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The reassuring effect of firms' technological innovations on workers' job insecurity*

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Abstract

We analyse how the adoption of technological innovations correlates with workers' perceived levels of job insecurity, and what factors mediate such relationship, by exploiting a recent, large and dedicated survey distributed to a representative sample of Italian workers. The dedicated survey allows us to look at both cognitive and affective job insecurity as well as different technological innovations actually adopted by the companies where the workers are employed. The results show that the adoption of technological innovations by companies is related to a reduction in the level of job insecurity perceived by their workers and suggest that technological innovation is perceived by active workers as a signal of firms' health and of their commitment to preserving the activity. We also find that the reassuring effect of technological innovations is differentiated across companies and workers, due to the mediating role played by a number of factors, such as specific training and significant changes in workers' usual activities.

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JEL Classifications: J28, O33.

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1 Introduction

During the last decades, a large number of shocks and radical changes, ranging from technological progress to legal reforms, have affected labour markets and employment dynamics. Workers' perception of job security has been altered too. Globalization, the financial and economic crisis of 2008, immigration flows, population ageing, and the spread of digitalization and automation technologies are considered among the most relevant drivers of such profound changes, and one could probably add to the list also the COVID-19 pandemic and the policy measures adopted to slow its diffusion. The risks of technological unemployment, allegedly combined with the diffusion of new automation and digitalization solutions in production, are more and more often identified as a source of serious concerns for workers, worrying about job security. Is this truly the case? Do workers really perceive technological innovations in their companies a source of job insecurity? In this work, we shall exploit the information contained in a recent survey distributed to a large representative sample of Italian workers to address these questions and to uncover how the adoption of technological innovations correlates with workers' perceived levels of job insecurity.

A rich socio-economic literature has offered abundant evidence about the growing importance of firm innovation, digitalization and automation in determining employment dynamics. Robotization and artificial intelligence (hereafter AI) stand out as technological advances capable of affecting the structure of the labour market as well as the employment status of the individual workers. In fact, empirical studies have reached different and controversial conclusions about the actual effects of technological innovation on individuals, occupations, industries and regions (Acemoglu and Restrepo, 2019; 2020; Balsmeier and Woerter, 2019; Barbieri et al., 2019a; Brynjolfsson et al., 2018; Caselli et al., 2021; Damioli et al., 2021; Dosi and Virgillito, 2019; Dottori, 2021; Felten et al., 2018; Fleming, 2019; Frey and Osborne, 2017; Graetz and Michaels, 2018). Moreover, several empirical analyses conducted at the firm level, such as Koch et al. (2021), have suggested that employment grows, and does not fall, in those companies that adopt robots and automation solutions. Available empirical and anedoctal evidence suggest that this can be due to positive selection effects, whereby better performing firms also use more and more robots and keep on hiring, as well as to the fact that robot adoption generates productivity and output gains that lead, in turn, to net job creation. This uncertainty regarding the actual impact of technological innovations on employment dynamics is, *per se*, a good reason to explore how workers perceive the impact of technical change on job security.

As pointed out by various scholars, moreover, technical innovations are not only embodied (i.e., robots, machines) but can also be disembodied (i.e., R&D and patents) (see, for instance, Barbieri et al., 2019b; Dosi et al., 2021; Van Roy et al., 2018). All these different forms of innovation provide a heterogeneous contribution to the update of firms' processes and products: thus, they are likely to exert differentiated effects also on employment (both at the firm- and at the industry-level). Hence, the impact of technology on jobs is not only controversial, but different types of innovation potentially have different effects: certain advances are complementary to workers' activities, others generate demand-related compensation mechanisms within the same firm/industry, others end up replacing human workers (even once productivity and aggregate demand effects are taken into account). Given the uncertainty regarding the actual impact of the various technological innovations on employment dynamics and on specific jobs, the relationship between technological innovation and perceived job insecurity cannot but be an empirical issue.

Surprisingly, this issue has received limited attention in the empirical literature so far, possibly because of lack of adequate data to obtain robust and reliable results about workers' perceptions and firms' technological innovations. As will be illustrated in Section 2, the available evidence on the topic is indeed limited and partially inconclusive. First, the literature has mainly focused on the relationship between a worker's perception of job insecurity and either her technological awareness or her potential exposure to technology, but it has neglected whether the worker has or has not been directly exposed to technological innovations in the company where she is employed. In this work, we exploit a unique and recent survey covering Italian workers to ascertain whether perceived job insecurity depends on workers' direct experience of innovation in the company where they operate. Second, the literature has not tackled the fact that the effects of technological innovations can vary considerably across types of innovation, and that workers' perceptions about job insecurity may be differentiated across types of technological change. As ascertaining whether this is the case requires very detailed data, the literature has so far provided little evidence, whereas in this work we manage to consider various types of technological innovation and estimate their differentiated relationship with workers' perceived job insecurity. In particular, we distinguish both product and process innovation, on the one hand, and automation and other types of innovation, on the other hand. To the best of our knowledge, these two distinctive traits of our analysis (i.e., the focus on firms' technology adoption and the differentiation of technology innovation types) represent a major contribution to the literature as this is the first empirical study estimating how perceived job insecurity relates to the various types of technological change recently adopted by the firms in which the interviewees are employed. Notably, our analysis distinguishes both cognitive and affective insecurity as most recent studies do (see Borg and Elizur, 1992; Dengler and Gundert, 2021): the former captures the perception regarding the likelihood of a job loss, whereas the latter refers to the emotional elements associated with the possibility of losing the job.

Our study aims to answer the following questions: i) Does technological innovation affect workers' perceived job insecurity? ii) Is job insecurity affected differently by different types of technological advances? iii) Are cognitive and affective job insecurity equally affected by technological innovation? iv) What are the mediating factors affecting the relationship between job insecurity and technological innovation?

As previously mentioned, studying perceived job insecurity requires the use of data at the worker level as this is necessary to grasp the relationship between the introduction of technological innovation and workers' perceptions about the possibility of losing their jobs. For example, controlling for non-cognitive skills of workers, like their personality traits, may help to distinguish the ultimate determinants of people's perceptions. Moreover, to determine whether the worker has or has not been exposed to technological innovation where she is employed, it is necessary to have information about the company's characteristics and its innovation-related decisions. We resort to the 2018 wave of the Participation, Labour, Unemployment Survey (PLUS, hereafter), managed by the National Institute for the Analysis of Public Policies (INAPP), that specifically inquires about technological innovation and automation, on the one hand, and workers' perceived job insecurity, on the other. Despite the cross-sectional nature of the data prevents us from interpreting the results in terms of causal relationships, the richness of the survey allows us to employ various empirical specifications where we can control for many socio-demographic features of the worker (including, as mentioned, Big-five personality traits), as well as for the characteristics of the firm (including its past employment performance), the profession and the industry of employment, thereby accounting for various potential confounding factors. Another advantage is that the 2018 wave of the survey includes about 45000 respondents, a sample that is larger than that found in the majority of datasets used in previous empirical works. Incidentally, moreover, this work is also the first analysis of job insecurity and technology adoption among the Italian labour force.

To preview our main results, we find that the adoption of technological innovations by companies tend to reduce the level of job insecurity perceived by their workers. These results are robust across different types of innovations, definitions of job insecurity, and sets of controls for confounding factors. Our succinct interpretation of the entire set of results and robustness checks is as follows: the adoption of a technological innovation by a company tends to be perceived by the workers who remain active after its introduction as a signal of the firm's health and commitment to preserving its production levels and its employees. This reassuring effect of the adoption of technological innovations is indeed stronger among those who observe also an investment of the firm in specific technology-related training programs, whereas it is absent when the workers are aware that some former colleagues had been fired after and because of the introduction of new machines and robots. As to the different types of innovations, those that include machines explicitly meant to carrying out tasks previously performed by human workers tend to be perceived with less favour than the other types, although the insecurity-reducing effect is still present and significant. Between product and process innovation, only the latter is associated with lower insecurity, probably because process innovation is, as well as automation, perceived as a signal of the company's intent to preserve and probably strengthen production. Only few factors, among many potential candidates, contribute to alter the relationship between firms' technological innovation and workers' perceptions and, again, workers' direct experience stands out among the most relevant factors.

The remaining of the paper proceeds as follows. Section 2 introduces the conceptual framework and briefly illustrates the associated relevant literature. Section 3.1 describes the INAPP-PLUS survey and the other sources of data, and it also presents all the variables introduced in the estimations and the rationale for their choice. Section 4 offers a quick account of the estimation approach, namely the ordered logistic estimation method. The main results of the analysis are illustrated and discussed in Section 5, whereas the robustness checks and extensions are reported in Section 6. A discussion of the implications of our novel findings is offered in Section 7. Section 8 provides some closing remarks.

2 Conceptual framework and relevant literature

This paper is related to different strands of the economic literature. First, it refers to the literature on job insecurity (JI, hereafter), a topic that has been investigated through the lenses of various disciplines, such as psychology, sociology, political science and, somehow only marginally, economics (Erlinghagen, 2008; Gallie et al., 2017; Lubke and Erlinghagen, 2014). Due to its transdisciplinary nature, JI has been associated with several alternative definitions, all revolving around the concept of employment uncertainty in the future (for a review of the early literature, see Sverke and Hellgren, 2002; Witte, 2005; Keim et al., 2014).[1] The differences across the various definitions of JI used in the literature depend, for instance, on whether the researcher is interested in "objective" or "subjective" (i.e., perceived) insecurity. Objective job insecurity refers to general economic and employment conditions at the aggregate level, and the best predictors of the likelihood of losing the job are identified in macroeconomic and socio-demographic factors (Ashford et al., 1989). Subjective job insecurity, instead, can be defined as "the perceived threat and perceived probability of an involuntary job loss and the worries and concerns that relate to the future continuity of the current job" (Scicchitano et al., 2020a). This implies that subjective JI has to do with the worker's anticipation of such dramatic event in his/her working life, with particular reference to the case of involuntary job loss.

Subjective JI can be further distinguished into cognitive and affective insecurity (see Anderson and Pontusson, 2007; Borg and Elizur, 1992; and Dengler and Gundert, 2021). Cognitive job insecurity refers to the "the individually expected probability of losing one's job", while affective job insecurity depends on the personal sphere of the individual as it regards "the extent to which individuals are worried about the possibility of losing their job" (Dengler and Gundert, 2021). Cognitive and affective JI explain different dimensions of workers' perceptions: while the cognitive aspect is a necessary, but not sufficient, component of affective job insecurity, the latter depends also on the individual,Äôs subjective assessment of her situation after such event; this latter is based on individual-, firm-, industry- and job-specific characteristics, as well as to the social, political, and economic environment at the aggregate level. So far, only Dengler and Gundert (2021) explicitly investigated both cognitive and affective JI using a large-scale panel study from Germany: our work contributes to the literature by introducing such distinction in the analysis of the impact of technological innovation on JI in Italy.

Having clarified the terminology and main concepts used in this work, in what follows

[1] In addition, one could distinguish JI connected with job tenure loss and JI associated with threats to "valued job features", as discussed by Gallie et al. (2017).

we shall offer a brief account of the (limited) literature on technological innovation and perceived JI. This overview of the literature will serve to set a background against which to compare our results and to highlight the main differences of this work from previous studies, as well as its contribution to the debate.

Using two distinct samples of about 1000 respondents, Gallie et al. (2017) and Coupe (2019) study the impact of, respectively, advanced technology and robotization on workers' job insecurity in the UK and in the US. Gallie et al. (2017) find that advanced technology has a slightly positive association with job tenure insecurity, but has a negative (insignificant) relation with job status insecurity. In their estimations, Gallie and coauthors use an advanced technology index derived from four items: whether the job involves computers or automated equipment, the proportion of employees working with such equipment in the firm, the importance and the complexity of the use of computer or computerized equipment. As the technology index spans very different dimensions at the individual, occupational and firm levels, the mechanisms behind these results cannot be entirely clarified. Coupe (2019) analyzes whether a job-specific characteristic, i.e., being automation proof or not, can be associated with lower levels of JI: their analysis offers evidence that workers employed in automation-proof occupations are relatively less insecure, even though the share of respondents who state to fear losing their job due to automation over the next decades is relatively small.

Nam (2019) analyzes a U.S.-based survey of about 2000 respondents to explore the relationship between technology usage and innovation (such as robotics and AI) and perceived JI. The study finds that perceived JI is negatively associated with the individual use of simple technologies (e.g., internet usage, mobile phone usage, internet-based job search) because technologically-savvy workers feel more secure than others in the face of large-scale automation and machine replacement. Instead, those workers who believe that their job will be replaced by robots in a 50-year time period are also those who declare to be more insecure about their current job. This finding is important as it help to differentiate two distinct factors: the workers' beliefs about what occupations will be exposed to labor-saving technology in the future, on the one hand, and the workers' perception about their ability to complement current technology, on the other hand. However, as the empirical analysis cannot control for the actual adoption of technological innovations in the workplace where the respondents are employed, it is difficult to distinguish workers' beliefs about what occupations will be exposed to technology in the future and their past and current experience in the firm where they operate.

Focusing on workers' technology awareness, Lingmont and Alexiou (2020) empirically investigate a sample of 404 workers (reached via Amazon's Mechanical Turk) to assess the effect of smart technology, artificial intelligence, robotics and algorithms (STARA) awareness, as described by Brougham and Haar (2018), on perceived JI. Focusing on the industries expected to face very high degrees of automation, they find that individuals' STARA awareness is positively associated with perceived JI. While contrasting with Nam (2019)'s findings on simple technology usage (whereby usage reduces JI), these results are in line with the conclusions in Brougham and Haar (2018). The latter find that workers' perception that a technology might replace their job is positively associated with perceived JI. Also in these cases, the analyses regard workers' perceptions about technologically-related threats to their occupation, but they neglect the impact of the workers' direct experience of technology adoption in the company where they operate.

Dengler and Gundert (2021) investigate whether workers' perceived JI varies with the extent to which their occupational tasks are substitutable by computers or computer-controlled machines, and they conclude that this not the case. Moreover, they find that workers have more cognitive than affective insecurity vis-a-vis technology, because the organizational features of the firm shape workers' perceptions. Just recently Genz et al. (2021) analyze the adjustments of workers to firms,Äô investments into new digital technologies in Germany. They find that, depending on the type of technology, investments are associated with an improved employment stability.

Finally, Morikawa (2017) shows that about 30% of workers fear being replaced by robots and AI, in particular when it comes to young workers and non-regular employees, and the employees carrying out automated tasks. They show that workers who received a postgraduate education and studied natural sciences in higher education are less likely to perceive their jobs as replaceable by machines. Again, this analysis focuses on workers' education and on the characteristics of their occupation in terms of tasks, whereas firm-level considerations regarding technology adoption are not considered.

As anticipated, all the studies mentioned above investigate the relationship between a feature of the worker (i.e., STARA awareness in the case of Brougham and Haar, 2018 and Lingmont and Alexiou, 2020, the use of technology in the case of Nam, 2019, the exposure of occupational tasks to substitution by machines in the case of Dengler and Gundert, 2021, and education in the case of Morikawa, 2017) and her perceived job insecurity. On the contrary, in this work we assess whether the adoption of technological innovations by the firm in which the workers are employed exerts an impact on JI. While the different approaches have their own merits, it is crucial to highlight the differences between the research questions and the results in this study and those mentioned above. This helps to clarify the innovative component of our analysis, that is its aim to uncover the relationship between workers' concerns about their jobs and their recent experiences of technological adoption in the their workplaces. As mentioned, this original take is made possible by the distinctive features of the INAPP-PLUS survey as it covers both worker- and firm-level characteristics.

As mentioned in the Introduction, the strand of the literature on the effects of technological innovation on job insecurity refers to the broader literature on the impact of technological innovation on labor markets. Although this refers to a vexed question in the economic literature, a number of recent studies have focused on either the actual or the prospective impact of digitalization, automation, robotization and AI on employment dynamics and jobs. Frey and Osborne (2017), for instance, maintain that advanced forms of digitalization have the potential to affect many occupations in the future, and they estimate that 47% of jobs in the US will soon be at risk of automation. Similarly, Acemoglu and Restrepo (2020) find negative effects of robot adoption on employment and wages across U.S. commuting zones, and Brynjolfsson et al. (2018) claim that advances in machine learning (i.e., AI) will transform numerous occupations and industries because most occupations include tasks suitable for machine learning. Due to these works, most studies investigating the relationship between technology and JI adopt as their working hypothesis the existence of a positive correlation between perceived JI and technological innovations that are allegedly labor-saving. However, several empirical studies fail to find large negative effects of technology, robotization and automation on employment conditions, with the duly-noted exception of the most exposed workers (Arntz et al., 2017; Caselli et al., 2021; Dengler and Matthes, 2018; Graetz and Michaels, 2018; Dottori, 2021).

One may thus wonder whether positing a positive relationship between technological innovation and perceived JI remains a plausible working hypothesis to test. We believe that this is the case: even assuming no major negative effects on aggregate employment, technological innovations tend to increase inequality in the labour market due to their differentiated effects on certain groups of occupations and workers (such as migrants, less-skilled workers and employees carrying out manual and/or routine-intensive tasks, as shown by Fleming, 2019). Barth et al. (2020) show that in Norway, where the overall effect of automation on manufacturing wages is positive, the higher wages for high-skilled workers and for the employees in managerial positions tend to come at the expenses of other categories of workers. Indeed, there seems to be a wide consensus on the fact that automation and digitalization exert a highly differentiated impact on employment dynamics and wages across industries and occupational groups (see, among others, Caselli et al., 2021; Dauth et al., 2020; de Vries et al., 2020).

Not incidentally, the routine-biased technological change (RBTC) hypothesis, according to which recent technological developments have displaced workers performing routine-intensive activities, has become the dominant explanation for the differentials in employment and earnings patterns observed between the occupations at greater risk of automation and the others. Repetitive routine tasks, the reasoning goes, are more likely to be substituted by machines and algorithms than non-repetitive ones: cognitive activities are challenged by computers and AI, whereas manual tasks are threatened by robots and other types of automation.[2]. To account for such received wisdom, in our empirical analysis we control for the degree of routine intensity of the activities carried out by the workers. In addition to ascertain the direct impact of routine intensity on perceived JI, in this work we also investigate to what extent the workers employed in routine-intensive occupations tend to feel more insecure when their firms adopt technological innovations. This allows us to investigate the interaction between the routine-related characteristics of the jobs and workers' direct experience of technology adoption by the firm in which they operate.

Although it is reasonable to associate the literature on technology and employment dynamics, on the one hand, and technology and job insecurity, on the other hand, it should be kept in mind that workers' perceptions about the possibility of losing their jobs may not depend on the same determinants of the actual employment dynamics. Workers' expectations, as mentioned, can stray from what the empirical evidence suggests: to the extent that personal experience matters in shaping expectations, what the workers actually observe in their workplace is as important as the potential impact of technological innovation on the various occupations. This reflects a number of considerations. To start, not all firms adopt the technological innovations, in particular those that potentially threaten some workers. Moreover, if firms adopt innovative technologies with a view to expanding or improving their activities rather than to saving labor (as suggested by Koch et al., 2021, and other firm-level studies on the impact of automation on employment), workers could learn that automation is associated with an expansion, rather than a contraction, of opportunities. Differently from certain one-off events (such as mergers, down-sizing, and reorganizations), the introduction of technological innovations occurs on a more regular basis at the firm level: accordingly, workers may infer that

[2]Due to its emphasis on occupations' tasks, the RBTC hypothesis helps explaining employment and wage polarization better than the skill-bias technological change (SBTC) hypothesis (Acemoglu and Autor, 2011; Autor and Dorn, 2013; Goos and Manning, 2007; Goos et al., 2009; Van Reenen, 2011).

the impact of future innovations on jobs from the effects exerted by past innovations on them and their co-workers. Furthermore, as those workers who are negatively affected by innovations may not be technologically savvy (and vice versa), perceived and actual risks of technological dismissal can be disconnected in workers' perceptions.

Finally, this work is related to several papers that have investigated the relationship between subjective job insecurity, the organizational environment, workers' performance and psychological well-being.[3] In this work, instead, we focus on the determinants of JI and, in particular, on the impact of technological innovation, a factor that has received very limited coverage in the literature so far.

To sum up, it remains an empirical issue to determine which factors influence workers' perceptions about JI. They could either reflect publicly and privately available information about the general trends observed in the labor market, or be informed by the current and expected performance of the firm adopting the innovations, or stem from workers' direct experience about previous episodes of technological adoption. In this study we exploit the richness of the INAPP-PLUS survey to shed light on these issues as we can identify various types of innovations that were adopted by the companies where the respondents to the survey operate.

3 Data and descriptive statistics

3.1 Data sources

In this work we use a unique dataset spanning a number of characteristics of Italian workers in 2018, as well as of the firms in which they are employed and of the occupations they hold.

[3]The implications for work engagement are discussed by Chirumbolo et al. (2017b); Jose and Mampilly (2014); Cuyper et al. (2008) and Filippetti et al. (2019), whereas organizational commitment and job satisfaction are addressed by Callea et al. (2016) Chirumbolo and Hellgren (2003). Others have tackled the workers' perception about their own performance (Chirumbolo and Areni, 2010; Chirumbolo et al., 2017a; Reisel et al., 2007) and their identification with the organization (Hellgren et al., 1999). Few studies investigated job insecurity and wages (Maurin and Postel-Vinay, 2005; Campbell et al., 2007; Scicchitano et al., 2020b).

The main source we utilize is the eighth edition of the Participation, Labour, Unemployment Survey (PLUS), developed and administered by the National Institute for the Analysis of Public Policies (INAPP). INAPP-PLUS, in short, covers 45000 individuals aged between 18 and 74, and provides representative information about specific labor market phenomena that are only marginally explored by the Labor Force Survey, which is the survey run on a regular basis at the country level by the National Institute of Statistics (ISTAT) to map employment dynamics. INAPP-PLUS contains information on a wide range of individual characteristics of workers, ranging from standard socio-demographic information to most specific aspects of the jobs performed and of the firms in which they are employed.

The eighth wave of INAPP-PLUS is relatively recent, as information was gathered in 2018 and the data were released in the first half of 2019. Data collection was performed as follows. Dynamic computer-assisted telephone interviews (CATI) were used to contact participants, so that the survey does not rely on proxy interviews, and only the answers by the respondents were reported. This feature of the survey design reduces measurement errors and partial non-responses. As the questionnaire was distributed to a large group of residents according to a stratified random sampling procedure run over the working-age population, INAPP-PLUS is representative of the entire Italian labor force; accordingly, the dataset contains the individual weights necessary to account for non-response and attrition issues, which usually affect surveys. As done in empirical studies relying on this dataset (see, among others, Bonacini et al., 2021; Clementi and Giammatteo, 2014; Esposito and Scicchitano, 2020; Filippetti et al., 2019; Meliciani and Radicchia, 2011; 2016; Van Wolleghem et al., 2019), we report descriptive statistics and estimates by weighting all observations with such individual weights.

In Italy, INAPP-PLUS is the most suitable source of data for our research purposes. Beyond the usual variables regarding income, socio-demographic characteristics, and employment conditions of the respondents, the 2018 wave contains (for the first time) a 'Technology module' that tackles issues associated with firms' technological innovations and workers' concerns for their jobs. This module was explicitly designed to measure the extent and the consequences of product and process innovation, as well as other embodied technological solutions (e.g., robots and automated machines), by Italian firms. The explicit differentiation across alternative forms of technological innovations is very precious as it allows us to assess whether the impact of innovation on the subjective perception of job insecurity is differentiated or not.

The first relevant question in INAPP-PLUS is rather general in that it simply asks the worker whether any major technological innovation has been introduced in the previous two years by the firm where he/she is employed. Workers who answer affirmatively to this question can also specify whether the firm introduced either process innovations, or product innovations, or both. Moreover, those who answer positively to the first question, are asked whether these innovations were associated with the introduction of robots and automated machines with the specific goal of substituting tasks that were previously performed by human workers. This questions allows us to distinguish innovations that are specifically related to automation and technological innovations that are not associated with automation.

As to what concern job insecurity, in the 2018 wave of INAPP-PLUS one can find several questions that can help capturing various aspects of workers' perceptions: this information, as shall be explained in Section 3.2, allows us to measure both cognitive and affective job insecurity (as well as possible alternative proxies that we use in the robustness checks in Section 6).

A second dataset is used to account for the task-content of jobs and their potential exposure to robotization. Following the methodology developed by Caselli et al. (2021), we use the Survey of Professions (ICP) to identify the occupations characterized by tasks and activities that could be performed by specific robot applications (as defined by the International Federation of Robotics). This survey, whose last wave was released in 2013, is run by INAPP on about 16000 workers, and it covers about 800 occupations according to the 5-digit CP2011 classification (the Italian equivalent of the ISCO-08 classification by the International Labour Organization). The ICP is a rather unique source of information on skills, tasks and work contents of Italian professions: it explores the characteristics of occupations through a particularly fruitful and complex questionnaire framed in seven sections (knowledge, skills, attitudes, generalized work activities, values, work styles and working conditions). As a matter of fact, the ICP represents the Italian equivalent of the well-known American O*Net, and is one of the few surveys in the world replicating the O*NET structure.[4] Both the American O*Net and the Italian ICP focus on occupations, and occupation-level variables are built relying on both survey-based worker-level information and post-survey validation by experts' focus groups. The sample survey ensures its representativeness with respect to sector, occupation, firm size and geographical domains.

3.2 Variables and descriptive statistics

Job insecurity (JI) is our independent variable. As anticipated, we adopt two different measures of JI so as to capture two complementary dimensions, that is cognitive and affective insecurity. To do so, as anticipated, we exploit two separate questions available in INAPP-PLUS. It is worth noticing that these questions are directed only to the respondents who declare to be employed, and therefore they capture the perceptions of people holding a working position at the time of the survey.

For the first measure of JI, namely, affective insecurity as defined by Dengler and Gundert (2021), we look at the question "I am afraid to lose my job": each respondent can choose a value in the range from one (i.e., I totally disagree) to seven (i.e., I totally agree). These answers can be translated into an increasing measure of JI ranging from zero (least insecure) to six (most insecure). Cognitive insecurity is associated instead with the question: "How confident are you in your ability to keep your job over the next 12 months?", and respondents can answer to it by choosing an integer from zero (very insecure) to six (I totally agree).

[4] O*NET is the most comprehensive repertoire reporting qualitative and quantitative information on tasks, work context, organizational features of work places at a detailed level.

As discussed by Berglund et al. (2014) and Dengler and Gundert (2021), cognitive JI (that is the perceived risk of job loss) is a necessary but not sufficient condition for affective JI (namely, fear about losing the job). Workers could be concerned for the consequences of losing their job and, even if they believe that this is not a likely event, they might consider such a circumstance as highly unfortunate. Conversely, a worker could consider the risk of losing the job as very high, but the assessment of the economic situation and of his own skills could induce him not to be particularly afraid for the long-term consequences of a dismissal. Certainly, if the probability of losing the job is assessed as very low, it can hardly represent a source of serious concern.

As to the independent variables in the analysis, we explore as many determinants of JI and as many confounding factors as possible. Our choice of these variables borrows from previous findings in the literature as well as from economic logic. Of course, the choice of the variables depends also on whether INAPP-PLUS contains informative questions to build valid variables capturing the phenomenon of interest.

We start with the presentation of the variables capturing the main determinant of interest, that is technological innovation. As anticipated above, we aim at exploring the impact of different kinds of embodied and disembodied technology. First, we create the variable 'Introduction of technology' (*IntroTech*) by codifying the "yes/no" answers to the question "Has the company where you work introduced any kind of technology in the last two years?". To account for the differentiated consequences of various kinds of technological innovations, we distinguish different types of innovations.

Then, those respondents who answer "Yes" are asked whether such innovations regard either products/services or the production process, or both. We recall that product innovation refers to the introduction of new products/services in the market, whereas process innovation refers to the implementation of a new process in the production. We create three dummy variables: one (*Product*) captures if only product innovations were introduced; one (*Process*) takes value one if only process innovations were adopted; one (*Both*) has value one if the firm adopted both types of innovation. Once the three dummies are included in the estimation, the baseline category is implicitly represented by the workers employed in companies that did not adopt any types of innovation in the previous two years.

As previously mentioned, INAPP-PLUS also asks respondents the following question: "In the last two years, have robots and automated machines been introduced by the firm where you work with the explicit goal of doing tasks previously performed by human workers?" As this question is addressed only to those who answer that their company did introduce some forms of technological innovation, we can build a dummy variable (*Automation*) that takes values one when the firm introduced labour-saving automation-related technological innovations, and zero otherwise (*IntroTech - no automation*). As before, the baseline category consists of workers whose companies did not adopt any innovation in the previous two years.

Regarding the choice of the other explanatory variables and controls, we follow the literature and introduce a number of variables with a view to reducing the possibility that our estimates may be biased by omitted confounding factors. Following the models run by Bellani and Bosio (2019), Scicchitano et al. (2020a) and Morikawa (2017)), we start by controlling for individual covariates, that is the usual socio-demographic variables (namely gender, age, education, training) and, more innovatively, the big five personality traits. The gender-related dummy (*Gender*) takes value 1 if the worker is a man, and zero otherwise. Following Morikawa (2017), we build three classes of age, namely 18-24, 25-49 and 50-74. As the younger and less-experienced workers are typically more insecure, we keep this group as the baseline and introduce two dummy variables (*25_49*) and (*50+*) for the two other groups. Concerning education, we distinguish low/middle-educated and high-educated workers, thereby creating a dummy variable (*Edu*) that takes value 1 if the worker holds at least a bachelor degree. On the one hand, higher levels of education may decrease the probability of being dismissed and reduce JI; on the other hand, it may be associated with greater awareness of technological risks and increase JI. As discussed in Section 2, education and technological awareness may either soften or magnify concerns for technological unemployment, and the sign of the impact remains ambiguous. Recent participation of workers in general training activities can be a relevant determinant of JI as well because it signals commitment on the part of the worker and the firm. Hence, we include a dummy (*GenTraining*) to capture whether the worker undertook some training in the years before taking the survey.

As anticipated, we include some measures capturing the Big five personality traits, following the work by Sverke et al. (2004), who point out that the personality of workers influences their perceptions of JI. Workers with a proactive and sociable attitude might be less job insecure than workers who are shy and with an internal locus of control. Openness and conscientiousness may be correlated as well with lower insecurity. Neuroticism, instead, is expected to increase JI. The categorical variables associated with the Big 5 Traits vary in a range from 1 to 7. Workers' self-assessments in terms of anxiety and calm (two questions) are used to derive a single measure of neuroticism (*Big5Neuro*); those for extroversion and shyness held build a measure of extroversion (*Big5Extro*); those for an interest in new experiences and traditionalism determine the degree of openness (*Big5Open*); those for friendliness and litigiousness are used to derive a measure of agreeableness (*Big5Agree*); those for reliability and disorganization determine the variable consciousness (*Big5Consc*).

Another potentially relevant determinant of workers' insecurity is the presence of a skill mismatch. In particular, underskilled workers could find it more likely to lose their job, as well as be more concerned for the consequences of this occurrence. To address this, we consider the workers' answers to the question "To what extent do your job skills match those required by your current job?" (V43.1.b). We build the dummy *Overskilled*, taking value 1 when the worker is overqualified, and the dummy *Underskilled*, taking value 1 when the worker is underqualified. Notably, in this case we investigate neither the characteristics of the profession *per se*, nor the characteristics of the worker *per se*, but their combination and match (Scicchitano et al., 2020a). It could be argued that workers employed in a company that introduces technological innovations are probably more concerned about losing their jobs than others if they are underskilled, whereas overskilled workers may gain confidence from observing the technological evolution of the company. To test the possible existence of such mediating factors, we also interact these two variables with our dummies representing the introduction of new technologies (see Section 5.2). The relative effect for overskilled and underskilled workers is calculated against the control group made up by those with no relevant mismatch.

It could also be argued that workers who carry out tasks that recent robotic applications are capable of performing may perceive a higher risk of losing their jobs, and fear the consequences, more than others. Building on the taxonomy of professions exposed to robots proposed by Caselli et al. (2021), this latter built on the basis of a task-based matching between occupations and robot applications, we test whether workers with occupations exposed to robots (dummy variable *Robot*) are more insecure about their jobs. The original variable is a dummy calculated at the 5-digit occupation level (800 occupations). As INAPP-PLUS includes information on the 4-digit occupation level (511 occupations), we calculate an average value within 4-digit occupations. For the same reasons discussed above, it is plausible that those working in a company that introduced some technological innovations are more concerned when their job is among those exposed to robots. Hence, we test also the interaction between firms' technological innovations and the exposure to automation of the activities performed by the worker (see Section 5.2).

Inspired by the work by Bellani and Bosio (2019), Morikawa (2017) and Coupe (2019), we add controls for the characteristics of professions and workers' status within the firm. We also include various characteristics of companies. Controlling for professions' characteristics is important because professions are not equally exposed to the same technological shocks. If one occupation is more exposed to certain technological innovations as well as some non-technological shocks, failing to control for the profession may lead to biased estimates of the coefficients of interest. Introducing dummy variables for each class of occupations implies that the parameter capturing the impact of technological innovation on JI can be estimated by exploiting only individual variation within the profession. This variation, in turn, can depend on the sector of employment, on the firm in which the worker is employed, and on the characteristics of the worker and of her job in the firm. Accordingly, we first introduce a set of dummy variables for the different professional groups in Italy, taken at the first digit of the ISCO taxonomy. Then, we explore jobs' characteristics by controlling for various aspects. First, in line with Vannutelli et al. (2021), we look at the subjective perception of the worker regarding the routine intensity of the tasks performed. As mentioned, it is possible that workers who perform non-routine cognitive activities may feel less at risk than those carrying out routine and manual activities. Hence, we introduce two dummy variables, *NonRoutM* and *NonRoutC*, representing respectively jobs involving non-routine manual and non-routine cognitive tasks, while the group of workers performing routine tasks serves as the baseline group. Workers' subjective perception about the routine intensity of their jobs is derived from a specific question included in INAPP-PLUS.[5] Besides studying the direct effect of routineness on JI, we also consider the possibility that these affect the impact of technological innovations on JI (see Section 5.2).

The nature of the contractual relationship between the worker and the company may affect perceived JI because, under the current normative setting, workers are not subject to the same treatment. Moreover, the type of contract that is chosen to hire a person may reflect the (unobserved) preferences, expectations and concerns of both the firm and the worker. Part-time contracts, for instance, are often used to reduce employees' work-life conflicts, but there are also cases of involuntary part-time positions, that signal a limited commitment of the firm towards the worker. Fixed-term contracts, similarly, may be considered as intrinsically less protective than permanent ones, but it is known that fixed-term positions are often used before offering the worker an open-ended contract. We introduce three dummy variables, *PartTime*, *Permanent*, *FixedTerm*, representing

[5]An alternative approach would be to use non-subjective measures of routine intensity, as those calculated for each 5-digit profession using the information in ICP, as done by Autor and Dorn (2013). As the results are similar, we prefer to use subjective assessments by the worker based on the same survey as the rest of the variables.

respectively part-time, permanent and fixed-term contracts. We also introduce a dummy variable that takes value 1 if the company offered some extra welfare benefits to the worker (*Benefit*). Typically, extra benefits are used to increase workers' involvement in the company and this might be interpreted as a sign of commitment by the firm that one would like to control for in the estimation.

Adding controls capturing the characteristics of firms is important for similar reasons. The context in which a person works influences her perceived insecurity. To the extent that the adoption of technological innovation may be associated with some features of the firm, moreover, their omission in the estimation could raise serious identification issues. For this reason, we include all useful information regarding firms that is available in INAPP-PLUS. Thus, we take into account the following variables: size, geographical position and sector of activity. More precisely, we build five dummies to capture the traditional classes of firm size in terms of employment: *0_10*, *11_50*, *51_250*, *251_1000*, *1000+*.[6] The dummy *Sud* takes value 1 if the firm is located in the Southern regions of Italy, and this captures the famous regional divide that tends to penalize companies and workers in the Italian *Mezzogiorno*. To capture the sector of activity, we calculate two dummies at the first digit of the ATECO 2007 classification, that is one that combines the construction and industry sectors - *Ind* - and one for services *Serv*). As Balliester and Elsheikhi (2018) point out, the presence of trade unions is important too: where trade unions are strong, workers may feel to be more protected and involved in management decisions, and thus experience a lower level of JI. Thus, we include the dummy *Union* to acknowledge the presence of unions in the firm, or lack thereof. The past employment performance of the firm is also considered: two dummies capture if the company had either hired and/or dismissed workers (respectively, *Hiring* and *Firing*) in the previous 12 months, and one dummy (*CIG*) if the firm used the Italian furlough scheme (*Cassa Integrazione Guadagni*).

[6]The results are almost identical using a categorical variable with values ranging from 1, associated with the smallest firms, to 5 for the largest companies.

4 Empirical approach

Due the ordinal level of measurement of the dependent variable (that varies across seven levels i, ranging from 0 to 6), in what follows we will adopt the ordered logistic estimator. The functional form to estimate can be represented as follows:

$$Pr(JI_j = i) = Pr(\chi_{i-1} < \boldsymbol{Tech}_j'\boldsymbol{\beta} + \boldsymbol{x}_j'\boldsymbol{\alpha} + +\boldsymbol{z}_j'\boldsymbol{\delta} + \boldsymbol{k}_j'\boldsymbol{\gamma} + \varepsilon_j \leq \chi_i) \tag{1}$$

where i stands for one of the seven levels of the dependent variable, and j refers to workers. The vector $Tech_j$ refers to the main explanatory variables of interest, that is those measuring the adoption of technological innovation by the firm where the worker is employed, $\boldsymbol{x}_j$ includes the controls for worker-specific characteristics, $\boldsymbol{z}_j$ accounts for occupation-specific features, and $\boldsymbol{k}_j$ groups the controls for firm-specific factors. We refer to Section 3.2 for the description of the individual variables in the three groups.

In a logistic estimation each of the estimated parameters of the model can be interpreted as follows: given all of the other variables in the model are held constant, for a one unit increase in the explanatory variable of interest, one could expect a change in the log odds of being into a higher level of the dependent variable that is equal to the estimated parameter.

It is worth noticing that the cross-sectional nature of the INAPP-PLUS dataset does not allow to address all possible endogeneity issues, for instance by introducing individual fixed effects. Although our large set of control variables contributes to reduce the relevance of such problems, some potentially valid concerns remain. Accordingly, in what follows, we will interpret all our estimation results in terms of correlations, and will refrain from drawing any causal conclusions. Although it would have certainly been helpful to exploit a longitudinal dimension had the survey been repeated over time, we would like to stress that the main goal of this work is to shed light on the relationship between a worker's perception of job insecurity and the introduction of technological innovations by the firm in which she is employed: this ensures that the the decision to innovate pre-dates the survey and is made by agents (i.e., managers, entrepreneurs) that differ in most cases from the respondents. This implies that problems of selection and reverse causality are highly unlikely.

Due to the large number of controls that we include, we will start by introducing the results with a hierarchical approach. We begin with the most parsimonious model, where only workers' characteristics and personality traits are considered. Afterwards, we introduce the variables capturing the main features of occupations. Finally, we include the main characteristics of firms. This last addition reduces the size of the sample by almost one third.

To explore whether the impact of technological innovations on JI is differentiated across workers in accordance with their characteristics and/or with the features of their activities, in Section 5.2 we shall explore a battery of estimations to test for the presence of mediating factors. More precisely, the variables capturing technological innovations will be interacted with the following characteristics: education (with the dummy *DEdu*), skill-mismatch (with the dummies *DOverskilled* and *DUnderskilled*), routine activities (with the dummies *DNonRoutM* and *DNonRoutC*), occupation's exposure to robotization (with the variable *Robot*). The most complete and demanding specification with all controls will be used to explore the role of these potential mediating factors.

5 Results

5.1 Main results

Table 1 reports the results for the estimations using the simplest dummy variable regarding the introduction of technological innovations in the firm, that is *IntroTech*. Independently from the controls included in the specifications, both cognitive and affective JI are negatively affected by the introduction of innovation. In particular, cognitive JI seems to be particularly lower for the workers employed in firms that introduced innovations in recent years before the survey. The introduction of occupation-specific controls reduces the estimated parameters, and this confirms the importance of accounting for occupation-specific features whose omission would represent a confounding factor biasing the estimations. The reduction, in absolute terms, of the coefficients after the inclusion of these variables suggest that certain occupation seem to be characterised both by lower levels of JI and by a relatively higher incidence of technological innovations.

Table 1: Introduction of technology and job insecurity

	(1) Cognitive JI	(2) Cognitive JI	(3) Cognitive JI	(4) Affective JI	(5) Affective JI	(6) Affective JI
IntroTech	-0.468***	-0.331***	-0.355***	-0.330***	-0.172***	-0.188***
	(0.039)	(0.040)	(0.049)	(0.037)	(0.039)	(0.048)
Worker ctrl	✓	✓	✓	✓	✓	✓
Occupation ctrl		✓	✓		✓	✓
Firm ctrl			✓			✓
Observations	19,936	19,936	13,837	19,936	19,936	13,837

Notes: Robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

As explained above, the quality of the INAPP-PLUS dataset allows us to explore the differences associated with different types of innovations. The estimation results reported in Table 2 show that, once all controls are included, only workers employed in companies undertaking process innovation are characterised by lower JI. Product innovation, instead, is not significantly associated with lower levels of cognitive and affective JI.

The interpretation of these findings is not trivial. Product innovation is often considered as a type of technological innovation that is less likely to affect employment than process innovation, at least to the extent that process innovation is undertaken in order to reduce production costs. Our estimations suggest that this is not the case. One possibility to interpret this result is that process innovations are tangible signs of the firm's commitment to strengthen local production, where product innovations may lead to product churning rather than to the expansion of the range of products and turnover. Moreover, product innovations do not necessarily signal that local production has increased. Not incidentally, when firms undertake both types of innovation, workers tend to exhibit a much lower level of cognitive JI, *ceteris paribus.*

This result should however be taken with a grain of salt. When firm-level controls are not included, the coefficient of the dummy *DProduct* is negative and statistically significant for cognitive JI. Firm-level controls help to capture possible confounding factors, but they also absorb part of the explanatory power of the variables. Moreover, being mainly dummy variables, they tend to inflate the covariance matrix and reduce statistical significance. These things considered, the more nuanced and balanced reading of the results is that both cognitive and affective JI are negatively affected by technological innovation, and particularly more by process innovation. Cognitive JI seems to be more heavily impacted, as one would expect given that affective JI reflect also other considerations by the worker, such as the assessment of macroeconomic conditions and of her own ability to find new sources of income and a new job in case of job loss.

Table 2: Introduction of technology and job insecurity, process vs product innovation

	(1) Cognitive JI	(2) Cognitive JI	(3) Cognitive JI	(4) Affective JI	(5) Affective JI	(6) Affective JI
Process	-0.425***	-0.297***	-0.270***	-0.350***	-0.208***	-0.202***
	(0.056)	(0.057)	(0.074)	(0.050)	(0.051)	(0.066)
Product	-0.272***	-0.181**	-0.162	-0.158*	-0.037	-0.058
	(0.089)	(0.088)	(0.099)	(0.092)	(0.090)	(0.109)
Both	-0.564***	-0.408***	-0.490***	-0.358***	-0.177***	-0.214***
	(0.053)	(0.055)	(0.066)	(0.051)	(0.053)	(0.065)
Worker ctrl	✓	✓	✓	✓	✓	✓
Occupation ctrl		✓	✓		✓	✓
Firm ctrl			✓			✓
Observations	19,936	19,936	13,837	19,936	19,936	13,837

Notes: Robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

As explained in the Introduction, by exploiting two questions in the INAPP-PLUS, it is possible to distinguish between technological innovations directed to introduce automation-related solutions to save labor and other types of innovations. The results are reported in Table 3. Both types of innovations have a negative and significant impact on JI, and the effect is again larger for cognitive JI than affective JI. Statistically, it is hard to conclude that the two types of technological innovations have differentiated effects; at most, there is some evidence that the negative impact of automation on JI is lower than that of other types of technological innovations. Indeed, this negative impact of automation on JI is somehow surprising because the question about automation refers to innovations explicitly directed to substituting human workers. There are three possible explanations for these findings. The first one is that investment in automation are typically costly and workers perceived the associated sunk costs as a sign of the firm's commitment to continue producing. The second explanation refers to the fact that, due to the temporal lag between innovation and the survey, the respondents to the survey have already "survived" the innovation and are not concerned for their impact. The last explanation is that both automation and process innovations (which, incidentally, have similar estimated coefficients) tend to be introduced with the view of reducing unit costs, not necessarily total costs: this implies that companies may introduce innovations that are labor substituting at the margin but that, once price and demand effects are considered, tend to increase production and preserve employment. This interpretation, as mentioned, is in line with previous firm-level studies on robotization and automation.

It is important to clarify that the presence of firm-level controls regarding firms' firing and hiring helps to capture the current conditions of the firm. It follows that the technological-related variables do not proxy for the latter. Accordingly, it would be inappropriate to interpret the results above as a sign that firms in good conditions tend both to fire less (hire more) and to adopt more innovations, thereby making workers feel safer. Rather, the correct interpretation is that, for any given level of firms' hiring and firing behavior (that have, respectively, a negative and positive impact on JI), the presence of technological innovations seems to be associated with a lower level of perceived JI.

5.2 Mediating factors

In Section 5.1 we presented and discussed our main findings, and concluded that workers operating in companies that introduce technological innovations tend to exhibit lower cognitive and affective JI.

For the reasons discussed in Section 3.2, one could wonder whether the impact of firms' technological innovations on workers' JI is mediated by certain characteristics of

Table 3: Introduction of technology and job insecurity, automation

	(1) Cognitive JI	(2) Cognitive JI	(3) Cognitive JI	(4) Affective JI	(5) Affective JI	(6) Affective JI
IntroTech -	-0.504***	-0.376***	-0.394***	-0.351***	-0.197***	-0.187***
no automation	(0.042)	(0.043)	(0.053)	(0.040)	(0.042)	(0.052)
Automation	-0.342***	-0.174**	-0.230**	-0.256***	-0.086	-0.192**
	(0.081)	(0.082)	(0.096)	(0.071)	(0.073)	(0.086)
Worker ctrl	✓	✓	✓	✓	✓	✓
Occupation ctrl		✓	✓		✓	✓
Firm ctrl			✓			✓
Observations	19,936	19,936	13,837	19,936	19,936	13,837

Notes: Robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

the worker and the job. Following previous works, the first individual feature that we consider is the level of education of the worker. The results reported in Table 4 can be interpreted as follow. In all cases, the higher the level of education, the higher the level of cognitive JI, but not of affective JI. This is in line with the typical greater insecurity that characterise educated workers, who may recognize the high uncertainty surrounding Italian companies in 2018, but that are not particularly concerned about not being able to find another job, should they lose the current one. The interaction terms, capturing the mediating role of education, reveal that the impact of technological innovations on the educated workers' perception of cognitive JI is positive, reinforcing the direct effects of higher education on JI. The main exception to this is the case of automation-related innovation; in line with Morikawa (2017), educated workers are less likely to perceive their jobs as replaceable by machines, but remain concerned that other types of innovations may lead to a job loss.

The mismatch between workers' skills and job requirements can be a source of JI, as under-skilled workers may believe their job to be in jeopardy. Results reported in Table 5 confirm that this is the case for cognitive JI as the coefficient of the dummy for under-skilled workers is positive and highly statistically significant. Whether the presence of a skill mismatch makes the worker more or less concerned for the impact of technological innovations on JI, instead, remains an empirical issue. Our findings suggest that workers' cognitive JI in the face of technological innovations in their firms is not

Table 4: Introduction of technology and job insecurity: the role of education

	(1) Cognitive JI	(2) Cognitive JI	(3) Cognitive JI	(4) Affective JI	(5) Affective JI	(6) Affective JI
IntroTech	-0.406***			-0.169***		
	(0.060)			(0.058)		
* Edu	0.252***			-0.096		
	(0.084)			(0.078)		
Process		-0.286***			-0.195**	
		(0.090)			(0.081)	
* Edu		0.079			-0.034	
		(0.127)			(0.113)	
Product		-0.172			0.042	
		(0.124)			(0.137)	
* Edu		0.052			-0.416**	
		(0.172)			(0.181)	
Both		-0.578***			-0.204***	
		(0.079)			(0.077)	
* Edu		0.452***			-0.052	
		(0.115)			(0.105)	
IntroTech -			-0.450***			-0.160**
no automation			(0.065)			(0.064)
* Edu			0.260***			-0.126
			(0.091)			(0.087)
Automation			-0.278**			-0.192*
			(0.112)			(0.100)
* Edu			0.274			0.010
			(0.167)			(0.141)
Edu	0.146***	0.143***	0.144***	0.050	0.051	0.050
	(0.053)	(0.053)	(0.053)	(0.050)	(0.050)	(0.050)
Worker ctrl	✓	✓	✓	✓	✓	✓
Occupation ctrl	✓	✓	✓	✓	✓	✓
Firm ctrl	✓	✓	✓	✓	✓	✓
Observations	13,837	13,837	13,837	13,837	13,837	13,837

Notes: *Edu* takes value 1 if the worker holds at least a bachelor degree. Robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

impacted differently in accordance with the degree of skill mismatch; it seems, instead, that over-skilled workers are particularly less afraid of being without a job in the case of automation-related innovations and joint process-product innovations. This might indicate a sort of confirmation effect at work, whereby over-skilled workers that observe innovations appreciate the opportunities that may be connected with an upgrade of the firm production process.

Building on the literature on RBTC, we test whether the routine intensity of the activities carried out by the workers exerts an influence on perceived JI. Estimates reported in Table 6 show that workers engaged in non-routine-intensive cognitive activities

Table 5: Introduction of technology and job insecurity: the role of mismatch

	(1) Cognitive JI	(2) Cognitive JI	(3) Cognitive JI	(4) Affective JI	(5) Affective JI	(6) Affective JI
IntroTech	-0.332***			-0.144**		
	(0.062)			(0.061)		
* Overskilled	-0.082			-0.176**		
	(0.094)			(0.088)		
* Underskilled	-0.060			0.131		
	(0.246)			(0.247)		
Process		-0.221**			-0.213**	
		(0.098)			(0.087)	
* Overskilled		-0.162			0.019	
		(0.134)			(0.123)	
* Underskilled		-0.136			0.172	
		(0.444)			(0.522)	
Product		-0.104			0.033	
		(0.122)			(0.136)	
* Overskilled		-0.201			-0.297	
		(0.199)			(0.215)	
* Underskilled		-0.337			-0.727	
		(0.463)			(0.522)	
Both		-0.496***			-0.142*	
		(0.082)			(0.081)	
* Overskilled		0.011			-0.311***	
		(0.132)			(0.119)	
* Underskilled		0.095			0.288	
		(0.305)			(0.287)	
IntroTech -			-0.364***			-0.161**
no automation			(0.067)			(0.067)
* Overskilled			-0.107			-0.103
			(0.101)			(0.097)
* Underskilled			-0.095			0.056
			(0.265)			(0.290)
Automation			-0.232*			-0.097
			(0.122)			(0.107)
* Overskilled			0.000			-0.407**
			(0.182)			(0.160)
* Underskilled			0.074			0.329
			(0.496)			(0.390)
Overskilled	-0.056	-0.056	-0.057	0.012	0.012	0.012
	(0.050)	(0.050)	(0.050)	(0.047)	(0.047)	(0.047)
Underskilled	0.388***	0.388***	0.387***	-0.053	-0.053	-0.054
	(0.130)	(0.130)	(0.130)	(0.116)	(0.116)	(0.116)
Worker ctrl	✓	✓	✓	✓	✓	✓
Occupation ctrl	✓	✓	✓	✓	✓	✓
Firm ctrl	✓	✓	✓	✓	✓	✓
Observations	13,837	13,837	13,837	13,837	13,837	13,837

Notes: *Overskilled* and *Underskilled* represent jobs where the worker is overqualified and underqualified respectively. The baseline group is made up by workers with no relevant mismatch. Robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

are less insecure about their jobs and fear less the consequences of losing their jobs. This suggests that, neglecting the actual decisions made by the firms in terms of technological innovation, workers performing non-routine-intensive cognitive activities think to be less exposed to job losses and their consequences. This is in line with expectations. Moreover, workers carrying out routine-intensive activities and non-routine-intensive manual tasks do not appear to be statistically different in terms of JI. On the contrary, a different degree of routine intensity is not associated with a differentiated impact of technological innovations on perceived JI. This finding suggests that workers do not think that the introduction of technological innovations, not even automation-related solutions, is likely to impact more heavily on workers performing different activities.

An alternative way to see whether the impact of technological innovations on perceived JI is differentiated across workers in terms of the characteristics of their occupation is to distinguish those jobs that are exposed to robotic applications and those that are not. Table 7 shows that this is not the case. Moreover, as in the case of routine intensity, workers' perception of JI in the face of technological innovations does not vary with the potential exposure of their occupation to robotization. This surprising result can be explained through similar considerations as those introduced before. As the respondents to the survey that answer questions regarding technology introduction are all employed, they have obviously "survived' these innovation efforts. This makes the characteristics of their job less relevant for the formation of expectations and concerns; the effect that dominates, probably, is the belief that the companies able to introduce innovations are those performing better and employing relatively stronger workers.

6 Robustness checks and extensions

As pointed out in previous sections, cognitive JI is a necessary but insufficient component of affective insecurity. This observation suggests to carry out an additional empirical exercise whereby cognitive JI enters among the explanatory variables for affective JI.

Table 6: Introduction of technology and job insecurity: the role of routineness

	(1) Cognitive JI	(2) Cognitive JI	(3) Cognitive JI	(4) Affective JI	(5) Affective JI	(6) Affective JI
IntroTech	-0.356***			-0.236***		
	(0.080)			(0.076)		
* NonRoutM	-0.250			0.187		
	(0.211)			(0.194)		
* NonRoutC	0.056			0.057		
	(0.100)			(0.095)		
Process		-0.217*			-0.278***	
		(0.120)			(0.104)	
* NonRoutM		-0.285			0.130	
		(0.361)			(0.274)	
* NonRoutC		-0.042			0.124	
		(0.147)			(0.135)	
Product		-0.117			-0.081	
		(0.173)			(0.188)	
* NonRoutM		0.015			0.579	
		(0.464)			(0.454)	
* NonRoutC		-0.075			-0.059	
		(0.208)			(0.229)	
Both		-0.547***			-0.243**	
		(0.107)			(0.105)	
* NonRoutM		-0.340			0.119	
		(0.265)			(0.281)	
* NonRoutC		0.174			0.032	
		(0.136)			(0.130)	
IntroTech -			-0.418***			-0.237***
no automation			(0.090)			(0.085)
* NonRoutM			-0.219			0.194
			(0.225)			(0.222)
* NonRoutC			0.091			0.059
			(0.110)			(0.106)
Automation			-0.180			-0.235*
			(0.140)			(0.131)
* NonRoutM			-0.339			0.169
			(0.446)			(0.345)
* NonRoutC			-0.026			0.050
			(0.186)			(0.169)
NonRoutM	0.049	0.048	0.049	0.012	0.013	0.012
	(0.084)	(0.084)	(0.084)	(0.085)	(0.085)	(0.085)
NonRoutC	-0.169***	-0.170***	-0.170***	-0.255***	-0.255***	-0.255***
	(0.055)	(0.055)	(0.055)	(0.053)	(0.054)	(0.053)
Worker ctrl	✓	✓	✓	✓	✓	✓
Occupation ctrl	✓	✓	✓	✓	✓	✓
Firm ctrl	✓	✓	✓	✓	✓	✓
Observations	13,837	13,837	13,837	13,837	13,837	13,837

Notes: *NonRoutM* and *NonRoutC* represent respectively jobs involving non-routine manual and non-routine cognitive tasks, while the group of workers performing routine tasks serves as the baseline group. Robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 7: Introduction of technology and job insecurity: the role of exposure to robots

	(1) Cognitive JI	(2) Cognitive JI	(3) Cognitive JI	(4) Affective JI	(5) Affective JI	(6) Affective JI
IntroTech	-0.359***			-0.189***		
	(0.050)			(0.049)		
* Robot	0.039			0.006		
	(0.191)			(0.176)		
Process		-0.256***			-0.179***	
		(0.075)			(0.068)	
* Robot		-0.099			-0.177	
		(0.280)			(0.247)	
Product		-0.230**			-0.086	
		(0.103)			(0.111)	
* Robot		0.829**			0.417	
		(0.340)			(0.457)	
Both		-0.490***			-0.228***	
		(0.068)			(0.066)	
* Robot		-0.011			0.122	
		(0.256)			(0.238)	
IntroTech -			-0.394***			-0.198***
no automation			(0.054)			(0.054)
* Robot			0.002			0.123
			(0.225)			(0.199)
Automation			-0.233**			-0.159*
			(0.100)			(0.085)
* Robot			0.019			-0.190
			(0.300)			(0.281)
Robot	-0.019	-0.019	-0.013	0.078	0.078	0.078
	(0.119)	(0.119)	(0.119)	(0.108)	(0.108)	(0.108)
Worker ctrl	✓	✓	✓	✓	✓	✓
Occupation ctrl	✓	✓	✓	✓	✓	✓
Firm ctrl	✓	✓	✓	✓	✓	✓
Observations	13,837	13,837	13,837	13,837	13,837	13,837

Notes: Robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Such specification allows us to perform two joint tests: first, we can verify whether affective insecurity is positively correlated with cognitive insecurity (as theory predicts) or not; second, we can estimate the direct impact of technological innovation on affective JI once its indirect effects through cognitive insecurity are controlled for.

The estimates reported in Table 8 confirm that cognitive and affective insecurity are positively correlated, as expected. At the same time, the estimated coefficient is far lower than one and this corroborates the intuition that these concepts are correlated but different.

Focusing on the direct impact of technological innovations on perceived affective JI once its effects on cognitive insecurity are controlled for, we conclude that the main results produced in the paper are valid. The introduction of technological innovations in a firm reduces its workers' fear of losing their jobs, even once the impact of innovations on the perceived probability that this might happen is explicitly accounted for. Put it in other words, given the perceived likelihood of losing their job, workers employed in firms that innovate are less concerned for the possible loss of their jobs. To interpret such finding, one could argue that these workers are more trained and skilled thanks to the fact that innovative companies invest in human capital as much as in the technological innovation. Alternatively, one could argue that workers in innovative firms may perceive that their companies could eventually help them out in finding a new job.

Table 8: Cognitive job insecurity as a determinant of affective job insecurity

	(1) Affective JI	(2) Affective JI	(3) Affective JI
Cognitive_JI	0.197*** (0.017)	0.197*** (0.017)	0.198*** (0.017)
IntroTech	-0.147*** (0.048)		
Process		-0.178*** (0.067)	
Product		-0.028 (0.108)	
Both		-0.156** (0.065)	
IntroTech - no automation			-0.138*** (0.052)
Automation			-0.176** (0.086)
Worker ctrl	✓	✓	✓
Occupation ctrl	✓	✓	✓
Firm ctrl	✓	✓	✓
Observations	13,837	13,837	13,837

Notes: Robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Next, we test the robustness of our results by building alternative proxies for cognitive and affective insecurity that exploit different questions in the INAPP-PLUS. As an alternative measure of cognitive JI, we can resort to the answers to the question "I think my job will change in the near future", to which respondents can answer with a value close to 1 if they believe the job will change for the worse, and with a value close to 7 if they believe it will change for the better. To interpret this last question in a way similar to the others (i.e., larger values correspond to more insecurity), we use the inverse scale of values. As an alternative measure of affective JI, we consider the answers to the question "Regrettably, I think I may be out of work", to which respondents can associate a value going from 0 to 6 in accordance with how much they agree with the sentence. The estimates reported in Table 10 are quantitatively and qualitatively similar to the estimated parameters in columns (3) and (6) of Table 1, 2, and 3.

Table 9: Alternative definitions of job insecurity

	(1) Cognitive JI	(2) Cognitive JI	(3) Cognitive JI	(4) Affective JI	(5) Affective JI	(6) Affective JI
IntroTech	-0.206***			-0.190***		
	(0.049)			(0.047)		
Process		-0.125*			-0.126*	
		(0.072)			(0.066)	
Product		-0.187*			-0.107	
		(0.112)			(0.106)	
Both		-0.278***			-0.268***	
		(0.063)			(0.064)	
IntroTech -			-0.237***			-0.172***
no automation			(0.053)			(0.051)
Automation			-0.109			-0.246***
			(0.091)			(0.090)
Worker ctrl	✓	✓	✓	✓	✓	✓
Occupation ctrl	✓	✓	✓	✓	✓	✓
Firm ctrl	✓	✓	✓	✓	✓	✓
Observations	13,837	13,837	13,837	13,837	13,837	13,837

Notes: Robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

All in all, the main results remain valid, and perceived JI is lower for workers employed in firms that introduce technical innovation. Interestingly, workers whose companies introduced automation-related innovations tend to be relatively more concerned that the quality of their job might worsen.

To investigate further these findings, we exploit again the richness of the INAPP-PLUS database and, in particular, we analyse whether the impact of technological innovation on JI depends on how workers' perceptions about the impact of innovations on their activities. Workers are asked several "yes-no" questions about whether the innovations adopted by their firm: i) made their usual tasks easier (*IntroTech - simple*) or not (*In-*

troTech - no simple); ii) made more precise the assessment of their tasks (*IntroTech - precise*) or not (*IntroTech - no precise*). To those workers stating that their company introduced automation-related innovations directed to substitute tasks previously performed by human beings, the survey asks whether these innovations made their work more intense and continuous (*Automation - more intense*) or less intense and more discontinuous (*Automation - less intense*), or neither of the two (*Automation - no intense*). The baseline is that no innovations were adopted in all three cases.

The estimation results reproduced in Table 10 confirm that workers facing technological innovations are less insecure about their jobs, regardless of the actual impact of the innovations on their own activities. This corroborates our interpretation of the negative impact of technology on perceived JI in terms of a signalling effect about the commitment of the innovative firm to continue and possibly expand production. With regard to cognitive JI, workers who believe that innovations made their activities simpler, more precise and less intense and continuous tend also to exhibit a lower level of cognitive JI. In terms of affective JI, instead, most differences across workers are not statistically significant, with the exception of those workers whose activities were made more intense and continuous by the innovation, as they are relatively more concerned about losing their job. This result is not surprising as it is to be expected to find workers whose tasks are made more intense and continuous by innovations to be more afraid of being out of work.

As discussed previously, it is possible that respondents in our sample are workers who may tend to underestimate the impact of technology on employment conditions because they have kept their jobs after the introduction of innovations in the past. The question used to create the variable *Automation* asks whether robots and machines have been introduced to explicitly substitute humans in the realization of certain tasks, but this does not imply that they were introduced to substitute workers in all their activities. In the INAPP-PLUS another question addresses this issue as it asks: "Are you aware of any cases in which the introduction of technological innovations (robots, automated ma-

Table 10: Introduction of technology and job insecurity: effects on activities and tasks

	(1) Cognitive JI	(2) Cognitive JI	(3) Cognitive JI	(4) Affective JI	(5) Affective JI	(6) Affective JI
IntroTech - no simple	-0.238*** (0.078)			-0.230*** (0.074)		
IntroTech - simple	-0.400*** (0.057)			-0.172*** (0.055)		
IntroTech - no precise		-0.162** (0.082)			-0.169** (0.073)	
IntroTech - precise		-0.431*** (0.056)			-0.196*** (0.055)	
Automation - no intense			-0.324*** (0.065)			-0.224*** (0.064)
Automation - more intense			-0.260*** (0.075)			-0.107 (0.072)
Automation - less intense			-0.564*** (0.100)			-0.238*** (0.091)
Worker ctrl	✓	✓	✓	✓	✓	✓
Occupation ctrl	✓	✓	✓	✓	✓	✓
Firm ctrl	✓	✓	✓	✓	✓	✓
Observations	13,837	13,837	13,837	13,837	13,837	13,837

Notes: Robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

chines) explicitly aimed at performing tasks that were previously performed by humans have resulted in the dismissal of workers?". Using the answers to this question we manage to identify four categories of workers: those working in companies that did not introduce innovations (our baseline); those working in companies that introduced innovations not directly meant to substitute humans to carry out certain tasks (*IntroTech - no automation*); those working in companies that introduced forms of automation with the intent of substituting humans to carry out certain tasks, without dismissals that the respondent is aware of (*Automation - no dismiss*); those working in companies that introduced forms of automation with the intent of substituting humans to carry out certain tasks and that actually led to workers being fired (*Automation - dismiss*).

Table 11 reports the estimated coefficients that reveal results in line with expectations. Workers employed in companies that introduced innovations other than forms of automation directed to perform tasks carried out by human workers or automation-related solutions without the dismissal of the workers performing the tasks covered by the machines tend to exhibit lower job insecurity. On the contrary, people working in companies that introduced forms of automation and dismissed some of the workers carrying our the tasks performed by the machines tend to be more insecure.[7]

Table 11: Introduction of technology and job insecurity: automation-related dismissals

	(1) Cognitive JI	(2) Affective JI
IntroTech - no automation	-0.401***	-0.183***
	(0.054)	(0.053)
Automation - no dismiss	-0.286***	-0.240***
	(0.103)	(0.091)
Automation - dismiss	0.137	0.046
	(0.163)	(0.157)
Worker ctrl	✓	✓
Occupation ctrl	✓	✓
Firm ctrl	✓	✓
Observations	13,837	13,837

Notes: Robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

To corroborate our interpretation of the findings above, we can further explore whether the perception of job insecurity is different in those firms that developed ad hoc training programs after having introduced new technologies and those that did not. The INAPP-PLUS asks respondents stating that their firms did introduce some kind of innovation whether "Following the introduction of new technologies, have training activities been conducted to educate workers on how new technologies work and how to use them?". Accordingly, we can create a dummy variable (*IntroTech - specific training*) that takes value 1 if the firm introduced a new technology and also developed a training program associated with it and its complement (*IntroTech - no specific training*) if the firm introduced a new technology without an associated training program.

The estimations, whose results are reported in Table 12, provide some comforting evidence. To start, workers employed in companies that developed a specific training after having introduced a technological innovation appear to have a lower level of cognitive JI. This is consistent with the idea that firms that invest both in new technologies and in human capital are perceived as less likely to dismiss their labor force. On the contrary,

[7] Although the estimated parameters for *Automation - dismiss* are not significantly different from zero, the difference between this coefficient and those associated with the other two dummy variables are statistically significant.

workers' perception of affective JI seems not to differ across these two types of respondents. This is in line with the idea that firm- and technology-specific knowledge does not modify considerably the abilities and skills that can be used in the market in case of dismissal.

Table 12: Introduction of technology and job insecurity, specific training

	(1) Cognitive JI	(2) Affective JI
IntroTech - no specific training	-0.207**	-0.149*
	(0.089)	(0.084)
IntroTech - specific training	-0.408***	-0.198***
	(0.054)	(0.054)
Worker ctrl	✓	✓
Occupation ctrl	✓	✓
Firm ctrl	✓	✓
Observations	13,837	13,837

Notes: Robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

7 Discussion and implications

In contemporary capitalist societies, the risk of losing a job and, consequently, a steady flow of income capable of guaranteeing adequate standards of living is one major source of uncertainty. Such a condition impacts on many aspects of individual behaviour. The implications of workers' job insecurity span a number of socio-economic dimensions. Job insecurity impacts an individual's mental health, the quality of life of his/her family and more generally social relations, his/her expectations and actions, and the like. Moreover, the risk of losing a job and an income stream tends to reduce the propensity of the individual to consume (in the attempt of increasing precautionary saving) and, more generally, to lower the willingness to make risky choices, for instance on education, entrepreneurship, mobility, and the like. The high relevance of these effects on individual workers should not hide that employees' perceptions about the insecurity of their jobs exerts an impact on the ultimate functioning of the firm. The literature has shown that, from the point of view of the firm, it may be undesirable to have workers perceiving a high level of insecurity as this may negatively affect their approach and the functioning of the entire organization. Workers who are worried about their own situation tend to dedicate less attention to working tasks, let their performance worsen (Reisel et al., 2007), and generate withdrawal attitudes and cognitions. All these, in turn, tend to reduce the worker's commitment to the job and the organization.

This implies that, although our work does not directly explore the consequences of job insecurity, its findings about the determinants of insecurity do offer some novel insights that allow us to draw implications informing policymakers as well as entrepreneurs and managers operating in innovative firms.

Our findings, for instance, suggest that firms should not be too concerned that investing in technological innovations may impact negatively on workers' perceived insecurity and, indirectly, on their performance in the company. Our research shows, indeed, that what matters is why and how innovations are introduced. Their impact on workers' insecurity is lower in the presence of firm's simultaneous investment in training, when innovations and machines are not explicitly meant to substitute workers along the production chain, and when employment reduction plans are not under way. One potential interpretation is that workers try to see through the motivations behind the innovations and to combine them with information about the health of the company, so as to gauge whether the innovations are directed either to strengthen the firm's prospects or to cut costs in a defensive way.

From this, it follows that innovative firms are more likely to preserve workers' motivation and commitment if they develop a constructive dialogue with their employees. This dialogue could reduce the risks that workers make mistakes in drawing conclusions about the motivations and the impact of innovations on the company and on their job. Considering the importance of innovation in the Industry 4.0 era, this conclusion calls for strengthening social dialogue within the firm, and not only among workers and entrepreneurs' representatives.

The workers' personal experience is important as well: those workers whose activities are made more intense and continuous by the innovation tend to be more concerned about losing their job than other workers. This is a novel result with respect to the literature and our study manages to capture it because it considers the actual innovation carried out by firms in Italy during the period 2016-2018, rather than the potential exposure of occupations to technological unemployment. Our findings, thus, are complementary to those reached by previous studies focusing on occupations' features (i.e., being routine-intensive, being exposed to substitution by robots, and the like) and workers' characteristics (i.e., individual traits, level of education, skills). We show that workers sharing similar characteristics and occupations may perceive job insecurity differently and in accordance with their direct experience in the firm that innovates.

Finally, our results show that cognitive and affective job insecurity are positively associated, but their relationship with the introduction of technological innovation in a firm is diverse. Affective insecurity is affected by cognitive insecurity but it also depends on workers' perception about their potential employability in other companies and sectors. We find, for instance, that the development of specific training after the introduction of a technological innovation reduces the level of cognitive JI, but not affective JI. Firm-specific and technology-specific training does not improve the chance to obtain a job in another company in the future (which matters for affective JI), but it does signal the interest of the innovative firm in improving the interaction between trained workers and the innovations (which impacts on cognitive JI).

8 Closing remarks

Workers' perception of job insecurity is affected by a large number of subjective, as well as by macroeconomic and firm-related factors. The diffusion of technological innovations in firms is often depicted as a key driver of job insecurity, however the literature has said very little on whether workers perceive technological innovations in their companies as a source of job insecurity or not. By exploiting a recent, large and dedicated survey distributed to Italian workers, we analyse how the adoption of technological innovations correlates with workers' perceived levels of job insecurity, and what factors mediate such relationship.

While the literature on technology and job security has so far focused on workers' perceptions about insecurity, on one hand, and either their technological awareness or their jobs' potential exposure to substitution, on the other hand, this work tackles how cognitive and affective job insecurity correlate with technological innovations actually adopted by the companies where the workers are employed. Furthermore, the analysis explores the differentiated effects of diverse types of technological innovations by distinguishing product and process innovation, automation and other types of innovation.

All in all, the battery of estimations employed suggests that the adoption of technological innovations by companies tends to reduce the level of job insecurity perceived by their workers. These results are robust, and a series of extensions allows us to conclude that the adoption of a technological innovation by a company is perceived by the workers who remain active as a signal of the firm's health and of its commitment to preserving the activity. This reassuring effect of technological innovations, however, is differentiated across companies and workers, due to the mediating role played by a number of factors. While personal traits are not particularly relevant, workers' previous experiences associated with the introduction of innovation in the past do seem to matter the most. The reassuring effect of technological innovations is indeed stronger when the workers are aware that the firm has invested in technology-related training programs, when they have not witnessed workers' dismissals after (and because of) the introduction of new machines in the past, and when their own job has not changed too much because of the innovation. Future research should focus on establishing the causal impact of these different types of innovative efforts on job insecurity, possibly taking advantage of panel data based on the release of new waves of INAPP-PLUS in the future.

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Appendix

A Additional Tables

In the main text of the paper we did not report the estimated parameters for the control variables. Besides space-related concerns, the reason for omitting these terms is that they are introduced as controls and do not represent variables of interest. Yet, the reader could wonder whether our results are in line with the economic intuition and with previous findings.

Table A1 reproduces the estimated parameters of the entire list of controls. Workers in the age class between 25 and 49, as well as males, tend to exhibit lower levels of JI. The most educated workers have a higher level of cognitive JI, but they do not differ in terms of affective JI. Extroversion, openness, agreeableness and conscientiousness are also associated with lower insecurity, whereas neuroticism affects JI in the opposite direction as expected. Workers employed with permanent and fixed-term contracts are substantially different as the former (latter) have lower (higher) levels of JI. Part-Time contracts are associated with higher levels of affective JI and this may be interpreted as a sign that workers who ask for Part-Time contracts are concerned that this may negatively affect their fit to work should they lose their job. Workers performing non-routine-intensive cognitive tasks and over-skilled individuals are less insecure. Those receiving general training and extra benefits perceive more moderate levels of insecurity. The presence of trade unions in the company is not a relevant factor. The larger the firm, the higher the insecurity, although these findings are relatively weak. There is higher insecurity in the industry and service sectors, although there does not seem to be a relevant difference between the two. Workers in the South of Italy exhibit greater affective insecurity, probably because of the concerns regarding the difficult economic environment in which their labour market is. Firms that hire workers, fire workers and use furlough schemes, unsurprisingly, are associated with workers that have, respectively, lower, higher and higher levels of JI.

Table A1: Introduction of technology and job insecurity: controls

	(1) Cognitive JI		(2) Affective JI	
25_49	-0.219**	(0.099)	0.115	(0.093)
50+	-0.124	(0.103)	-0.027	(0.096)
Gender	-0.128***	(0.047)	-0.120***	(0.046)
Edu	0.241***	(0.047)	0.032	(0.043)
Big5Neuro	0.133***	(0.018)	0.159***	(0.018)
Big5Extro	-0.040**	(0.017)	-0.039**	(0.016)
Big5Open	-0.067***	(0.020)	-0.004	(0.019)
Big5Agree	-0.018	(0.021)	-0.050**	(0.021)
Big5Consc	-0.220***	(0.022)	-0.037*	(0.021)
PartTime	0.065	(0.059)	0.230***	(0.058)
Permanent	-0.206***	(0.064)	-0.188***	(0.062)
FixedTerm	0.445***	(0.087)	0.629***	(0.087)
NonRoutM	0.032	(0.078)	0.059	(0.077)
NonRoutC	-0.155***	(0.047)	-0.239***	(0.046)
OverSkilled	-0.084**	(0.042)	-0.041	(0.039)
UnderSkilled	0.371***	(0.110)	-0.013	(0.103)
Benefit	-0.156**	(0.069)	-0.107*	(0.061)
GenTraining	-0.310***	(0.045)	-0.095**	(0.044)
ProfGroup2	0.198*	(0.105)	0.242**	(0.097)
ProfGroup3	0.107	(0.104)	0.217**	(0.097)
ProfGroup4	0.253**	(0.109)	0.285***	(0.101)
ProfGroup5	0.050	(0.115)	0.251**	(0.109)
ProfGroup6	0.056	(0.114)	0.385***	(0.108)
ProfGroup7	0.052	(0.144)	0.483***	(0.134)
ProfGroup8	0.086	(0.142)	0.553***	(0.135)
Union	-0.054	(0.061)	0.040	(0.057)
11_50	0.109*	(0.063)	0.100*	(0.060)
51_250	0.119	(0.077)	0.174**	(0.072)
251_1000	0.322***	(0.093)	0.169*	(0.094)
1000+	0.135	(0.123)	-0.006	(0.105)
Ind	0.252**	(0.119)	0.963***	(0.123)
Serv	0.241**	(0.116)	0.921***	(0.119)
Sud	0.067	(0.053)	0.328***	(0.052)
Firing	0.272***	(0.058)	0.313***	(0.053)
Hiring	-0.315***	(0.054)	-0.338***	(0.051)
CIG	0.264**	(0.123)	0.577***	(0.110)
Observations	13,837		13,837	

Notes: Robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.