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Is Fear of Robots Stealing Jobs Haunting European Workers? A Multilevel Study of Automation Insecurity in the EU

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Abstract: The paper examines how workers in the EU perceive impact of technological changes on employment and whether they experience automation insecurity, or fear of robots stealing their jobs. In particular, the paper seeks to determine whether subjectively perceived automation insecurity reflects workers' vulnerability and exposure to objective automation risk. The paper analyzes representative survey data from Eurobarometer for all 28 EU member countries and uses multilevel logistic regression models to model workers' probability of automation insecurity as a function of their individual characteristics, contextual characteristics of countries they live in and as of possible interactions between the two. The results show that European workers are greatly concerned with labor-substituting effects of new technologies, and that this subjective insecurity to a great extent reflects their vulnerability and exposure to objective automation risk.

Keywords: automation; robotization; social impacts of automation; international surveys; statistical analysis; regression analysis.

1. INTRODUCTION

The fourth industrial revolution brought a renewed round of interest in questions which fascinated thinkers for centuries: Is human labor going to be rendered completely obsolete by technological advancements? Is it going to happen any time soon? And most importantly, is it a normatively good or a bad thing that machines may entirely replace human labor in the production process?

While concerns about labor-substituting effect of machines are nothing new, it is the technological context which the revolution changed substantially. First, capabilities of new technologies increased unprecedently. Recent developments in automation, robotics, machine learning and artificial intelligence rendered even jobs not traditionally thought to be easily automatable to face much higher risk of substitutability by machines or algorithms. The most recent study estimated that as many as 14% of adult EU employees are currently in jobs that are highly automatable, while another 40% face a risk of significant change of their work (Pouliakas, 2018). Second, different is also the remarkable pace with which technological change proceeds. In 2018, installations of industrial robots in Europe have increased by 14% to 75560 units, which was a new peak for the sixth year in a row (International Federation of Robotics, 2019). Given current developments, this number is likely to increase in the near future.

Social sciences have reflected these changes and analyzed different aspects of objective structural changes brought about by technological advancements in automation. The debate often emphasizes the labor-replacing aspect of new technologies. However, the effects of automation on overall employment are complex. New labor-saving technologies can create demand for jobs which complement them and even increase employment in the most affected industries where their implementation leads to substantial reduction of production costs (Goos et al., 2014). There is a consensus that both positive and negative employment effects of technological change are unevenly distributed among workers. According to skill-biased technological change hypothesis, new technologies are more skill demanding and lead to labor demand which disproportionally favors skilled workers over the less skilled ones (Katz and Murphy, 1992). On the other hand, routine-biased technological change hypothesis describes employment changes induced by technologies as biased against routine job tasks prevalent mostly in middle-skilled clerical, administrative, production, and operative occupations (Acemoglu and Autor, 2011; Autor et al., 2003; Author and Dorn, 2013; Goos et al., 2014). Automation of routine tasks can thus lead to job polarization, i.e. to a change in employment structure which favors both high and low skilled occupations (Autor et al., 2003; Goos and Manning, 2007).

Another line of research in this area explores how feasible is to automate existing jobs with current and supposed level of technological development. Several scholars examined the extent to which new technologies can replace human labor and estimated which jobs, occupations, industries and even countries face the greatest risk of job loss or significant change of work content (Arntz et al., 2016; Frey and Osborne, 2017; Nedelkoska and Quintini, 2018; Pouliakas, 2018). However, these estimates reflect only technical feasibility and there is no definiteness that firms will adopt labor-replacing solutions in such an extent. Furthermore, the extent of labor-replacing depends additionally on costs of machines substituting human labor (Acemoglu and Restrepo, 2017).

An important issue still remaining relatively underexplored is a subjective perception of those processes by those arguably affected the most – workers themselves. In a situation where some of the jobs are about to cease to exist entirely while content of others is being altered greatly it is unlikely to expect workers being indifferent about those processes. On the contrary, it seems plausible to assume that these developments will reinforce workers' cognitively perceived job insecurity and lead to their hostility and suspicion with regard to implementation of new technologies. So far, there has only been one study which examined workers' fear of robots at work (Dekker et al., 2017). The authors have demonstrated that the fear is related to individuals' socio-economic interest, but they did not pay much attention to the question of interrelatedness between this subjective fear and objective risk spurring from technological advancements.

This study aims to fill the gap in empirical literature and examines subjectively perceived automation insecurity, i.e. fear of job loss due to technological change among EU workers. In particular, it investigates whether and to what extent workers' automation insecurity reflects their vulnerability and exposure to objective automation risk. We assume that workers in countries that face higher automation risk are more prone to be worried about labor-replacing capabilities of new technologies. On the other hand, workers from countries where technologies have already played significant role in replacing labor may perceive their substituting capabilities with a lesser concern.

Country-level estimates of automation risk are based on Nedelkoska and Quintini's recent study (2018) and reflect share of jobs with high automatability potential. Overall exposure to automation is operationalized through country-level shares of workers that have job-related experience with robots. While this approach focuses mostly on effects of robotization and does not account for other labor-substituting technologies, we believe it leads to relatively simple and internationally comparable measures of countries' general technological endowments. The paper uses survey data from Special Eurobarometer 460 for 28 EU countries and applies multilevel logistic regression to address three specific hypotheses about relationship between subjectively perceived automation insecurity and objective automation risk.

First, since previous research demonstrated that workers who are at the highest risk of automation are working in routine manual jobs which do not require high levels of skills and education (Arntz et al., 2016; Nedelkoska and Quintini, 2018; Pouliakas, 2018) we would expect *a) low skilled and b) manual workers to be more likely to experience automation insecurity than their high-skilled counterparts and managerial or professional occupations, respectively (H1*).

Second, it has been speculated that countries with high average automatability risks are those which do not invest sufficiently in adoption of new technologies and have high unused potential for automation (Arntz et al., 2016). Since adoption of technologies in such contexts would likely result in more substantial losses of employment, this could lead to higher subjective insecurity of workers in such societies. On the other hand, it was observed that the risk is comparatively lower in technologically advanced societies where jobs most prone to replacement were already automated (Arntz et al., 2016; Nedelkoska and Quintini, 2018). Workers in such contexts could feel relatively more secure as jobs that remained are likely not as easily replaceable. Drawing upon these observations, we would expect *a) individuals living in societies with higher average automatability risk to be more prone to experience subjective fear of displacement by robots and artificial intelligence, and b) workers from countries where use of advanced technologies in production is more common to feel more secure and hence have lower likelihood of automation insecurity (H2)*.

Finally, if our hypotheses about structural grounds of automation insecurity hold we would expect *even workers who are in a better position with respect to automatability prospects of their jobs (i.e. highly skilled and those in managerial and professional occupations) to have a) a generally higher probability of fear of robots in country contexts where the automation risk is high, and b) lower propensity in technologically more advanced societies (H3)*.

2. ANALYSED DATA

Survey data used in the analysis come from the Special Eurobarometer 460 – Attitudes towards the impact of digitalization and automation in daily life. The survey was conducted in March 2017 at the request of European Commission and addressed nationally representative samples of all EU member countries (TNS opinion & social 2017). We restricted our focus to subpopulation of respondents who were at the time formally employed. After listwise deletion of observations with missing responses, the sample consisted of 12500 respondents clustered within 28 EU countries.

3. METHOD OF ANALYSIS

Given hierarchical structure of the data, all presented models were estimated as multilevel logistic regressions. Multilevel models are essentially an extension of linear regression developed for data, analysis where individual-level observations are clustered within higher-level groups (e.g.

countries) and independent errors assumption of the classical regression does not hold. Additionally, multilevel models allow for a simultaneous estimation of effects at different levels of data hierarchy (Finch et al., 2014). In the present study, multilevel methods are used to model respondents' propensity to fear that robots and artificial intelligence are stealing jobs as a function of a) their individual characteristics, b) contextual characteristics of countries they live in, and as of c) interaction between the two. Because the outcome variable is binary (see below), logistic multilevel regression is applied, and results are interpreted in terms of predicted probabilities on a 0-100% scale.

4. MEASURES OF VARIABLES

4.1 Dependent variable

Automation insecurity was conceptualized as fear of labor-saving effects due to advancements in artificial intelligence and robotization. Respondents' agreement with a statement 'Robots and artificial intelligence steal peoples' jobs' was used to operationalize such concern. Responses measured on the 1-4 scale (1 = 'strongly agree', 4 = 'strongly disagree') were recoded into a binary variable with value 1 assigned to those who expressed any type of agreement with the statement (1-2), and 0 for those who disagreed (3-4). Main reason for dichotomization was highly skewed distribution of responses, indicating potential problems with distribution of residuals (Finch et al. 2014: 37). A binary variable, on the other hand, makes it possible to use logistic regression, which allows a more straightforward interpretation of results in terms of predicted probabilities.

4.2 Predictors at the individual-level

To control for compositional differences between countries, all models include a standard set of socio-demographic predictors, i.e. gender (binary variable for women), age (three categories for respondents younger than 29 years, between 30-49 years and for 50-year and older) and subjective assessment of respondents' financial situation (binary variable measuring whether respondents had any problems paying bills in the last year, or not).

Educational attainment and occupational class were included as proxy indicators for objective risk of respondent's job being automated. Previous research demonstrated that low-skilled workers and manual laborers constitute categories of workers most prone to be affected by labor savings effects of new technologies. Education is measured by the age when a respondent finished his education and distinguishes between low (completed at the age 15 or younger), medium (between 16-19 years) and high level (20 years and older). Predictor of occupational class categorizes respondents as either managers, self-employed, non-manual intermediary or manual workers. More detailed and standardized measures of respondents' skills and occupational classes would be ideal, however the used variables were unfortunately the only available in the data file.

4.3 Predictors at the country-level

Country-level predictors were selected to capture average objective risk of automatability of a job in a national economy as well as the extent to which countries' labor markets already rely on use advanced automation technologies.

The measure of average national automation risk was calculated in three steps. First, estimated automatability risks for occupations measured at the ISCO-08 2-digits level were extracted from the OECD's most recent study on impact of technologies on employment (Nedelkoska and Quintini, 2018). In the second step, extracted data on automation risk for occupations were paired with observations from the latest wave of European Working Conditions Survey, a representative survey of workers 15 years and older in all EU member states. Finally, automatability risk for each EU member state was calculated as a percentage of all jobs in the national economy which have above median automatability risk.

The indicator of technological development was extracted directly from the Eurobarometer data, as a percentage of workers in the given country who have used or are currently using a robot in their work. We are aware of limitations of the measure which does not take into account labor-replacing technologies other than robotization (for instance AI, or software-based solutions). However, we are not aware of any available measures for these other technologies. Moreover, such simplification is common also in the relevant literature (e.g. Acemoglu and Restrepo 2017).

5. EVALUATION OF RESULTS

Fig. 1 indicates that automation insecurity is very common among European workers irrespective of their country of origin. In almost every EU country, a majority of workers is concerned with labor-substituting effects resulting from implementation of advanced technologies. The insecurity is most prevalent in the Southern European countries with Portuguese (97%), Spanish (91%) and Greek (88%) workers being most fearful. On the other hand, automation insecurity is the lowest in the Northern Europe, especially in Netherlands (40%) and Denmark (49%) – the only two countries where majority of workers does not think robots and artificial intelligence steal jobs.

Could this cross-national variation in subjectively perceived automation insecurity reflect varying extent to which workers from different countries are exposed to objective automatability risk? To answer the question, we fitted a series of multilevel logistic regressions. In the first step we fitted a model containing only the individual-level predictors and controls. The Model A1 in Fig. 2 shows that automation insecurity is significantly related to both indicators of workers' vulnerability to automation.

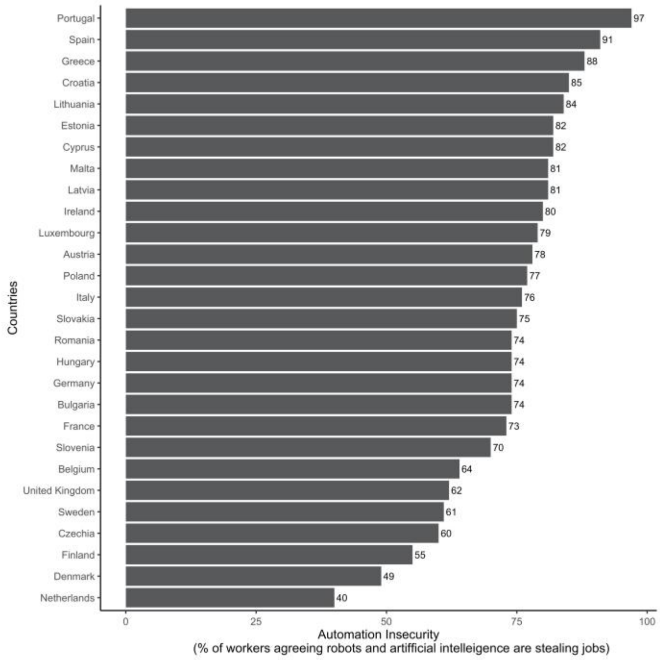

Fig. 1. Average automation insecurity in the EU countries (working population, 15 years and older, weighted data). Source: Special Eurobarometer 460 (authors' own calculations).

Expressed in predicted probabilities, workers with low education are by far the most likely to experience automation insecurity (86 %). This predicted probability is 13% higher than that of workers with high education (73%), and 6% higher than that of their counterparts with medium education (73%). With respect to occupational differences, workers in manual professions have highest probability of being concerned with robots stealing jobs (80%) followed by intermediary-non manual workers (78%), self-employed (74%) and managers who are the least fearful (72%). All in all, this evidence indicates that subjectively perceived insecurity of losing one's jobs due to robots and artificial intelligence is related to workers' objective propensity of their job being actually affected by these technological advancements.

To test whether countries with high automation insecurity are those labor markets where workers are most likely to be impacted by technological changes, we fitted other two multilevel regressions. These contained all individual-level predictors together with two country-level predictors of automation risk and automation stage.

From Fig. 3 it is obvious that the effect of both country-level predictors is significant, and that they are related to automation insecurity exactly in direction expected by the hypothesis H2.

First, workers from countries with a higher share of jobs at risk of being automated are more afraid of labor-saving impact of robots and artificial intelligence (Model B1). To illustrate the effect, we calculated and plotted predicted probabilities for the whole range of empirically observed values of the predictor. The results show that Greek workers subjected to the highest average automation risk (automation risk 64.2%) are 22% more likely to experience automation insecurity than their Swedish counterparts who operate in a labor market context where average automation risk is the lowest (automation risk 32.4%). In more general terms, our model predicts that a one percentual increase in country's average automation risk results in 0.8% increase in predicted probability of experiencing automation insecurity.

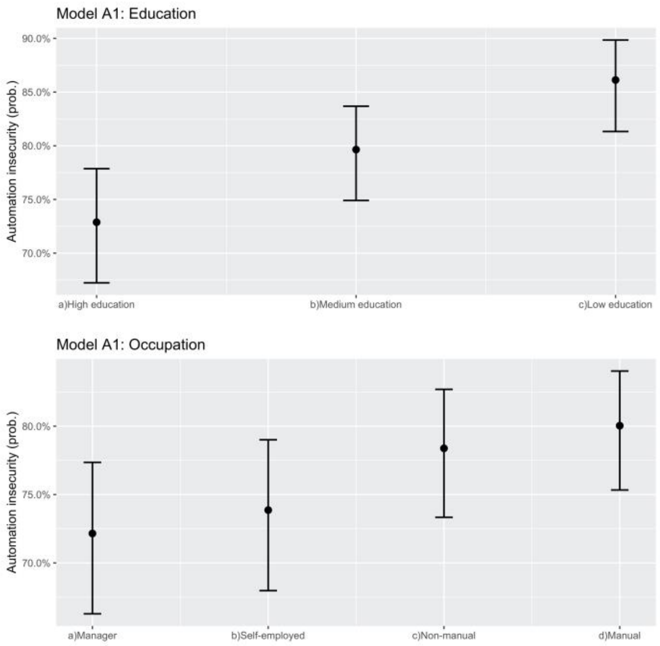

Fig. 2. Model A1: Predicted probabilities of automation insecurity for workers with different educational levels and occupational classes, controlling for gender, age and financial situation (individual-level). Note: Error bars represent a 95% confidence intervals of the estimates.

Second, workers form country-contexts where advanced technologies are more widely implemented in the labor process have a significantly lower probability of automation insecurity (Model B2). This is also in line with the hypothesis H2. The difference in probability of automation insecurity between respondents from Denmark where use of robots is the highest (robot density 19.7%) of all EU countries, and Cyprus where robots are used the least (robot density 1.38%) is interestingly also 22%. To put it differently, according to the model a one-percent increase in robot density is associated with a 0.9% decrease in probability workers experience automation insecurity.

Overall results indicate that workers' automation insecurity may be rationally grounded in objective risk structures of labor market and economies they are embedded in. Workers are more fearful if they operate within country-contexts which are generally more likely to be adversely affected by implementation of new technologies. On the other hand, workers from countries which already adopted advanced technologies are characterized by a lower propensity to fear robots and artificial intelligence, potentially reflecting the fact that most vulnerable jobs were already affected, and labor force's skills were adjusted.

To further corroborate the hypothesis about objective grounds of subjectively perceived automation insecurity, we examined whether the effect of skills and occupational class depend on the context workers are embedded in. If our hypothesis holds true, even categories of workers of jobs which are not as prone to be impacted by automation should experience higher automation insecurity in countries where the risk is objectively higher. To do so, we set coefficients for individual-level predictors of education and occupation to vary randomly across countries and tested a series of cross-level interactions between them and our two country-level indicators.

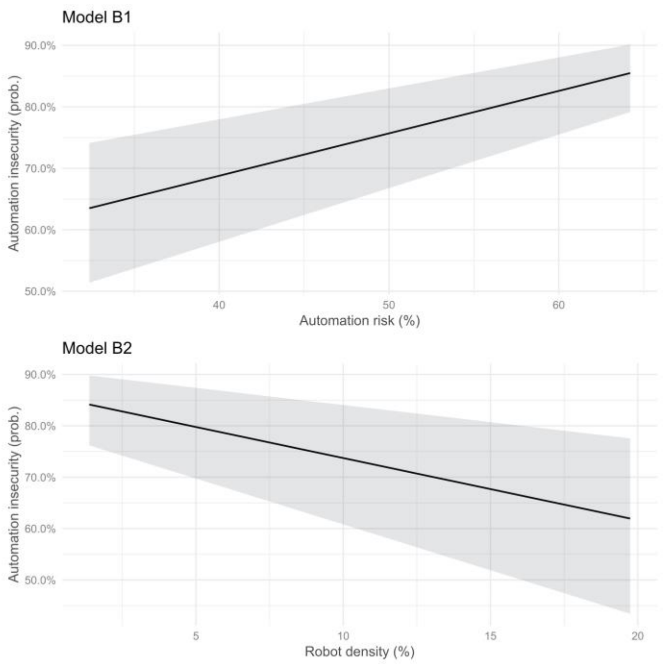

Fig. 3. Models B1 and B2: Predicted probabilities of automation insecurity for all observed values of automation risk and robot density (country-level). Note: Shaded areas represent 95% confidence bands of the estimates.

The results seem to confirm the hypothesis H3 only partially. With respect to skill levels, the effect of educational attainment on automation insecurity is the same in all national contexts irrespective of the average automation risk or automation stage. Hence, low education is the strongest individual predictor of automation insecurity while high education is associated with lower insecurity in all countries alike.

On the other hand, the effect of occupational class differs depending on both the automation risk as well as the robot density. Model C1 (Fig. 4) shows predicted probabilities of automation insecurity for different occupational categories in a country with the lowest (blue lines) and highest (red) observed automation risks. Interestingly, manual occupations are the only category which has the same probability in high- and low-risk automation contexts alike. Other occupations have significantly higher and more uniform probabilities in high-risk context, and lower and more differentiated probabilities in labor market contexts with low automation risk. Take managers as an example: in a low-risk context, their probability of automation insecurity is more than 30% lower than the probability this group has in a high-risk context. The same goes for self-employed and non-manual workers where the differences between high- and low-risk contexts are 29% and 23%, respectively.

Strikingly similar picture emerges when the effect of occupational class is examined for minimal and maximal levels of robot density. Predicted probabilities from the Model C2 in Fig. 4 indicate that the difference between managers from countries with high robot density and those from context where robots are not as widely used is as much as 38%. Similar difference of 37% was predicted with respect to self-employed professionals and business owners, but the effect of non-manual and manual professions seems not to be mediated by the automation stage of a country they live in.

To sum up, the results from interaction models provide further evidence in support of the hypothesis that automation insecurity is not just a random fear of unknown technologies but rather a new type of labor market insecurity which reflects workers vulnerability and objective probability of being negatively affected by labor substituting effect of new technologies.

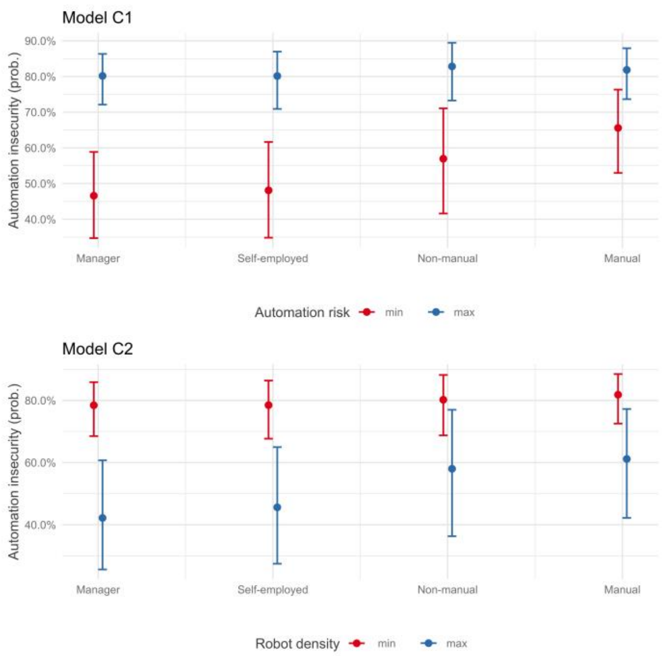

Fig. 4. Models C1 and C2: Predicted probabilities of automation insecurity for different occupational classes in countries with minimal and maximal levels of automation risk and robot density (cross-level interaction). Note: Error bars represent 95% confidence intervals of the estimates.

6. CONCLUSION

In this paper we examined how workers in the EU perceive impact of technological changes on employment and whether they experience what we refer to as automation insecurity or fear of robots stealing their jobs. We were specifically interested in whether subjectively perceived insecurity reflects workers' vulnerability and exposure to objective automation risk. We analyzed survey data from Eurobarometer for all 28 EU member countries, and estimated our models as multilevel logistic regressions. The results supported the expectations and indicated that workers in virtually every EU country are greatly concerned with labor substituting effect of new technologies. As our models further demonstrated, automation insecurity is not an irrational fear of unknown but rather a rational reflection of automatability risks to which workers and labor markets they are embedded in are exposed to. However, generalizability of our results is to some extent limited by availability of relevant data which allowed to capture country-level technological exposure mostly with respect to robotization. Still, given the exploratory nature of our study we believe that the results have important implications for policy makers as well as for future research in the field of social impacts of automation. The results emphasize the need for further implementation of skill-development policies for the labor force. Be it lifelong learning programs, on-the-job-learning schemes or retraining programs for the unemployed, workers are in need of new skillsets which would simultaneously facilitate their adaptations to requirements of the new jobs in the digital economy but also provide them with subjective sense of security. That said, we encourage future research to look at various skill-development policies and to examine whether evidence can be found in support of their capability to decrease workers' fears and worries related to technological change. Future research should also investigate the broader context of automation insecurity, especially the role played by national culture as well as a more general economic insecurity in potentially mediating the relationship between the objective risk and its subjective perception.

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