Displaced or depressed? The effect of working in automatable jobs on mental health

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Abstract

Automation may destroy jobs, change the labor demand structure or different aspects of work, and therefore may impact workers' health and well-being. Using French individual survey data, we estimate the effects of working in automatable jobs on mental health. Implementing the propensity score matching method to solve the issue of endogenous exposure to automation risk, we find that workers whose job is at risk of automation in the future have a higher probability to suffer from a major depressive episode or a generalize anxiety disorder at present by about 4 percentage points. Fear of job loss within the year and fear of qualification or occupational changes within the next three years seem relevant channels to explain this negative effect on mental health.

Keywords— Mental Health, Automation, Work intensity, Job insecurity, Propensity score matching.
JEL codes— I14, J24.

1 Introduction

Over the past decades, the development of new technologies have profoundly changed the labour market and the working conditions. With the artificial intelligence and the recent technical advances—referred to

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as the “fourth industrial revolution” (Brynjolfsson and McAfee, 2012; DeCanio, 2016)—the debate around the “end of work” or “robots versus workers” has been revived, with a wider range of workers exposed to the risk of automation. Josten and Lordan (2019) estimate that 47% of jobs in the EU are at least partially automotable 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 studied the consequences of automation on employment and labour demand (Acemoglu and Autor, 2011; Acemoglu and Restrepo, 2019; Autor et al., 2003; Frey and Osborne, 2017), there is little evidence about the effects on (mental) health, Patel et al. (2018) being a notable exception. Yet measuring and understanding the possible health effects of a major labour market change, such as automation—an important work-related risk factor of workers’ mental health—is of crucial interest for policy makers considering the associated costs. 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-leaves, and the losses in employment and productivity). Therefore, the identification of new health hazards could help design effective prevention policies and thereby help limit costs of mental illness. In this paper, we aim to evaluate to which extent working in automatable jobs impacts well-being and mental health.

Health effects of automation exposure are theoretically undetermined. On the one hand, automation risk may deteriorate workers’ mental health because of increased work intensity (Green, 2004; Karasek, 1979), job insecurity (Abeliansky and Beulmann, 2019; Cottini and Ghinetti, 2018; Patel et al., 2018; Reichert and Tauchmann, 2017; Schwabe and Castellacci, 2020) and lower wage dynamics (Acemoglu and Restrepo, 2020). On the other hand, automation could improve working conditions and health if it reduces repetitive and routine tasks (Autor, 2015; Maurin and Thesmar, 2004), if the new technologies are used as a support to workers (who thereby get more freedom to engage in more self-fulfilling tasks), and if it thereby improves job quality prospects. All in all, the effects of automation risk on the quality of working conditions and in turn on workers’ mental health is 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 that provide detailed information about working conditions, labour market history and health status for about 28,000 individuals, representative of the working-age population. 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. We define as working in automatable jobs, workers whose job meets three conditions: repetitive tasks, close monitoring and detailed instructions. Our definition basically assumes that jobs exposed to the risk of automation are jobs that

[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.” Previous estimate indicated that 9% of jobs in 21 OECD countries were automatable (Arntz et al., 2016). In France, 10% of current jobs have high vulnerabilities in the automation context, and 50% should see their content significantly transformed within the next fifteen years (COE, 2017).

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 practices at the workplace 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). In particular, besides the standard demographic variables (gender, age, marital status, number of children, level of education, nationality), we also condition on labour market and health previous histories.

Results indicate that workers who have an automatable job face a higher probability to declare anxiety or depression by 4 pp. We find heterogeneous effects with respect to age and education, with middle-aged and mid-educated workers being more affected than others. An analysis of intermediary outcomes indicates that workers who have an automatable job are more likely to report a feeling of job insecurity. Workers exposed to the risk of automation also report in greater proportions 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 the skill demand on the labor market (Acemoglu and Autor, 2011; Acemoglu and Restrepo, 2019, 2020; Autor et al., 2003). By looking at the implications of these changes in working conditions on workers' well-being and mental health, we expand the literature to a new dimension. Recently, Innocenti and Golin (2022) show that all workers are not equally worried about the risk of automation and that workers who are worried about being displaced by a machine or algorithm are also those who 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 have induced 40% of the workers that are currently in employment to fear that their work might be replaced by a smart machine in the future. Such fear of future replacement does negatively affect workers job satisfaction at present. This negative effect is driven by low-skilled workers, which are those carrying out routine-based tasks, and who are therefore more exposed to the risks of automation. To the best of our knowledge, the health effects of automation risk have not been documented at a micro level yet. Only Patel et al. (2018) have documented the detrimental effects of automation risk on health (both physical and mental), using aggregate data (county-level) and with a focus on the job insecurity mechanism. We explore alternative channels that have not been empirically tested yet, 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 and discuss possible mechanisms in Section 4 and Section 6 concludes and draws policy implications.

2 Data

2.1 Sample construction

We use the working conditions surveys (*Conditions de travail* and *Conditions de travail - Risques Psycho-sociaux*) produced by the statistical Department of the French Ministry of Labour. These surveys are 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 working as employed or self-employed workers. Questions are asked mostly face-to-face, and individuals are also given 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 various and detailed measures of mental health[2].

As we aim to evaluate in 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 labour market and health statuses, as required in our empirical strategy 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 have job loss (hence job insecurity) and job changes well under control, unlike employed workers. We built 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. Men represent about half of it. Around one third is aged 45 years and more. 12% of individuals in the sample have no diploma while a quarter has a university degree and executives represent 20% of the sample. Services is by far the most represented sector of activity (about three quarters).

2.2 Measure of automation risk

We define as working in automatable jobs, workers who (i) execute repetitive tasks, (ii) have a job that can be easily monitored (due to constrained pace) and (iii) have to follow detailed instructions, with no latitude

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

in the tasks and in the manner to perform the tasks.[3,4] 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 jobs are more intensive in routine tasks are more likely to be displaced by computers.

These three conditions are in many ways close to the ones found in papers where the O*NET data are used to identify occupations intensive in routine tasks (Acemoglu and Autor, 2011; Frey and Osborne, 2017). But we lack information about fine dexterity (that may protect from automation) which means that we may classify as working in automatable jobs workers who actually do not. Moreover, we cannot assess the importance of the routine tasks amongst all the tasks that define a job. Ideally, we would have liked to know the amount (or share) of tasks that are automatable to determine the salience of the risk of displacement and/or change in the job description. Our assumption 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, so that we 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 occupational-approach by accounting for the fact that all workers within a given occupation may not be equally exposed to the risk of automation because of diverse practices at the workplace and 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. From detailed task data, they show that, when taking into account the spectrum of tasks within occupations, the automation risk of US jobs drops from 38% to 9%. Adopting an individual approach is all the more important in our data that there are some variations in our automation risk indicator within occupations: for about 50% of occupations, one out of five workers disagrees with the main view about automation within the occupation (Figure B.1 in Appendix B).

To assess how our measure of automation risk relates to the main approaches found in the literature, we compare the distribution of our measure of automation risk—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 between the international classification ISCO displayed 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

[3]In panel A of Table TBC in Appendix B, we list the exact questions used to construct our measure of working in automatable jobs.

[4]In Table B.3 in Appendix B, we look at 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. Amongst individuals reporting having a repetitive job, only half are considered as working in automatable jobs (i.e., meets the three conditions), while 22% have latitude and 32% have no pace constraints.

computerisation computed by (Frey and Osborne, 2017). Both alternative measures rely on the assumptions that jobs attributes are the same in France and in the US. Figures B.2 and B.3 in Appendix B show that our measure (redefined at the occupation-level) is positively correlated with both the Autor and Dorn's measure and the Frey and Osborne's measure.

With our current definition, about 19% of workers in our sample worked in automatable jobs in 2016. Table B.1 in Appendix B reports the rate of automation risk by occupation and Table B.2 displays the 10 jobs with the highest and lowest shares of workers in automatable jobs. While the hierarchy of occupations and jobs seem consistent with what was expected, both tables show that there are important 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 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 neuro-vegetative 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 destabilizing factor, may be continuous or include several events over a period of at least 6 months.

As people may experience mental troubles without reaching 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 generalized anxiety disorder), the World Health Organisation-Five well-being index (WHO-5) and self-assessed global 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 automation risk 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 who are not.[5] Additionally, workers in automatable jobs are more likely to work in the construction industry and to report harder working conditions (higher exposure to physical risks, atypical working hours, changing and/or unpredictable schedule) and a work environment that was subject to technology and/or organizational changes in the past year. All in all, workers at risk of automation present features that may have detrimental health effects. The challenge is then to disentangle the possible causal effect of automation risk on mental health from the selection into jobs and careers threaten by automation on the one hand, and from the action of confounding factors on the other hand.

We make use of the richness of our data to solve the selection issue by implementing matching, which consists in comparing individuals working in automatable jobs to individuals who do not, but who are otherwise comparable in terms of observables.[6] Specifically, we use the propensity score matching method (Rosenbaum and 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) is measured as the difference on average outcomes between the "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 conditional independence assumption, CIA) and common support (or overlap).[7] When interested in the ATT, these assumptions write:

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

[6] Alternatively, the selection issue can be solved using trade exposure as instrument for the risk of automation (Autor et al., 2003; Patel et al., 2018). The underlying idea is that the international competition pressures firms to invest in automation.

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

$$(CIA) \qquad Y(0) \perp\!\!\!\perp D \mid p(X) \forall X$$

$$(CS) \qquad p(X) = P(D = 1 \mid X) < 1$$

where $p(X)$ is the propensity score.

The literature shows that conditioning on past outcomes and events significantly improves matching quality and 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 previous histories. In particular, we control for having experienced family or health events in the childhood or in the past three years, and for health and labour market statuses in 2013. Controlling for past health outcomes is all the more important that our treatment indicator relies on workers' subjective reports of working conditions. We use questions that aim at describing as factually as possible the working conditions, but some subjectivity may subsist in the answers. Differences in subjective appreciation of a given situation between workers 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 condition for working conditions that could be correlated both with working conditions used to define our treatment and with the health status. Therefore, we control for the sector of activity, the income, the type of contract, exposure to physical risks and to means constraints, the unpredictable or atypical working hours, for the quality of management and for organizational, technology or any other changes in the past twelve months.[8]

In our preferred specification, we estimate the propensity score with a logit 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.[9]

Figures 1 and 2 show the quality of the covariates distribution and of the common support after matching. Covariates are well balanced and we can be confident in the matching procedure.

[8]The full list of covariates is detailed in Table 1.

[9]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: Standardised % bias across covariates

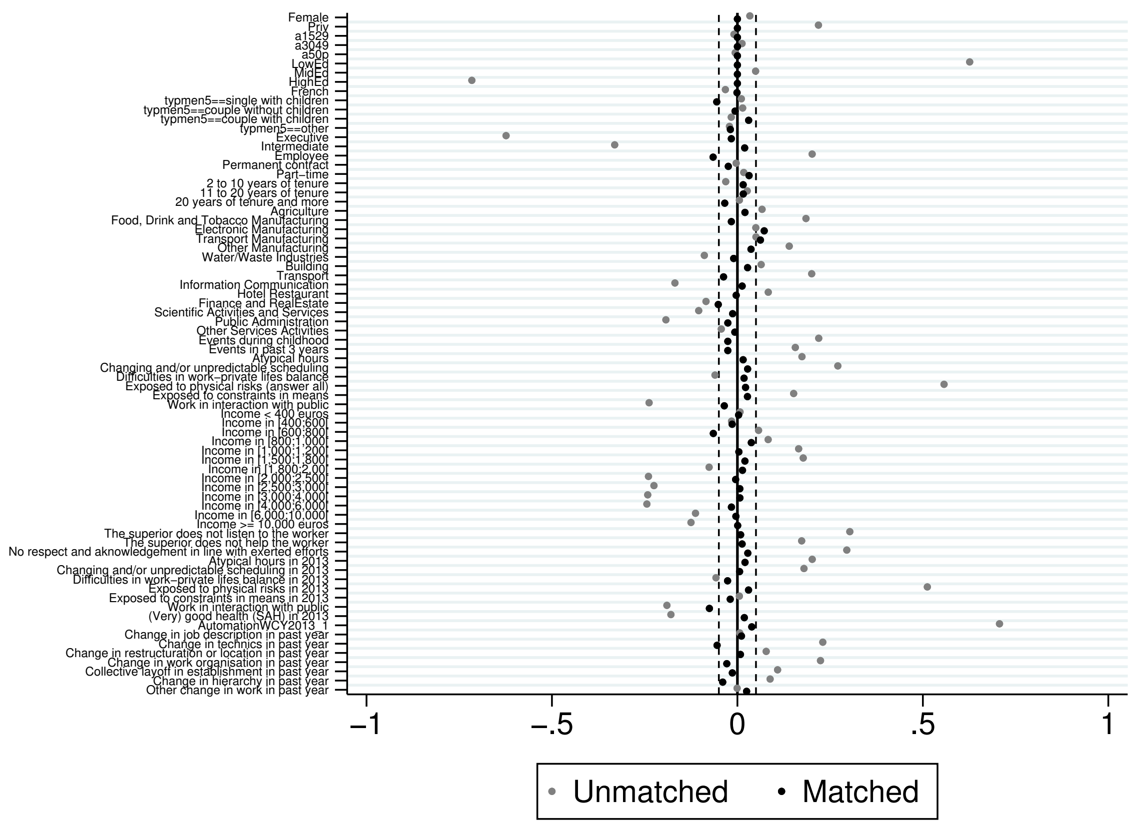
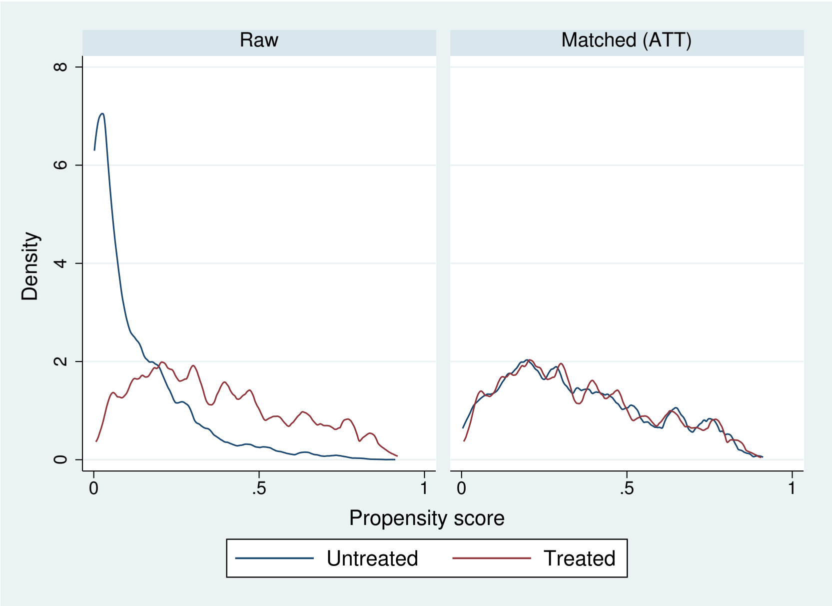


Figure 2: Distribution of the propensity score on the matched and unmatched samples



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 treated and controls, Columns (2) to (5) present estimates once the endogenous exposure to the 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 have a 3.8 pp higher probability of reporting at present symptoms of a MDE or a GAD than if they were not. Considering the baseline at 9.4% (Table A.1 in Appendix A), this actually implies a 40% increase in the probability of suffering from a mental disorder among the treated. This is a substantial increase, partly due to a rather infrequent outcome under consideration.

Our negative results are in line with Patel et al. (2018) who find with a 2SLS estimation a negative impact of automation risk at the county-level on mental health.

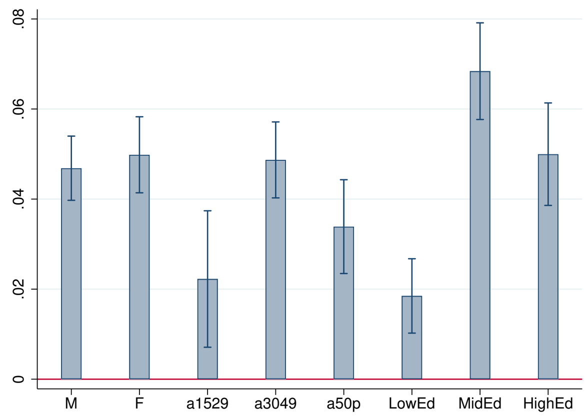
Table 1: Effect of working in automatable jobs on the probability of declaring a MDE or GAD

	(1)	(2)	(3)	(4)	(5)
ATT	0.077***	0.072***	0.058***	0.039***	0.038***
	(0.002)	(0.002)	(0.002)	(0.003)	(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 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) categories 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-demographics characteristics (Figure 3). 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.

Figure 3: Heterogeneous effects of automation risk on the probability of declaring a MDE or GAD (ATT)



Source: French Working Conditions Survey 2013 and 2016. 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 C.2. 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) categories combined with propensity score-kernel matching (see Figure 1 for the list of variables included in the propensity score estimation). Bootstrapped standard errors.

Sensitivity analysis In addition to MDE and GAD, we consider alternative health measures. Results are presented in Table C.1 in Appendix C. While we find overall similar negative impacts of automation risk on mental health, the effect seems slightly stronger on anxiety than on overall self-assessed health.

We also compare the sensitivity of the main results to our definition of working in automatable jobs. As explained in Section 2, we lack information about some aspects of the job (especially fine dexterity) that may prevent 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 Frey and Osborne (2017). This ensures that we do not include in the treatment group workers who are actually not at risk of automation. Results are unchanged when we add this condition (3.4pp).

As shown in Figure C.1 in Appendix C, results are overall unchanged when we consider alternative matching algorithms and distances or inverse-probability weighting.[10]

[10]We do not show results from the multidimensional nearest neighbour matching which leads to poor balancing

Lastly, we investigate the credibility of the unconfoundedness assumption by calculating the Rosenbaum bounds (Becker and Caliendo, 2007; Rosenbaum, 2002).[11] 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 between the treated and the controls by 2.1. 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

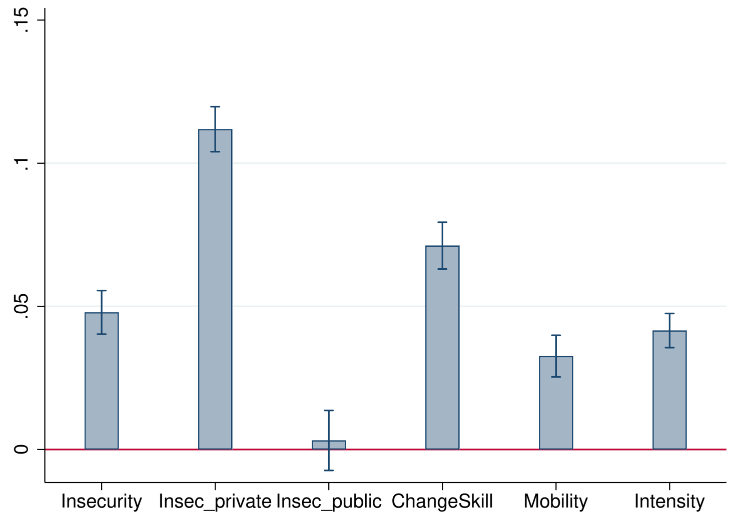
Our hypothesis to explain the findings is that working in an automatable job may negatively impact mental health if workers internalize that their job is at risk of automation and will experience changes in their career path. To test this mechanism, we replicate the analysis using intermediary outcomes as dependent variables. This provides indicative evidence of the relevance of possible channels, without testing them directly though. Figure 4 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 job within the workplace against the will (fifth bar), all being significantly positive. We further check the relevance of job insecurity channel by pulling apart 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 seems relevant to explain why working in automatable jobs has a negative effect on mental health.

In light of these channels, we can look back on the heterogeneous effects of working in automatable jobs on mental health. Middle-age workers may perceive automation as a risk of disruption in their career path (with possible job loss and undesired job mobility), feeling less able to adapt to the upcoming changes. On the contrary, older workers may feel protected from automation by the horizon effect (*ie.* the prospect of retiring shortly).

performances.

[11] 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. Therefore, we are unable to perform such a complementary analysis.

Figure 4: 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) categories 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.

Back to the measure of automation, one can argue that jobs classified as at risk of automation in the future might actually already be partly automated at present (e.g., checkout assistants, forklift operators and forklift drivers). Two cases may occur, 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 in the control group instead. This implies that we overestimate the negative effect of automation on mental health because some people who would benefit from automation are not considered as 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 contrary, 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 closed monitoring), and are then classified as treated. Such a scenario does not bias our results. Replicating the analysis with work intensity as dependent variable, we actually find that working in automotable jobs increases the probability of feeling rushed at work by 4pp.

As an alternative mechanism to the fear of automation to explain the findings, bad working conditions could be a candidate. Indeed, jobs classified as automatable in the future share attributes with jobs that have bad working conditions by nature. Therefore, independently of the risk of automation, workers would have poor mental health because of bad working conditions. Nevertheless, this mechanism cannot be the main driver of our results. First, we control for the net monthly income as well as various past and present working conditions in the estimation of the propensity score.[12] 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 rather similar (0.039 for low-income workers *vs.* 0.034 for high-income workers). We also note that 21% of the treated group is made of high-income individuals, so a significant share of treated workers are in good jobs.

Bad management could also be another possible channel to explain 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 (as bad working conditions do not). Again, we can providence evidence in favor our hypothesis (the fear of automation as main mechanism). Besides including a dummy capturing bad management,[13] we broke the sample between individuals exposed to bad management and those who are not, and we replicate the analysis on those two 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).

All in all, we are confident in our ability to capture well enough the fear of automation (in our measure of automation risk) in order to explain the results. Bad working conditions and bad management cannot be ruled out for sure but cannot be the main mechanisms in light of these findings.

6 Conclusion

We offer the first study looking at the effects of automation risk in the future on workers' mental health at present, at the individual level. 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 indicative evidence that job insecurity and fear of qualification or organisational change are related to automation risk and may be good candidates to explain our results.

The consequences of automation do not restrict to its impact on the employment level and the employment structure, but also affects workers' mental health. That effect occurs even before tasks are actually

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

[13] 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.

automated. We can assume that policy programs that help workers be better prepared to face and overcome technological changes will have benefits on the well-being of workers. Decreasing lower mental health hazards may enhance productivity and reduce sickness leaves, which will in turn reinforce the positive economic and labour market impacts of prevention policies. The question remains how to better support workers through this change though.

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A Appendix: sample description

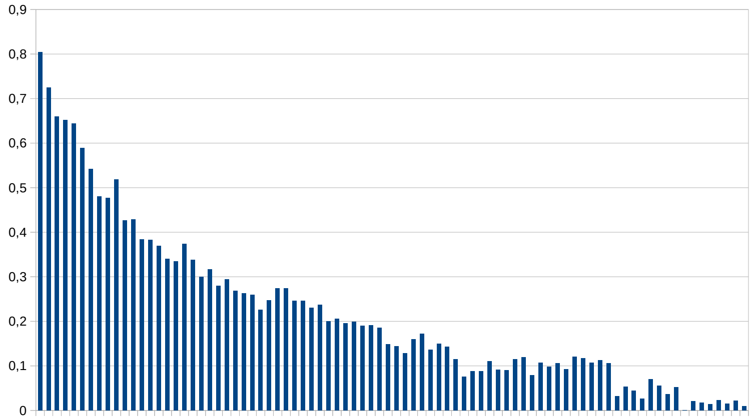
Table A.1: Sample composition

	mean
Female	0.477
below 25 years old	0.121
25-35 years old	0.240
35-45 years old	0.288
45-55 years old	0.278
55 years old and above	0.073
French	0.969
Single without children	0.143
Single with children	0.073
Couple without children	0.212
Couple with children	0.539
Other family status	0.033
No or low diploma	0.116
CAP-BEP	0.258
High-school degree (bac)	0.196
College degree (bac+2)	0.141
University degree (> bac+2)	0.289
Wage-earner - public employer	0.325
Wage-earner - private employer	0.675
Executive	0.207
Intermediate	0.285
Employee	0.288
Worker	0.220
Permanent contract	0.918
Part-time	0.155
0 or 1 year of tenure	0.099
2 to 10 years of tenure	0.400
11 to 20 years of tenure	0.265
20 years of tenure and more	0.235
1 to 49 employees	0.330
50 to 499 employees	0.231
500 employees and above	0.440
Multi-establishment firm	0.602
Agriculture	0.011
Manufacturing	0.169
Construction industry	0.050
Service industries	0.771

Source: 2016 French Working Conditions Survey.
Sample: workers employed in the private or public sectors in 2016 who were interviewed in 2013.
Weighted statistics.

B Appendix: exposure to the risk of automation

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



Source: French Working Conditions Survey 2016. Each bar represent an occupation. Restriction to occupations containing at least 10 surveyed individuals.

Table B.1: 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 to private employers	.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. Sample: analysis restricted to the occupation categories containing at least 20 surveyed individuals. Weighted statistics.

Table B.2: 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
Cashiers and ticket agents	.586	52
Mail 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 designer	.007	47
pharmacist	.006	36
Primary school teachers	.003	342
Psychologists	0	45
Directors and executives 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. Sample: analysis restricted to the jobs containing at least 20 surveyed individuals. Weighted statistics

Figure B.2: Comparison between the Acemoglu and Autor (2011) measure and our main measure of the occupational exposure to the risk of automation.

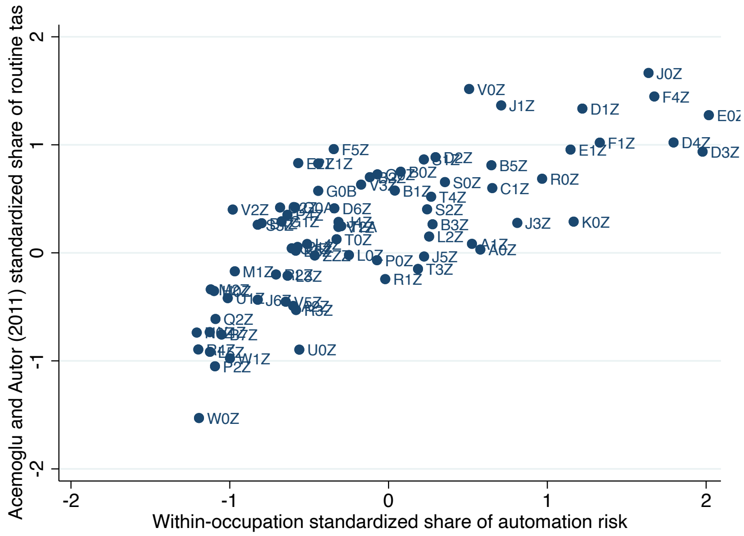


Figure B.3: Comparison between the Frey and Osborne (2017) measure and our main measure of the occupational exposure to the risk of automation.

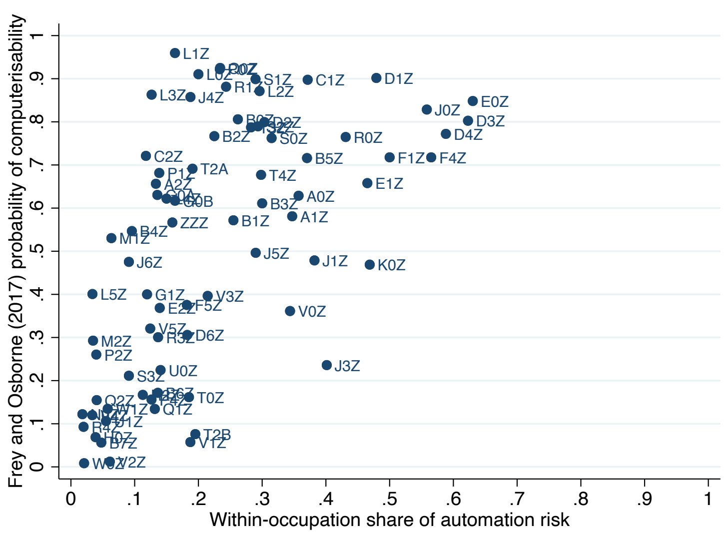


Table B.3: Components of the measure of automation risk

	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. Sample of wage earners with non missing relevant observables interviewed both in 2013 and 2016 and employed in the private or public sector in 2016. Measure of automation risk defined in section 2.2. Reading: 49.4% of workers who declare having a routine job are classified as being exposed to the risk of automation.

Table B.4: Sample composition - by exposure to automation (in %)

	Automation risk		
	No	Yes	
Female	0.476	0.484	
below 25 years old	0.117	0.138	***
25-35 years old	0.245	0.218	***
35-45 years old	0.288	0.291	
45-55 years old	0.274	0.295	**
55 years old and above	0.076	0.058	***
French	0.970	0.966	
No or low diploma	0.095	0.205	***
CAP-BEP	0.223	0.410	***
High-school degree (bac)	0.192	0.213	**
College degree (bac+2)	0.153	0.088	***
University degree (> bac+2)	0.337	0.084	***
Wage-earner - private employer	0.655	0.759	***
Executive	0.246	0.037	***
Intermediate	0.312	0.172	***
Employee	0.272	0.355	***
Worker	0.170	0.436	***
Permanent contract	0.922	0.902	***
Part-time	0.155	0.156	
Multi-establissement firm	0.599	0.613	
Agriculture	0.010	0.017	***
Manufacturing	0.151	0.242	***
Construction industry	0.047	0.062	***
Service industries	0.792	0.680	***
Events during childhood	0.531	0.633	***
Events in past 3 years	0.489	0.566	***
(Very) good health (SAH) in 2013	0.802	0.725	***
Atypical hours	0.610	0.695	***
Changing and/or unpredictable scheduling	0.470	0.611	***
Difficulties in work-private lifes balance	0.742	0.715	***
Exposed to physical risks (answer all)	0.757	0.949	***
Exposed to constraints in means	0.671	0.741	***
Change in job description in past year	0.179	0.183	
Change in technics in past year	0.136	0.226	***
Change in restructuration or location in past year	0.150	0.180	***
Change in work organisation in past year	0.228	0.330	***
Collective layoff in establishment in past year	0.039	0.065	***
Change in hierarchy in past year	0.153	0.187	***
Other change in work in past year	0.075	0.075	
N	1139	2824	

Source: French Working Conditions Survey 2013 and 2016. Sample of wage earners with non missing relevant observables interviewed both in 2013 and 2016 and employed in the private or public sector in 2016. Weighted statistics.

C Robustness analysis

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

	Health outcome					
	MDE or GAD	MDE	GAD	Anxiety	Low who-5	(Very) good health
ATT	.038***	.027***	.034***	.04***	.03***	-.003
	(.003)	(.002)	(.002)	(.003)	(.004)	(.004)
N	14221	14221	14221	14221	14221	14221

Note: French Working Conditions Survey 2013 and 2016. Sample of wage earners with non missing relevant observables interviewed both in 2013 and 2016 and employed in the private or public sector in 2016. Measure of automation risk defined in section 2.2. 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 C.1: ATT estimates using alternative matching techniques - health outcome: MDE-GAD; main automation risk measure

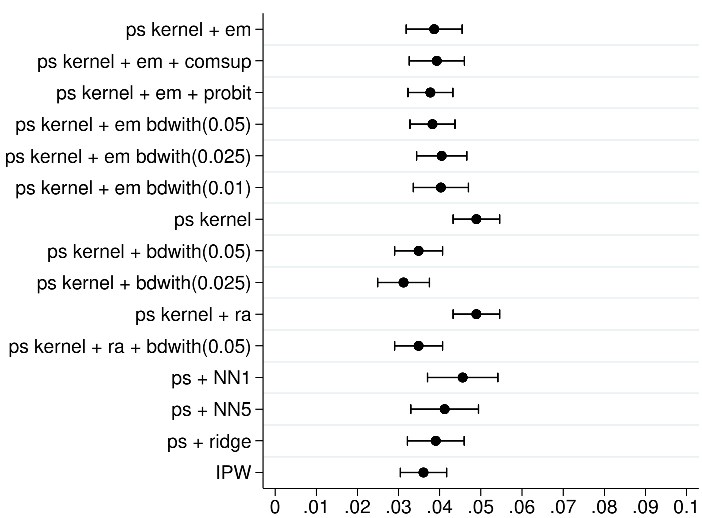
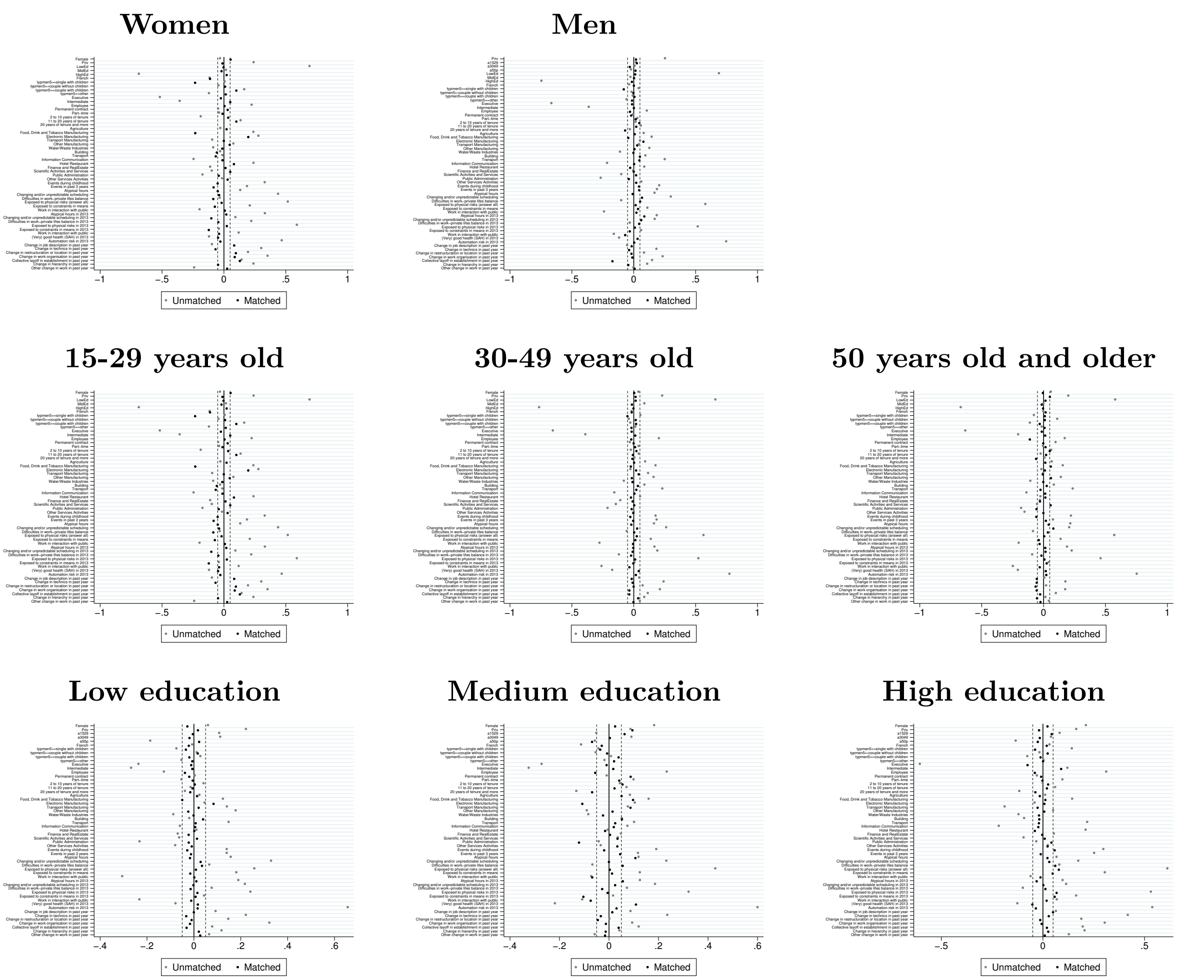


Figure C.2: Standardised % bias across covariates for estimation by sub-populations



[14]ource: French Working Conditions Survey 2013 and 2016. Separate analysis on 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.