INSTITUTE
OF ECONOMICS

Scuola Superiore Sant'Anna

LEM | Laboratory of Economics and Management

Institute of Economics
Scuola Superiore Sant'Anna

Piazza Martiri della Libertà, 33 - 56127 Pisa, Italy
ph. +39 050 88.33.43
institute.economics@sssup.it

# LEM
# WORKING PAPER SERIES

## Technology, risk and social policy. An empirical investigation

Dario Guarascio [a]
Stefano Sacchi [b]

[a] Sapienza University of Rome, Italy.
[b] Polytechnic University of Turin, Italy.

2021/16 April 2021
ISSN(ONLINE) 2284-0400

# Technology, risk and social policy. An empirical investigation

Dario Guarascio* and Stefano Sacchi**

* Sapienza – University of Rome email: dario.guarascio@uniroma1.it
** Polytechnic University of Turin email: stefano.sacchi@polito.it

Abstract

This paper investigates the role of exposure to technological risk in shaping social policy preferences, specifically on support for universal basic income and means-tested generalised minimum income. Evidence is provided for Italy, to exploit the availability of high-quality data, allowing measures of two dimensions of technological risk. Objective risk hinges upon the degree of substitutability of one's occupation by machines, while subjective risk concerns a worker's perception of their substitutability.
We posit that exposure to technological risk induces individuals to ask for protection, and thus increases support for social policy. We test two hypotheses: first, that exposure to objective risk of replacement by machines is correlated with support for both safety nets; second, that such effect is increased by high perception of risk.
On the whole, results confirm a strong relationship between exposure to technological risk and support for social safety nets, once objective risk is disentangled from subjective perceptions. However, we find that such relationship only holds for men, while it cannot be confirmed for women.

Keywords: technological change; routine occupations; social policy; generalised minimum income; universal basic income; safety nets

JEL Classification: I3 - Welfare, Well-Being and Poverty; J08 - Labor Economics Policies; O33 - Technological Change: Choices, Consequences and Diffusion Processes.

***A revised version of this paper will be published in Busemeyer, M., Kemmerling, A., Marx, P., and Van Kersbergen, K. (forthcoming), Digitalization and the Welfare State, Oxford: Oxford University Press.***

## 1. Introduction

The new wave of technological innovation, based on automation and digitisation, machine learning, artificial intelligence and the availability and use of big data, has originated two camps: Those who highlight the novelty of the 'fourth industrial revolution' (Schwab, 2016; Brynjolfsson and McAfee, 2014) and those who downplay it (Atkinson and Wu, 2017; Cetrulo and Nuvolari, 2019). Although the impact of technology on overall employment is mixed, as it flows through several causal mechanisms (Acemoglu and Restrepo, 2019), there is consensus about the fact that technological change affects occupations differently and evidence of task-biased and routine-biased technological change continues to abound (Arntz et al, 2017; Autor 2015; Autor and Dorn, 2013; Frey and Osborne, 2019; Goos et al, 2009). In any case, even if the reinstatement effect of technology should outweigh its displacement effect, as happened in the previous rounds of technological innovations (Atkinson and Wu 2017), the transition will no doubt be painful (Levy 2018), and social policy will be sorely needed.

Against this backdrop, it makes sense to ask whether higher exposure to the employment risks associated with technological change (henceforth: technological risk) affects workers' preferences for social policy measures. A large body of comparative and international political economy literature has investigated the conditions under which individuals support social policy measures, particularly relating to social insurance when exposed to job and income related risks stemming from their labour market position, skills and occupational 'offshorability' (Sacchi et al. 2020). Rueda and Thewissen (2019) were among the first to probe the relation between the risk associated to technological change as operationalised by the degree of routineness of one's occupation, and support for redistribution. Kurer and Häusermann (forthcoming) show that those exposed to automation risk demand traditional passive insurance (most notably, unemployment benefits) against the risk of job loss rather than social investment. Martinelli and Chrisp (forthcoming) explore the determinants of support for universal basic income in the context of rapid technological change.

This paper investigates the role of exposure to technological risk in shaping social policy preferences, and specifically on support for universal basic income (UBI) and means-tested generalised minimum income (GMI) in Italy. We are interested in protection against technological risks, or, to recall the defining dimensions of social security identified long ago by Flora and Heidenheimer (1981), in the stabilisation of life chances against the potential disruption caused by technology (see also Rehm 2016; Kurer and Palier 2019). The obvious candidates for this task are social-insurance income maintenance schemes, such as short-time work and unemployment benefits, and this is investigated by Kurer and Häusermann (forthcoming). However, current policy debates on the future of work, its socio-economic correlates and how to compensate the current and prospective losers from technological change, often revolve around more ecumenical safety nets that are not dependent on the welfare-work nexus (be they means-tested or not). Roosma and Van Ooorschot (2000) hypothesise that high support for UBI in Europe may come from 'the fact that it provides (poor) people with guaranteed minimum income' (p. 203), rather than from its being unconditional or universalistic in nature.

Irrespective of their differences, UBI and GMI can both be considered, from the standpoint of workers, less actual and more remote options than short-time work or unemployment insurance. It therefore makes sense to consider them in the same class of policy measures, that of *social safety nets*. The suppositional nature of both UBI and GMI is even stronger in our case, Italy, as a nation-wide GMI scheme was only introduced in 2018 (Sacchi 2018), while before there was no baseline policy measure. As noted by Vlandas (2021), assessing the distributional consequences of schemes that are not in place should reduce the space for individual-level variables to shape policy preferences. This makes our case a very apt test-bed for assessing the impact of individual exposure to technological risk on policy preferences, as the prior probability of a strong impact on support for our two schemes is low, and any evidence in favour of it should be held in high regard.

## 2. Analytical framework

Following Sacchi et al (2020), and similar to Kurer and Häusermann (forthcoming), we distinguish two dimensions of technological risk, namely: the objective, and subjective types. Exposure to objective risk hinges upon the degree of substitutability (by machines) of one's occupation – and more specifically, of the tasks comprising such occupations. If occupations are conceived of as bundles of tasks (Autor and Handel, 2013), then the proper focus of analysis is the task content of occupations, rather than occupations per se. The larger the share of routine tasks comprising a given occupation, the greater the potential for machine substitution and thus of declining occupation share in total employment. Consistently with this approach, we operationalise objective risk with a measure of task routineness pertaining to each occupation (Routine Task Index, RTI: see section 4).

The subjective dimension of technological risk has to do with a worker's perception of their own exposure to objective risk. We believe such perception can be mediated by many factors, but it is primarily grounded in the worker's occupation. We are not claiming that explicit recognition of one's objective risk occurs all, or even most, of the time. Neither are we claiming that any recognition is necessary for objective risk to be operational. Such a claim would indeed analytically subsume subjective risk under objective risk, and make the two observationally indistinguishable, or model perceptions as an intervening variable between objective risk and policy preferences, which we regard as unwarranted. Following Kitschelt and Rehm (2014), we believe occupations are sites of preference formation, and this occurs even if the occupation 'in itself' has not become 'for itself', to borrow from Marxian debates. Preference formation may originate from subconscious learning within occupational networks, based on operational occupational experiences and socialisation patterns, and can become differentiated according to exposure to objective risk. Subjective perception of objective risk need not occur for the latter to be consequential; when it occurs, however, it is rooted in such operational occupational experiences and socialisation patterns, and tends to reinforce the effects of exposure to objective risk.

Moreover, occupation-based subjective perception of risk may come from individual judgment formation processes, given our operationalisation of subjective risk as the respondent's estimate of how many workers *performing the same job as theirs* will lose their job as a result of being replaced by machines in the next ten years. According to a social psychology theory, social sampling theory (Galesic et al, 2018), to make judgments about characteristics of a given group (called 'reference class'), people first sample from memory those instances of their own social environments 'that are in some way similar to the reference class they are asked about' (p. 365), then estimate how many in the reference class have a certain ('target') characteristic by activating those sampled instances that possess such characteristics.

In our case, when asked to estimate the share of workers performing their own job (reference class) that will be replaced by machines (target characteristic), respondents will sample from their own work environment and then activate instances based on their own performed occupation, which, inter alia, embeds routineness. While routineness may be only one among several 'sampling clues' that are used by the respondent, the basic root of social sampling in our setting is the occupation. Therefore, this channel may result in the recognition of subjective risk, reinforcing the effects of exposure to objective risk.

Finally, consistent with regarding occupations as bundles of tasks, our operationalisation of subjective risk allows for 'partial' substitution by machines (as in Arntz et al, 2017), whereby some tasks are replaced while some are not, and not all workers in a given occupation need to lose their job, particularly if reskilling measures are activated.

In this paper, our claim is that exposure to the technological risk induces individuals to ask for protection, and thus increases support for social policy measures. Our argument is based on two expectations, which we aim to test. As mentioned, we consider the objective risk as our key variable, which affects preferences for social policy. Therefore, our main hypothesis is that exposure to the objective risk of replacement by machines, as measured by occupational routineness, is correlated with support for both UBI and GMI. The effect of exposure to objective risk is then increased by the perception of subjective risk, that occurs by explicit recognition of one's objective risk, in its turn rooted in one's occupation. Therefore, our second (and secondary) hypothesis is that the effect of exposure to objective risk is increased by high perception of risk.

We believe the key contribution of this paper lies in the exploration of the relationship between exposure to technological risk and social safety nets, in the light of high plausibility of the null hypothesis and given Roosma and van Oorschot's (2020) intuition about UBI being perceived in its guaranteed minimum income function. Still, differences between support for UBI and GMI with respect to technological risk exposure may well arise, and it may be worth to develop theoretical expectations regarding them.

As a matter of fact, UBI is often advocated in policy debates as the de rigueur social policy response to technology-related risks (Dermont and Weisstanner 2020); at the same time, however, comparative evidence shows that support for it tends to be uncorrelated with exposure to (objective) technological risk (ibidem; Martinelli 2019). Moreover, the institutional environment in which social policy measures are (to be) embedded does make a difference (Parolin and Siöland 2020): in its purest form, UBI does not add up, but merely replaces other social policy programmes, as it actually did in the Finnish basic income experiment.

We can posit that those exposed to technological risk are generally core workers (Kurer and Palier 2019). As such, they generally are entitled to social insurance. Therefore, we expect that the more UBI should replace social insurance programmes, the lower its support would be among such risk categories, following both theoretical intuitions (the feeling of having earned social insurance benefits through contributions, see Esping-Andersen 1996) and empirical evidence (Kurer and Häusermann forthcoming).

As we will see, our operationalisation of support for UBI and GMI is based on questions in the European Social Survey (ESS) which leave many institutional features undecided. We note, however, that the survey question on UBI mentions that it would replace 'many other benefits', while the GMI question does not (see Table 1). The questions may thus engender in the respondent the expectation that UBI – but not GMI – could replace social insurance. Also, the UBI question explicitly mentions that everyone receives the same amount regardless of whether or not they are working, while the GMI question explicitly mentions labour market activation and benefit conditionality. Recent evidence shows that exposure to technological risk is correlated with support for activation of beneficiaries (Jie Im and Komp-Leukkunen 2021). Combining the two intuitions, we expect support for GMI among workers to be higher than for UBI, and a lower likelihood of subjective risk strengthening the relationship between objective risk and support for UBI as compared to GMI, so our second hypothesis less likely to be confirmed for UBI, while we do not expect any difference with regard to our first hypothesis, which pertains to objective risk.

After justifying our empirical support and presenting the data we use and our empirical strategy, we will carry out some descriptive analyses, before testing our hypotheses. The empirical evidence supports our first hypothesis for both policy measures, while our second hypothesis is confirmed for UBI only.

On the whole, our analysis empirically upholds our claim of a strong relationship between the technological risk and support for social safety nets, in a context of low prior probability for such relationship. We consider this a relevant and valuable result in the face of existing empirical evidence, presumably due to high data quality and, in particular, the inclusion of a measure of subjective risk. However, we find that the relation between technology-related risk and social policy only holds for men, while no such relation can be observed for women. We believe this is a consequential result as well.

## 3. The case of Italy

We probe the relations between technological risk and support for UBI and GMI in Italy because of three factors: data quality, considerations on the object of citizens' preferences and considerations on the drivers of risk.

First, the availability of excellent (and unique) data. We calculate RTI based on the only replication of US Occupational Information Network (O*NET) outside the US, thus avoiding the oddity of analysing non-US occupations by means of the inner constituents of the US economy in order to get a more correct measure of RTI (see below). Other variables are based on ESS Rounds 8 and 9, fielded in autumn 2017 and winter 2018 respectively. Subjective risk and support for GMI are measured by building on a question asked only in both rounds of the Italian country-specific section of the ESS. This is particularly relevant as it allows to include a high-quality measure for subjective risk, which sits at the core of our analytical framework and empirical analysis. Support for UBI and a crucial control variable of 'perception of individual unemployment risk in the next year', were polled for all countries in ESS Round 8, but again only for Italy in Round 9.

Second, the suppositional nature of both UBI and GMI in Italy, as even the latter was not introduced before the fielding of Round 8. Following Vlandas (2021), this reduces the prior probability of finding a significant relationship between individual-level variables and preferences for these policy measures. The scheme introduced as of January 2018 – the '*reddito di inclusione*' ('inclusion income') scheme – envisaged a governance system centred on social services and aimed at both labour market and social inclusion, but provided only relatively meagre benefits. When combined with low means-testing thresholds, this resulted in a relatively low level of coverage of the target population, ultimately accounting for less than 0.15% of Italy's GDP. Also, there was little debate in the media about its introduction, so it went largely unnoticed to the general public (Gori 2020). Such scheme was then substituted in March 2019 (after the fielding of Round 9) by a more generous '*reddito di cittadinanza'* (citizenship income) scheme, which, despite its misleading name, is also a means-tested social assistance measure, with a higher focus on labour market insertion (and stricter conditionality) than its predecessor. *Reddito di cittadinanza* accounted for about 0.35% of Italy's GDP before the onset of the COVID-19 pandemic, which is in line with outlays for GMIs in most European welfare states except Germany. This time, the debate over the introduction of a new scheme to replace the previous one was heated (ibidem), but details of the new measure were kept covered until March 2019, so it would be difficult to put forward expectations on how it may have influenced respondents. Figure 2 below shows how support for GMI has not changed dramatically between ESS rounds 8 and 9.

Third, Italy's incomplete transition towards high-tech standards. In the EU, the country stands second for manufacturing output and third for the exportation of goods. Moreover, its export structure is similar to that of Germany, given its specialisation pattern that has been classified by the OECD as 'medium-high-tech' to 'high-tech' (Heimberger and Krowall, 2020). Therefore, it is an economically relevant case. At the same time, Italy definitely lags behind other advanced capitalist economies in terms of digitalisation, as has been shown by the European Commission DESI (Digital Economy and Society Index[1]) where Italy ranks 24th in the EU-27 according to the overall index, and 21st according to the business digitalisation subdimension. This makes it a non-trivial case, where advanced technologies are embodied in manufactured goods, but digitisation has not been fully exploited and the technology frontier not yet reached. This is confirmed by occupational patterns. While Gualtieri et al (2018) find no traces of occupational change that may be consistent with routine-biased technological change (RBTC) in the period 2005-2010 in Italy, they show that in the most recent period, following 2010, the impact of technological change on occupations clearly corroborates RBTC, particularly in the service sector.

## 4. Data and empirical strategy

[1] https://ec.europa.eu/digital-single-market/en/desi

*4.1 Operational variables: Measures of technological risk exposure*

To operationalise objective and perceived risk, our independent variables, we use data from three surveys: the Italian Survey on Occupations (ISO), the Italian Labour Force Survey (ILFS), and the ESS.

The objective risk is operationalised through the RTI calculated for each occupation. For each occupation, the RTI captures the relative intensity of routine/encodable tasks it is comprised of. Following Autor et al (2003), the RTI is the result of the difference between the sum of components pertaining to the degree of routineness and encodability of manual and cognitive tasks, and the sum of components pertaining to less routine tasks – that is those tasks (be they manual of cognitive) involving a relevant degree of autonomy and discretion on the part of the worker. The relevant information on the routine content of tasks is usually based on the task descriptions provided by the O*NET (www.onetcenter.org), which is sponsored by the US Department of Labor. The main shortcoming of doing so outside the US is that the inner structure of the US economy, in terms of occupations, tasks, and the way of performing such tasks, will structurally underlay the analysis of non-US economies and labour markets.

This is not the case for Italy, as the ISO is modelled on the US O*NET analytical grid, and represents the only replication of O*NET outside the US[2]. This allows us to construct the RTI for each occupation at a 5-digit level. The availability of the ISO results in an ontologically correct construction of the RTI, as information on each occupation is based on the real tasks and work contents that such occupation is actually comprised of in the Italian labour market.

The dataset is then combined with data from the ILFS, which provides detailed information on employment shares and labour force composition for each occupation. This allows us to calculate the RTI index on a 3-digit level, which will be used in the analysis.

We then use ESS Rounds 8 and 9 for Italy (ESS, 2016; ESS, 2018). ESS includes a standardised occupational identifier on the 4-digit ISCO-08 level. We re-classify the occupations on a 3-digit level and assign to each individual in the sample an RTI value.

The Italian release of the ESS also provides us with a measure of the perceived technological risk. We operationalise this through the answer to a question that was part of the special (Italian-specific) modules of the ESS Rounds 8 and 9 (module X)[3]. A randomly-drawn half sample of the employed individuals was asked the following question (Question X8, ESS 2016; ESS, 2018): 'Imagine 100

[2] The ISO involves a representative sample of 16,000 workers covering the spectrum of the Italian 5-digit occupations (811 occupational codes). Based on 1-hour long face-to-face interviews, the ISO provides more than 400 variables relating to occupations including skills, work content, attitudes and tasks.

[3] The text and consistency of country-specific questions is validated by the ESS ERIC Core Scientific Team according to the general ESS standards.

persons doing the same job as yours. Of these 100, how many do you think will lose their jobs in the next 10 years because they will be replaced by machines?'[4].

In this paper, the objective risk is measured using the RTI as a continuous variable, while the perceived risk has been recoded as a dummy, taking value 1 if the individual's subjective risk perception is above the median level (15%).

*4.2. Dependent variables: Measures of preferences for social policy measures*

ESS Rounds 8 and 9 provide us with a variety of questions to operationalise preferences for redistributive and social policy measures (see Table 1).

A standard question, repeated in every round of the survey, deals with support for measures to reduce differences in income levels (Question B33, ESS 2016; ESS, 2018), namely: 'The government should take measures to reduce differences in income levels'. Round 8 of the ESS then featured a rotating module on welfare, common across all participating countries, which included a question on support for UBI (Question E36, ESS, 2016), with detailed features of the scheme. Given the fact that Italy had never had a nation-wide GMI scheme until the one introduced in 2018, the Italian-specific module within the ESS Round 8 questionnaire asked a question regarding support for GMI (Question X11, ESS, 2016), again with detailed features of the scheme and worded in a way that was similar to the former question on UBI[5]. For Round 9, since the Round 8 question on UBI was no longer asked in the core questionnaire across all countries, it was included in the Italian-specific module questionnaire and asked to a randomly-drawn half sample of the Italian ESS respondents (Question X12, ESS, 2018), while the other randomly-drawn half sample was asked the question on GMI (Question X11, ESS, 2018). For each of these questions, a dummy was created, taking value 1 if an individual agrees or strongly agrees with support for redistribution. We want to focus on the impact of risk related to technological change on specific support for UBI and for GMI as our main dependent variables, net of the general attitudes toward redistribution that an individual might have independently of the specific risk circumstances. Therefore, we use general support for redistribution as a control.

*4.3. Controls*

The ESS provides us also with a wide set of socio-demographic information that we use as additional controls in our analysis. Building on determinants identified by the literature on preferences for redistribution (see Sacchi et al., 2020, see also Martinelli and Chrisp forthcoming), we include a

[4] The other half-sample was polled on globalisation.

[5] See Table 1 for the exact wording of the two questions.

battery of controls, listed in Table 1. In what follows, we discuss only those whose operationalisation or rationale may not be immediately straightforward.

In order to purge the effects of the perception of technological risk from general worry about individual-level unemployment, we include a binary measure of individual job insecurity obtained by recoding answers to the following question: 'How likely is it that during the next 12 months you will be unemployed and looking for work for at least four consecutive weeks?'[6]. As for political preferences, alongside self-placement on the left-right continuum, we operationalise the emergence of a new value-based dimension pitting universalism vs particularism (Häusermann and Kriesi, 2015) by means of a variable that measures attitudes toward immigrants' inclusion in social benefits, as captured by the answer to the question: 'Thinking of people coming to live in Italy from other countries, when do you think they should obtain the same rights to social benefits and services as citizens already living here?'[7]. We deem this to be a particularly relevant control both per se, and considering that inward migration can be seen as yet another source of occupational risk.

Given Italy's many structural divides between the North and the (Centre-)South of the country, we include a control variable on living in the North (as opposed to the rest of Italy)[8]. We also include a set of controls at the macroregional (NUTS 1) level, including unemployment rate in 2016, its variation relative to 2006 levels (as a relative increase may generate more anxiety than the level itself, particularly in regions where structural unemployment is historically low), the level of openness to trade, measured as the total of imports and exports as a share to macroregional GDP, and the interaction between this variable and the variation in the unemployment rate, so as to capture relative exposure to trade and globalisation as a competing factor to technological change.

Table 2 provides also summary statistics of the variables we use in the sample of those in employment.

### *4.4. Empirical strategy*

To test the hypotheses set out in the introduction, we run a set of ordinary least squares (OLS) regressions. Our most general specification is the following (Equation 1):

[6] This question was part of the rotating module on welfare in Round 8 (Question E39, ESS, 2016) and included in the country-specific module for Italy in Round 9 (Question X16, ESS ,2018).

[7] This question was part of the rotating module on welfare in ESS Round 8 (Question E15, ESS, 2016) and was included in the country-specific module for Italy in Round 9 (Question X15, ESS, 2018). We recode answers 'Once they have become an Italian citizen' and 'They should never get the same rights' together, given the strict rules for acquiring citizenship in Italy, as 1: 'Never'; 'Only after they have worked and paid taxes for at least a year' as 2; 'Immediately on arrival' and 'After living in Italy for a year, whether or not they have worked' together, as 3: 'No conditions'.

[8] In 2018, per-capita GDP in the North-West was 25% higher than the national average, in North-East 20% higher, in the South 35% lower (Istat, 2020).

$$Y_i = \beta RTI_i + \gamma Risk_i + \delta RTI_i * Risk_i + X_i'\zeta + R_r'\theta + \epsilon_i$$

The dependent variable is support for UBI, or support for GMI. The coefficients of interests are beta, and delta. The beta coefficient is of interest in a specification that disregards the interaction between objective and perceived risk (where delta is exogenously set at zero), aimed at assessing the validity of our general argument about exposure to objective risk and support for social policy measures. Delta is then of interest in the full specification of the model, since it pertains to the interaction between the objective and perceived risk and is thus aimed at assessing the validity of our further hypothesis, about the effect of exposure to objective risk being increased by recognition of high rates of perceived risk. In this case, beta is no longer of interest per se. As mentioned, all econometric models include a large number of individual, sectoral and occupation-level controls (see Table 2).

**5. Descriptive analysis**

Figure 1 shows the distribution of perceived and objective risk by 1-digit ISCO-08 occupations. The distribution of RTI across occupations is in line with what the RBTC literature would predict, as the average risk increases moving from managerial to elementary occupations. While the pattern of our subjective measure of technology-related risk is less clear-cut, perception of risk tends to be higher among more routine occupations. Objective and subjective risks, however, tend not to be strongly correlated, which testifies in our view to the importance of including subjective risk measures in the analysis of preferences for social policy motivated by exposure to technological change.

Support for redistribution and our investigated social policy measures is shown in the overall sample (Table 2) and split between the two ESS Rounds (Figure 2).

A striking result is indeed the high level of support across the board, as general support for government redistribution hovers around 95%, specific support for GMI at 76%, and for UBI at 58% (Table 2). Although support for UBI in Italy is comparatively high (Roosma and van Oorschot, 2020, figure 1, p. 198), these descriptive statistics are consistent with our expectation on relative support for GMI and UBI, and match what found in the literature regarding support for UBI being lower than for general redistribution (Dermont and Weisstanner 2020). Figure 2 shows that no significant changes can be observed between the two rounds. This may be taken to confirm the suppositional nature of the two safety nets in the Italian context, given the fact that neither was operational in fall 2017, while *Reddito di inclusione* had gone largely unnoticed before winter 2018.

## 6. Econometric analysis

In tables 3 and 4, we investigate the impact of exposure to technological risk on support for safety nets – respectively, UBI and GMI. For each dependent variable, we run four different OLS regressions. Column (1) includes only the controls, column (2) adds RTI, column (3) includes the perceived technological risk. Finally, column (4) includes the interaction term between perceived and objective risk indicators, as in equation (1).

### *6.1. Support for UBI*

Although an inquiry into the determinants of support for either of our safety nets is not the focus of this paper, as we are interested in the effect of exposure to technological risk, in the first column of table 3 we see that most determinants of preferences identified in the literature (see Martinelli and Chrisp forthcoming; Roosma and van Oorschot, 2020; Vlandas, 2021) have limited power to predict support for UBI in our case. This should be assessed in the light of the limited number of observations, due to restricting the sample to those employed, and the many controls introduced. For a relationship to acquire significance, evidence needed to deviate from the null hypothesis must therefore be very compelling.

In column (2), RTI alone is not significant, which may seem to cast doubt on our argument. However, things change when in column (3) we also include our measure of subjective risk, which further reduces sample size as only half sample was randomly polled for this question (see section 4.1). While perceived risk is not significant per se, its inclusion makes exposure to objective risk highly significant. In this model, political preferences become highly significant and relevant, as identifying as right-wing decreases support for UBI by more than 10% as compared to identifying as centrist.

Finally, in column (4), we run the full model. This allows us to test the second step of our argument, relating to the mediating role of perceptions. The most relevant coefficient in this regression is the one relating to the interaction term, which is positive and highly significant, and its magnitude is three times as large as that of the objective risk alone in the former model.

These results relating to UBI are thus extremely relevant in the context of the extant literature on support for UBI (see Martinelli and Chrisp, forthcoming; Dermont and Weisstanner 2020). Specifically, while factors related to income, education levels, labour market vulnerability, and trade union membership are not significant, politics clearly matters, as right-wingers tend to be more skeptical of UBI. Above all, technology also matters, and our argument on the role of technological risk is fully upheld.

### *6.2. Support for GMI*

With respect to standard determinants of support for redistribution and social policy, results for GMI (Table 4) are more mainstream. In the first column, we immediately see that 'usual-suspect determinants' play a relevant role here. More importantly, they remain significant in our model specifications of interest, that is when our objective and subjective measures of exposure to technological risk are included (columns 2 to 4). Specifically, support for government redistribution and education are positively correlated with support for GMI and moderately significant. Meanwhile, the value dimension of politics comes to the fore as a relevant one. Support for GMI strongly correlates with access of migrants to welfare state benefits and services after working and paying taxes for a year, which can be taken as a proxy of 'distributive deservingness' (Häusermann and Kriesi, 2015) in social assistance policy. Union membership is now negatively correlated with support for GMI and is strongly significant, despite Italian unions having turned their hostility of yore towards the introduction of GMI into acceptance, and even support (Natili, 2018; Sacchi, 2018). A possible explanation is that the introduction of GMI is seen by union members as potentially competing with established social insurance measures such as unemployment insurance and short-time work, thus leading to a loss of social entitlements. This however runs counter to the absence of significance in the case of UBI, where such fear should actually be stronger, as per our expectation in section 3 (although no relationship between union membership and support for UBI is found in comparative studies by Roosma and van Oorschot, 2020 and Vlandas, 2021, for that matter). Also, labour market status variables are not significant. Further research is thus needed in this regard.

Moving away from controls to focus on our relation of interest, the pattern is very similar to that of support for UBI. RTI alone is not significant (column 2), but things do change when subjective risk is included in the analysis (column 3): While the perceived technological risk is not significant per se, its inclusion makes RTI extremely significant. The only difference between support for UBI and for GMI regards the mediating role of perceptions, as column 4 shows that the interaction term bears no significance in the case of GMI.

To summarise the results regarding exposure to technological risk as a relevant driver of preferences for social safety nets in the new technological revolution. The import of objective risk is fully confirmed in the case of support for both policy measures, while the intensifying effect of perception is only apparent in support for UBI.

### *6.3. Robustness checks*

To check robustness, we also ran models (results available from the authors) including social class (using Oesch 8-class schema) and a categorical operationalisation of educational attainment alongside the numerical one. Neither inclusion affects our main results.

More specifically, self-employed professionals and large employers are consistently more supportive of both UBI and GMI as compared to production workers. Membership of such classes is associated with higher support for UBI by between 36% and 49% as compared to production workers, depending on models (significance level 1%). Impact on support for GMI ranges between 22% and 28% (significance level 5%). Technical professionals and semi-professionals, by contrast, are consistently about 10% less supportive of UBI than production workers (significance level 5%). The most striking result, however, is that technological risk remains significant also when social class membership is accounted for, a result that is not at all trivial, if one considers how our measure of objective risk, the RTI, is rooted in occupations, that also form the basis of Weberian-Goldthorpian approaches to social class definitions. The fact that objective risk stays highly significant for GMI in the model with no interaction, and that interaction between objective and subjective risk remains significant for UBI (significance level 10%), is indeed a strong and unexpected result, which testifies to the relevance of technology risk in accounting for social policy preferences.

### *6.4. A gendered impact?*

Gingrich and Kuo (forthcoming) raise a very serious issue, claiming that the impact of technological change on preferences for redistributive policies can be gendered, and ‘far less relevant for women’. While women are, on average, as exposed as men to technological (objective) risks, the logic governing the nexus between technological risk and support for social policy can operate differently for women vis-à-vis men, as the former face alternative sources of labour market risk.

Gingrich and Kuo find convincing evidence for their claim, which is also supported by our own findings. We run separate regressions with our two dependent variables for men and women (Table 5). Results, reported only for the full models, are striking. Technological risks, be they objective or subjective, are only relevant in the case of men. When the subsample is restricted to women, by contrast, the role of technology literally disappears, as no effect of objective or subjective risk can be detected. This is not driven by substantial differences in exposure to objective risks, as the mean value for women is 0.50 (s.d. 0.24) and for men is 0.55 (s.d. 0.22).

Some individual labour market related variables emerge as highly significant in accounting for support for GMI among women, namely working part-time (which is positively correlated to support), and working in the services sector (which is negatively correlated).

On the whole, these results testify to two different logics of influence of technological risk on social policy preferences. The logic sketched out so far is operative for men, whereas among women, the structural conditions are there, as exposure to objective risk is on average similar to that for men, but they pale into insignificance vis-à-vis other structural factors and constraints, mostly relating to labour market vulnerabilities. The effect of part-time work is particularly telling in this regard, in a country where the incidence of involuntary part-time among female part-timers reached 60% after the Great Recession, as compared to about 15% in the OECD and 20% in the EU (OECD Statistics).

## 7. Discussion and conclusion

This paper has focused on the relation between technology, risk and social policy preferences. We have investigated whether higher exposure to technological risk affects workers' preferences for social safety nets. We have made use of the case of Italy, by exploiting high quality granular data on occupations, and the availability of survey data which allow us to calculate both objective and subjective measures of risks stemming from the adoption of new technologies, as well as to assess support for two social safety nets, namely: UBI and GMI.

In the introduction to this paper we have sketched out a general framework on the mechanics of influence of technology-related risk on social policy preferences, building on insights from literature locating preference-formation into occupations, and on social psychology. Our argument calls into play two dimensions of technological risk, both objective and subjective, thus making our approach two-tiered in nature. We consider objective risk as our key variable, which affects preferences for social policy measures. Our main hypothesis is that exposure to the objective risk of replacement by machines, as measured by occupational routineness, associates with higher support for both UBI and GMI. In addition, a further hypothesis states that the effect of exposure to objective risk is positively affected by high perceptions of risk.

The empirical evidence we collected clearly and strongly supports our first hypothesis for both policy measures. This result is all the more significant, inasmuch as the prior probability of finding strong confirmation to our hypothesis was low, because of case selection, the policy measures considered and the relatively limited number of observations, which militate against findings that would significantly run counter to the null hypothesis – yet, they do. Also, robustness is attained by controlling for social class. Our second hypothesis is strongly confirmed by evidence of support for UBI, while it is not as regards GMI.

Two considerations are in order here. First: Why is our second hypothesis confirmed for UBI but not for GMI? Based on our expectation in section 2, we would have expected, if anything, the reverse. While we highlight the limited number of observations and the large number of controls, factors that stifle significance of any interaction term – which in turn makes the result for UBI quite compelling – part of the reason for this difference may be actually explained by the higher and rather homogenous level of support for GMI in the population as a whole as compared to UBI (see figure 2). In other words, the room for risk perception to increase support for GMI among those already more exposed to objective risk, in a context of limited observations, may not be sufficient for a significant association to emerge. Further analyses (available from the authors) show that, in descriptive statistics, support for GMI among those at high objective risk does increase alongside risk perception, but it is already quite high among those with low risk perception. Second: Our findings run counter to comparative evidence put forth in other studies, which find no correlation between technological (objective) risk exposure and support for UBI (Dermont and Weisstanner 2020, Martinelli 2019). Our explanation here is twofold. Our hunch is that high quality granular data on occupations can make a difference. More importantly, as it is apparent from comparing columns 2 and 3 in Tables 3 and 4, that is, models respectively excluding and including subjective risk as a regressor, it is clear that the inclusion of technological risk perceptions does make a difference for both UBI and GMI, by allowing for a better alignment of the empirical strategy to the analytical relationship between objective risk exposure and support for policy measures.

On the whole, our analysis empirically supports our claim of the existence of a strong relationship between exposure to technological risk and support for specific social policies, in particular once the effect of objective risk is disentangled from that of subjective perceptions.

However, all this is only true in a man’s world. Following Gingrich and Kuo (forthcoming), we find that the relation between technological risk and support for safety nets does fade away by dint of other labour market related risks, vulnerabilities and constraints that women have to deal with.

In conclusion, this paper has shown that exposure to technological risk has a strongly significant impact on support for social policy, but that this statement must be qualified, as it is true for men, but not for women.

Both are important results that will need to be investigated in future research, possibly also contributing to analytical reflections on the interplay between the exposure to objective and subjective risks, and the channels of occupation-based learning and recognition of such risks.

**References:**

Acemoglu, Daron, and Pascual Restrepo. 2019. "Automation and New Tasks: How Technology Displaces and Reinstates Labor." *Journal of Economic Perspectives* 33(2):3–30.

Arntz, Melanie, Terry Gregory, and Ulrich Zierahn. 2017. "Revisiting the Risk of Automation." *Economics Letters* 159:157-160.

Atkinson, Robert D., and John Wu. 2017. "False Alarmism: Technological Disruption and the U.S. Labor Market." *Information Technology & Innovation Foundation (ITIF)*, Retrieved from (https://itif.org/publications/2017/05/08/false-alarmism-technological-disruption-and-us-labor-market-1850-2015).

Autor, David H. 2015. "Why Are There Still So Many Jobs? The History and Future of Workplace Automation." *Journal of Economic Perspectives* 29(3):3-30.

Autor, David H., and David Dorn. 2013. "The Growth of Low-Skill Service Jobs and the Polarisation of the US Labor Market." *American Economic Review* 103 (5):1553-1597.

Autor, David H., and Michael J. Handel. 2013. "Putting Tasks to the Test: Human Capital, Job Tasks, and Wages." *Journal of Labor Economics* 31(1):59-96.

Autor, David H., Frank Levy, and Richard J. Murnane. 2003. "The Skill Content of Recent Technological Change: An Empirical Exploration." *Quarterly Journal of Economics* 118(4):1279–133.

Brynjolfsson, Erik, and Andrew McAfee. 2014. *The second machine age: Work, progress, and prosperity in a time of brilliant technologies.* New York: WW Norton & Co.

Cetrulo, Armanda, and Alessandro Nuvolari. 2019. "Industry 4.0: revolution or hype? Reassessing recent technological trends and their impact on labour." *Journal of Industrial and Business Economics* 46:391-402.

Dermont, Clau, and David Weisstanner. 2020. "Automation and the future of the welfare state: basic income as a response to technological change?" *Political Research Exchange* 2(1):1-11.

Esping-Andersen, Gösta. 1996. *Welfare States in Transition.* London: Sage.

Flora, Peter, and Arnold J. Heidenheimer, eds. 1981, *The Development of Welfare States in Europe and America*. New Brunswick, NJ: Transaction Publishers.

Frey, Carl Benedikt, and Michael A. Osborne. 2017. "The future of employment: How susceptible are jobs to computerisation?" *Technological Forecasting and Social Change* 114:254-280.

Galesic, Mirta, Henrik Olsson, and Jörg Rieskamp. 2018. "A sampling model of social judgment." *Psychological Review,* 125(3):363-39.

Gingrich, Jane and Kuo, Alexander forthcoming. "Gender, Technology, and Voting", in Busemeyer, M., Kemmerling, A., Marx, P., and Van Kersbergen, K. (forthcoming), Digitalization and the Welfare State, Oxford: Oxford University Press.

Goos, Maarten, Alan Manning, and Anna Salomons. 2009. "Job Polarisation in Europe." *American Economic Review: Papers & Proceedings* 99(2):58–63.

Gori, Cristiano. 2020. *Combattere la povertà*. Roma-Bari: Laterza.

Gualtieri, Valentina, Dario Guarascio, and Roberto Quaranta. 2018. "Routine Tasks and the Dynamics of Italian Employment." *Inapp Policy Brief* 7.

Häusermann, Silja, and Hanspeter Kriesi. 2015. "What do voters want? Dimensions and configurations in individual-level preferences and party choice." Pp. 202-230 in *The Politics of*

*Advanced Capitalism,* edited by P. Beramendi, S. Hausermann, H. Kitschelt, and H. Kriesi. Cambridge: Cambridge University Press.

Heimberger, Philipp, and Nikolaus Krowall. 2020. "Seven 'surprising' facts about the Italian economy." *Social Europe,* From (https://www.socialeurope.eu/seven-surprising-facts-about-the-italian-economy)

Jie Im, Zhen, and Komp-Leukkunen, Kathrin. 2021. "Automation and public support for workfare", *Journal of European Social Policy,* https://doi.org/10.1177/09589287211002432

Kitschelt, Herbert, and Philipp Rehm. 2014. "Occupations as a Site of Political Preference Formation." *Comparative Political Studies* 47(12):1670-1706.

Kurer, Thomas. and Häusermann, Sjlia. 2021. "Automation and social policy: Which policy responses do at-risk workers support?", Welfare Priorities, Working Paper 2/2021, Zurich: University of Zurich.

Kurer, Thomas, and Bruno Palier. 2019. "Shrinking and shouting: the political revolt of the declining middle in times of employment polarization." *Research & Politics,* 6:1:1-6.

Levy, Frank. 2018. "Computers and populism: artificial intelligence, jobs, and politics in the near term". *Oxford Review of Economic Policy,* 34: 3:393–417.

Martinelli, Luke. 2019. *Basic Income, Automation, and Labour Market Change*. Bath: Institute for Public Policy Research, University of Bath

Martinelli, Luke and Chrisp, Joe (forthcoming) "The political feasibility of a basic income in the emergent digitalized economy", in Busemeyer, M., Kemmerling, A., Marx, P., and Van Kersbergen, K. (forthcoming), Digitalization and the Welfare State, Oxford: Oxford University Press.

Natili, Marcello. 2018. *The Politics of Minimum Income. Explaining Path Departure and Policy Reversal in the Age of Austerity*. London: Palgrave.

Parolin, Zachary, and Linus Siöland. 2020. "Support for a universal basic income: A demand–capacity paradox?" *Journal of European Social Policy*, 30(1):5-19.

Rehm, Philippe. 2016. *Risk Inequality and Welfare States Social Policy Preferences, Development, and Dynamics*. Cambridge: Cambridge University Press

Roosma, Femke, and Van Oorschot, Wim. 2020. "Public opinion on basic income: Mapping European support for a radical alternative for welfare provision." *Journal of European Social Policy*, 30(2), 190-205.

Thewissen, Stefan, and David Rueda. 2019. "Automation and the Welfare State: Technological Change as a Determinant of Redistribution Preferences." *Comparative Political Studies* 52: 171–208.

Sacchi, Stefano. 2018. "The Italian Welfare State in the Crisis: Learning to Adjust?" *South European Society and Politics* 23(1):29-46.

Sacchi, Stefano, Dario Guarascio and Silvia Vannutelli. 2020. "Risk of technological unemployment and support for redistributive policies." In: *The European Social Model Under Pressure* Berlin: Springer, pp. 277-295.

Schwab, Klaus. 2016. *The Fourth Industrial Revolution,* Geneva: World Economic Forum.

Vlandas, Tim. 2021. "The political economy of individual-level support for the basic income in Europe." *Journal of European Social Policy,* 31(1), 62-77.

**Figure 1**. Objective (RTI) and subjective risk by occupation (first digit, ISCO-08)

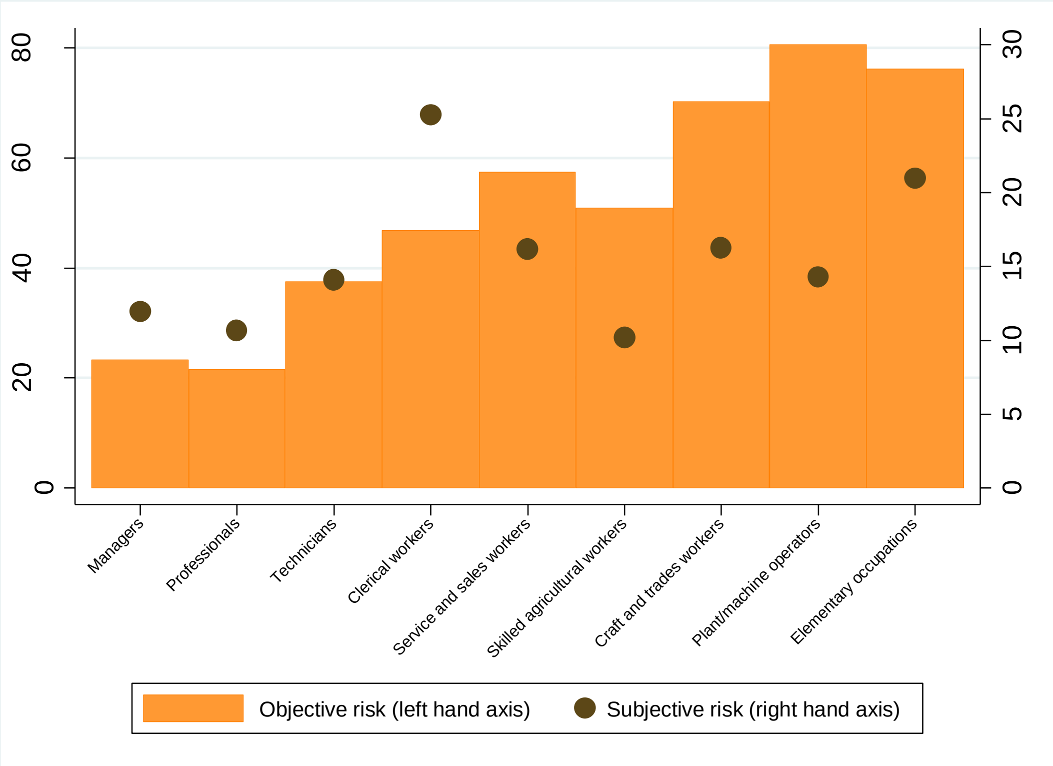

**Figure 2**. Support for social policy measures, by ESS Round

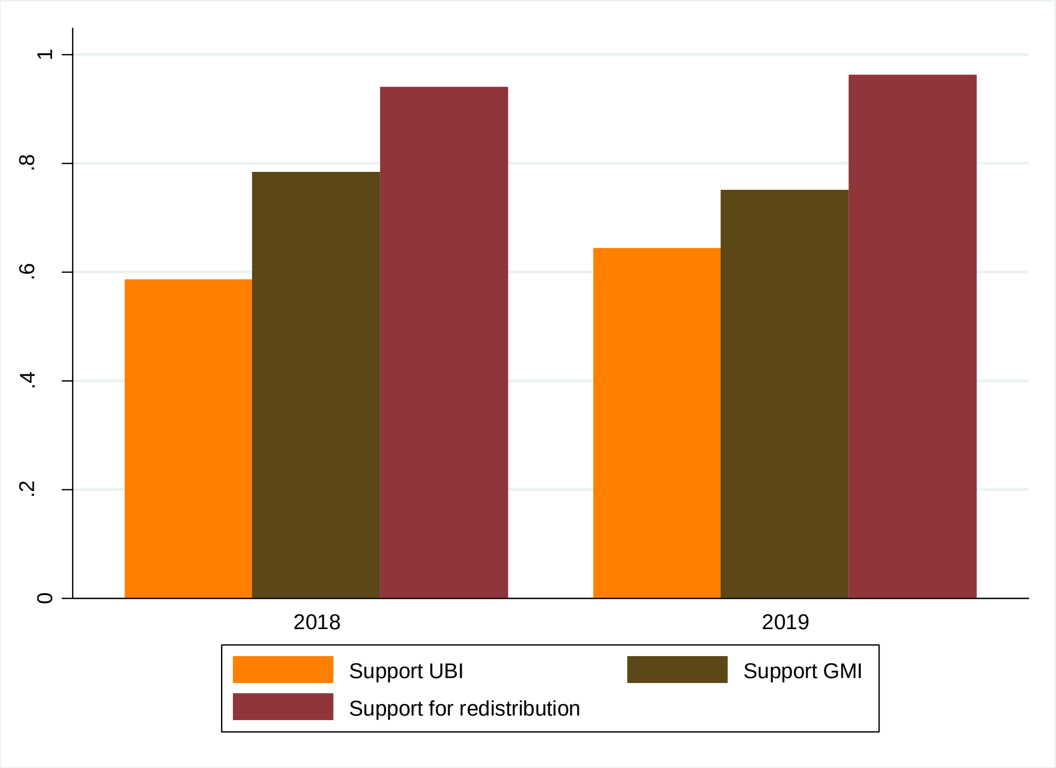

**Table 1.** ESS questions for UBI and GMI

| ESS question | Wording |
|---|---|
| **UBI**<br>Question E36 ESS Round 8 (all countries)<br>Question X12 ESS Round 9 (only Italy, half sample) | Some countries are currently talking about introducing a basic income scheme. In a moment I will ask you to tell me whether you are against or in favour of this scheme. First, I will give you some more details. The highlighted box at the top of this card shows the main features of the scheme. A basic income scheme includes all of the following:<br>• The government pays everyone a monthly income to cover essential living costs.<br>• It replaces many other social benefits.<br>• The purpose is to guarantee everyone a minimum standard of living.<br>• Everyone receives the same amount regardless of whether or not they are working.<br>• People also keep the money they earn from work or other sources.<br>• This scheme is paid for by taxes.<br>Overall, would you be against or in favour of having this scheme in Italy? |
| **GMI**<br>Question X11 ESS Round 8 (only Italy, whole sample)<br>Question X11 ESS Round 9 (only Italy, half sample) | Some countries are currently talking about introducing a minimum income scheme. In a moment I will ask you to tell me whether you are against or in favour of this scheme. First, I will give you some more details. The highlighted box at the top of this card shows the main features of the scheme. A minimum income scheme includes all of the following:<br>• The government pays a monthly income to all households whose income is below a set threshold.<br>• The purpose is to guarantee everyone a minimum standard of living.<br>• The received amount covers the difference between the household income and the set threshold.<br>• It is only given to those with no substantial real estate property.<br>• It is only given if household members who are able to work accept to actively seek for work and it is interrupted if they refuse a suitable job offer.<br>• This scheme is paid for by taxes.<br>Overall, would you be against or in favour of having this scheme in Italy? |

**Table 2**. Summary statistics total sample of those employed

| | Mean | Median | S.D. | Relative frequency |
|---|---|---|---|---|
| Supports UBI | 0.58 | 1.00 | 0.49 | |
| Supports GMI | 0.76 | 1.00 | 0.43 | |
| *Household income* (% of mean income) | 1.00 | .99 | 0.48 | |
| Woman | 0.47 | 0.00 | 0.50 | |
| Age | 52.23 | 52.00 | 17.09 | |
| News about politics and current affairs, watching, reading or listening, in minutes (*News*) | 3.35 | 1.00 | 4.89 | |
| Years of full-time *education* completed | 11.78 | 13.00 | 4.30 | |
| Left-Right Scale (5 classes) | 3.07 | 3.00 | 0.99 | |
| Migrants Access to Social Benefits and Services (*MigrSoc*) | 0.88 | 1.00 | 1.36 | |
| 0= *Never*+citizenship | | | | 0.452 |
| 1= After 1 year, only *if they work* and pay taxes | | | | 0.365 |
| 2= Immediately+After 1 year, *no conditions* | | | | 0.152 |
| Union Member | 0.20 | 0.00 | 0.40 | |
| *Supports* Government *Redistribution* | 0.95 | 1.00 | 0.22 | |
| *Struggles* on Present Income | 0.26 | 0.00 | 0.44 | |
| Likely to become unemployed in the next 12 months (*Job insecurity*) | 0.24 | 0.00 | 0.42 | |
| *Ever unemployed* for more than 3 months | 0.34 | 0.00 | 0.47 | |
| Self-employed | 0.22 | 0.00 | 0.42 | |
| Part-time | 0.10 | 0.00 | 0.30 | |
| Temporary | 0.21 | 0.00 | 0.40 | |
| Employed in *services* | 0.74 | 1.00 | 0.44 | |
| Variation of employment rate 2016-2006 at NUTS 1 (*delta_empl_rate*) | 0.20 | 0.20 | 0.02 | |
| Unemployment rate 2016 at NUTS 1 (*unempl_rate*) | 0.12 | 0.08 | 0.05 | |
| Variation of unemployment rate 2016-2006 at NUTS 1 (*delta_unempl_rate*) | 0.88 | 0.90 | 0.21 | |
| Living in the *North* | 0.52 | 1.00 | 0.50 | |
| Openness to trade at NUTS 1 (*opentrade*) | 0.44 | 0.56 | 0.15 | |
| opentrade*delta_u_rate | 0.41 | 0.53 | 0.20 | |
| RTI | 0.53 | 0.54 | 0.24 | |
| *Perceived risk* of technological unemployment | 0.23 | 0.15 | 0.23 | |
| **Total number: 3,917** | | | | |

**Table 3**. Support for UBI
OLS estimation (Clustered std errors at the 1st digit ISCO level)

| | (1)<br>Supports UBI | (2)<br>Supports UBI | (3)<br>Supports UBI | (4)<br>Supports UBI |
|---|---|---|---|---|
| Household income | -0.009 | -0.011 | -0.003 | -0.001 |
| | [0.049] | [0.051] | [0.040] | [0.041] |
| Woman | -0.066 | -0.067 | -0.038 | -0.038 |
| | [0.050] | [0.053] | [0.057] | [0.056] |
| Age | -0.003$^{**}$ | -0.003$^{**}$ | -0.001 | -0.001 |
| | [0.001] | [0.001] | [0.002] | [0.002] |
| News | -0.001 | -0.001 | 0.000 | 0.000 |
| | [0.004] | [0.004] | [0.006] | [0.006] |
| Education | -0.001 | -0.002 | 0.001 | 0.001 |
| | [0.005] | [0.007] | [0.004] | [0.004] |
| Right | -0.045 | -0.045 | -0.114$^{**}$ | -0.105$^{**}$ |
| | [0.030] | [0.029] | [0.041] | [0.039] |
| Left | -0.033 | -0.032 | 0.007 | 0.013 |
| | [0.035] | [0.036] | [0.042] | [0.046] |
| MigrSoc: if they work | 0.057$^{*}$ | 0.057$^{*}$ | -0.011 | -0.006 |
| | [0.025] | [0.026] | [0.027] | [0.028] |
| Migr-Soc: no conditions | 0.125$^{***}$ | 0.125$^{***}$ | 0.045 | 0.045 |
| | [0.033] | [0.034] | [0.062] | [0.063] |
| Services | -0.016 | -0.019 | -0.005 | 0.003 |
| | [0.060] | [0.060] | [0.057] | [0.055] |
| Union Member | -0.061 | -0.062 | -0.072 | -0.076 |
| | [0.038] | [0.037] | [0.047] | [0.045] |
| Struggles | -0.032 | -0.030 | 0.000 | 0.004 |
| | [0.033] | [0.038] | [0.043] | [0.041] |
| Job Insecurity | 0.052 | 0.054 | 0.041 | 0.039 |
| | [0.047] | [0.049] | [0.062] | [0.062] |
| Supports Redistribution | 0.065 | 0.067 | 0.017 | 0.027 |
| | [0.045] | [0.048] | [0.091] | [0.087] |
| Ever Unemployed | 0.005 | 0.006 | -0.042 | -0.044 |
| | [0.052] | [0.051] | [0.047] | [0.050] |

| | | | | |
|---|---|---|---|---|
| Self-employed | -0.072 | -0.072 | -0.050 | -0.051 |
| | [0.048] | [0.049] | [0.052] | [0.053] |
| Part-time | 0.086 | 0.083 | 0.039 | 0.036 |
| | [0.058] | [0.053] | [0.073] | [0.072] |
| Temporary | -0.046* | -0.045* | 0.056 | 0.051 |
| | [0.024] | [0.022] | [0.062] | [0.064] |
| delta_empl_rate | -2.441 | -2.380 | -1.674 | -1.756 |
| | [2.178] | [2.117] | [2.788] | [2.746] |
| unempl_rate | 0.154 | 0.118 | 0.374 | 0.413 |
| | [0.488] | [0.593] | [0.581] | [0.614] |
| delta_unempl_rate | 0.478 | 0.469 | 0.240 | 0.243 |
| | [0.302] | [0.303] | [0.365] | [0.354] |
| North | -0.267 | -0.267 | -0.125 | -0.125 |
| | [0.152] | [0.152] | [0.142] | [0.139] |
| RTI | | -0.002 | 0.005** | -0.004 |
| | | [0.007] | [0.002] | [0.004] |
| High Perceived Risk | | | -0.023 | 0.116 |
| | | | [0.042] | [0.080] |
| High Perceived Risk# RTI | | | | 0.016** |
| | | | | [0.007] |
| Constant | 0.874* | 0.880* | 0.881 | 0.789 |
| | [0.451] | [0.472] | [0.528] | [0.513] |
| Observations | 832 | 832 | 597 | 597 |
| R-sq | 0.049 | 0.050 | 0.042 | 0.049 |

Notes:
See Table 1 for labels.
Macroregional variables on openness to trade and trade intensity omitted due to collinearity.

**Table 4**. Support for GMI
OLS estimation (Clustered std errors at the 1st digit ISCO level)

| | (5)<br>Supports GMI | (6)<br>Supports GMI | (7)<br>Supports GMI | (8)<br>Supports GMI |
|---|---|---|---|---|
| Household income | 0.042 | 0.043 | 0.022 | 0.021 |
| | [0.028] | [0.028] | [0.031] | [0.032] |
| Woman | 0.016 | 0.016 | 0.055 | 0.057 |
| | [0.023] | [0.023] | [0.038] | [0.037] |
| Age | -0.003* | -0.003* | -0.000 | -0.000 |
| | [0.001] | [0.001] | [0.002] | [0.002] |
| News | 0.002 | 0.002 | 0.002 | 0.002 |
| | [0.002] | [0.002] | [0.003] | [0.003] |
| Education | 0.005** | 0.005* | 0.011* | 0.011* |
| | [0.002] | [0.002] | [0.006] | [0.006] |
| Right | -0.023 | -0.022 | -0.065 | -0.065* |
| | [0.034] | [0.034] | [0.036] | [0.035] |
| Left | 0.026 | 0.026 | 0.065 | 0.064 |
| | [0.028] | [0.028] | [0.051] | [0.050] |
| MigrSoc: if they work | 0.146*** | 0.145*** | 0.087** | 0.086** |
| | [0.029] | [0.029] | [0.037] | [0.037] |
| Migr-Soc: no conditions | 0.121*** | 0.121*** | 0.070 | 0.072 |
| | [0.030] | [0.030] | [0.068] | [0.067] |
| Services | -0.124*** | -0.122*** | -0.023 | -0.025 |
| | [0.019] | [0.019] | [0.052] | [0.052] |
| Union Member | -0.071** | -0.071** | -0.121*** | -0.119*** |
| | [0.025] | [0.025] | [0.033] | [0.034] |
| Struggles | -0.004 | -0.005 | -0.002 | -0.004 |
| | [0.034] | [0.035] | [0.072] | [0.073] |
| Job Insecurity | 0.042 | 0.041 | 0.006 | 0.008 |
| | [0.036] | [0.038] | [0.051] | [0.049] |
| Supports Redistribution | 0.183*** | 0.182*** | 0.139* | 0.136* |
| | [0.040] | [0.039] | [0.070] | [0.071] |
| Ever Unemployed | -0.011 | -0.012 | -0.019 | -0.018 |
| | [0.034] | [0.033] | [0.039] | [0.039] |
| Self-employed | -0.052 | -0.052 | -0.025 | -0.023 |

| | | | | |
|---|---|---|---|---|
| | [0.034] | [0.033] | [0.046] | [0.046] |
| Part-time | 0.069* | 0.071* | 0.073 | 0.073 |
| | [0.033] | [0.033] | [0.056] | [0.056] |
| Temporary | 0.003 | 0.003 | 0.058 | 0.060 |
| | [0.022] | [0.023] | [0.052] | [0.053] |
| delta_empl_rate | -0.216 | -0.243 | 1.550 | 1.492 |
| | [1.416] | [1.391] | [1.522] | [1.599] |
| unempl_rate | 1.240** | 1.255** | 1.079 | 1.079 |
| | [0.391] | [0.401] | [0.625] | [0.616] |
| delta_unempl_rate | 0.384** | 0.388** | -0.012 | 0.001 |
| | [0.165] | [0.162] | [0.257] | [0.259] |
| North | -0.107 | -0.108 | 0.021 | 0.017 |
| | [0.076] | [0.075] | [0.082] | [0.085] |
| RTI | | 0.001 | 0.009*** | 0.013*** |
| | | [0.003] | [0.002] | [0.003] |
| High Perceived Risk | | | -0.039 | -0.091 |
| | | | [0.026] | [0.059] |
| High Perceived Risk# RTI | | | | -0.006 |
| | | | | [0.006] |
| Constant | 0.260 | 0.257 | 0.105 | 0.147 |
| | [0.228] | [0.226] | [0.320] | [0.346] |
| Observations | 819 | 819 | 594 | 594 |
| R-sq | 0.098 | 0.098 | 0.085 | 0.086 |

Notes:
See Table 1 for labels.
Macroregional variables on openness to trade and trade intensity omitted due to collinearity.

**Table 5**. Support for UBI and for GMI – Men and Women subsamples
OLS estimation (Clustered std errors at the 1st digit ISCO level)

| | Men Supports UBI | Women Supports UBI | Men Supports GMI | Women Supports GMI |
|---|---|---|---|---|
| Household income | -0.011 | 0.013 | 0.009 | 0.039 |
| | [0.036] | [0.060] | [0.039] | [0.065] |
| Age | -0.000 | 0.000 | 0.002 | -0.003 |
| | [0.002] | [0.003] | [0.002] | [0.003] |
| News | 0.006 | -0.004 | 0.004 | 0.001 |
| | [0.005] | [0.007] | [0.005] | [0.005] |
| Education | -0.009 | 0.014 | $0.017^{**}$ | -0.001 |
| | [0.010] | [0.009] | [0.006] | [0.009] |
| Right | -0.054 | $-0.177^{**}$ | -0.051 | -0.095 |
| | [0.044] | [0.072] | [0.041] | [0.057] |
| Left | 0.080 | -0.063 | $0.123^{*}$ | -0.037 |
| | [0.075] | [0.111] | [0.058] | [0.057] |
| MigrSoc: if they work | 0.078 | -0.076 | 0.062 | 0.103 |
| | [0.057] | [0.081] | [0.078] | [0.062] |
| Migr-Soc: no conditions | $0.132^{*}$ | -0.093 | 0.080 | 0.042 |
| | [0.067] | [0.149] | [0.049] | [0.104] |
| Services | 0.001 | -0.017 | 0.043 | $-0.193^{***}$ |
| | [0.067] | [0.162] | [0.067] | [0.050] |
| Union Member | -0.138 | -0.011 | $-0.157^{*}$ | -0.095 |
| | [0.078] | [0.133] | [0.076] | [0.068] |
| Supports Redistribution | -0.095 | $0.299^{*}$ | 0.083 | 0.309 |
| | [0.072] | [0.147] | [0.057] | [0.173] |
| Struggles | -0.010 | 0.024 | 0.015 | -0.059 |
| | [0.050] | [0.065] | [0.065] | [0.087] |
| Job Insecurity | 0.085 | -0.023 | 0.053 | -0.053 |
| | [0.137] | [0.148] | [0.096] | [0.088] |
| Ever Unemployed | -0.041 | -0.061 | -0.019 | 0.024 |
| | [0.078] | [0.082] | [0.074] | [0.052] |
| Self-employed | -0.005 | $-0.127^{*}$ | -0.067 | 0.079 |
| | [0.056] | [0.059] | [0.053] | [0.047] |
| Part_time | -0.083 | 0.097 | 0.042 | $0.161^{**}$ |

| | | | | |
|---|---|---|---|---|
| | [0.144] | [0.096] | [0.157] | [0.053] |
| Temporary | 0.171** | -0.003 | 0.065 | 0.053 |
| | [0.067] | [0.131] | [0.059] | [0.078] |
| delta_empl_rate | -0.956 | -2.452 | 1.531 | 1.607 |
| | [3.486] | [2.109] | [2.663] | [1.247] |
| unempl_rate | -0.099 | 0.882 | 0.803 | 1.747 |
| | [1.330] | [1.481] | [0.478] | [1.546] |
| delta_unempl_rate | 0.317 | 0.128 | 0.008 | -0.059 |
| | [0.535] | [0.397] | [0.348] | [0.393] |
| North | -0.173 | -0.056 | -0.015 | 0.082 |
| | [0.127] | [0.248] | [0.132] | [0.088] |
| RTI | -0.016** | 0.006 | 0.015*** | 0.009 |
| | [0.006] | [0.007] | [0.004] | [0.005] |
| High Perceived Risk | 0.240*** | -0.041 | -0.109 | -0.053 |
| | [0.055] | [0.245] | [0.088] | [0.049] |
| High Perceived Risk # RTI | 0.033*** | -0.001 | -0.005 | -0.007 |
| | [0.007] | [0.021] | [0.009] | [0.006] |
| Constant | 0.669 | 0.586 | 0.048 | 0.318 |
| | [0.710] | [0.737] | [0.435] | [0.365] |
| Observations | 339 | 258 | 332 | 262 |
| R-sq | 0.120 | 0.080 | 0.111 | 0.129 |

Notes:
See Table 1 for labels.
Macroregional variables on openness to trade and trade intensity omitted due to collinearity.