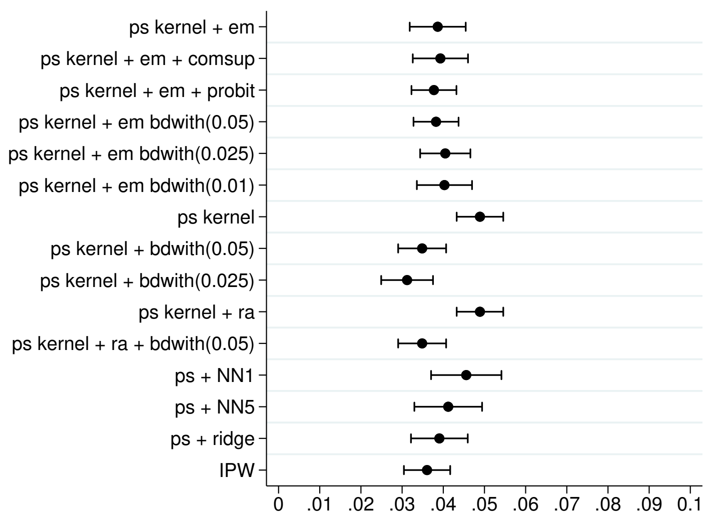
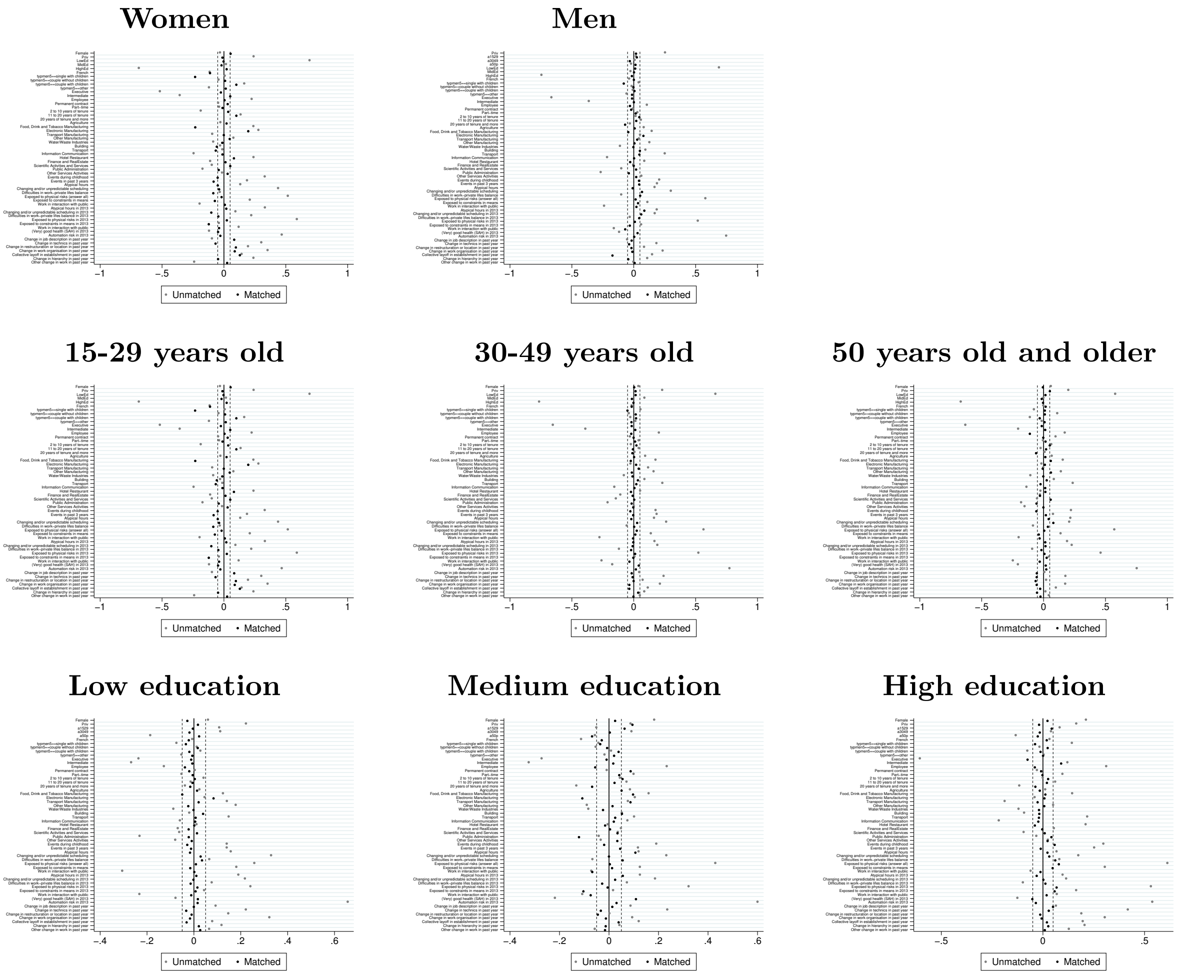


Figure B.2: ATT estimates using alternative matching techniques - health outcome: MDE-GAD; main automation risk measure



Source: French Working Conditions Survey 2013 and 2016.
Notes: Separate analysis on sub-samples among wage earners with non missing relevant observables interviewed both in 2013 and 2016.

Figure B.3: Standardized % bias across covariates for estimation by sub-populations



Source: French Working Conditions Survey 2013 and 2016.

Notes: Separate analysis on sub-samples among wage earners with non-missing relevant observables interviewed both in 2013 and 2016.

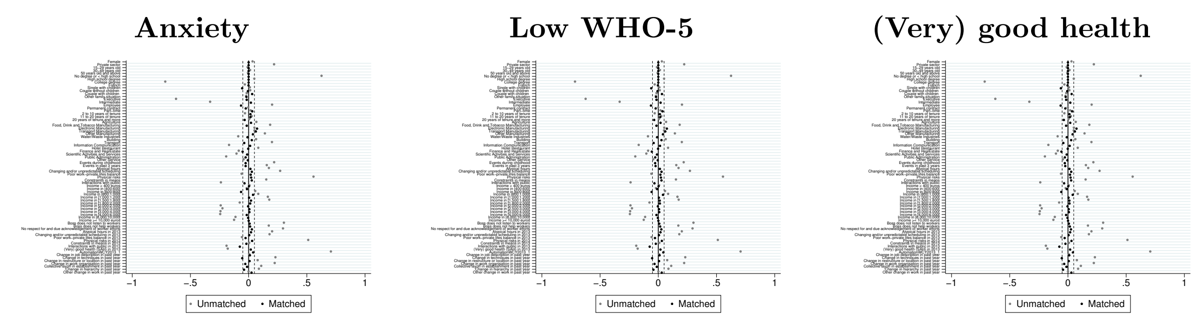
Table B.1: Estimates of the effect of risk of automation on alternative health outcomes

	MDE or GAD	Anxiety	Low WHO-5	(Very) good health
ATT	.038***	.04***	.03***	-.003
	(.003)	(.003)	(.004)	(.004)
N	14221	14221	14221	14221

Source: French Working Conditions Survey 2013 and 2016.

Notes: Sample of wage earners with non-missing relevant observables interviewed both in 2013 and 2016. Measure of automation risk defined in Section 2. Exact matching on gender, age, education and sector (private/public) categories combined with propensity score-kernel matching with the full set of controls (see Figure 1 for the list of variables included in the propensity score estimation). Bootstrapped standard errors.

Figure B.4: Standardized % bias across covariates for estimation by health outcomes



Source: French Working Conditions Survey 2013 and 2016.

Notes: Separate analysis on sub-samples among wage earners with non-missing relevant observables interviewed both in 2013 and 2016.