



Automation risks versus skill requirements: occupational determinants of expectations and political preferences in knowledge societies

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ABSTRACT

Over the past half-century, structural developments in production systems and labour markets have brought about substantial shifts in the occupational structure. Individuals' positions within these societal transformations are widely understood to shape their expectations of the future and their political preferences. While the focus in much recent research in this regard has been on occupations' susceptibility to automation, this study places the level of skill requirements at the centre of the analysis. Using data from the European Social Survey, we find robust support for this perspective. Individuals in occupations with higher skill requirements tend to anticipate fewer personal economic difficulties and hold more positive views about the direction of societal development, while also being less supportive of government redistribution and less inclined to vote for the radical right. In contrast, the theoretically expected relationships between automation-risk measures and these outcomes generally disappear once skill-level requirements are controlled for. Our theoretical arguments and empirical findings suggest that the role of automation risk may be overstated in understanding how occupational positions shape social and political outcomes, and that the level of skill requirements carries greater explanatory weight in shaping individuals' expectations about the future and their political preferences in knowledge societies.

KEYWORDS Political preferences; social pessimism; automation; skill requirements; structural change; radical right

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1. Introduction

Over the past half-century, evolving structural developments in production systems and labour markets have brought profound shifts in the occupational structure. There is a common conception across the social sciences that these ongoing structural processes create short- to medium-run “winners” and “losers”, with far-reaching social and political implications (Acemoglu and Johnson, 2023; Dekker, Salomons and van der Waal, 2017; Dengler and Gundert, 2021; Frey, 2019; Gallego and Kurer, 2022; Im *et al.*, 2019). This idea has deep historical roots. For example, during the early industrial phase, Marx and Engels (1848/1967) anticipated that the lower middle class of shopkeepers, artisans, and peasants would become reactionary as they struggled to preserve their livelihoods amid the Industrial Revolution. Similarly, during the early transition to a post-industrial society, Bell (1973) forecasted that highly skilled jobs and occupations would expand and gain in social standing, economic advantage, and political influence, as the post-industrial knowledge society emerged. However, he also cautioned that the growing emphasis on expertise and advanced skills as a determinant of economic and social resources might provoke social and economic grievances among those excluded from advantaged positions—an opening that anti-system political parties and candidates would exploit.

This study examines how occupational positions shape individuals’ expectations of the future and their political preferences in the context of structural change in capitalist knowledge societies. Alongside the growth of high-skill occupations involving complex job tasks, a growing body of literature has pointed to the fact that individuals in “routine” occupations susceptible to automation are especially vulnerable to losing their social and economic foothold owing to ongoing technological changes (Autor, Katz and Krueger, 1998; Goldin and Katz, 2009). This automation perspective claims that advances in computing power have transformed many “routine” tasks into manageable tasks for robots and computers to the extent that they are capable of fully replacing human labour in certain, typically mid-skilled, jobs (Autor, Levy and Murnane, 2003; Frey and Osborne, 2017). While computerisation and other technological advancements tend to complement human labour in high-skilled occupations—potentially benefitting workers in these jobs—positions in the middle of the occupational hierarchy are frequently highlighted as especially exposed to automation-driven substitution risks (Autor and Dorn, 2013; Goos, Manning and Salomons, 2014).

Many have argued that such threats of being replaced by robots or computers have political consequences at the individual level (see Gallego and Kurer, 2022, for a review). Although empirical findings are mixed, several studies seem to

support this overarching proposition, identifying effects ranging from “left-leaning” reactions, such as support for government redistribution (Thewissen and Rueda, 2019; Weisstanner, 2023), to “right-leaning” responses, such as support for radical right parties (e.g., Anelli, Colantone and Stanig, 2021; Im *et al.*, 2019; Kurer, 2017). Based on such findings, automation risk has become widely viewed as a key component linking occupational experiences to a range of individual outcomes.

We aim to critically assess and nuance this narrative by asking the following questions: Are automation-driven substitution risks a central factor linking individuals’ occupational positions to their expectations of the future, support for redistribution, and likelihood of voting for the radical right? Or is it rather the skill-level requirements of occupations that drive these associations? Motivating the second question, our theoretical framework emphasises not only what machines can and cannot do, but also the extent to which occupations involve complex work tasks requiring advanced skills and expertise that are demanding for humans to acquire. Although skill requirements and susceptibility to automation are intertwined—since the automatability of tasks has historically tended to be inversely related to the level of human skill required to perform them—the empirical question is which of these perspectives, if either, provides a more fundamental explanation of social and political outcomes. Crucially, the importance of automation risk may be exaggerated if the level of skill requirements is not accounted for.

In focusing on the level of skill requirements, we build on a long tradition of sociological stratification research that treats occupation as a main locus of social and economic advantage and inequality. In this large literature, it is well-established that skill requirements structure the hierarchy of occupations in terms of both economic and social opportunities (Ganzeboom, De Graaf and Treiman, 1992; Oesch, 2006; Treiman, 1977; Tåhlin, 2007; Wright, 1997). Moreover, as noted above with reference to Bell (1973), and further emphasised in research on “skill-biased” technological change, the transition to a post-industrial economy tends to promote complex work tasks requiring advanced skills, mainly to the advantage and expansion of jobs and occupations that include them, and to the disadvantage and displacement of those that do not (Autor, Katz and Krueger, 1998; Bell, 1973; Goldin and Katz, 2009; Katz and Murphy, 1992; Liu and Grusky, 2013; Oesch, 2013).

Since previous research on political preferences has often overlooked the level of skill requirements as a foundational dimension of vertical occupational differentiation and ongoing structural change, this oversight may have led to premature or overstated conclusions about the significance of automation risks for individual outcomes. We seek to address this shortcoming by examining how

occupational skill requirements and automation risks *compare* in shaping individuals' expectations of the future, as well as their support for government redistribution and likelihood to vote for the radical right. Using data from multiple rounds of the European Social Survey (ESS) covering eleven European countries, we test how these outcomes relate to various automation-risk measures, including the Routine Task Intensity (RTI) measure developed by Autor and Dorn (2013) and adapted to ISCO-88 codes by Goos, Manning and Salomons (2014); the Frey and Osborne (2017) measure of the susceptibility of computerisation; and the Arntz, Gregory and Zierahn (2016) scale, which also incorporates task variations and other job characteristics within occupations. Following the same methodological reasoning, we also deploy two occupational measures of skill-level requirements, one of which enables a granular assessment that is crucial for capturing variation among occupations in the middle of the skill hierarchy.

2. Occupations, expectations of the future, and political preferences

In this study, we take an occupational perspective as our point of departure. Occupations can be conceptualised as structural positions within labour markets and production systems, comprising collections of jobs that involve similar sets of work tasks. Risks and rewards stem from these occupational positions, which are conceptually distinct from the individuals who hold them. This means that individuals are exposed to such risks and rewards through their occupational location (Sørensen, 1996; Tåhlin, 2023). We aim to contrast the automation risk and the level of skill requirements as two distinct—although correlated—traits of occupational positions. We begin with the automation perspective and then contrast it with the skill requirements framework.

2.1. Automation risks

Research on the political consequences of automation often draws on earlier empirical studies of changes in the job structure of the United States. According to the perspective of “routine-biased” technological change frequently invoked in this context, technological advancements not only increase the share of jobs involving complex tasks and advanced skills but also tend to substitute workers in jobs with routine tasks that machines can perform. This process is argued to contribute to labour market polarisation by disproportionately erasing routine jobs situated around the middle of the occupational hierarchy (Autor, Levy and Murnane, 2003; Goos, Manning and Salomons, 2014).

Previous studies of political preferences have commonly measured job susceptibility to automation at the occupational level. We consider three analytical approaches, which we view as broadly representative of how automation-driven substitution risks have been operationalised in previous research.

The first is the Routine Task Intensity (RTI) index developed by Autor and Dorn (2013). Conceptually, the RTI index distinguishes between “routine” tasks, expected to be more susceptible to automation, and “non-routine” tasks, which are less so. Routine cognitive tasks include repetitive and fairly simple cognitive activities such as calculation and record-keeping. In the domain of manual work, the RTI index is intended to capture the degree to which occupations involve repetitive routine manipulations of physical objects that do not require advanced eye-hand co-ordination.

The RTI index has been criticised for not adequately capturing recent advances in computerisation, including rapid innovations in artificial intelligence. Frey and Osborne (2017) argue that technology has advanced to the point where it also poses automation threats to tasks involving relatively complex non-routine operations. They therefore developed an alternative scale intended to capture the probability of future computerisation based on anticipated developments in computing and artificial intelligence, while assuming that skills like creativity and social intelligence remain harder to automate.

Another influential approach is that proposed by Arntz, Gregory and Zierahn (2016, 2017). They argue that assessing automation risk requires recognising that jobs and occupations are more varied in task content than previous approaches have assumed. For instance, occupations that involve calculative tasks that are automatable in principle often also include tasks such as interpreting, contextualising, and explaining data to clients, which are far less automatable. Occupations also vary internally in the task content of individual jobs. They therefore aim to estimate the automatability of individual jobs rather than occupations, building on the expert assessments provided by Frey and Osborne (2017) but adjusting them based on various job characteristics (such as educational requirements) and individual characteristics (such as workers’ own education and gender) (Arntz, Gregory and Zierahn, 2017).

While Arntz, Gregory and Zierahn (2016) make the case for comparing jobs rather than occupations, they also provide an aggregated occupational-level version of their index. Like the other two occupational scales, this version has been used in previous research on political outcomes (e.g., Im *et al.*, 2019). Still, it should be acknowledged that, given its incorporation of both job-level features and characteristics of jobholders, the measure’s meaning at the occupational level is not entirely clear-cut. Particularly relevant for this study, its stated design

suggests that it more explicitly weaves occupational skill requirements into its construction than do the other indices.

Across measurement approaches, the proposed core mechanism linking automation risk to individual political preferences is the threat of losing one's economic or social foothold because of deteriorating occupational prospects (Frey, 2019; Gallego and Kurer, 2022). To test this theory, one line of research examines policy preferences. For example, Thewissen and Rueda (2019) argue that a higher risk of future job and income loss due to automation should generate greater support for economic protection and compensation through government redistribution, and find a significant positive relationship between RTI and preferences for redistribution. Other studies similarly report a positive association between automation risk and support for unemployment benefits (Im and Komp-Leukkunen, 2021; Sacchi, Guarascio and Vannutelli, 2020; Weisstanner, 2023), whereas support for social-investment programmes or basic income schemes—which are less directly about compensation for job displacement—appears weakly or even negatively related to automation risk (Busemeyer and Sahm, 2022; Dermont and Weisstanner, 2020; Kurer and Häusermann, 2022).

While theory assumes that individuals are aware of and internalise automation threats, the few empirical studies that have specifically examined individuals' subjective assessments of their own exposure to automation actually find only a modest positive correlation with objective occupational measures (Gallego *et al.*, 2022; Kurer and Häusermann, 2022). However, exposure to automation risks could still spill over to more general negative expectations of the future—a proposition that, to the best of our knowledge, has not been systematically tested. This is somewhat surprising, considering that individuals' perceptions of future social and economic opportunities for themselves (and their children, if any) have been found to be associated with vote choice: positive expectations with higher support for mainstream parties and negative expectations with higher support for radical parties advocating systemic change (Häusermann, Kurer and Zollinger, 2023; Steenvoorden and Harteveld, 2018).

When theorising the relationship between automation risk and vote choice, most research has focused on radical right support (Anelli, Colantone and Stanig, 2021; Im *et al.*, 2019; Kurer, 2020). In this context, scholars often argue that the electoral effects of automation risk largely operate through social grievances. Most notably, automation pressures are proposed to threaten the social status to which occupational incumbents have been accustomed, generating status anxiety and resentment toward perceived outgroups seen as competing for social recognition (Gidron and Hall, 2017; Küpper, Wolf and Zick, 2010). Such processes may also foster societal pessimism, including the belief that society is in decline or developing for the worse (Steenvoorden and van der Meer, 2017).

Several empirical studies provide some support for this perspective. For example, using the International Social Survey Programme, Gingrich (2019) finds that people in occupations with a high automation risk (as measured by the RTI index) are more likely to support the radical right (or the mainstream left) than other parties. Using the Arntz, Gregory and Zierahn (2016) index and European Social Survey data, Im *et al.* (2019) find that people located in occupations with high automation risk are more inclined to support the radical right. Based on a panel analysis, Kurer (2020) finds that those who remain in routine occupations are more likely to support radical right and conservative parties than those who become unemployed from such occupations. In a similar vein, Anelli, Colantone and Stanig (2021) argue that many losers of structural change have already been displaced from automation-pressured occupations, and therefore claim that analyses concentrated on individuals' current occupation could lead to misleading results and conclusions. In their alternative modelling strategy, they do not use an individual's current occupation, but instead estimate what occupation the individual could have held in a pre-automation labour market (given their region, education, and gender), finding that those with a high probability of being employed in an automation-susceptible occupation are more likely to support the radical right.

Based on this discussion, we can formulate several hypotheses reflecting core propositions in previous research on the social and political consequences of occupational automation risk:

(H1) *A higher occupational automation risk is associated with greater . . .*

- (a) *. . . expectations of future personal economic difficulties.*
- (b) *. . . expectations of societal decline.*
- (c) *. . . support for government redistribution.*
- (d) *. . . likelihood of voting for the radical right.*

2.2. The level of skill requirements

Analogous to how automation risks are tied to the routineness of tasks, skill-level requirements are anchored in the tasks and organisation of work itself rather than in the characteristics of current jobholders. The level of skill requirements refers to the general degree of skills typically needed to perform a job within a particular occupation. These requirements are a function of the complexity of the job, such as tasks that demand complex problem-solving, expertise, and operational decision-making (Tählin, 2023; Williams and Bol, 2018). Social closure mechanisms, such as the formalisation of occupational entry requirements, may further restrict access (Bol and Weeden, 2015).

Skill requirements are thus conceptually distinct from the education or abilities of individual employees, an insight that is likely to be important in relation to the outcomes studied here. For instance, having a medical degree offers relatively limited social and economic advantages for the individual if it does not lead to entry into paid work within the medical profession. Similarly, being located in an occupation with low skill requirements is typically associated with low rewards and high risks, even among occupational incumbents who are overqualified for the job in terms of their own formal educational attainment. Although one's own education might affect the outcomes studied here beyond facilitating access to higher-skilled occupations, such effects are conceptually distinct from those of occupational location and are hence not the focus of the present paper.

Diverse theoretical perspectives in social stratification research conceptualise the level of occupational skill requirements as a central foundation of socio-economic hierarchy. In social class analysis, for example, the primary dimension of widely used schemas is either theoretically grounded in or empirically operationalised through skill level (Erikson and Goldthorpe, 1992; Oesch, 2006; Tåhlin, 2007; Wright, 1997). Likewise, theories of social prestige treat expertise and advanced skills as important determinants of the social prestige of occupations (Treiman, 1977).

Over the past half-century, structural change in emerging knowledge economies has largely involved technological advancements that contributed to a general skill upgrading, increasing the demand for advanced skills and decreasing the demand for low-skilled roles (Baumol, 2007; Goldin and Katz, 2009; Katz and Margo, 2014; Liu and Grusky, 2013; Ngai and Pissarides, 2007). Automation and computerisation have certainly contributed to this process (Autor, Katz and Krueger, 1998; Autor, Levy and Murnane, 2003). Yet, skill upgrading is part of a more encompassing structural process, involving changes in work organisation and sectoral composition, as well as increasing demand for expert roles in management, governance, and specialised services (Handel, 2020; Oesch, 2013; Westerman and Syk, 2023). Empirical studies confirm the continuance of this trajectory in contemporary Europe, showing that labour markets are characterised more by an expansion of high-skilled jobs than by a disproportionate erosion of the mid-skilled segment (Haslberger, 2021; Oesch and Piccitto, 2019).

For our purposes, the level of skill requirements should ideally be measured on a continuous scale to enable direct comparison with the widely used automation measures described above. A most commonly available indicator is the grading of skill levels forming the vertical structure of the International Standard Classification of Occupations (ISCO), which is derived from *formal educational requirements*, *on-the-job training*, and *continuous learning* (ILO, 2012). A limitation of the ISCO skill-level classification, however, is that it distinguishes only

four broad categories, yielding a rather crude grouping. To address this issue, we adopt a more granular approach that aggregates to the occupational level employees' assessments of the three job-level factors stated by ISCO (Andersson and Lindh, 2023; Tählin, 2011). Empirically, skill-level requirements generated through this procedure correlate very highly with the ISCO skill-level classification (see empirical section), while offering much finer granularity and thus distinguishing occupations more clearly within the middle of the skill distribution.

Several mechanisms connect the skill-level requirements of occupations to individual expectations and political preferences. As a starting point, high-skilled occupations tend to offer higher wages and lower unemployment risks than low-skilled occupations (Le Grand and Tählin, 2013; Wright, 1997). Authority, autonomy, and prestige in daily work are also closely associated with the level of skill requirements, and these factors enhance the individual's sense of social status, recognition, and efficacy in society (Andersson and Lindh, 2023; Kohn and Schooler, 1983; Treiman, 1976). All else equal, we may therefore expect individuals located in high-skilled occupations to hold more positive expectations of their future economic opportunities and to be less supportive of government redistribution.

In addition, the structural process of skill upgrading—including the expansion of higher-skill job chances alongside the decline of lower-skill opportunities—may strengthen the link between occupational skill requirements and social and economic grievances. Beyond possibly fostering more negative expectations of future economic opportunities and greater support for economic redistribution, seeing one's accessible employment opportunities shrink may contribute to a broader sense of social devaluation and marginalisation in society, which can spill over into a general belief in societal decline. Such pessimistic views may make individuals in occupations with low skill requirements more receptive to radical right ideologies that challenge the current direction of societal change, while promising to restore a more economically prosperous and socially stable past (Borwein *et al.*, 2025; Steenvoorden and Harteveld, 2018). By contrast, among those in high-skilled occupations, the prevailing trajectory of societal development in knowledge-based societies may reinforce the experience of being socially recognised and valued by society (Bell, 1973). Moreover, even those in occupations with high skill requirements that are in *decline* may maintain positive expectations about the future, given their experience with varied work situations and continuous learning—features linked to the perceptions that it is feasible to transition to other jobs should that become necessary (Tählin, 2007).

Although few previous studies of political preferences have explicitly incorporated occupational skill requirements as systematically as automation risk,

suggestive evidence of its relevance emerges from research on class politics: individuals in working-class (lower-skill) positions are, for instance, typically more supportive of redistribution than those in middle-class (higher-skill) positions (Häusermann and Kriesi, 2015; Lindh and McCall, 2020). Regarding radical right support, many empirical studies have focused on individual education, sometimes alongside analyses of regional skill clusters in local economies (e.g., Consiglio and Kurer, 2025; Iversen and Soskice, 2019), but surprisingly few have explicitly considered occupational position through the lens of skill-level requirements. However, suggestive evidence from research on social class indicates that individuals in working-class (lower-skilled) positions tend to be more supportive of the radical right than those in middle-class (higher-skilled) positions (Oesch and Rennwald, 2018).

To summarise this discussion on occupational skill requirements, we can formulate the following hypotheses paralleling those above concerning automation risk:

(H2) *A higher occupational skill requirement is associated with lower...*

- (a) ... expectations of future personal economic difficulties.
- (b) ... expectations of societal decline.
- (c) ... support for government redistribution.
- (d) ... likelihood of voting for the radical right.

3. Data and methods

3.1. Data

We use the European Social Survey (ESS) rounds 2 and 5–11 (ESS, 2012, 2023a, 2023b, 2023c, 2023d, 2023e, 2023f, 2025). An advantage of using the ESS is its frequent use in previous research on automation risk and political preferences. In particular, the module on personal well-being in round 6 and the module on welfare attitudes in round 8 contain suitable items. In addition, the second and fifth rounds provide information about the level of skill requirements in jobs. The bulk of our analysis uses rounds 5 through 11, collected between 2010 and 2023, since these cover the period when radical right parties gained their broad electoral breakthrough in many countries.

In our main analysis, we use one or several of these ESS rounds, depending on the availability of each outcome (see more on this below). The analytical sample is restricted to those in the working-age, non-military population with viable occupational information, who are either currently employed or unemployed. We focus on the group of Western European countries for which the examined automation scales are available, and that had established radical right parties during the study period (cf. Im *et al.*, 2019). These countries are

Austria, Belgium, Denmark, Finland, France, Germany, Great Britain, Italy, the Netherlands, Norway, and Sweden.

3.2. Outcomes

Expectations of the future can be divided into personal and societal components (Schweizer and Schneider, 1997). *Expectations of personal economic difficulties* is measured with an additive scale of the following two items: (1) “How likely is it that during the next 12 months you will be unemployed and looking for work for at least four consecutive weeks?” (2) “During the next 12 months, how likely is it that there will be some periods when you don’t have enough money to cover your household necessities?” Both items are scaled from 1 (“not at all likely”) to 4 (“very likely”) and are moderately correlated ($R = 0.51$). This combination of items is included in round 8 of the ESS. To increase the number of cases included in the analysis, the index scores for respondents with missing values in one of the two items are calculated by doubling the value of the non-missing item (this procedure is especially relevant for Austria, where the second item was not fielded).

The measure of *expectations of societal decline* is also based on an additive scale including two moderately correlated ($R = 0.45$) items asking respondents whether “For most people in [COUNTRY] life is getting worse rather than better” and “The way things are now, I find it hard to be hopeful about the future of the world”. Both items are measured on a Likert scale ranging from 1 (“agree strongly”) to 5 (“disagree strongly”), which we reverse-coded into a standardised scale. These questions are included in the sixth ESS round. As with the previous measure, the scale is based on a single item in cases where one of the two items is missing.

Support for government redistribution is measured with a standard item asking respondents about whether “The government should take measures to reduce differences in income levels”. It is originally scaled 1 (“agree strongly”) to 5 (“disagree strongly”), and we have reverse-coded it so that a higher score signifies more support for redistribution. It is included in all ESS rounds.

Radical right voting is measured by the party voted for in the last general national election. We include all respondents eligible to vote and use a dichotomous measure (1 = voted for the radical right, 0 = did not vote for the radical right), based on PopuList 3.0’s classification of far-right populist parties (Rooduijn *et al.*, 2024). Voting information is included in all ESS rounds. See Table 1 for descriptive statistics of all variables included in the analysis.

3.3. Occupational automation risks

We include the three automation measures discussed above. The first, the Autor and Dorn (2013) RTI index, was originally derived from task descriptions

Table 1. Descriptive statistics.

	Mean	SD	Min	Max
<i>Outcomes</i>				
Expectations of personal economic difficulties	3.66	1.59	2.00	8.00
Expectations of societal decline	6.42	1.79	2.00	10.00
Support for government redistribution	2.75	1.04	0.00	4.00
Voting for the radical right	0.06	0.24	0.00	1.00
<i>Occupational measures</i>				
Goos, Manning and Salomons (2014)	− 0.18	0.92	− 1.52	2.24
Frey and Osborne (2017)	0.48	0.35	0.00	0.99
Arntz, Gregory and Zierahn (2016)	0.11	0.13	0.00	0.57
Skill requirements (index)	0.14	1.05	− 2.16	1.65
<i>Control variables</i>				
<i>Demographics</i>				
Age	43.55	12.03	14.00	65.00
Woman	0.48		0.00	1.00
Citizen of country	0.94		0.00	1.00
Born in country	0.88		0.00	1.00
Father born in country	0.84		0.00	1.00
Mother born in country	0.84		0.00	1.00
<i>Educational level</i>				
Low	0.12		0.00	1.00
Medium	0.45		0.00	1.00
High	0.43		0.00	1.00
<i>Place of residence</i>				
A big city	0.18		0.00	1.00
Suburbs or outskirts of big city	0.14		0.00	1.00
Town or small city	0.32		0.00	1.00
Country village	0.30		0.00	1.00
Farm or home in countryside	0.07		0.00	1.00

Note: Based on the analytical sample. Values before z-standardisation.

from the American database “Dictionary of Occupational Titles” (DOT, 1979 edition) (Autor, Levy and Murnane, 2003). We use the version adapted to European occupational data by Goos, Manning and Salomons (2014), which is available for most ISCO-88 two-digit occupational groups. To match the ISCO-08 coding of occupational data in ESS 6–11, we apply Jann’s (2019) crosswalk between ISCO-08 and ISCO-88.

The second measure, developed by Frey and Osborne (2017), was originally constructed using multiple items from the US “O*net” database (replacing the DOT), complemented by expert assessments of automation risk for specific occupations. As the original scale was based on using the American SOC-10 occupational scale, we match it to the ISCO-08 codes in ESS 6–11, using the official crosswalk from SOC-2010 to ISCO-08 (US Bureau of Labor Statistics, 2015). In cases where multiple SOC codes correspond to a single ISCO-08 code, we take the unweighted average of those SOC codes.

The third measure, developed by Arntz, Gregory and Zierahn (2016), combines the Frey and Osborne (2017) index with data on self-reported job content in the Programme for the International Assessment of Adult Competencies (PIAAC). They link various individual and job characteristics to occupational automation risk in the United States edition of the survey, and use this model to impute the automatability of individual jobs (Arntz, Gregory and Zierahn, 2017). They then extend this approach to all PIAAC countries using the job-content indicators. We match each country-specific occupational version of this scale to two-digit ISCO groups in our data.

3.4. Level of occupational skill requirements

We use two measurement approaches to ensure that our findings are robust across alternative viable indicators of the level of skill requirements. First, we construct a weighted index by means of principal component analysis of three job skill-level components covered in ESS 2 and 5: (1) *educational requirements of the job* (measured by two items: “If someone was applying nowadays for the job you do now, would they need any education or vocational schooling beyond compulsory education?”, and, if the answer is yes, “About how many years of education or vocational schooling beyond compulsory education would they need?”); (2) *initial on-the-job training* (“If somebody with the right education and qualifications replaced you in your job, how long would it take for them to learn to do the job reasonably well?”); and (3) *continuous learning* (“My job requires that I learn new things”). The scores from the first factor solution are aggregated to occupational ISCO groups, resulting in a continuous and granular scale of occupational skill-level requirements (see also Tählin, 2023). We compute this scale for both sub-major and minor groups to ensure that their graduality matches that of the automation measure used in the same model. While these questions are included only in ESS 5 and ESS 2, we impute scores across all ESS rounds based on respondents’ occupational information, using Jann’s (2019) crosswalk between ISCO-88 and ISCO-08, as ESS rounds 2 and 5 use ISCO-88 while ESS rounds 6–11 use ISCO-08.

For supplementary analyses (Figures S1–S4), we use the four-level ISCO classification as a second measure of vertical skill requirements. This gradient is derived by the International Labour Office (ILO, 2012), based on formal educational requirements, on-the-job training, and informal training.

Table 2 presents the respective scores of these two measures by ISCO sub-major groups (two digits), revealing an almost identical occupational ranking across the measures. The main difference is that our primary granular measure

Table 2. Level of occupational skill requirements in ISCO sub-major groups.

ISCO code	ISCO label	Level of occupational skill requirements	
		Index	ISCO four levels
22	Life science and health professionals	1.56	4
23	Teaching professionals	1.35	4
21	Physical, mathematical, and engineering science professionals	1.31	4
24	Other professionals	1.12	4
12	Corporate managers	1.09	3 or 4
11	Legislators and senior officials	1.04	3 or 4
31	Physical and engineering science associate professionals	0.63	3
33	Teaching associate professionals	0.63	3
13	General managers	0.61	3 or 4
32	Life science and health associate professionals	0.57	3
34	Other associate professionals	0.45	3
72	Metal, machinery, and related trades workers	0.03	2
73	Precision, handicraft, printing, and related trades workers	-0.16	2
71	Extraction and building trades workers	-0.27	2
41	Office clerks	-0.30	2
40	Clerks	-0.30	2
80	Plant and machine operators and assemblers	-0.61	2
42	Customer services clerks	-0.62	2
81	Stationary-plant and related operators	-0.68	2
61	Market-oriented skilled agricultural and fishery workers	-0.68	2
51	Personal and protective services workers	-0.71	2
74	Other craft and related trades workers	-0.75	2
83	Drivers and mobile-plant operators	-1.01	2
82	Machine operators and assemblers	-1.02	2
52	Models, salespersons, and demonstrators	-1.10	2
90	Elementary occupations	-1.33	1
93	Labourers in mining, construction, manufacturing, and transport	-1.55	1
92	Agricultural, fishery, and related labourers	-1.95	1
91	Sales and services elementary occupations	-2.12	1

captures considerable variation within the second ISCO skill level, for instance, between higher- and lower-skilled manual workers.

3.5. *Control variables*

We include control variables capturing sociodemographic characteristics, including binary gender, age in years, urban versus rural residence, and whether the respondent and their parents were born in the country of residence. Since we are interested in the level of skill requirements as a job characteristic tied to occupational positions, we regard individual education not mediated through occupational skill requirements as a potential confounder, and we hence control for the respondent's level of education (measured by grouping ISCED categories). Finally, to account for variation in outcomes across countries and survey rounds, we include country and survey-wave fixed effects.

Household income, employment status (employed/unemployed), and past experience of unemployment are probable mediators of the relationship between our main occupational characteristics and outcomes, meaning that controlling for them would introduce an overcontrol bias. For this reason, these factors are not accounted for in the analysis.

3.6. *Analytical strategy*

We estimate seven regression models for each outcome. In the first three models (M1–3), we replicate the setup of previous automation-oriented studies by estimating the relationship between each automation measure (one per model) and the outcome without including skill requirements (i.e., only the control variables are included). The fourth model (M4) introduces our primary measure of occupational skill requirements to assess its relationship with each outcome without considering automation risk. In the final three models (M5–7), we include skill-level requirements alongside each automation measure (again, one per model) to examine how controlling for the other alters the estimated associations. We use ordinary least squares (OLS) regressions for expectations of personal economic difficulties, societal decline, and support for government redistribution. For radical right voting, we use linear probability models. ESS design weights and robust standard errors are applied in all models.

To maintain consistency with the original construction of each automation measure, we adopt a conservative approach by using listwise deletion for occupational categories without original automation scores, rather than imputing values for categories not included in the original measures. Consequently, the number of observations varies across models owing to differences in occupational coding between the automation measures. The main results are presented in figures

displaying the estimated coefficients, while the underlying regression models are reported in the Supplemental Information (Tables S1–S4).

For comparability of associations across different outcomes and occupational scales, we standardise the continuous outcome variables (expectations of the future and redistribution) as well as the occupational measures to a scale with a mean of zero and a standard deviation of one (z-scores).

4. Empirical results

4.1. Correlations between occupational measures of automation risks and skill requirements

Before comparing how automation risk and the level of skill requirements relate to each outcome, we first examine the associations between the occupational scales intended to capture these two explanatory constructs. Table 3 presents the pairwise correlations between the five occupational measures used in the study.

As highlighted earlier, our primary granular index of skill-level requirements is almost perfectly correlated with the cruder skill-level measure provided by ISCO (0.962), underscoring the strong reliability of these measures. In contrast, the correlations among the automation measures are more moderate, likely in part reflecting slight differences in their conceptual focus and measurement strategies. Notably, the Goos, Manning and Salomons (2014) RTI measure is rather

Table 3. Pairwise correlations between occupational measures.

	Skill requirements (index)	Skill requirements (ISCO four levels)	Goos, Manning and Salomons (2014)	Frey and Osborne (2017)
Skill requirements (index)	.			
Skill requirements (ISCO four levels)	0.962	.		
Goos, Manning and Salomons (2014)	– 0.380	– 0.515	.	
Frey and Osborne (2017)	– 0.629	– 0.664	0.595	.
Arntz, Gregory and Zierahn (2016)	– 0.773	– 0.727	0.290	0.558

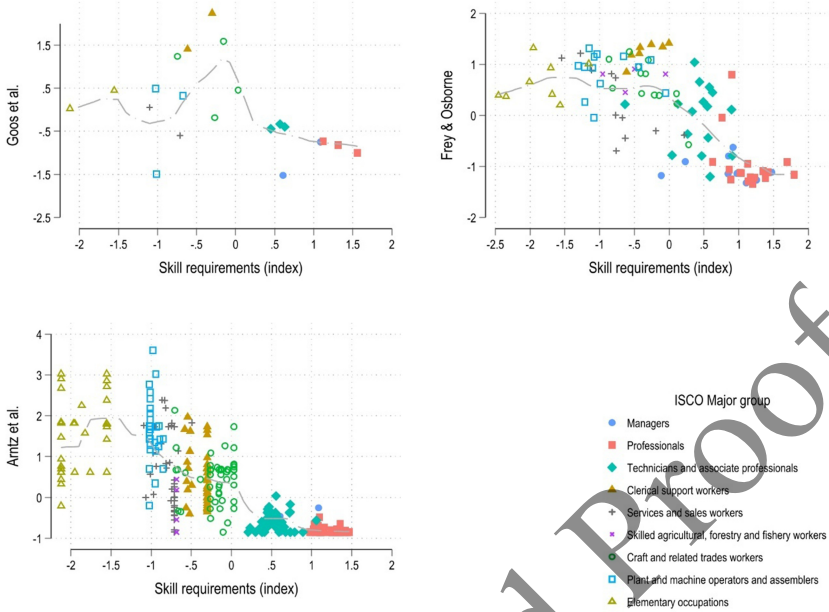


Figure 1. Associations between occupational automation risks and the level of skill requirements.

Note: Goos, Manning and Salomons (2014) is computed for 21 sub-major ISCO-88 groups, Frey and Osborne (2017) 109 minor (3-digit) ISCO-08 groups, and Arntz, Gregory and Zierahn (2016) on major and sub-major ISCO-08 groups with estimates differing by country (in total 267 values). Lines are based on kernel-weighted local polynomial regression. All scales are presented as z-scores.

modestly correlated with the Arntz, Gregory and Zierahn (2016) measure ($r = 0.290$), while the Frey and Osborne (2017) measure shows moderately strong correlations with both of the other automation indices.

Regarding correlations across the two conceptual constructs, the Goos, Manning and Salomons (2014) scale shows a relatively modest positive correlation with the granular skill requirements index ($r = -0.388$). In contrast, the Frey and Osborne (2017) ($r = -0.635$) and especially the Arntz, Gregory and Zierahn (2016) ($r = -0.776$) scales display much stronger negative correlations with the level of skill requirements. To provide a more detailed view of these associations, Figure 1 plots each automation scale against occupational skill level. The plots display ISCO major groups as symbols and include a polynomial regression line to indicate any non-linear associations between the two constructs.

The plot reveals that the relatively modest correlation between the Goos, Manning and Salomons (2014) measure and skill requirements can be traced to a subset of mid-skill occupations with high RTI scores, consistent with the idea of a “declining middle” often highlighted in the literature on routine-biased

technological change. Examples include office clerks (a sub-group of clerical support workers) and precision, handicraft, and printing workers (a sub-group of craft and related trades workers). However, the two more recently developed automation measures do not exhibit this distinct kink among mid-skill occupations. Although they assign high automation risks to some mid-skilled groups, such as clerical support workers, they also predict similarly high automation risks for many elementary occupations with low skill requirements.

In sum, although the automation scales differ somewhat in their conceptual focus and methodological design, they all correlate with the level of skill requirements: automation risks tend to be higher in lower-skilled occupations. The association is particularly strong for the more recently developed scales, both of which show a largely linear negative relationship with skill level. This pattern may partly reflect the fact that these measures—and especially the Artzt et al. index—incorporate elements of skill requirements in their construction. It is therefore important to account explicitly for the level of skill requirements before concluding the relevance of automation risk for other outcomes. We now proceed to this part of the analysis in the following section.

4.2. *Expectations of the future*

Figure 2 presents the results for expectations of personal economic difficulties, while Figure 3 shows the results for societal decline (see Tables S1 and S2 for full regression results). According to the automation hypotheses, individuals in occupations with a higher risk of automation should score higher on both outcomes (H1a, H1b). As hypothesised, the first model set (M1–3, Figure 2) indicates that all three automation measures predict higher expectations of personal economic difficulties, and the Frey and Osborne (2017) and the Arntz, Gregory and Zierahn (2016) measures show significant associations with expectations of societal decline (M1–3, Figure 3).

The fourth model replaces automation risk with skill requirements and, as illustrated toward the bottom of Figures 2 and 3, produces statistically significant negative coefficients for both outcomes. This indicates that individuals in higher-skilled occupations have lower expectations of economic difficulties and societal decline, in line with hypotheses H2a and H2b. These initial models thus provide preliminary support for both automation risk (H1a/b) and skill requirements (H2a/b) as influential factors. But what happens when both are included in the same model?

In the next set of models, we include both automation risk and skill requirements (M5–7). The pattern that emerges is striking. The level of skill requirements retains its significant negative association with both expectations of

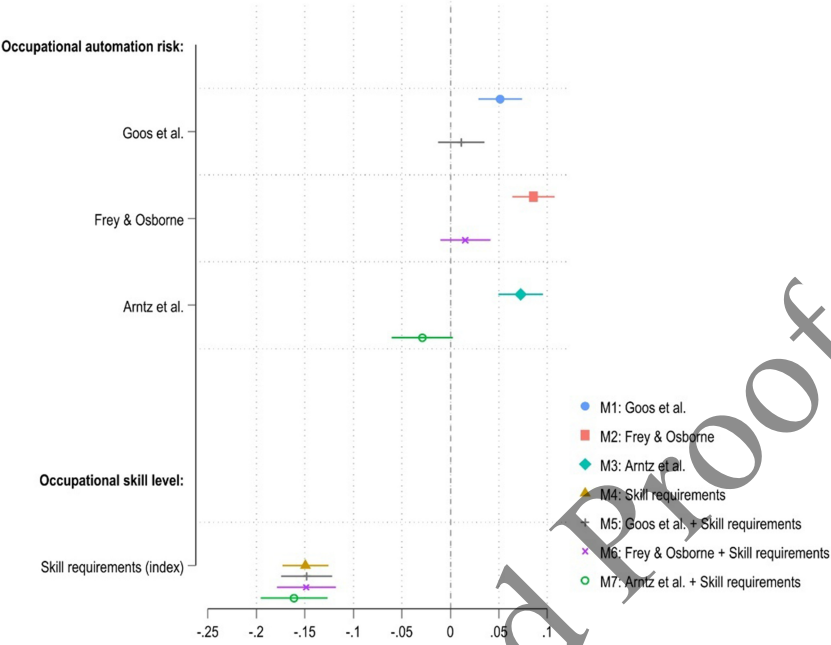


Figure 2. Expectations of personal economic difficulties by occupational automation risks and the level of skill requirements.

Note: All shown coefficients are based on standardised variables. Based on OLS regression with robust standard errors. All models include the control for education and sociodemographic variables listed in Table 1 and country dummies. Error bars represent 95% confidence intervals. *N* in Models 1 and 5 = 9,373; in Models 2 and 6 = 9,291; in Models 3 and 7 = 9,720; and in Model 4 = 10,366.

economic difficulties and societal decline, with coefficients similar in size to those in the previous model set, regardless of which automation measure it is compared with. A 1 standard deviation increase in skill requirements is, on average, associated with a 0.15 standard deviation decrease in expectations of personal economic difficulties and a 0.10 standard deviation decrease in expectations of societal decline. These results reinforce empirical support for hypotheses 2a and 2b.

In contrast, once the level of skill requirements is controlled for, the coefficients for all three automation measures wash out, becoming negligible and statistically insignificant. This indicates that individuals in occupations highly susceptible to automation are no more negative in their expectations about the future—either for themselves or for society at large—than those in occupations facing low automation risks, provided they are located at the same skill level. In other words, when controlling for the level of skill requirements, automation hypotheses 1a and 1b no longer receive empirical support.

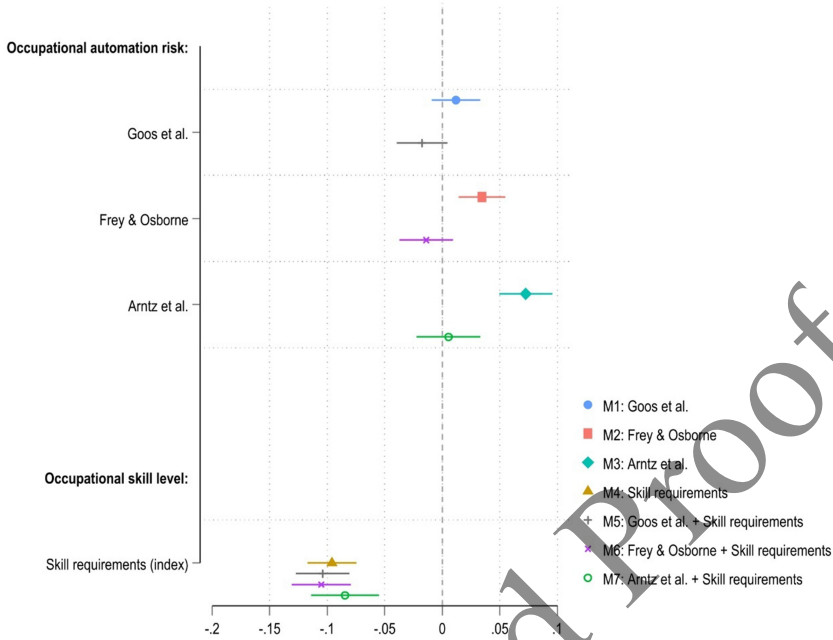


Figure 3. Expectations of societal decline by occupational automation risks and the level of skill requirements.

Note: All shown coefficients are based on standardised variables. Based on OLS regression with robust standard errors. Error bars represent 95% confidence intervals. All models include the control for education and sociodemographic variables listed in Table 1 and country dummies. N in Models 1 and 5 = 8,956; in Models 2 and 6 = 9,164; in Models 3 and 7 = 9,401; and in Model 4 = 9,955.

4.3. Political preferences

Next, we turn to political preferences, beginning with support for government redistribution, as shown in Figure 4 (see Table S3 for full regression results). According to the automation hypothesis, people in occupations at risk of automation should be more supportive of economic redistribution (H1c). The results from the first set of models (M1–3, Figure 4) fit with this expectation: all three automation-risk measures are positively and significantly associated with support for government redistribution.

Further down in Figure 4 (M4), we find preliminary support for the corresponding skill requirements hypothesis (H2c), indicating, consistent with expectations, that individuals in higher-skilled occupations are less supportive of redistribution. However, when both automation risk and skill requirements are included in the same model (M5–7, Figure 4), the regression coefficients for all three automation measures approach zero and even turn slightly negative for the Frey and Osborne (2017) measure. Meanwhile, the estimated negative

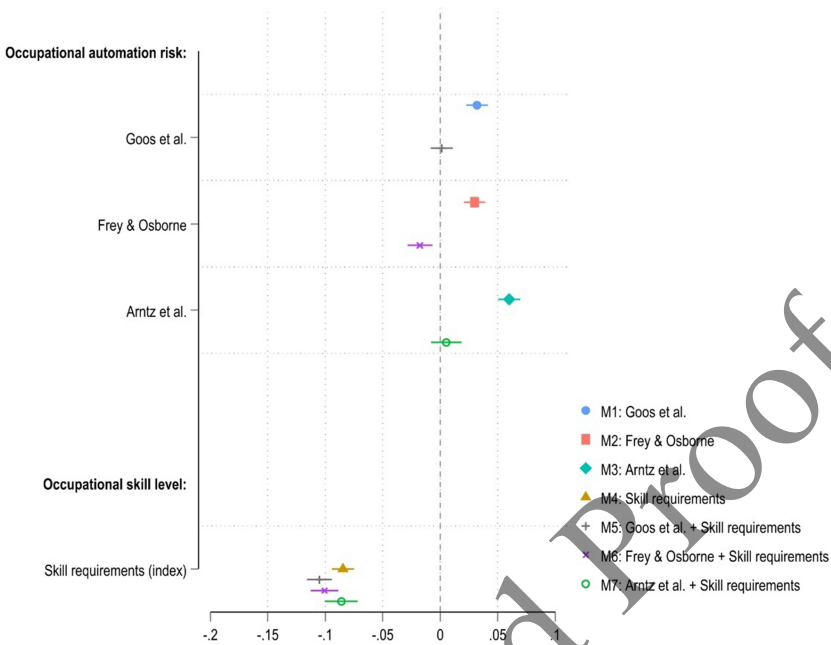


Figure 4. Support for government redistribution by occupational automation risks and the level of skill requirements.

Note: All shown coefficients are based on standardised variables. Based on OLS regression with robust standard errors. Error bars represent 95% confidence intervals. All models include the control for education and sociodemographic variables listed in Table 1, time and country dummies. *N* in Models 1 and 5 = 55,508; in Models 2 and 6 = 55,141; in Models 3 and 7 = 58,102; and in Model 4 = 61,495.

coefficient for skill requirements remains statistically significant and of similar magnitude to that in the previous model. A 1 standard deviation increase in skill requirements is, on average, associated with a 0.09 standard deviation decrease in support for government redistribution. These results support hypothesis 2c but not hypothesis 1c.

Our fourth and final outcome concerns radical right voting. The automation hypothesis predicts that individuals in occupations facing higher automation risk are more inclined to vote for the radical right (H1d). As shown in Figure 5, the initial models (M1–3) indicate that higher automation risk—as measured by the Frey and Osborne (2017) and the Arntz, Gregory and Zierahn (2016) scales, but not Goos, Manning and Salomons (2014)—is associated with a higher likelihood of voting for the radical right (see Table S4 for full regression results). In the fourth model (M4, Figure 5), we similarly find that higher skill requirements are associated with a lower likelihood of voting for such parties. However, the now well-familiar follow-up question arises: Do these relationships hold once we control for the other explanatory factor?

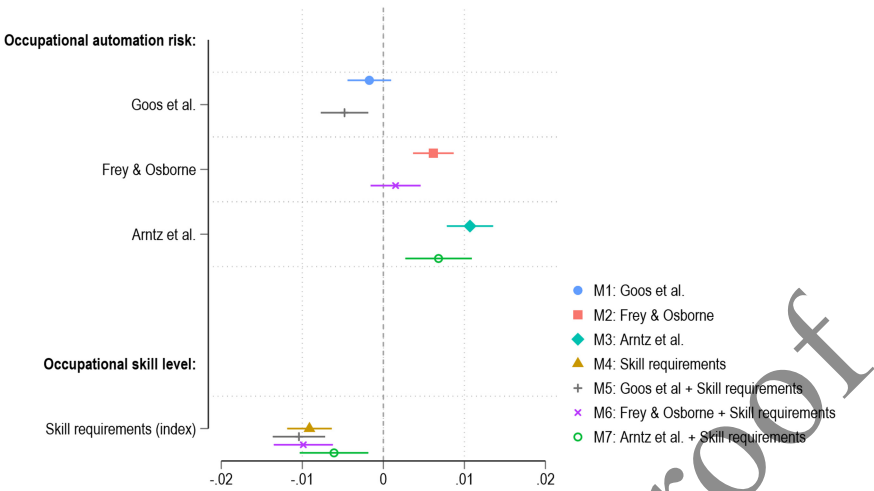


Figure 5. Radical right voting by occupational automation risks and the level of skill requirements.

Note: All shown coefficients are based on standardised variables. Based on a linear probability model with robust standard errors. Error bars represent 95% confidence intervals. All models include the control for education and sociodemographic variables listed in Table 1, time and country dummies. *N* in Models 1 and 5 = 53,722; in Models 2 and 6 = 53,401; in Models 3 and 7 = 56,336; and in Model 4 = 59,607.

To address this question, we estimate the next set of models (M5–7, Figure 5). The results continue to show a statistically significant negative relationship between the level of skill requirements and radical right voting, regardless of which automation-risk scale is included in the same model, although the coefficient is somewhat smaller when the Arntz, Gregory and Zierahn (2016) measure is included. A 1 standard deviation increase in occupational skill requirements is, on average, associated with a 0.9 percentage point decrease in the probability of voting for the radical right.

Moreover, once the level of skill requirements is controlled for, the coefficients for automation measures shrink markedly: they become statistically insignificant for Frey and Osborne (2017) and significantly *negative* for Goos, Manning and Salomons (2014), while the coefficient remains positive and significant for the Arntz, Gregory and Zierahn (2016) measure. Thus, the results are not as clear-cut as for the other outcomes since one automation measure remains significant. Yet, since neither of the other automation measures shows theoretically expected significant relationships to radical right voting once controlling for skill requirements, we interpret the results overall as speaking against the automation hypothesis (1d) while underscoring the consistent explanatory power of occupational skill level, supporting hypothesis 2d. We therefore consider it tentative but plausible that the remaining explanatory

power of the Arntz, Gregory and Zierahn (2016) measure could have more to do with the numerous individual and job characteristics used to construct the index, rather than occupational automation risk *per se*.

4.4. Sensitivity analyses

We have run several additional models to test the robustness of our results using alternative measures and specifications. First, we examine whether the main results are sensitive to the particular measure of skill requirements used. Figures S1–S4 present results from models similar to those in Figures 2–5, with the only difference being the use of the alternative skill-level measure, derived from the ISCO skill levels as defined by the ILO. While the ISCO-based measure accounts for slightly less of the variation in outcomes compared with the granular measure of occupational skill requirements, the overall results remain highly consistent.

Second, we run a set of country-specific regression analyses to examine whether our main results are stable across countries. Regarding expectations of the future and support for government redistribution, the results show that the coefficient for skill requirements is in the expected direction and significant in almost all models and countries, although effect sizes vary. For automation risk, evidence is scattered, with no country showing systematic results in line with the automation perspective across all automation-risk measures. For radical right voting, results are more mixed across countries. The level of skill requirements is a significant predictor in many, but not all, countries. As in the main analysis, the only automation-risk measure that yields any significant coefficients in the expected direction in models including occupational skill level is Arntz, Gregory and Zierahn (2016), but the results from the country-specific regressions suggest that this association is not systematic across countries.

5. Discussion and conclusions

Ongoing structural transformations in emerging knowledge societies involve both skill upgrading and widespread automation pressures, leading to major shifts in the occupational structure. Against this background, we critically examine the increasingly popular thesis that exposure to automation risk constitutes the main occupational channel through which structural change shapes individuals' expectations and their political preferences. Our primary reservation toward much previous research is that it tends to overlook the skill-level requirements of jobs, potentially leading to premature or overstated conclusions about the significance of automation risks *per se* in shaping these outcomes.

Using multiple rounds of the European Social Survey, we empirically compared how different occupational measures of automation risk and skill requirements predict individuals' expectations of personal economic difficulties and societal decline, support for government redistribution, and radical right voting across eleven Western European countries. The main takeaways of our analysis can be summarised as follows.

First, we were largely successful in replicating the results of previous automation-oriented studies using similar data and methods. When occupational skill requirements were omitted, as is common in prior research, higher automation risks appeared to be associated with expectations of economic difficulties and societal decline, greater support for economic redistribution, and a higher likelihood of voting for the radical right. Although the more recent automation-risk measures performed better in predicting these outcomes, they also correlated more strongly with the level of skill requirements. Especially in the case of the Arntz, Gregory and Zierahn (2016) measure, this may largely be because it more clearly weaves occupational skill requirements into its construction. This reinforces our argument that automation-based results should be interpreted cautiously unless the level of skill requirements is explicitly accounted for in the analysis.

Second, when the level of skill requirements was included in the models, we consistently found that individuals in occupations with higher skill requirements have expectations about the future that are less negative, are less supportive of economic redistribution, and are less inclined to vote for the radical right. By contrast, once occupational skill level was taken into account, automation-risk measures generally failed to show the theoretically expected relationships with expectations of the future or political preferences.

Taken together, these findings suggest that a narrow focus on automation risk overstates its impact on political preferences. While automation pressures are an integral element of the broader structural transformation toward knowledge societies, our theoretical framework and empirical results call into question whether automation risk constitutes the primary channel through which individual expectations of the future and political preferences are affected. Instead, our results indicate that the skill-level requirements of occupations—reinforced by the process of skill upgrading—carry greater explanatory weight in shaping individual expectations, policy preferences, and voting behaviours.

Whether the observed effect sizes for skill requirements should be considered large or modest is, to some extent, a matter of perspective. It is therefore noteworthy that the observed effects of occupational skill level were larger or at least on par with those of automation risk in our analysis (when not controlling for skill requirements). This suggests that the substantive importance of the level of

occupational skill requirements is equal to, and quite possibly greater than, what has previously been attributed solely to automation risk.

As in several automation-oriented studies, a limitation of this study is the reliance on observational and cross-sectional data; this approach prevents us from adequately accounting for how individual life course trajectories may contribute to these relationships. This means that the occupations serving as comparison groups might be muddled by people who have already lost their jobs because of automation and/or managed to switch to other occupations with lower automation risk (cf. Anelli, Colantone and Stanig, 2021). Nevertheless, insofar as the core mechanism of automation risk involves the *threat* of job loss rather than the experience of such loss, the focal unit of analysis should generally be individuals' current employment position. Taken together, while our empirical strategy certainly is not without shortcomings, it should be sufficient to detect meaningful effects if automation risk indeed constitutes a major driver of the outcomes studied.

It is also important to acknowledge that we have not aimed to provide an exhaustive account of all aspects of occupational skill requirements that may be relevant to these outcomes. Future research could, for example, incorporate horizontal skill requirements tied to different types of work tasks and logics—such as working with people, data, or things—or consider the transferability of required job skills (e.g., Pardos-Prado and Xena, 2019). Similarly, future studies could broaden the scope of political preferences; for example, by considering support for social investment or immigration policies, or by comparing support for mainstream versus non-mainstream parties on both the left and the right. It would also be valuable for future research to theorise and rigorously analyse how skill components at different analytical levels interact in shaping social and political outcomes, ranging from individual education and job skill requirements to regional skill clusters and national skill systems. Finally, future research could utilise this framework to investigate whether the large-scale breakthrough of artificial intelligence may recalibrate the examined relationships.

To conclude, we have elaborated on the perspective of Bell (1973) and others that socioeconomic inequalities in capitalist knowledge economies are largely structured around skills in working life. Differentiating “winning” from “losing” positions amid ongoing structural shifts toward knowledge societies requires close attention to their place in the occupational skill hierarchy. While economically advantaged and socially prestigious expert roles in management, governance, and specialised services sit at the forefront of societal development, individuals in occupations with low skill requirements more often face stagnating social and economic opportunities. Our study suggests that these structural inequalities generate social and economic grievances as well as political divides,

marked by bleak expectations of the future, demands for economic redistribution, and support for populist radical right parties among sizable parts of the population.

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AI use disclosure

AI was not used in the conduct of the research. It was used solely to assist with proofreading the manuscript.

Data and code availability

All data are available in public data repositories or in the replication package, which can be found at the following link: https://osf.io/u2edm/overview?view_only=240ed260c49c417d8204a3f638b10bdc.

Declaration of interest statement

The authors declare no conflicts of interest related to this research.

Ethical approval

In line with the Swedish Ethical Review Authority guidelines, no ethical approval was necessary for this study as we do not conduct research on humans, human tissue, or sensitive personal data.

Supplements

Supplemental data for this article can be accessed online at <https://doi.org/10.1162/EUSO.a.100>.

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Uncorrected Proof