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Automation, Globalization and the (Mis)perception of Risks: New Evidence from Six Advanced Economies*

Gregorio Buzzelli

A growing literature investigates the political implications of automation and globalization, lacking an explanation for the similarity between the nationalist stances triggered by both economic changes. I provide an empirical explanation based on risk perception, showing that automation «losers» misattribute the cause of their material concerns toward migrants. I put forward an interpretation of misattribution based on status loss against which I test a rational-choice hypothesis. I run multivariate models on a novel survey dataset testing the effects of the regional, sectoral, and occupational impact of automation and globalization on risk perception. I find that the exposure to automation is associated with the fear of migrants, regardless of other individual vulnerabilities. On the contrary, the exposure to imports from China only weakly and positively correlate with fear of globalization.

Keywords: Automation; Globalization; Blame misattribution; Risk perception; Labor market.

1. Introduction

Throughout human history, structural changes of the economy have always had important political and societal repercussions. The creation of a new trade route with the American colonies in the 16th century dramatically undermined the international prestige and power of the Republic of Venice (Calimani 2019), while the dramatic societal implications of early industrialization led to the birth of new political

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movements and the welfare state (Berman 2006; Polanyi 1944). In the last three decades, the integration of international markets and the advent of Information and Communication Technologies (ICT) have exerted a remarkable influence on advanced labor markets (Autor *et al.* 2003; Thewissen and van Vliet 2019), fostering political conflicts between «winners» and «losers» of these transformations (Kurer and Palier 2019; Rogowski 1987). Research on public opinion has been focusing on the micro-foundations of post-industrial politics (Busemeyer and Garritzmann 2019; Gallego *et al.* 2022), uncovering a causal link between the exposure to the economic threats posed by automation and trade openness and the rise of nationalist and protectionist stances (Anelli *et al.* 2019; Colantone and Stanig 2018; Gallego and Kurer 2022).

However, doubts emerge regarding the validity of approaches based on material self-interested reasoning (i.e., economic voting) to interpret the political repercussions of automation. While nationalist and protectionist attitudes sound a «rational» response to the economic threats posed by the increasing import competition, the link with technological replaceability on the labor market is more puzzling. I argue that this puzzle can be addressed by looking at the perceptual reactions triggered by the exposure to the distributional consequences of these structural changes. In most cases, the existing contributions test the relation between individual risk exposure and the perception of its correlated distributional impact or the fear of unemployment (Kurer and Häusermann 2022; Walter 2017). But individuals might misattribute the cause of the sensed material threat. Regarding automation, a newborn stream of the literature shows that vulnerable workers tend to divert the blame for their material concerns from technology toward globalization and migrants (Kaihovaara and Im 2020; Wu 2021). Nonetheless, the literature lacks both a theoretical understanding and a robust empirical assessment of the phenomenon.

This article aims to strengthen the micro-foundations of post-industrial politics, testing whether individuals misattribute the source of economic risks brought by automation, while being aware of globalization threats. First, I put forward an interpretation of misattribution based on a review of a fragmentary literature that refers to the status decline of automation «losers» (Anelli *et al.* 2019; Gallego and Kurer 2022; Kaihovaara and Im 2020; Kurer 2020; Wu 2021). Then, I present an innovative and encompassing empirical strategy aimed at charting the perceptual channels whereby individuals perceive the occupational impact of automation and globalization. Lastly, I provide evidence against a rational-choice interpretation of misattribution, strengthening the status-based perspective presented in this paper. To my knowledge, this is the first work comparing individuals' perceptions of the occupational consequences of automation and globalization. Another empirical novelty lies in the adoption of risk perceptions – instead of political attitudes or preferences – to operationalize individuals' understanding of these structural economic changes.

Using a novel survey (INAPP 2022), I test the impact of exposure to these structural changes on the perception of the economic risks linked to automation, globalization, and migration. The sample used includes 15,000 respondents ca from six European countries (Germany, Italy, the Netherlands, Poland, Sweden, the United Kingdom). I rely on a comprehensive set of regional, sectoral, and occupational indexes to estimate individuals' level of exposure to the labor market's impact of automation and globalization. In line with the literature on risk misattribution (Wu 2021), I find a strong and positive correlation between exposure to automation and fear of migrants. On the contrary, sectoral exposure to Chinese import correlates with concerns related to globalization, although this association is partially questioned by some robustness checks. Lastly, I provide evidence against a rational-choice interpretation of blame misattribution, showing that individuals exposed to other sources of material concerns have similar chances to their counterpart to ascribe the pressure of automation to migrants.

The paper is structured as follows. The next two sections review the literature on the occupational and political consequences of automation and globalization. In the subsequent section, I present two possible perceptual reactions to these structural economic changes, providing a tentative mechanism lying behind blame misattribution. The following two sections present the empirical strategy and the findings. In the last section, I discuss the results and the broad implications of this work.

2. The Impact of Globalization and Automation on the Labor Market

The interest of political economists in the occupational implications of globalization dates back several decades (Samuelson 1971; Stolper and Samuelson 1941), whereas the research on the impact of technological change on the labor market has a shorter history (Autor *et al.* 2003; Murnane *et al.* 1995). The attempt to clearly identify the «winners» and «losers» of these structural changes inevitably comes up against their compound nature. Technological change and globalization are characterized by a high level of abstraction (Sartori 1970), and scholars have adopted different operational drivers to assess their effects.

International trade is arguably the most widely studied engine of globalization, especially since trade barriers were lowered in the 1990s by a series of international treaties. Exports of manufacturing goods from low-income countries toward advanced economies boomed thanks to their availability of low-wage labor (OECD 2012). China undoubtedly won the lion's share of global trade, becoming the world's largest exporter of goods between the 1990s and 2010s (OECD 2012). Similarly, Central-Eastern European countries benefited from the fall of the Iron Curtain and the following EU enlargements, engaging in a catch-up growth supported by rising exports towards the West (Nicoli *et al.* 2021).

Consistently with a factor-specific model (Stolper and Samuelson 1941), major distributional consequences in advanced market economies are recorded at the sector level. Employment declines have been detected in manufacturing sectors, highly exposed to rising imports from «low-income» countries (Polgár and Wörz, 2010; Thewissen and van Vliet 2019). Hence, workers employed in tradeable manufacturing sectors are usually defined as the main group of globalization «losers». In addition, different scholars show that rising imports produce spill-over effects at the regional level – i.e., increasing unemployment, reducing wages and labor participation – (Chiquiar 2008; Kovak 2013; Topalova 2010), especially when local labor markets are highly reliant on manufacturing employment (Autor *et al.* 2013).

Unlike globalization, the impact of technological change on the labor market was a relatively uncharted terrain until the 1990s. The first group of scholars investigating this topic argued that automation would have raised the demand for skilled workers at the expense of the unskilled ones – known as the «skill-biased technical change» (SBTC) (Manning 2004). However, Autor *et al.* (2003) challenged the SBTC model, showing that middle-skill occupations are the actual «losers» of automation – a framework called the «routine-biased technical change» (RBTC). The reason lies in the routine nature of the tasks composing those occupations (e.g., production workers, clerks, etc.), which are easily codifiable and replaceable by Information and Communication Technologies (ICT) (Autor 2015). On the contrary, both low- and high-skill occupations involving creativity, adaptability, and in-person interactions act as a complement to technology. It should be also mentioned that, similar to trade, technological change can trigger disruptive economic consequences at the regional level in manufacturing-intensive labor markets, particularly due to the increasing usage of industrial robots (Acemoglu and Restrepo 2020; Anelli *et al.* 2019).

Although the RBTC has become the reference model in the literature, recent contributions show that only a small minority of routine workers actually lose their job. The decline of middle-skill occupations is mainly caused by a phase-out with more exits of old workers than entries of the new generations (Cortes 2015; Kurer and Gallego 2019). Limited impact on employment dynamics is also found with regard to industrial robots (Caselli *et al.* 2021; Klenert *et al.* 2022). Nonetheless, workers vulnerable to automation are likely to experience a frustrating stagnation in their current job or a relocation to lower-skill tasks, while career advancement opportunities are reserved for their colleagues whose skills better complement technology (Autor 2013; Küstermann 2022).

Finally, the interaction of automation and globalization produces distributional consequences worth to be mentioned. Most importantly, political economists show that the advent of ICT, together with the liberalization of FDI, was crucial to enabling the tradability of services that previously required in-person contact (e.g., financial services) (Wren 2013). As a result, lots of occupations have become «offshorable» to low-wage countries, generating a new source of labor market risk for middle- and high-skill workers (Blinder 2009; Blinder and Krueger 2013).

Overall, it seems hard to identify clear groups of «winners» and «losers» of the post-industrial transition. Different manifestations of automation and globalization – and their interaction – affect different social groups through distinct occupational effects, hence they require to be investigated separately. Various proxies of risk exposure should be considered since the same sources of labor market change produce distributional consequences at different levels, i.e., region, sector, and occupation. The complexity of this picture is mirrored in the studies investigating the political conflicts that emerge from those changes.

3. The Micro-Foundations of the Post-Industrial Politics in the Literature

The sizeable distributional effects of automation and globalization can be reasonably expected to have an impact on the political arena. The success of public opinion studies witnessed over the last two decades has come forward also in this field, and researchers committed to investigating the micro-foundations of post-industrial politics (Busemeyer and Garritzmann 2019; Gallego *et al.* 2022). The broad reference theory of these contributions is economic voting (Lewis-Beck and Stegmaier 2019), as the material concerns resulting from the exposure to occupational risks are usually addressed as the main determinants of political preferences (Guarascio and Sacchi 2022; Kurer and Häusermann 2022; Sacchi *et al.* 2020; Walter 2017). The interest of researchers mainly clustered around two broad streams: electoral behavior and social policy preferences.

Automation and globalization appear to foster similar voting choices. Nationalist parties result to be particularly able to harvest voters amidst both the «losers» of automation and market openness (Caselli *et al.* 2020; Colantone and Stanig 2018; Dal Bò *et al.* 2019). Evidence of the relation between risk exposure and the propensity to vote for far-right parties has been found both at the individual and regional levels (Anelli *et al.* 2019; Im *et al.* 2019; Milner 2021). However, as already pointed out, the causal story related to automation appears more puzzling. While a backlash against globalization can arguably benefit nationalist parties (Walter 2021), the role of automation in fostering the far right needs some further explanations.

Another puzzling finding comes from the literature on policy preferences. The strong support for redistributive and compensatory policies by the «losers» of automation and globalization is not bewildering (Guarascio and Sacchi, 2022; Rehm 2009; Sacchi *et al.* 2020; Thewissen and Rueda 2019; Walter 2017), and it is interpreted as a demand of immediate protection (Burgoon 2001; Busemeyer and Sahm 2021; Kurer and Häusermann 2022; Weisstanner 2021)[1]. What may leave the reader perplexed is the finding presented in a recent paper by di Tella and Rodrik (2020), where the authors show that individuals prefer protectionist measures in the face of different causes of labor-market shocks, including both technological change and international trade. While the positive effect of trade shocks on support for protectionist tariffs is in line with different previous contributions (Mayda and Rodrik 2005; Rho and Tomz 2017), the finding related to automation sounds counterintuitive. These findings resonate with the lack of differentiation in the socio-economic policies demanded in response to automation and globalization found in a recent conjoint survey experiment run by INAPP (2022).

[1] Nonetheless, few recent contributions present different evidence, showing support of at-risk workers for social investment policies (Busemeyer and Garritzmann 2019; Im 2021).

To sum up, the negative distributional consequences of these structural changes of the economy appear to be associated with a political backlash against globalization. These preferences can be interpreted as a self-interested response to the economic threats posed by globalization, whereas the same cannot be said for automation. As a result, the application of the economic voting theory to automation is challenged[2]. However, little attention is devoted to individuals' perception of the risks associated with economic structural changes. Individual's capability to formulate preferences consistent with their interests is heavily dependent on the information gathered and used during decision-making (Ahrens 2022). Most of the existing literature focuses on the relation between the objective measurement of risk and perceived job insecurity (Rehm 2009; Scheve and Slaughter 2004; Walter 2017), while only a few studies detect a positive correlation between risk exposure and the awareness of being threatened by a structural-specific risk (Gallego *et al.* 2022; Guarascio and Sacchi 2022; Kurer and Häusermann 2022; Stantcheva 2022).

Nonetheless, recent contributions show that individuals tend to overestimate the impact of globalization on layoffs, overlooking the effects of automation (Mutz 2021; Zhang 2019). Kaihovaara and Im (2020) demonstrate that individuals performing automatable occupations are more likely to show anti-migrant attitudes. This evidence supports the pioneering work of Wu (2021), who argues that replaceable workers tend to misattribute the cause of their material concerns, blaming globalization and migrants instead of automation. As a result, people exposed to the risk of automation are more prone to support protectionist policies. The author lists three possible drivers of misattribution: intense media coverage of globalization, people's familiarity with technology, and politically motivated framing by elites.

[2] A possible alternative to the self-interest explanation may come from the growing branch of the economic voting literature exploring sociotropical behaviors (Kiewiet and Lewis-Beck 2011; Kinder and Kiewiet 1981). These studies show that individuals' preferences are grounded on judgments regarding country-level economic factors, rather than the personal pocketbook. However, sociotropic reasoning should not be conflated with altruism (Schaffer and Spilker 2019), since the key difference between the former and egoistic calculus is just a matter of informational source – i.e., national and personal economic circumstances – and not of motivation (Kinder and Kiewiet 1981). Therefore, personal material concerns are always at the core of the economic voting theory, and its applicability to the investigation of the political consequences of automation is questioned. As regards research on «genuine» sociotropic reasoning, the very early stage of its development only allows preliminary speculations, but recent advancements may open interesting new avenues (van der Duin, n.d.).

The latter, particularly, leverage group cues that trigger emotional reactions against outgroups (Brader *et al.* 2008), reinforcing preexisting beliefs of at-risk workers about labor-market competition as a zero-sum game. Nonetheless, a top-down supply-side story does not account for a sufficient theoretical explanation. A causal mechanism supporting misattribution at micro-level has not been formulated yet.

Overall, the misattribution hypothesis appears to be the most solid explanation for the backlash against globalization associated with the occupational impact of automation. It helps frame the latter within the theory of economic voting, composing the material and cultural concerns brought by automation. However, some theoretical and methodological advancements are needed to strengthen this interpretation and, more generally, the study of the micro-foundations of post-industrial politics. In the next section, I present an argument – even though tentative – explaining the correlation between automation-related risks and the fear of migrants.

4. The (Mis) Perception of Automation and Globalization Economic Risks

The theoretical argument presented in this section addresses the gap in political economy's literature regarding the perception of automation and globalization. I present two possible perceptual reactions to these economic threats, i.e., risk awareness and the misattribution of blame. Acknowledging the little theoretical reflection on the latter, I put forward a tentative mechanism lying behind the misattribution of the automation risk, against which I test a rival hypothesis.

Sorting through the literature on economic voting, we find that most of the contributions refer to a general sense of job or income insecurity when investigating the perceptual reactions to the negative distributional consequences of automation and globalization (Burgoon and Dekker 2010; Rehm 2009; Scheve and Slaughter 2004; Walter 2017). More recently, scholars have shown interest in individuals' awareness of being exposed to a specific risk (Gallego *et al.* 2022; Guarascio and Sacchi 2022; Kurer and Häusermann 2022; Stantcheva 2022). The latter can be particularly informative on the political repercussions of economic transformations, since rational individuals are expected to demand different policies to address specific economic challenges.

However, as pointed out in the previous section, automation and globalization «losers» show similar political reactions in spite of the distinct threats they are exposed to (Anelli *et al.* 2019; Colantone and Stanig 2018; Dal Bò *et al.* 2019; di Tella and Rodrik 2020; Milner 2021). This puzzling finding drives the novel research on a third perceptual reaction to structural economic changes, which is illustrated by the positive correlation between technological replaceability and fear of migrants (Kaihovaara and Im 2020; Wu 2021). Existing contributions only provide a supply-side explanation for blame misattribution, suggesting that media and political elites have played a key role in the social acceptance of technology. More specifically, these scholars emphasize a stark difference between a positive framing of technological advancements, while both media and populist political leaders have been repeatedly blaming globalization as the main cause of disruptive labor market changes (Benanav 2020; Gallego and Kurer 2022; Wu 2021). As a result, individuals exposed to the negative consequences of automation may develop reactionist stances following the cultural and political framing of structural economic changes.

This mechanism is worth to be further investigated, but it can hardly be the only driver of misattribution. A complementary demand-side investigation can start from the wide literature in sociology and political science that underlines the positive correlation elapsing between existential insecurity and cultural conservatism (Inglehart 1975, 2018; Schaller and Park 2011; Thornhill and Fincher 2014). Nonetheless, this interpretation faces two major inconsistencies. First, economic hardship is not unequivocally associated with support for exclusionary and reactionist preferences (Arndt 2013; Caiani and Graziano 2019; Lisi *et al.* 2019). Moreover, as mentioned in the previous section, the large majority of automation «losers» experience a frustrating stagnation in less-valuable jobs instead of the material insecurity brought by unemployment (Autor 2013; Kurer and Gallego 2019; Küstermann 2022).

An effective demand-side interpretation of blame misattribution requires an argument tailored to the specific distributional impact of automation. It is well established in the literature that automation «losers» perform typical middle-class occupations once tied to opportunities of upward societal mobility (Iversen and Soskice 2019; Kurer and Palier 2019). The stagnating and downgrading position of workers in those occupations can arguably frustrate their economic aspirations, boosting reactionist and nativist sentiments (Ballard-Rosa *et al.* 2022; Bolet 2022; Burgoon *et al.* 2019; Gidron and Hall 2017; Häusermann *et al.* 2021; Im *et al.* 2022; Iversen and Soskice 2019). Similarly, the limited impact of robotization on labor share might be mirrored by rising low-quality jobs for manufacturing-intensive regions, although corroborated findings are still missing (Caselli *et al.* 2021; Klenert *et al.* 2022). The mechanism lies in the loss of a once-prestigious societal position experienced by automation «losers», rather than a full-blown occupational risk (Kurer, 2020). The literature on social psychology shows that such a threat to ingroup value, both cultural and material, is likely to trigger hostility against low-status outgroups (Küpper *et al.* 2010; Riek *et al.* 2006). Hence, migrants may be misperceived as an economic threat by automation «losers» in need of social enhancement. This argument resonates with the contributions suggesting that the loss of social status experienced by replaceable middle-class workers may represent the mediating factor that triggers nationalist stances (Anelli *et al.* 2019; Gallego and Kurer 2022; Kaihovaara and Im 2020; Kurer 2020). In short, I argue that the negative distributional effects of automation are mainly associated with status concerns rather than strictly material hardship, leading at-risk individuals to direct their anxiety towards migrants as «outsiders» threatening their societal position.

Although the mediating role of social status cannot be tested in the present work, I put forward a rival hypothesis, expecting to falsify a rational-choice interpretation of misattribution. In contrast with the argument just presented, at-risk workers might fear migrants because technological replaceability brings them to compete with non-native workers for low-skilled jobs and poor services (Cremaschi *et al.* n.d.; Kaihovaara and Im 2020; Mayda 2006; Oesch and Rodriguez Menes 2011; Scheve and Slaughter 2001). Instead of missing the target of blame because of cultural-psychological reasons, individuals exposed to the negative occupational consequences of automation may simply have economic motivations to fear migrants. A strict rational-choice explanation would rule out any possible cultural driver behind automation misperception, jeopardizing the role of status loss, which comprises both economic and cultural concerns (Ciccolini 2021). This rival hypothesis is confirmed if the correlation between the automation risk and the fear of migrants is mainly driven by individuals threatened by additional material concerns. On the contrary, intentional economic calculus is seriously undermined if individuals' socioeconomic conditions do not alter the relation under scrutiny.

In line with the argument presented in this section, I posit that the exposure to automation risk is channeled through misattributed concerns for rising immigration. On the contrary, individuals exposed to the tangible and disruptive consequences of markets' integration are expected to correctly trace their material concerns back to globalization. Finally, I expect the misattribution of automation risks towards the fear of migrants to remain consistent across groups with different socioeconomic conditions. These expectations are formalized in the following three hypotheses:

H1. The exposure to automation-related economic risk at different levels is correlated with a greater concern for rising immigration.

H2. The exposure to globalization-related economic risk at different levels is correlated with a greater concern for globalization.

H3. The exposure to automation-related economic risk has similar effects on the fear of migrants for economically vulnerable and non-vulnerable individuals.

5. Data and Empirical Strategy

I rely on a novel dataset collected in November 2020 as part of a conjoint survey experiment investigating the preferences on policies aimed to soften the impact of technological change and globalization on the labor market (INAPP 2022)[3]. I use a sample of the observational data – which follows the experiment – from six European countries (Germany, Italy, the Netherlands, Poland, Sweden, the United Kingdom), including only respondents in employment at the time of the survey. The sample ensures variation of political-economic institutional configurations and economic performance in the last 10 years (INAPP 2022). To my knowledge, this is the first empirical study that compares the impact of automation and globalization on economic risk perception. I use linear regression models with high-dimensional fixed effects (Correia 2017) to assess the impact of seven indexes of risk exposure on three possible perceptual reactions. Standard errors are simultaneously clustered at the regional, sectoral, or occupational level. I run traditional OLS, ordered logistic[4], and logit models as robustness checks, with continuous and binary versions of the dependent variables. As additional robustness tests, I run separate models for

[3] Data were collected by IPSOS-IT in the second half of 2020 in eight countries (Germany, Italy, Japan, the Netherlands, Poland, Sweden, the United Kingdom and the United States of America), including 20,000 respondents. Hard quotas have been applied for gender, age, education, region, and employment status, while soft quotas have been applied for occupation (ISCO08 1-digit) and sector of employment (NACE Rev.2 1-digit). For this paper, we only rely on the observational data, but it should be noted that the survey is completed by a randomized conjoint experiment that investigates individuals' preferences for policies aimed to soften the occupational impact of technological change and globalization. Main results are presented in INAPP (2022).

[4] The Brant test suggests that the parallel slopes assumption is not violated.

each index of exposure. Lastly, I run a split sample regression analysis in order to test the rational-choice interpretation of misattribution. The full model estimating the effects of risk exposure on the fear of migrants is run for sub-samples of respondents with different socio-economic conditions. This technique enables testing whether the correlation between automation risk and the fear of migrants remains consistent between economically vulnerable and non-vulnerable groups.

Dependent Variables

Another element of novelty concerns the operationalization of individuals' judgment about automation and globalization. This dataset gives the unique opportunity to adopt dependent variables that capture the perception of three structural risks of post-industrial societies (i.e., technological change, globalization, and immigration), rather than using attitudes or policy preferences like previous studies did (Kaihovaara and Im 2020; Wu 2021). This strategy is aimed to better capture the immediate perception of those phenomena by respondents. Structural risks perceptions are operationalized through a triplet of 10-point scale items that refer to the following question: «how worried are you for yourself and/or your country about the following developments?: economic globalization (e.g., trade)/technological change (e.g., robotics)/migration into your country». Dummified versions of these dependent variables are used in the robustness checks[5]. This control is theoretically meaningful since the present work is particularly interested in testing whether risk exposure brings individuals to be worried of specific changes. As an additional robustness test, I replicate the analysis using three binary variables that provide information on which risk is the most daunting for each respondent[6].

[5] Dummy variables for automation, globalization, and migrants risk perception take value 1 when the corresponding ordinal variables score greater than or equal to 8 (out of 10).

[6] I build three binary variables, one for each risk, that take value 1 for the risk perception that scores highest among the three (e.g., if a respondent is mostly scared by migration, the dummy for that risk will take value 1, whereas the other two assume value 0).

Independent Variables

I use a set of seven indexes to operationalize risk exposure at the regional, sectoral, and occupational levels. Occupation is measured at ISCO-08 3-digit, sector of employment at NACE Rev.2 2-digit, while regions are measured either at NUTS1 or NUTS2 level according to the country[7].

Similar to Acemoglu and Restrepo (2018) and Autor *et al.* (2013), I build three regional measurements estimating the impact of the adoption of robots and net imports from China and Central-Eastern EU countries[8] on local labor markets. A high score is supposed to entail negative economic spill-over effects at the regional level, which is expected to increase individuals' risk perception.

$$Regional\ Net\ Import|Robot\ shock = \sum_{s} \frac{L_{crs(t_0)}}{L_{cr(t_0)}} * \frac{\Delta\ (Import|Export|Robot)_{cst}}{L_{cs(t_0)}}$$

Variation of import and export is measured by averaging 5-year differences at the national-sectoral level, ranging from 1990 to 2019. Variation in robots' adoption is measured by averaging 3-year changes in the operational stock at the national-sectoral level, spanning from 1993 to 20189. For each index, the quantity of interest is weighted for the sectoral employment at the national level ($L_{cs(t_0)}$) and multiplied by the ratio of region-sector-specific employment ($L_{crs(t_0)}$) over regional workforce ($L_{cr(t_0)}$) at t_0[10]. The indexes of net exposure to trade

[7] NUTS1: Italy, the United Kingdom, Germany. NUTS2: the Netherlands, Sweden, Poland. See online repository for details on macro data: https://github.com/gregoriobuzzelli/buzzelli_2023_ripp_automation_misperception.git.

[8] Bulgaria, Estonia, Lithuania, Latvia, Romania, Hungary, Czechia, Slovakia, Poland, Slovenia.

[9] For the Netherlands and Poland, robot data disaggregated by industry are available from 2003. Following Anelli *et al.* (2019), I allocated the total number of robots to industries based on the average country-industry share of total robots in years with full information.

[10] Germany (1995), Sweden (1995), Italy (1996), the United Kingdom (1998),

with China and Central-Eastern EU are the differences between the regional exposure to import and export (Dippel *et al.* 2015). Data on employment[11] and trade[12] are sourced from Eurostat (except for employment data from Italy, source: Istat[13]), while data on robots are from the International Federation of Robotics. These data refer to manufacturing sub-sectors, coded at NACE Rev.1 2-digit level[14].

Drawing from the literature on the distributional consequences of globalization (Jude and Silaghi 2016; Liu 2012; Stolper and Samuelson 1941), I build two industry-level measures estimating the sectoral impact of net imports from China and the Central-Eastern EU. Data on trade are sourced from Eurostat[15]. I recode each manufacturing subsector as import-competing by looking at the sign of the adjusted net import, which is averaged over the period 2015-2019. Similar to Mayda and Rodrik (2005), I calculate the latter by subtracting from the annual sector's net import ($M_{ics} - X_{ics}$) the product of the adjustment factor and the annual industry's gross import (λM_{ics}). The adjustment factor is the ratio of net import over gross import at the national level[16]. This procedure is meant to correct for overall trade imbalances. I expect working in import-competing sectors to increase risk perception (Walter 2017). I define the sectoral variables estimating the import-competitiveness as follows:

the Netherlands(1995), Poland (1999).

[11] Available at https://ec.europa.eu/eurostat/web/regions/data/database.

[12] Available at http://epp.eurostat.ec.europa.eu/newxtweb/submitformatselect.do.

[13] Available at http://dati.istat.it/index.aspx?queryid=23190.

[14] Data on robots are converted from NACE Rev.2 to Rev.1.

[15] Available at http://epp.eurostat.ec.europa.eu/newxtweb/submitformatselect.do.

[16] $\lambda = \frac{\sum_s (M_s - X_s)}{\sum_s M_s}$.

$$Import\text{-}competing\ sector = \begin{cases} 1\ , if\ \dfrac{1}{5}\displaystyle\sum_{i=2015}^{2019}(M_{ics} - X_{ics} - \lambda M_{ics}) > 0 \\ 0\ , if\ \dfrac{1}{5}\displaystyle\sum_{i=2015}^{2019}(M_{ics} - X_{ics} - \lambda M_{ics}) < 0\ or\ if\ non\text{-}tradable\ sector \end{cases}$$

In order to control for different accounting principles of extra-EU trade statistics, I replicate the analysis using indexes of regional and sectoral exposure to trade with China built on data sourced from Comtrade[17] (see Garcia-Herrero *et al.* 2020; Malgouyres 2017)[18].

With regard to the occupational level of exposure, I rely on indexes widely used in the literature: the Routine Task Index (RTI) and the offshorability measurement. The former estimates the technological replaceability of occupations, assigning a growing score to professions that entail routine tasks. RTI is calculated on the American O*Net database, using the formula of Acemoglu and Autor (2011)[19]. The offshorability index assigns higher scores to occupations that do not require in-person contact, hence easily relocatable abroad (Blinder 2009). To build this index, I rely on the country-year-specific dataset recently created by Mahutga *et al.* (2018)[20], averaging the score by occupation across all European countries included with the ISCO-08 code[21]. Higher scores for both indexes entail a higher

[17] Https://comtrade.un.org/data/.

[18] Eurostat adopts the country-of-origin principle when recording information on extra-EU trade, assigning greater imports to the countries that host the point of entry of goods dispatched to other member states (i.e., the «Rotterdam effect»). Hence, I replicate the indexes of regional and sectoral exposure to trade with China using data sourced from Comtrade (https://comtrade.un.org/data/), which provides better information on the bilateral trade balances of EU countries with China (Garcia-Herrero *et al.* 2020). Similar to Malgouyres (2017), I convert HS-1992 6-digit data on products into NACE Rev.1 and 2 2-digit classification respectively to build the regional and the sectoral measurements. Differently from the calculation of the previous version of the regional index, the timespan ranges from 1995 to 2019.

[19] I thank Dario Guarascio and Roberto Quaranta for sharing the data on RTI.

[20] Available at https://matthewcm.ucr.edu/data.html.

[21] The sample includes AT (2013), CZ (2013), DK (2013), EE (2013), FI (2013), GR (2013), IE (2010), LT (2013), LU (2013), NL (2013), PL (2013), SI

risk of job loss, which supposedly increases economic risk perception.

Lastly, since low-skilled individuals working in tradable sectors and offshorable jobs are expected to encounter major economic difficulties (Natili and Negri 2022; Rommel and Walter 2018; Walter 2017), I run additional models including the interaction between the number of years in full-time education and the sectoral and occupational indexes of globalization-related risks.

Control Variables

The battery of controls includes both mind-dependent and mind-independent variables. I include conventional controls about sociodemographic (gender, years of education, age category, trade union membership) and economic features (dummy variable for low income). Building on the risk analysis literature (Kasperson *et al.* 1988; Liu *et al.* 2019; Slovic 2000; van der Linden 2015), I include the following ideational controls in order not to overlook the concurrent role of cultural factors in risk perception: political attitudes are recoded as a 5-categories variable from the survey item of left-right self-placement, and distrust in government is recoded as a dummy variable. I also add other perceived economic risks as potential co-determinants, i.e., dummy variables for the perceived level of income, job insecurity, and perceived impact of the COVID-19 crisis on household's income. Country-fixed effects are always included.

Moderating Variables

Finally, in order to run the split-sample models to test the rational-choice interpretation of misattribution, I build five binary variables accounting for individual economic vulnerability in the labor market: the level of education, income, sector of employment, and position along the insider-outsider and centre-periphery divides[22]. Building on

(2012), ES (2013), CH (2013).

[22] Relying on survey items, the moderators are operationalized as follows: level of education (below ISCED 2 vs above ISCED 3), level of income (first three deciles of the distribution against the others), sector of employment (mining and manufacturing versus the others), dualization (open-ended contract vs fixed-term and temporary agency contract, apprenticeship, and non-contract based job), and geographical divide (suburbs, small towns, and rural areas vs big cities and large towns).

economic and sociological literature, the selection and operationalization of the moderators are aimed at separating individuals according to their chance to engage in distributional conflicts with migrants on the labor market[23] (Cramer 2016; Cremaschi *et al.*, n.d.; Häusermann and Schwander 2012; Natili and Negri 2022; Oesch and Rodriguez Menes 2011; Wren 2013).

6. Findings

In this section, I present the inferential results regarding the impact of risks exposure on threat perceptions. Although this contribution does not investigate the economic consequences of risk exposure, descriptive evidence suggests higher labor market vulnerabilities for automation and globalization «losers» (i.e., low-mid levels of income and education), whereas individuals in offshorable occupations result to be wealthier and better educated[24]. For the inferential analysis, I regress the three perceptual reactions (i.e., fear of automation, globalization, and migrants) on the indexes of exposure to automation and globalization. All continuous measurements of objective risk are standardized. The models presented include the entire battery of exposure indexes and controls[25]. Looking at the main models (Fig. 1) and the robustness tests (A1-3 and online repository[26]), we observe fairly clear patterns in the relation between objective and structural-specific subjective risks which support our expectations.

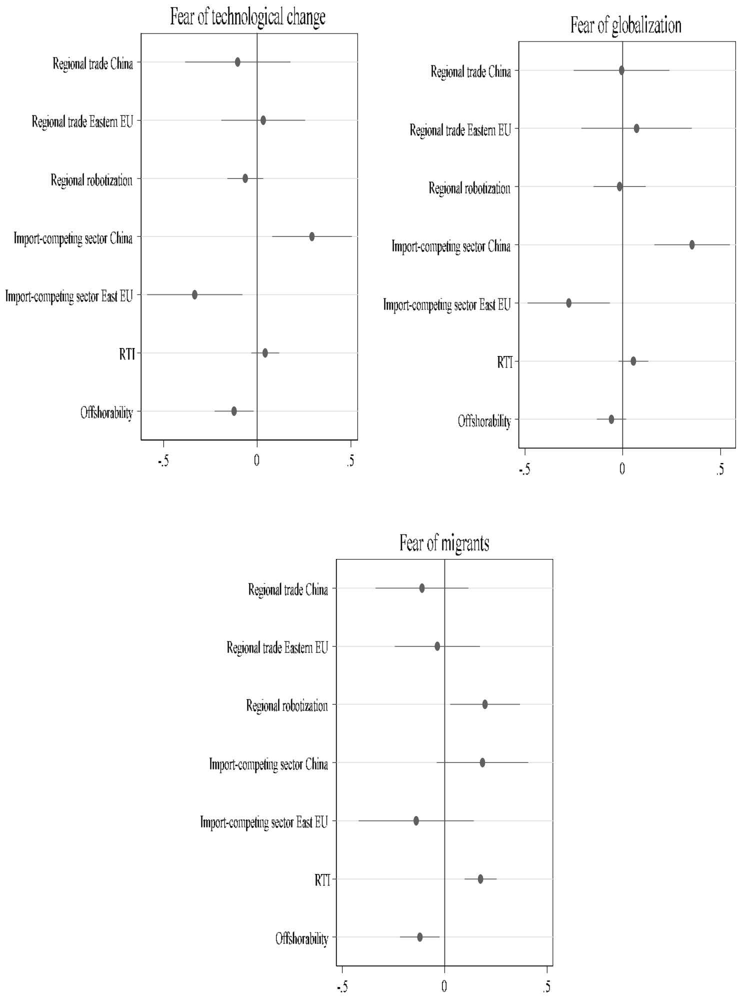
[23] The level of income is included in the analysis being a robust predictor of individuals' economic insecurity (Weisstanner and Armingeon 2022). The level of education is particularly relevant for this analysis, since replaceable workers are likely to compete with migrants for low-skilled jobs (Oesch and Rodriguez Menes 2011). Similar considerations apply to the labor market dualization, since the precariousness of outsiders' jobs remarkably contributes to their economic vulnerability (Häusermann and Schwander 2012; Natili and Negri 2022). Regarding the sector of employment, working in the industrial segment (i.e., mining and manufacturing) is thought to strengthen the economic vulnerability in times of transition towards the service economy (Wren 2013). Finally, individuals living in peripheral areas are more likely to show resentment against migrants for economic grievances and lack of public services (Cramer 2016; Cremaschi *et al.*, n.d.).

[24] Cfr. https://github.com/gregoriobuzzelli/buzzelli_2023_ripp_automation_misperception.git.

[25] Complete tables in A1.

[26] Cfr. https://github.com/gregoriobuzzelli/buzzelli_2023_ripp_automation_misperception.git.

FIG. 1. *Main models with high-dimensional fixed effects («reghdfe»).*



Note: Only the coefficients of the exposure indexes are reported in the graphs.
Source: Dataset from INAPP (2022).

In line with the first hypothesis (H1), automation risks, both at the occupational (RTI) and regional (robotization) levels, positively and exclusively correlate with the fear of migrants. The effects remain consistent in all model specifications tested, including the model estimating the impact of structural risks on migration perceived as the most urgent threat (A3, the only significant coefficients in this set of models). Concerning the second hypothesis (H2), the empirical test provides less clear-cut evidence. Sectoral exposure to imports from China and Central-Eastern Europe exerts opposite effects – respectively positive and negative – on both automation and globalization risk perceptions. On the contrary, the models run using binary versions of the dependent variables meet the theoretical expectation, showing a unique positive correlation between sectoral exposure to Chinese trade and fear of globalization (A1-2 and online repository[27]). However, none of these trade-related effects remain significant when using Comtrade-based indexes[28]. Another unexpected result concerns the offshorability index, which negatively correlates with automation and migration risk perception in the main models. Nonetheless, the robustness of these findings is seriously undermined in various model specifications. Lastly, the level of respondents' education does not alter the effects related to the sectoral and occupational indexes of globalization-related risks[29].

Therefore, while the correlation between exposure and perception of globalization risks is only weakly confirmed in the data (H2), the analysis provides robust evidence in support of the misattribution of the automation risk towards the fear of migrants (H1). However, the status-based interpretation of misattribution provided in section 3 is yet to be confirmed. In order to rule out the rival rational-choice interpretation of this phenomenon, I run split-sample models to test whether the correlation between the automation risk – at regional and occupational levels – and the fear of migrants holds regardless of individuals' economic conditions (Fig. 2).

[27] *Ibidem.*
[28] *Ibidem.*
[29] *Ibidem.*

FIG. 2. *Split-sample models with high-dimensional fixed effects («reghdfe»).*

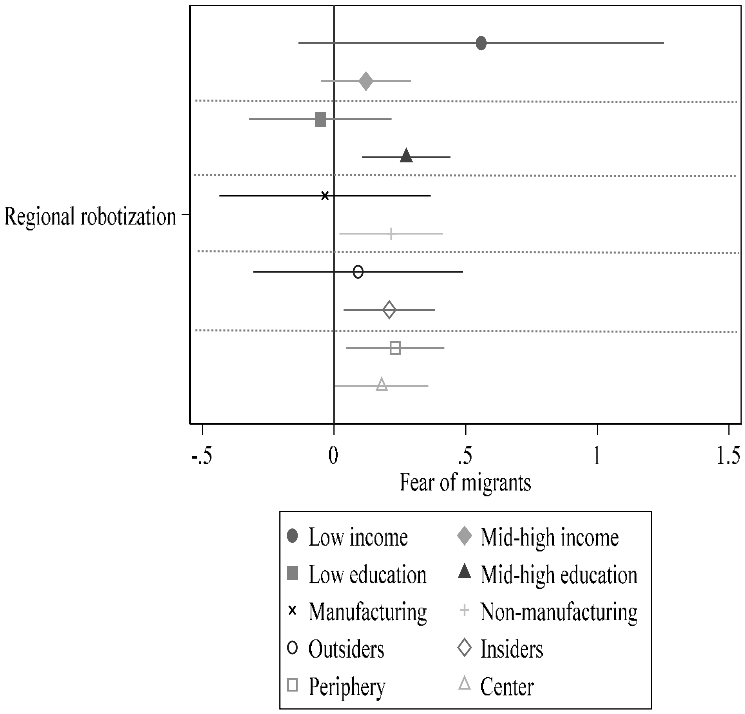
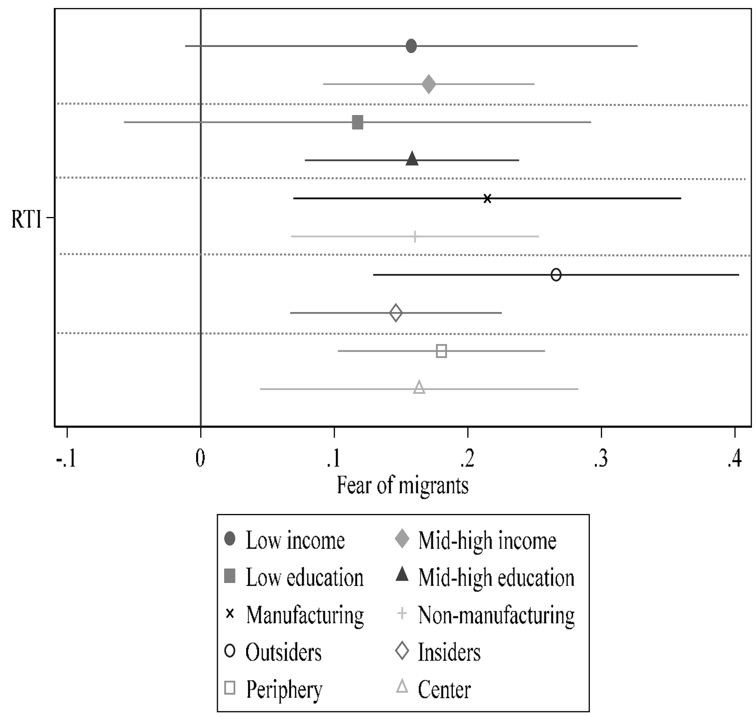


FIG. 2. *Split-sample models with high-dimensional fixed effects («reghdfe»). (Continued).*



Note: Only the coefficients of the automation indexes are reported in the graphs.
Source: Dataset from INAPP (2022).

In line with the hypothesis (H3), the effect of automation exposure on fear of migrants – when significant – has the same direction in economically vulnerable and non-vulnerable groups. In addition, the effect of automation risk is not significant in some vulnerable groups, which, according to the rational-based rival hypothesis, were expected to show a positive effect[30]. The regional index is also found to lose

[30] The regional index of robotization has a non-significant effect on fear of migrants for low-income and low-educated individuals, employed in the industrial sector, and with atypical contracts. RTI has a non-significant effect for low-income and low-educated individuals.

significance when split according to income levels. Therefore, the positive effect of exposure to automation on migration-related risk perception does not seem to be driven by a strict economic rationale. Although this evidence does not directly prove the status-based interpretation presented in this work, it seriously weakens the rational-choice hypothesis. Hence, the effect of vulnerability to automation on anti-migrants sentiment can be addressed as a misperception, plausibly linked to status concerns rather than simple economic hardship.

7. Conclusion

The hypotheses posited are partially corroborated by the results of the empirical analysis. Individuals exposed to occupational risks due to the impact of automation on the labor market tend to misattribute the cause of their material concerns toward rising migration (H1). This evidence is confirmed using both regional and occupational measurements of risk exposure. This correlation does not appear to be driven by strict economic considerations regarding competition between vulnerable native workers and migrants for jobs and services (H3). Thus, cultural reasons should have a strong role in driving misattribution as the argument based on status decline suggests (Anelli *et al.* 2019; Gallego and Kurer 2022; Kaihovaara and Im 2020; Kurer 2020). The shrinking Fordist middle class seems to blame migrants – a low-status outgroup – as a strategy to pursue status enhancement (Küpper *et al.* 2010), possibly shifting toward more conservative postmaterialist stances (Engler and Weisstanner 2021; Gidron and Hall 2017).

On the other hand, the posited correlation between globalization-related risks and their correct perception (H2) finds weak support in the data. Particularly, I detect a positive effect of sectoral exposure to import from China on the fear of globalization that holds only when the measurement is based on Eurostat data, while losing significance when built using Comtrade data. Therefore, we can only cautiously argue that «globalization» losers are aware of the specific source of their material concerns.

The main empirical limitations of this work regard the sample size and issue of endogeneity, both affecting the reliability of the indexes of regional exposure. The relatively small sample (six countries) does not prevent inferential analysis using those measurements since the variable referring to regions is provided with a large number of attributes (69 regions). Nonetheless, a larger sample size would guarantee a more representative estimation of the impact of automation and globalization on advanced local labor markets. The problem of endogeneity of trade and robot shocks with respect to behavioral outcomes is usually addressed by performing robustness checks with instrumental variables (Autor *et al.* 2016; Colantone and Stanig 2018), despite this technique has been criticized in recent contributions (Nicoli *et al.* 2021). The present work does not tackle this issue. Furthermore, it should be noted that qualitative research might fruitfully contribute to this stream of investigation, possibly providing deeper insights on individuals' interpretation of economic transformations.

Overall, these results provide a robust confirmation of blame misattribution associated with the impact of automation on the labor market. An implication for public opinion study concerns the applicability of economic voting to the investigation of the political consequences of automation. The nationalist stances supported by automation «losers» do not transcend self-interest reasoning, being a «rational» response to a (mis)perceived status threat. In short, the misattribution hypothesis blurs the boundaries between economic and cultural concerns, framing the political demands of automation «losers» as ill-informed rational judgments.

More broadly, these findings confirm that the impact of automation on the labor market may account for a key driver of the far-right success. The loss of perceived social status associated with the occupational stagnation experienced by at-risk workers (Küstermann 2022) is a crucial determinant of nationalist and protectionist sentiments (Anelli *et al.* 2019; Gallego and Kurer 2022; Kaihovaara and Im 2020; Kurer 2020). However, further empirical research is needed to strengthen this argument. First, the impact of automation on job quality and opportunities needs to be carefully assessed as a precondition of frustrating societal stagnation. Moreover, empirical investigation is required to directly test the mediating role of social status in the relation between exposure to automation risk and political behavior. Lastly, this stream of research should be also complemented by a «supply-side» story, focusing on the role of the political and cultural framing of structural economic changes by media and political elites (Benanav 2020; Wu 2021). Similar to the role played by fascist and nationalist movements in diverting economic anxieties brought by early industrialization toward outgroups (Berman 2006), a new political agency may lie behind the misattribution of the automation risk.

In conclusion, some suggestions can be drawn for policymaking interested in softening the disruptive effects of structural economic changes. First, the distinct distributional and perceptual impacts of automation and globalization suggest different and specific policy responses for each phenomenon. On the one hand, social protection and compensation appear to be an adequate response to the needs and demands of globalization «losers». On the other hand, the inconsistency between the requests and the economic needs of automation «losers» creates difficulties for policymaking. Scaling down trade openness and immigration would not mitigate the distributional consequences of automation, failing to meet the societal aspirations of middle-class workers. Policy interventions should be, instead, aimed to improve job quality and opportunities for middle-skill workers. Better pay and working conditions, together with effective retraining schemes and job-matching services, can improve the actual and perceived position of at-risk workers in the labor market. Nonetheless, the strength of cultural concerns of frustrated voters and the short-termism of policymakers may hinder a smooth technological transition.

APPENDIX

Complete regression tables.

A1. Linear regression models with high-dimensional fixed effects («reghdfe»).

Note: Country fixed effects do not compare in the table representation of this command («reghdfe») but are always included in the models.

VARIABLES	(1) Tech change risk	(2) Globalization risk	(3) Migrants risk
Regional trade China	-0.104	-0.006	-0.111
	(0.141)	(0.122)	(0.113)
Regional trade Eastern EU	0.032	0.071	-0.036
	(0.112)	(0.141)	(0.104)
Regional robotization	-0.064	-0.015	0.196**
	(0.048)	(0.067)	(0.085)
Import-competing sector China = 1	0.292***	0.354***	0.184
	(0.107)	(0.097)	(0.112)
Import-competing sector East EU = 1	-0.334**	-0.276**	-0.140
	(0.128)	(0.106)	(0.141)
RTI	0.042	0.055	0.175***
	(0.037)	(0.038)	(0.039)
Offshorability	-0.124**	-0.057	-0.122**
	(0.052)	(0.038)	(0.049)
Female	0.387***	0.296***	0.141*
	(0.062)	(0.050)	(0.075)
Age class (quota) = 2, 30-49 y.o.	-0.279*	0.068	0.273***
	(0.155)	(0.123)	(0.088)
Age class (quota) = 3, 50 +	-0.133	0.349***	0.717***
	(0.151)	(0.129)	(0.100)
Year education	-0.004	-0.002	-0.020**
	(0.007)	(0.007)	(0.008)
Political attitudes = 1, Centre-left	0.030	0.007	0.670***
	(0.102)	(0.080)	(0.140)
Political attitudes = 2, Centre	0.360***	0.257**	2.026***
	(0.117)	(0.110)	(0.178)
Political attitudes = 3, Centre-right	0.135	0.177	2.493***
	(0.114)	(0.118)	(0.191)
Political attitudes = 4, Far-right	0.405***	0.606***	3.621***
	(0.128)	(0.103)	(0.184)
Distrust government	0.015	0.616***	0.585***
	(0.084)	(0.071)	(0.161)
Low income	0.009	-0.052	-0.032
	(0.088)	(0.093)	(0.071)
Perceived low income	0.370***	0.363***	0.125
	(0.085)	(0.072)	(0.085)
Trade Union member	0.306***	0.328***	0.121*
	(0.100)	(0.078)	(0.064)
Perceived covid impact	0.837***	0.617***	0.364***
	(0.117)	(0.113)	(0.106)
Job insecurity (dummy)	1.095***	0.959***	0.569***
	(0.095)	(0.090)	(0.080)
Constant	4.131***	4.436***	3.507***
	(0.146)	(0.150)	(0.215)
Observations	16,564	16,446	16,668
R-squared	0.103	0.103	0.229

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

VARIABLES	(1) Tech change risk (binary)	(2) Globalization risk (binary)	(3) Migrants risk (binary)
Regional trade China	-0.002	-0.016	0.002
	(0.026)	(0.030)	(0.021)
Regional trade Eastern EU	0.005	-0.005	-0.001
	(0.032)	(0.031)	(0.022)
Regional robotization	-0.022	-0.020	0.029**
	(0.014)	(0.013)	(0.012)
Import-competing sector China = 1	0.025	0.050***	0.014
	(0.016)	(0.016)	(0.012)
Import-competing sector East EU = 1	-0.029*	-0.034*	-0.009
	(0.016)	(0.017)	(0.013)
RTI	-0.005	-0.003	0.022***
	(0.006)	(0.007)	(0.006)
Offshorability	-0.009	-0.001	-0.005
	(0.006)	(0.006)	(0.009)
Female	0.022**	0.011	0.016
	(0.009)	(0.010)	(0.012)
Age class (quota) = 2, 30-49 y.o.	-0.053**	-0.027	0.049***
	(0.020)	(0.026)	(0.016)
Age class (quota) = 3, 50 +	-0.033	0.038	0.127***
	(0.021)	(0.025)	(0.018)
Year education	0.000	-0.000	-0.003**
	(0.001)	(0.001)	(0.001)
Political attitudes = 1, Centre-left	-0.026*	-0.041***	-0.001
	(0.015)	(0.015)	(0.016)
Political attitudes = 2, Centre	0.012	-0.016	0.170***
	(0.017)	(0.013)	(0.024)
Political attitudes = 3, Centre-right	0.003	-0.007	0.235***
	(0.015)	(0.014)	(0.021)
Political attitudes = 4, Far-right	0.097***	0.114***	0.461***
	(0.023)	(0.018)	(0.023)
Distrust government	0.016	0.111***	0.131***
	(0.012)	(0.013)	(0.022)
Low income	-0.022*	-0.023	-0.032**
	(0.012)	(0.018)	(0.013)
Perceived low income	0.046***	0.072***	0.036*
	(0.015)	(0.015)	(0.018)
Trade Union member	0.070***	0.081***	0.053***
	(0.014)	(0.017)	(0.011)
Perceived covid impact	0.126***	0.127***	0.059***
	(0.020)	(0.020)	(0.016)
Job insecurity (dummy)	0.163***	0.154***	0.102***
	(0.016)	(0.019)	(0.013)
Constant	0.084***	0.090***	0.036
	(0.022)	(0.022)	(0.030)
Observations	16,564	16,446	16,668
R-squared	0.109	0.109	0.186

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

A2. OLS models (run with the traditional multi-way standard error clustering – Stata «reg» command).

VARIABLES	(1) Tech change risk	(2) Globalization risk	(3) Migrants risk
Regional trade China	-0.104	-0.006	-0.111
	(0.117)	(0.111)	(0.118)
Regional trade Eastern EU	0.032	0.071	-0.036
	(0.152)	(0.147)	(0.150)
Regional robotization	-0.064	-0.015	0.196**
	(0.084)	(0.076)	(0.086)
Import-competing sector China = 1	0.292***	0.354***	0.184*
	(0.099)	(0.081)	(0.094)
Import-competing sector East EU = 1	-0.334***	-0.276***	-0.140
	(0.105)	(0.089)	(0.102)
RTI	0.042	0.055**	0.175***
	(0.030)	(0.027)	(0.029)
Offshorability	-0.124***	-0.057	-0.122***
	(0.038)	(0.035)	(0.039)
Female	0.387***	0.296***	0.141**
	(0.058)	(0.054)	(0.059)
Age class (quota) = 2, 30-49 y.o.	-0.279***	0.068	0.273***
	(0.083)	(0.075)	(0.077)
Age class (quota) = 3, 50 +	-0.133	0.349***	0.717***
	(0.087)	(0.079)	(0.083)
Year education	-0.004	-0.002	-0.020***
	(0.006)	(0.005)	(0.006)
Political attitudes = 1, Centre-left	0.030	0.007	0.670***
	(0.102)	(0.098)	(0.115)
Political attitudes = 2, Centre	0.360***	0.257***	2.026***
	(0.102)	(0.096)	(0.112)
Political attitudes = 3, Centre-right	0.135	0.177*	2.493***
	(0.101)	(0.097)	(0.110)
Political attitudes = 4, Far-right	0.405***	0.606***	3.621***
	(0.111)	(0.104)	(0.112)
Distrust government	0.015	0.616***	0.585***
	(0.063)	(0.058)	(0.063)
Low income	0.009	-0.052	-0.032
	(0.078)	(0.070)	(0.076)
Perceived low income	0.370***	0.363***	0.125
	(0.080)	(0.075)	(0.081)
Trade Union member	0.306***	0.328***	0.121*
	(0.071)	(0.065)	(0.070)
Perceived covid impact	0.837***	0.617***	0.364***
	(0.076)	(0.070)	(0.073)
Job insecurity (dummy)	1.095***	0.959***	0.569***
	(0.066)	(0.060)	(0.067)
Country code = 2, Germany	0.487**	0.326	0.418*
	(0.227)	(0.213)	(0.225)
Country code = 3, Italy	0.609***	0.382**	0.818***
	(0.163)	(0.156)	(0.161)
Country code = 5, Netherlands	0.448*	0.001	0.714***
	(0.265)	(0.244)	(0.251)
Country code = 6, Poland	-0.054	-0.389***	-0.269**
	(0.123)	(0.118)	(0.125)
Country code = 7, Sweden	-0.316**	-0.480***	0.363**
	(0.152)	(0.142)	(0.155)
Constant	3.957***	4.483***	3.178***
	(0.191)	(0.179)	(0.195)
Observations	16,564	16,446	16,668
R-squared	0.103	0.103	0.229

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

VARIABLES	(1) Tech change risk (binary)	(2) Globalization risk (binary)	(3) Migrants risk (binary)
Regional trade China	-0.002	-0.016	0.002
	(0.016)	(0.018)	(0.020)
Regional trade Eastern EU	0.005	-0.005	-0.001
	(0.021)	(0.025)	(0.026)
Regional robotization	-0.022*	-0.020	0.029**
	(0.012)	(0.014)	(0.014)
Import-competing sector China = 1	0.025*	0.050***	0.014
	(0.014)	(0.015)	(0.016)
Import-competing sector East EU = 1	-0.029**	-0.034**	-0.009
	(0.014)	(0.016)	(0.017)
RTI	-0.005	-0.003	0.022***
	(0.004)	(0.005)	(0.005)
Offshorability	-0.009	-0.001	-0.005
	(0.006)	(0.006)	(0.007)
Female	0.022**	0.011	0.016
	(0.009)	(0.010)	(0.010)
Age class (quota) = 2, 30-49 y.o.	-0.053***	-0.027**	0.049***
	(0.012)	(0.012)	(0.013)
Age class (quota) = 3, 50 +	-0.033***	0.038***	0.127***
	(0.013)	(0.013)	(0.014)
Year education	0.000	-0.000	-0.003***
	(0.001)	(0.001)	(0.001)
Political attitudes = 1, Centre-left	-0.026*	-0.041**	-0.001
	(0.014)	(0.016)	(0.015)
Political attitudes = 2, Centre	0.012	-0.016	0.170***
	(0.014)	(0.016)	(0.016)
Political attitudes = 3, Centre-right	0.003	-0.007	0.235***
	(0.014)	(0.016)	(0.016)
Political attitudes = 4, Far-right	0.097***	0.114***	0.461***
	(0.016)	(0.017)	(0.017)
Distrust government	0.016*	0.111***	0.131***
	(0.009)	(0.011)	(0.011)
Low income	-0.022*	-0.023*	-0.032**
	(0.011)	(0.012)	(0.013)
Perceived low income	0.046***	0.072***	0.036***
	(0.013)	(0.014)	(0.014)
Trade Union member	0.070***	0.081***	0.053***
	(0.010)	(0.011)	(0.012)
Perceived covid impact	0.126***	0.127***	0.059***
	(0.012)	(0.012)	(0.013)
Job insecurity (dummy)	0.163***	0.154***	0.102***
	(0.010)	(0.011)	(0.011)
Country code = 2, Germany	0.107***	0.091**	0.075**
	(0.033)	(0.037)	(0.037)
Country code = 3, Italy	0.087***	0.051*	0.088***
	(0.024)	(0.027)	(0.028)
Country code = 5, Netherlands	0.054	0.023	0.043
	(0.038)	(0.041)	(0.044)
Country code = 6, Poland	0.027	-0.040**	-0.100***
	(0.018)	(0.020)	(0.020)
Country code = 7, Sweden	-0.002	-0.035	0.024
	(0.021)	(0.025)	(0.026)
Constant	0.040	0.076**	0.016
	(0.026)	(0.030)	(0.031)
Observations	16,564	16,446	16,668
R-squared	0.109	0.109	0.186

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

A3. Dependent variables: most scaring risk among technological change, globalization, and migrants. Linear models with high-dimensional fixed effects («reghdfe»).

VARIABLES	(1) Tech change (most scared)	(2) Globalization (most scared)	(3) Migrants (most scared)
Regional trade China	0.010	0.017	-0.027
	(0.017)	(0.020)	(0.024)
Regional trade Eastern EU	0.005	0.017	-0.023
	(0.015)	(0.031)	(0.028)
Regional robotization	0.004	-0.043**	0.040**
	(0.017)	(0.017)	(0.018)
Import-competing sector China = 1	0.021	0.018	-0.039
	(0.034)	(0.028)	(0.028)
Import-competing sector East EU = 1	-0.034	-0.005	0.039
	(0.029)	(0.022)	(0.029)
RTI	-0.015*	-0.019**	0.035***
	(0.008)	(0.008)	(0.008)
Offshorability	-0.009	0.017*	-0.008
	(0.007)	(0.010)	(0.010)
Female	-0.014	0.003	0.010
	(0.011)	(0.014)	(0.016)
Age class (quota) = 2, 30-49 y.o.	-0.101***	-0.001	0.102***
	(0.022)	(0.019)	(0.025)
Age class (quota) = 3, 50 +	-0.153***	-0.015	0.168***
	(0.022)	(0.017)	(0.030)
Year education	0.001	0.002	-0.004**
	(0.001)	(0.002)	(0.002)
Political attitudes = 1, Centre-left	-0.028	-0.056**	0.084***
	(0.023)	(0.024)	(0.022)
Political attitudes = 2, Centre	-0.056*	-0.206***	0.262***
	(0.028)	(0.033)	(0.038)
Political attitudes = 3, Centre-right	-0.127***	-0.248***	0.375***
	(0.021)	(0.035)	(0.037)
Political attitudes = 4, Far-right	-0.129***	-0.356***	0.485***
	(0.023)	(0.031)	(0.034)
Distrust government	-0.061***	0.020	0.042*
	(0.015)	(0.019)	(0.025)
Low income	0.026	-0.015	-0.011
	(0.023)	(0.023)	(0.019)
Perceived low income	0.005	0.005	-0.009
	(0.018)	(0.018)	(0.019)
Trade Union member	-0.016	0.043***	-0.028**
	(0.014)	(0.016)	(0.014)
Perceived covid impact	0.042***	0.036**	-0.078***
	(0.014)	(0.017)	(0.018)
Job insecurity (dummy)	0.035***	0.036**	-0.071***
	(0.011)	(0.017)	(0.020)
Constant	0.319***	0.427***	0.253***
	(0.032)	(0.040)	(0.050)
Observations	10,900	10,900	10,900
R-squared	0.065	0.097	0.163

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

A4. Split-sample regression models (with high-dimensional fixed effects – «reghdfe»).

VARIABLES	(1) Migrants risk Low income	(2) Migrants risk Mid-high income
Regional trade China	-0.521**	-0.023
	(0.243)	(0.074)
Regional trade Eastern EU	-0.491	0.069
	(0.329)	(0.044)
Regional robotization	0.559	0.121
	(0.348)	(0.086)
Import-competing sector China = 1	0.177	0.201
	(0.198)	(0.123)
Import-competing sector East EU = 1	-0.141	-0.148
	(0.278)	(0.144)
RTI	0.158*	0.171***
	(0.085)	(0.040)
Offshorability	-0.111	-0.120**
	(0.104)	(0.049)
Female	0.201**	0.123
	(0.086)	(0.092)
Age class (quota) = 2, 30-49 y.o.	0.508**	0.190*
	(0.204)	(0.112)
Age class (quota) = 3, 50 +	1.037***	0.617***
	(0.173)	(0.123)
Year education	-0.012	-0.023**
	(0.013)	(0.010)
Political attitudes = 1, Centre-left	0.656**	0.708***
	(0.251)	(0.150)
Political attitudes = 2, Centre	1.598***	2.160***
	(0.281)	(0.183)
Political attitudes = 3, Centre-right	2.204***	2.583***
	(0.285)	(0.201)
Political attitudes = 4, Far-right	2.930***	3.787***
	(0.283)	(0.184)
Distrust government	0.803***	0.534***
	(0.186)	(0.179)
Low income	0.000	0.000
	(0.000)	(0.000)
Perceived low income	0.158	0.089
	(0.167)	(0.089)
Trade Union member	0.149	0.102
	(0.153)	(0.079)
Perceived covid impact	0.173	0.396***
	(0.215)	(0.106)
Job insecurity (dummy)	0.506***	0.564***
	(0.132)	(0.093)
Constant	3.470***	3.542***
	(0.337)	(0.221)
Observations	3,290	13,378
R-squared	0.200	0.239

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

VARIABLES	(1) Migrants risk Low education	(2) Migrants risk Mid-high education
Regional trade China	-0.254	-0.120
	(0.264)	(0.137)
Regional trade Eastern EU	-0.341	-0.034
	(0.266)	(0.147)
Regional robotization	-0.051	0.275***
	(0.135)	(0.084)
Import-competing sector China = 1	0.275*	0.119
	(0.156)	(0.131)
Import-competing sector East EU = 1	-0.435*	-0.052
	(0.221)	(0.154)
RTI	0.117	0.158***
	(0.088)	(0.040)
Offshorability	0.127*	-0.172***
	(0.066)	(0.049)
Female	0.251*	0.122
	(0.149)	(0.091)
Age class (quota) = 2, 30-49 y.o.	0.505**	0.239**
	(0.204)	(0.111)
Age class (quota) = 3, 50 +	1.305***	0.512***
	(0.158)	(0.124)
Year education	-0.008	-0.013*
	(0.014)	(0.008)
Political attitudes = 1, Centre-left	0.369	0.738***
	(0.277)	(0.128)
Political attitudes = 2, Centre	1.496***	2.072***
	(0.332)	(0.159)
Political attitudes = 3, Centre-right	1.962***	2.578***
	(0.328)	(0.201)
Political attitudes = 4, Far-right	2.959***	3.739***
	(0.323)	(0.197)
Distrust government	0.557**	0.631***
	(0.232)	(0.167)
Low income	-0.191	-0.017
	(0.131)	(0.083)
Perceived low income	0.248	0.054
	(0.172)	(0.099)
Trade Union member	0.314**	0.096
	(0.143)	(0.080)
Perceived covid impact	0.372***	0.308**
	(0.133)	(0.117)
Job insecurity (dummy)	0.338**	0.611***
	(0.146)	(0.085)
Constant	4.088***	3.335***
	(0.381)	(0.204)
Observations	3,218	13,450
R-squared	0.211	0.228

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

VARIABLES	(1) Migrants risk Manufactu- ring	(2) Migrants risk Non-manu- facturing
Regional trade China	-0.686*	-0.016
	(0.339)	(0.132)
Regional trade Eastern EU	-0.210	-0.005
	(0.447)	(0.138)
Regional robotization	-0.034	0.218**
	(0.196)	(0.098)
Import-competing sector China = 1	-0.123	0.275*
	(0.155)	(0.156)
Import-competing sector East EU = 1	0.060	-0.320*
	(0.159)	(0.173)
RTI	0.215***	0.161***
	(0.071)	(0.046)
Offshorability	-0.133	-0.150***
	(0.083)	(0.053)
Female	-0.053	0.203***
	(0.193)	(0.076)
Age class (quota) = 2, 30-49 y.o.	0.431**	0.225**
	(0.181)	(0.094)
Age class (quota) = 3, 50 +	0.833***	0.680***
	(0.249)	(0.096)
Year education	-0.017	-0.019**
	(0.016)	(0.009)
Political attitudes = 1, Centre-left	0.342	0.693***
	(0.363)	(0.135)
Political attitudes = 2, Centre	1.557***	2.073***
	(0.268)	(0.187)
Political attitudes = 3, Centre-right	1.786***	2.586***
	(0.261)	(0.193)
Political attitudes = 4, Far-right	2.880***	3.701***
	(0.303)	(0.184)
Distrust government	0.859***	0.564***
	(0.196)	(0.169)
Low income	-0.210	0.008
	(0.235)	(0.067)
Perceived low income	-0.067	0.147
	(0.167)	(0.097)
Trade Union member	0.437*	0.056
	(0.216)	(0.074)
Perceived covid impact	0.082	0.425***
	(0.192)	(0.105)
Job insecurity (dummy)	0.657***	0.551***
	(0.192)	(0.081)
Constant	4.278***	3.416***
	(0.299)	(0.230)
Observations	2,416	14,252
R-squared	0.233	0.232

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

VARIABLES	(1) Migrants risk Outsiders	(2) Migrants risk Insiders
Regional trade China	-0.484*	0.018
	(0.274)	(0.124)
Regional trade Eastern EU	-0.427*	0.123
	(0.249)	(0.119)
Regional robotization	0.092	0.210**
	(0.200)	(0.087)
Import-competing sector China = 1	0.043	0.215
	(0.192)	(0.133)
Import-competing sector East EU = 1	-0.001	-0.145
	(0.228)	(0.144)
RTI	0.266***	0.146***
	(0.069)	(0.040)
Offshorability	-0.099	-0.135**
	(0.071)	(0.055)
Female	0.238*	0.134
	(0.130)	(0.089)
Age class (quota) = 2, 30-49 y.o.	0.303*	0.197*
	(0.177)	(0.106)
Age class (quota) = 3, 50 +	0.546***	0.673***
	(0.203)	(0.108)
Year education	-0.019	-0.022**
	(0.015)	(0.010)
Political attitudes = 1, Centre-left	0.398*	0.716***
	(0.213)	(0.166)
Political attitudes = 2, Centre	1.957***	1.989***
	(0.238)	(0.177)
Political attitudes = 3, Centre-right	2.251***	2.536***
	(0.310)	(0.189)
Political attitudes = 4, Far-right	3.680***	3.540***
	(0.316)	(0.182)
Distrust government	0.507***	0.611***
	(0.166)	(0.175)
Low income	-0.106	0.035
	(0.138)	(0.086)
Perceived low income	0.060	0.162*
	(0.165)	(0.091)
Trade Union member	0.019	0.160**
	(0.209)	(0.071)
Perceived covid impact	0.358*	0.395***
	(0.200)	(0.112)
Job insecurity (dummy)	0.173	0.750***
	(0.138)	(0.097)
Constant	3.783***	3.522***
	(0.296)	(0.244)
Observations	3,868	12,470
R-squared	0.241	0.231

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

VARIABLES	(1) Migrants risk Periphery	(2) Migrants risk Center
Regional trade China	-0.089	-0.165
	(0.155)	(0.157)
Regional trade Eastern EU	-0.016	-0.095
	(0.231)	(0.086)
Regional robotization	0.233**	0.182**
	(0.093)	(0.089)
Import-competing sector China = 1	0.210	0.155
	(0.153)	(0.168)
Import-competing sector East EU = 1	-0.171	-0.107
	(0.219)	(0.188)
RTI	0.180***	0.164***
	(0.039)	(0.060)
Offshorability	-0.070	-0.170**
	(0.065)	(0.065)
Female	0.193**	0.102
	(0.093)	(0.095)
Age class (quota) = 2, 30-49 y.o.	0.341**	0.243**
	(0.139)	(0.107)
Age class (quota) = 3, 50 +	0.823***	0.625***
	(0.130)	(0.123)
Year education	-0.021**	-0.019**
	(0.010)	(0.009)
Political attitudes = 1, Centre-left	0.761***	0.581***
	(0.215)	(0.137)
Political attitudes = 2, Centre	2.049***	1.989***
	(0.205)	(0.188)
Political attitudes = 3, Centre-right	2.655***	2.315***
	(0.230)	(0.181)
Political attitudes = 4, Far-right	3.686***	3.519***
	(0.209)	(0.210)
Distrust government	0.654***	0.528***
	(0.190)	(0.158)
Low income	0.144	-0.184
	(0.093)	(0.129)
Perceived low income	0.025	0.204
	(0.129)	(0.123)
Trade Union member	0.032	0.195*
	(0.120)	(0.103)
Perceived covid impact	0.105	0.594***
	(0.100)	(0.149)
Job insecurity (dummy)	0.696***	0.445***
	(0.094)	(0.099)
Constant	3.418***	3.563***
	(0.245)	(0.249)
Observations	7,948	8,720
R-squared	0.240	0.223

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

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