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Preferred policy responses to technological change: Survey evidence from OECD countries

Marius R. Busemeyer,[1,*] Mia Gandenberger,[2] Carlo Knotz [3] and Tobias Tober[1]

[1]Politics and Public Administration, University of Konstanz, Konstanz, Germany; [2]Swiss Graduate School of Public Administration, University of Lausanne, Lausanne, Vaud, Switzerland and [3]Department of Media and Social Sciences, University of Stavanger, Stavanger, Norway

**Correspondence: tobias.tober@uni-konstanz.de*

Abstract

How do the labor market risks associated with technological change affect policy preferences? We argue that higher perceptions of technology-related risks should increase support for compensation and decrease support for social investment. We expect the opposite effect for individuals who use technology constantly at work, have a university degree and earn higher incomes. However, as the perception of technology-related employment risks in the latter group of individuals increases, so does their preference for compensatory and protective policy solutions to technological change. Our expectations are confirmed by novel data from a survey of 24 diverse Organisation for Economic Co-operation and Development (OECD) countries that includes specifically designed questions on technology-related risks and policy preferences. The results suggest that technology-related risks not only correlate with certain demographic and occupational characteristics, but also cross-cut them. Thus, technology-related risks might not only become a source of new cleavages between the losers and winners of technological change, but also the basis for new cross-class coalitions.

Keywords: technological change, policy preferences, comparative political economy

JEL classification: O33 Technological Change, Choices and Consequences

1. Introduction

Rapid technological change in the form of digitalization and automation is transforming labor markets in OECD countries and is likely to have significant repercussions for the future of welfare states in the long term. The most dramatic predictions, such as mass unemployment and a fundamental crisis of democratic capitalism (Ford, 2016), have not yet materialized. However, there is solid evidence for a 'hollowing out of the middle' effect, i.e. increasing levels of labor market polarization as wages and employment opportunities of the middle classes fall victim to technological change (Goos *et al.*, 2009, 2014; Autor and Dorn, 2013; Michaels *et al.*, 2014; OECD, 2019).

In comparative welfare state research, scholars have started to assess the political and social policy implications of the digitalization and intensified automation of work. Social policy responses to this challenge are hampered by the fact that governments' policy options are constrained by pressures of fiscal austerity, forcing governments to prioritize (cf. Adolph et al., 2020). One strand of scholarship in this field finds that the 'losers' of technological change, who experience a subjective loss in social status as well as real economic decline, increasingly turn to right-wing populist parties rather than (re-)empowering mainstream left-wing parties and unions (Frey *et al.*, 2018; Anelli *et al.*, 2019; Im *et al.*, 2019; Kurer and Palier, 2019; Kurer, 2020). A second strand of scholarship, which is more relevant for this article, has started to explore the association between rapid technological change and social policy attitudes.

Starting with the pioneering work of Thewissen and Rueda (2019), these studies probe whether individuals whose job is at high risk of being automated or otherwise eliminated due to technological change hold particular preferences regarding the welfare state (Zhang, 2019; Dermont and Weisstanner, 2020; Jeffrey, 2021; Sacchi *et al.*, 2019; Gallego *et al.*, 2022; Im, 2021; Kurer and Häusermann, 2021). At a deeper level, the underlying questions are on the one hand whether technology-related employment risks are partially independent or even orthogonal to other dimensions of labor market risk like economic globalization, and on the other hand whether the emerging social risks in connection with technological change provoke demand for new, innovative social policies or simply increase the demand for compensation through traditional policy tools.

We focus primarily on the latter question in this article. Our main theoretical contribution is that we develop more detailed insights about how technology-related risks both correlate with and cross-cut demographic and occupational characteristics and, in doing so, shape policy preferences. Specifically, we show that many of those who could be expected to be clear beneficiaries of automation and digitalization—parts of the highly educated and of those who regularly use information technology at work—are in fact quite concerned about technology-related job loss. Accordingly, they share the policy preferences of more typical 'technology losers'. In other words, we qualify the view that future labor markets will be characterized by an increasing divide between 'brains' and their 'servants' (Palier, 2019) in showing that many supposed 'brains' actually share the risk perceptions and policy preferences of their 'servants'. Technology-related risks could therefore become not only a source of new cleavages, but also a basis for new cross-class coalitions, similar to income (Rehm *et al.*, 2012) or education (Häusermann *et al.*, 2015).

From an empirical perspective, our article makes use of a novel and specifically designed battery of questions on technology-related social policy preferences, featured in the latest wave of the OECD's *Risks that Matter* (RTM) survey. While previous studies had to work with existing data such as the European Social Survey or self-collected data available for single countries only, ours is the first study of tech-related policy preferences using novel data from a large comparative survey covering 24 countries. It features items which were specifically designed to capture perceptions of workplace automation and digitalization and related policy preferences.

Our core result is that individuals who fear that their job will be lost due to technological change are more likely to demand short-term compensatory and protective policies such as more generous unemployment benefits or a tax on robots and technology companies than longer term-oriented policies such as higher spending on education or re-training. Conversely, individuals who regularly use technology on their jobs, have a university degree and earn high incomes are more likely to support investments in human capital.[1] However, we also find that subjective technology risk has a moderating effect on the policy preferences of this latter group of individuals: When tech-savvy, university-educated and high-income-earning individuals begin to perceive automation and digitalization as a personal employment risk, they increasingly prefer compensation and protection to social investment.

The remainder of this article proceeds as follows: The Section 2 develops our theoretical argument. Section 3 presents our data, methods and empirical findings. The final section concludes.

2. Technological change and policy preferences

2.1 The range of policy options

In line with previous work on the association between risk and social policy preferences (Iversen and Soskice, 2001; Rehm, 2009, 2016), the recent study by Thewissen and Rueda (2019) confirms that individual automation risk is positively related to demand for redistribution in OECD countries (see also Kurer and Häusermann, 2021; note, however, that some other studies do not find evidence for such an effect, see Zhang, 2019; Jeffrey, 2021).

Our argument builds on this work, but we suggest it is important to adopt a broader perspective on potential policy responses to technological change that goes beyond merely redistributive policies, even though not all of these alternative policy solutions will be equally attractive to those who feel at risk. We focus on policy responses here that have a direct connection to both technological change as well as individual labor market experiences. For instance, we exclude policies such as pensions and health care, which arguably play a crucial role in contemporary welfare states but are more distant potential policy options when it comes to addressing the immediate labor market effects of technological change. Moreover, as is well-known in social policy literature, many social policies do not only (re-)distribute resources, but can in fact accelerate technological change and boost economic development and innovation. We posit that the patterns of support and opposition for these different policy options should be strongly conditioned by cleavages between the winners and losers of technological change, as we discuss in greater detail in the following.

A first policy option, and arguably the one that is most naturally associated with 'redistribution', focuses on social compensation and related protective regulatory policies. The common element across these different policy options is to protect and/or compensate those adversely affected by technological change. A straightforward example for a compensatory

1 While we are in principle interested in analyzing social policy preferences across a broad range of issues, we do not consider workfare ('demanding' labor market activation) policies (e.g. Rueda, 2015). As shown in recent research by Im and his collaborators (Im, 2021; Im and Komp-Leukkunen, 2021), attitudes toward these policies may also be related to automation risk in that 'automation losers' tend to support strict activation policies out of a desire to protect themselves against competition for access to social protection from even more vulnerable groups. We nevertheless return briefly to this issue in the Conclusion.

policy would be to increase the generosity of unemployment benefits and similar social transfers. A more radical proposal to deal with the negative side effects of technological change via redistribution is the introduction of a universal basic income (UBI) (Pulkka, 2017; Van Parijs and Vanderborght, 2017; Martinelli, 2020). A UBI would be less targeted compared to the above discussed measures, and it would be less redistributive because it would benefit all income strata. However, it would not only provide a secure income for those laid-off due to technological change, but also provide an additional source of income for those working as independent or semi-dependent workers in the platform economy and the creative digital industries. This may be one of the reasons why this policy proposal is often discussed in the context of rapid technological change. Given that social policies targeted specifically at the poor are broadly less popular (Korpi and Palme, 1998; van Oorschot, 2006), introducing a UBI could receive broader support, including from members in the middle class who are worried about the implications of technological change.

Complementing social transfers, additional regulatory protective policies could further buffer the negative side effects of technological change. A commonly discussed proposal in this regard is the (forced) reduction of working hours: As robots and software take over many tasks traditionally performed by humans, the remaining and shrinking amount of work should be distributed more equally, so the argument goes. Finally, another policy option could be to raise a special tax on companies that rely heavily on the use of technology ('robot tax'). A robot tax would be levied in addition to existing taxes, thereby setting incentives for firms to not over-invest in technology to the detriment of human workers. In promoting a more reactive and protective policy response rather than pro-actively investing in skills, all of these policy proposals are similar to compensation policies, even though they are regulatory rather than spending-oriented policies.

A second possible policy response to radical technological change would be to boost investments in human capital formation and the digital infrastructure. Compared to compensation, the investment-oriented strategy focuses more on the long-term perspective, i.e. how to train workers as well as young people to be able to more effectively meet the challenges of the digitalized 'knowledge economy'. Thus, investment-oriented policy measures related to technological change could, on the one hand, be directed at improving the qualifications of the coming generation by investing in university education and vocational training opportunities for young people. On the other hand, investing in human capital formation can also be directed at currently employed workers, e.g. by expanding spending on active labor market policies (ALMP) and continuous education.

In sum, this brief discussion shows that there is a wide range of social policy options available in response to the challenges of rapid technological change, some of which are more related to traditional compensatory measures, while others focus more on human capital formation and social investment as well as taxes and regulation. In the following, we develop a number of hypotheses on factors that might explain the variation in preferences toward these policies.

2.2 Technology risk and policy preferences

A first, arguably obvious expectation that can be derived directly from the existing work on labor market risks and policy preferences (Iversen and Soskice, 2001; Rehm, 2009, 2016; Thewissen and Rueda, 2019) is that workers who feel at risk of losing their job due to technological change should have a stronger demand for policies that compensate them for their real or expected income losses and/or protect them from rapidly advancing technological change (Hypothesis 1). These policies include more generous unemployment benefits and related cash transfer programs, the introduction of a UBI, as well as proposals to limit and redistribute work hours. Equally attractive to these workers should be tax policies that target firms that invest heavily in automation, i.e. robot taxes. These robot taxes have a protectionist streak, as they slow down the pace of technological change, potentially reducing the need for further compensatory measures at least in the short term. Furthermore, the revenues generated from such additional taxes can be used to finance benefit programs. Since workers who were made redundant by technology are unlikely to pay such robot taxes, they would clearly be net beneficiaries.

Matters are different when it comes to investment-oriented policies. Intuitively, one may expect that the likely losers of technological change would equally welcome measures that help them adapt to a changing work environment, including investments in education and labor market training. Such policies are commonly recommended by experts (e.g. Colin and Palier, 2015; McAfee and Brynjolfsson, 2016) and, if successful, could indeed help workers to not only cope with change but even to upgrade their status in the labor market. But from the perspective of a worker threatened by technological change, the problem is that the success of investment-oriented polices is not exactly certain. (Re-)enrollment in higher education is likely not an option for many workers, and even participation in high-quality labor market training programs may be interpreted as a negative rather than positive signal by potential future employers (Liechti *et al.*, 2017). In contrast, purely ‘passive’ cash benefits are a more tangible and reliable form of compensation, even though their generosity is of course limited. Additionally, according to firmly established insights from psychological research, humans tend to prefer less valuable but certain options over more valuable but uncertain ones (Kahneman and Tversky, 2013). Further investments into the physical digital infrastructure, finally, should be clearly unattractive to workers already threatened by technological change since this is likely to further undermine demand for their skills. Hence, in sum, our second hypothesis is that at-risk workers are less likely to support social (and physical) investment policies (Hypothesis 2).

2.3 The varying effects of technology risk

It can be tempting to see technology risk as essentially collinear with other demographic and occupational characteristics, in particular education, income and the use of technology at work. Especially the theory and findings from research on technology-related labor market polarization (e.g. Autor *et al.*, 2003; Goos and Manning, 2007; Goos *et al.*, 2009, 2014; Autor, 2015) suggest an image of labor markets as increasingly divided between ‘lousy’ and ‘lovely’ jobs, or between ‘brains’ and their ‘servants’ (Palier, 2019). On the one side are those with a high level of education and skills, who complement and are complemented by information technology. Not only should their risk of technological redundancy be negligible, but they should also benefit from continuous demand for their labor and thus an upward pull on their incomes. On the other side are those with middle or lower levels of education and income. Those in the middle, who tend to specialize in routine tasks, are increasingly replaced by machines and left with the choice between leaving the active labor force or joining those at the lower end of the skill distribution, who provide services that are difficult to automate (caring or serving) but also unlikely to generate large incomes.

While we find the underlying theory about the differential impacts of technology at different skill levels convincing in principle, there are nevertheless reasons to expect the actual empirical picture to be more nuanced in some important respects (see also Oesch, 2013). Consider, for a start, the case of education. A higher level of education does of course provide the skills that are rewarded in a digital, knowledge-based economy, including abstract reasoning, numerical and technical abilities or self-organization and managerial skills (Grundke *et al.*, 2018). Thus, education and technology risk are likely to be correlated to a certain degree and, as a consequence, the policy preferences of the higher educated are likely to correspond to those with a low technology risk: a preference for active, investment-oriented policies and less for passive, compensating policies. The same should hold for high-income individuals.

At the same time, there are reasons to expect that at least some high-income and highly educated workers may still be concerned about technological change. One reason is that not all workers, higher educated or not, find employment in jobs corresponding to their skill levels, for instance due to variation in innate abilities (e.g. Bauer, 2002; Åberg, 2003; Spitz-Oener, 2006; Carroll and Tani, 2013). To the extent that the jobs they do find are more routine-intensive, this puts even some higher-educated individuals at risk of technological redundancy. The implication is that there will be some higher-educated workers who still feel threatened by technological change, and who thus share the policy preferences of the lower skilled. A similar logic applies to high-income individuals. Even though they are generally less supportive of expansive social policies (e.g. Meltzer and Richard, 1981), some labor market risks remain even for high-income workers (e.g. Rehm *et al.*, 2012) who might also be worried about steeper losses in income (relatively speaking) in the case of job loss compared to lower income individuals.

Finally, besides high-income and highly educated individuals, we look at those who routinely use information technology in their work. In principle, it can be expected that—compared to those who do not or only rarely use such technology at work—those who already rely regularly on computers and software should feel less threatened by technology. Thus, their policy preferences should reflect a lower desire for compensation and stronger support for investment-oriented policies. At the same time, the use of technology at work is at this point so widespread across occupations and skill levels (e.g. Spitz-Oener, 2006) that there is likely great variation within the group of technology users. Simply put, many in this group will be highly skilled ‘brains’ that are well versed in digital technologies and enthusiastic about further developments (e.g. software engineers), but there are also many that still work in mid-level occupations who nevertheless rely heavily on digital technology (e.g. administration workers). The latter group is likely to see technology more as a threat and will thus have policy preferences that are more in line with those who rarely or never use technology at work.

Taken together, we therefore expect to find a number of interaction effects between the perception of technology-related employment risks and various personal characteristics of respondents. More specifically, we expect that those who regularly use technology on their jobs, are highly educated and have high incomes to be generally more supportive of investment-type policies and less supportive of purely compensatory measures (Hypothesis 3). However, as argued above, there are good reasons to assume that within the different sub-groups of the highly educated, high-income earners and regular tech users, there remains a significant degree of heterogeneity regarding subjective perceptions of technology-related labor market risks. Hence, we expect that a higher level of (perceived) technology risk will mediate the associations between education, income and tech usage on the job, effectively leading to a convergence of preferences toward compensatory and protective policies for those at high risk, independent of their personal background (Hypothesis 4).

3. Empirical analysis

3.1 The OECD RTM survey

For our empirical analysis, we draw on original data from a recent cross-country survey organized by the OECD, the RTM survey. This survey builds on an earlier one with the same title conducted in 2018 and is mainly concerned with perceptions of social and economic risks and the extent to which governments are doing enough to provide protection against them. In this round, we and several other colleagues contributed new survey items specifically related to individuals' perceptions of digital transformation, the social risks generated by it and their desired policy responses. The survey was conducted in 24 OECD member countries (Austria, Belgium, Canada, Switzerland, Chile, Germany, Denmark, Spain, Estonia, Finland, France, Greece, Ireland, Italy, South Korea, Lithuania, Mexico, Netherlands, Norway, Poland, Portugal, Slovenia, Turkey and the USA) and was fielded in the early fall of 2020. It goes without saying that the fieldwork coincided with the COVID-19 pandemic, a period of extraordinary economic, social and also political upheaval. The generalizability of our findings is therefore conditioned by these exceptional circumstances. But the fact that our findings correspond closely to those obtained with data from other sources and time points (Busemeyer and Sahm, 2021; Kurer and Häusermann, 2021) gives us confidence that our results are not too much affected by the pandemic context.

Our main independent variable is respondents' subjective risk of losing their job due to technological change. Specifically, we use the following three items from the RTM survey: *How likely do you think it is that the following will happen to your job (or job opportunities) over the next 5 years?*

(1) My job will be replaced by a robot, computer software, an algorithm or artificial intelligence.
(2) My job will be replaced by a person providing a similar service on an internet platform.
(3) I will lose my job because I am not good enough with new technology or because I will be replaced by someone with better technological skills.

Respondents were asked whether they considered the three scenarios as very unlikely, unlikely, likely or very likely. Applying a rotated principal component analysis, we use these three survey items to create an index of subjective risk that tries to capture whether an individual perceives technology as a threat to her job. The three survey items have a high degree of internal consistency (Cronbach's $\alpha = 0.81$). We base the index on the first component of the principal component analysis, which explains about three-quarters of the variation in the data. Note that the three questions used to construct the index of technological risk assume that respondents were employed at the time of the survey, and were accordingly only shown to currently employed respondents. Thus, our analysis is limited to employed individuals.

In using a subjective measure of individuals' technology risk, we deviate from many previous studies. These have mostly used objective measures of technology risk such as the measure of routine task intensity (RTI) initially developed by Autor *et al.* (2003) or forward-looking measures that estimate the future potential of particular occupations to become automated (based on the work by Frey and Osborne, 2017). While we recognize that there are obvious downsides of using subjective measures, including that they may come along with biases in perceptions that are not unrelated to other attitudes (e.g. policy preferences), we still see important advantages in using them over objective measures (see also Heinrich and Witko, 2021 for a related argument).

For one, some objective measures often capture technological risk only at relatively aggregated levels like larger occupational groups. An example is the widely used measure by Goos *et al.* (2014), which measures risk at the two-digit level of the International Standard Classification of Occupations (ISCO). This approach risks neglecting significant variation in technology-related risks between individuals in the same occupation, potentially related to specific characteristics of employers, workplaces or countries. Others are more fine grained when it comes to occupational categories but capture risk only via the dominant type of task in an occupation, resulting in relatively rough categorical measurements (e.g. Oesch, 2013). A further problem with some objective measures is that these were developed some time ago and they therefore do not necessarily reflect the more recent increases in the use of technology in many previously 'low-tech' areas (self-scan checkout machines in supermarkets are a case in point).

Subjective measures, in contrast, can capture technology risks even when they vary within occupational groups and across countries, and are more reflective of the current state of technological progress. Nevertheless, it cannot be completely ruled out that there are unobserved respondent characteristics that affect both risk perceptions and policy preferences. Thus, ideally, one would use objective as well as subjective measures of risk, but unfortunately the RTM survey does not include detailed data on occupations that would allow us to use the objective measures of risk used in the previous studies. Consequently, our choice of a subjective risk measure is also partly driven by these data constraints.

Our other central independent variables are a measure of respondents' level of education, their income and the extent to which these individuals use information technology at work. For the latter, we use an item that asked respondents how frequently they use information technology such as a computer, laptop or tablet in their work. Responses range from 'never' over 'less than several times a month', 'several times a month', 'several times a week', 'several times a day' to 'constantly, most of the day'. About half of all respondents fall into the last category (see Supplementary Appendix Figure A10) and the remainder is distributed over the other categories. To avoid running estimations with very small cells, we dichotomize the measure into a dummy that takes on the value of 1 for respondents who constantly work with information technology and 0 for all others.

Income is measured as the log-transformed disposable annual income equalized for household size. We use purchasing power parities from the OECD to standardize incomes across countries to US dollars. As for our measure for individuals' level of education, we use a simple dummy that takes on the value of 1 for those who have a tertiary degree or at least some tertiary education and 0 for all others. About 60% fall into the latter category, while around 40% of all respondents are higher-educated.

We also control for a range of macro-level variables to take into account that the countries we cover vary considerable with respect to existing welfare state institutions and labor market conditions, all of which might conceivably have a confounding effect on both policy preferences and individuals' concerns about technological change. First, we control for public spending on active and passive labor market policies to take into account that technology risk might have more muted effects on policy preferences in countries where spending is already high (cf. Soroka and Wlezien, 2010). Second, we control for the overall unemployment rate, since higher levels of unemployment might make concerns about job loss due to technological change more pressing and thus reinforce both these concerns and demand for public support. Finally, we control for the extent to which technological change is currently affecting countries' occupational structures. Conceivably, concerns about technological change might be more acute in countries where the digital transformation has already advanced quite far (e.g. Korea) compared to countries that are still developing in many respects (e.g. Chile). To capture these differing cross-country experiences with technology-related occupational change, we compute the total change in the share of workers in high-routine occupations (ISCO-08 groups 4, 6, 7, 8, 9) between 2011 and 2019.[2] A stronger decline in the share of this group in a given country suggests that this country is more strongly experiencing the effects of technological change.

Our dependent variables are two composite measures of respondents' policy attitudes, one for their attitudes toward compensatory or protective policies and one for their attitudes toward investment-oriented (or 'active') policies. Following what is widely practiced in research on social policy attitudes (e.g. Iversen and Soskice, 2001; Fossati and Häusermann, 2014), we construct these from a battery of items that capture respondents' attitudes toward a set of compensatory/protective and social investment policies using factor analysis.[3] Respondents were asked to state whether they oppose or support different policies to deal with the effects of technological change, after an introduction that specifically asked respondents to consider the policies' potential costs and benefits for themselves and their families. The policies in question are the following:

- investing more in university education and vocational training opportunities for young people;
- investing more in re-training opportunities for working age people;
- investing more in digital infrastructure, such as the broadband network;
- introducing (or increasing) a tax on robots and/or technology companies;
- introducing (or lowering) a limit on working hours, so that work can be shared across more workers;
- making public benefits and services, such as unemployment benefits, more generous to provide a better safety net for workers facing possible job loss; and
- Introducing a UBI that covers essential living costs to everyone, regardless of their financial situation.

Responses were recorded on a five-point Likert scale ranging from 1 ('strongly oppose') to 5 ('strongly support').[4] We provide descriptive statistics for each item in the Supplementary

2 The start year is 2013 in the case of Mexico. The time-series for Canada and Chile are even shorter and they have accordingly been excluded.

3 Note that this battery included also an item that captured respondents' support for skilled migration to their country. However, migration policy is typically neither considered a social investment nor a protective/compensatory policy. Indeed, it turns out that the migration item loads only weakly on either of the two factors we identify. We therefore exclude this item from our analysis.

4 Respondents could also state that they 'cannot choose'; we excluded these individuals from our analysis.

Appendix Figures A2–A8, but can generally note that—overall—three of the social investment measures (investment in education, training and infrastructure) are supported or strongly supported by considerably more than 50% of all respondents. Among the compensatory/protective measures, work-sharing, more generous social protection programs and a UBI are also supported by more than half of respondents, yet the majorities are noticeably smaller than in the case of the social investment measures. While respondents appear to be more undecided about robot taxes, there are still more respondents who favor them than oppose them.

The results of our factor analysis are presented in Table 1. The results suggest that the responses do indeed fall into two separate factors. All compensatory/protective measures form Factor 1, whereas three of the active measures, investment in education, re-training and digital infrastructure form the second factor. As expected, the items load highly on their respective factors.

The two graphs in Figure 1 show the distribution of policy attitudes as captured by the two composite variables. We plot the data across countries here (we provide simple histograms in the Supplementary Appendix Figure A9), since we do have hierarchical data and considering the extent of variation in the data at the upper level is important, not least for our subsequent regression analysis. It is immediately apparent that there is variation across countries in how strongly different policy types are supported. The first impression from looking at attitudes toward compensatory/protective policies is that these reflect 'thermostatic' dynamics (Soroka and Wlezien, 2010), i.e. support is lower in countries that already have large and developed welfare states (Denmark, Norway, the Netherlands or Belgium) but high in countries where this is less the case (Chile, Turkey, Slovenia or Portugal). This is similar in the case of social investment policies, in particular for countries with a developed digital infrastructure. Korea, for instance, stands out as the country with the lowest demand for investment-oriented policies, which might reflect the fact that the country has a well-developed broadband infrastructure (albeit its welfare state is rather lean). This contrasts with Germany, which is more of a laggard in this regard (see OECD, 2017). While these findings do not necessarily point to a strong role of these particular macro-level variables (and we also substantiate this further below), the mere fact that there are visible differences in policy preferences at the country level indicates that it is important to account for (unexplained) cross-country variation in our estimations.

Table 1 Policy attitudes fall into two factors

Policy	Factor 1	Factor 2
Education and vocational training	0.218	0.755
Re-training	0.253	0.733
Digital infrastructure	0.017	0.770
Robot taxes	0.652	0.001
Work-sharing	0.653	0.217
Social protection	0.699	0.278
Universal basic income	0.743	0.169

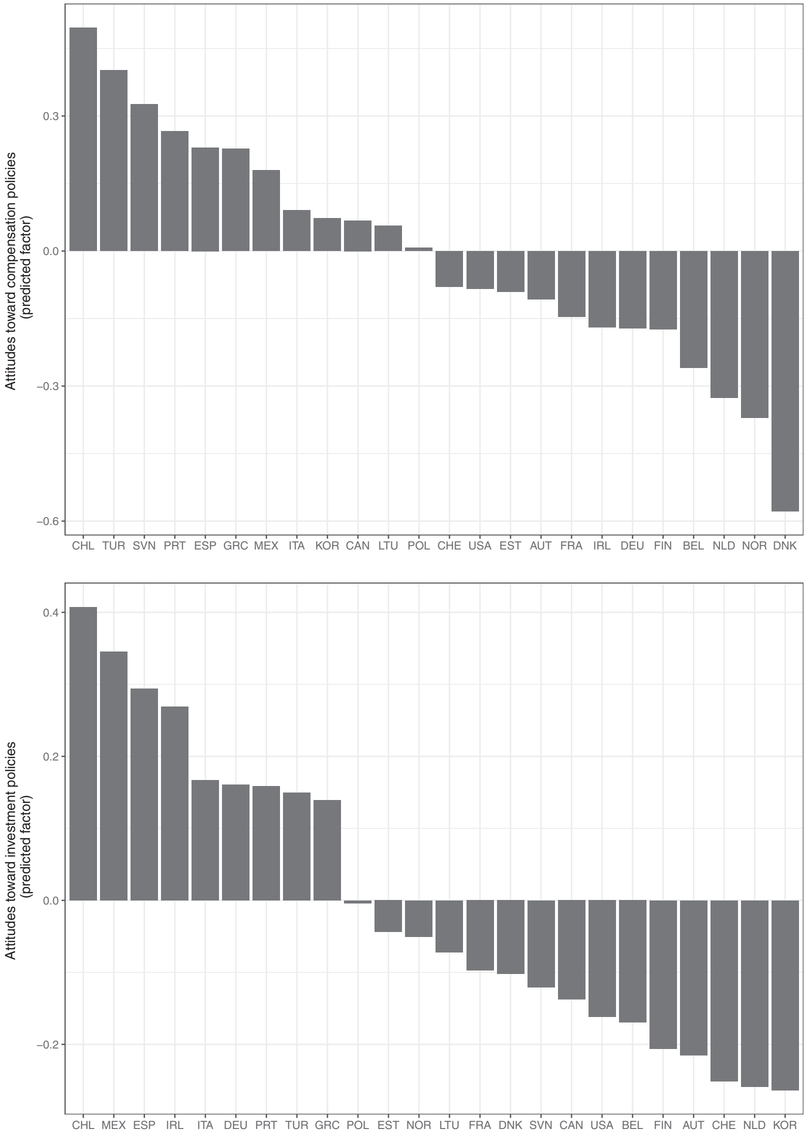

Figure 1 Attitudes toward compensating and investment oriented policies vary across countries.

We also consider the variation in our key independent variable—the subjective technology risk—across countries. The shares of respondents in each country which see it as either likely or very likely that they will be replaced by technology, replaced by another person on an internet platform or lose their job due to a lack of technological skills in the next 5 years are depicted in Figure 2. Here, we find that concerns about technology are highest in a rather diverse set of countries, including Turkey, Chile and Mexico but also Korea or the USA. The least concerned individuals live mainly in countries of Central and Northern Europe. This

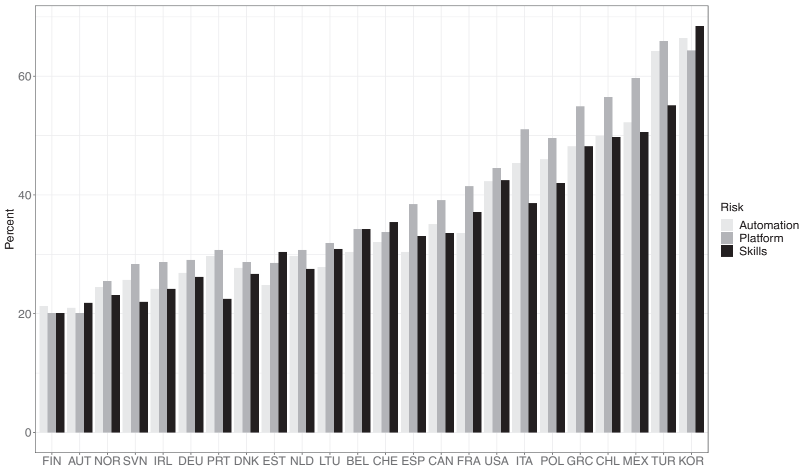

Figure 2 Perceived technology risks vary across countries.

Table 2 Subjective technology risk is not strongly associated with either higher education or technology use at work

	Concerned by					
	Automation		Platform		Skills	
Education and ICT use	No (%)	Yes (%)	No (%)	Yes (%)	No (%)	Yes (%)
No tertiary education	62	38	59	41	61	39
Tertiary education	68	32	64	36	69	31
No constant ICT use	61	39	58	42	59	41
Constant ICT use	68	32	63	37	69	31

suggests that concerns about technological change are mitigated by the presence of strong labor markets institutions, which is why we find on average lower levels of concern in some of the European welfare states.[5]

As a final step in the descriptive analysis, we consider the covariation between subjective technology risk on the one hand and educational attainment, the use of technology at work and income on the other hand.[6] Table 2 shows the percentages of respondents that see it as likely or very likely that they could be replaced by technology, replaced by another person on an internet platform or lose their job because of lacking technological skills, broken down by their level of education (non-/tertiary educational attainment) and the use of

5 A descriptive analysis in the Supplementary Appendix Figures A14–A16 indeed suggests a negative relationship between existing levels of spending on active and passive labor market policies on the one side and perceived technology risk on the other.

6 Note that we also show in the Supplementary Appendix Figure A12 that having a higher education is only weakly associated with the use of information technology at work.

information and communication technology (ICT) devices at work (non-/constant use). In both cases, there is an association in the expected direction—higher educated individuals and constant ICT users are less concerned about technology risks—but the relationships are not particularly strong. There are still quite sizable percentages of both high-educated individuals and constant technology users who are concerned about the various labor market implications of technological change. Figure 3 confirms this impression across different income deciles (with certain signs of curvilinearity). Even in the income decile with the lowest subjective technology risks (i.e. the seventh decile), roughly 30% of those surveyed fear a job loss due to technological change in the near future.[7] These numbers correspond closely to our argument that technology-related risks not only correlate with certain demographic and occupational characteristics, but also cross-cut them.

3.2 Regression analysis

To test our hypotheses in a more systematic manner, we estimate Bayesian hierarchical models with country-varying intercepts. Our basic regression equation is given by

$$\begin{aligned}\text{Preferences}*_{ic} = {} & \beta_1 \text{TechRisk}_{ic} + \beta_2 \text{TechUsers}_{ic} + \beta_3 \text{TertEdu}_{ic} + \beta_4 \text{Income}_{ic} \\ & + \beta_5 \boldsymbol{x}_{ic} + \alpha_0 + u_c + \epsilon_{ic},\end{aligned} \tag{1}$$

where $\text{Preferences}*_{ic}$ are the policy preferences for either social investment or compensatory/protective measures of individual i living in country c, TechRisk_{ic} are the subjective perceptions of technology risk, TechUsers_{ic} is the binary indicator for constant use of information

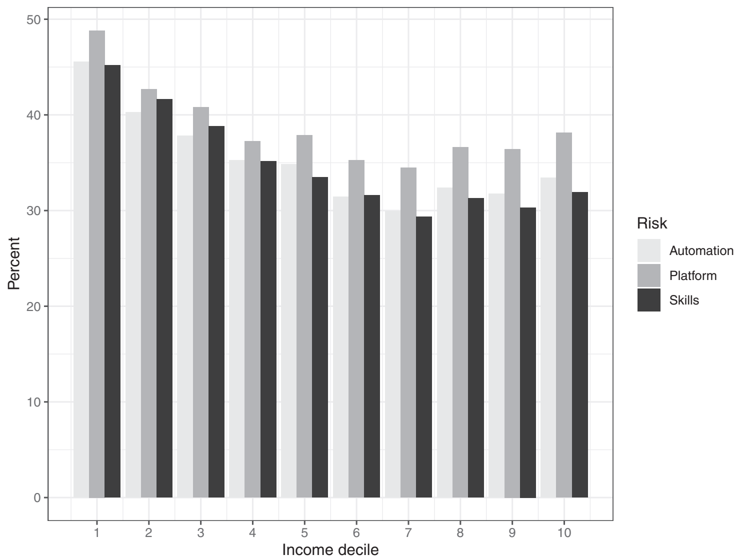

Figure 3 Individuals perceive technology risks across all income deciles.

7 In addition, we show in the Supplementary Appendix Figure A13 that perceived technology risks are only weakly stratified across occupational groups.

technology in a job, TertEdu_{ic} is another binary indicator for tertiary educational attainment, Income_{ic} is the log-transformed disposable annual income equalized for household size, $\boldsymbol{x}_{ic}$ is the vector of additional individual- and country-level controls, α_0 is the grand mean, u_c are the country-random residuals and finally the term ϵ_{ic} denotes the within-country residuals at the individual level.

To recall, we expect that individuals with higher levels of perceived technology risk demand more compensatory/protective policies (Hypothesis 1) and are less likely to express support for social investment policies (Hypothesis 2). In contrast, we expect the opposite effect for constant technology users, individuals with higher (tertiary) education and high-income earners (Hypothesis 3). However, we also theorize that those in the tech-savvy, highly trained and high-earning group who fear the job implications of technological innovation become increasingly likely to support compensatory/protective measures (Hypothesis 4). Thus, to test the relationship between these variables and the subjective perception of technology risk, we estimate the following interaction models:

$$\begin{aligned}\text{Preferences}*_{ic} = {} & \gamma_1 \text{TechRisk}_{ic} + \gamma_2 \text{TechUsers}|\text{TertEdu}|\text{Income}_{ic} \\ & + \gamma_3 (\text{TechRisk}_{ic} \cdot \text{TechUsers}|\text{TertEdu}|\text{Income}_{ic}) \\ & + \gamma_4 \boldsymbol{x}_{ic} + \alpha_0 + \boldsymbol{u}_c + \epsilon_{ic},\end{aligned} \tag{2}$$

where the interactive term $(\text{TechRisk}_{ic} \cdot \text{TechUsers}|\text{TertEdu}|\text{Income}_{ic})$ models the effect of job-related technology usage, tertiary education or income on policy preferences conditional on perceptions of technology risk. In the case of social investment policies, we expect that the coefficient of each interaction has a negative sign (i.e. $\gamma_{3,\text{investment}} < 0$), indicating that the positive relationship between each of these variables and support for active policies decreases as the subjective technology risk increases. More importantly, support for compensatory/protective policies among the corresponding individuals should strongly increase with the perception of technological risk (i.e. $\gamma_{3,\text{compensation}} > 0$).

We estimate these models in a Bayesian framework using the brms package in R (Bürkner, 2017). Beyond reasons of statistical philosophy, the Bayesian approach avoids the alleged anti-conservative bias in likelihood-based estimates of hierarchical models (e.g. Stegmueller, 2013; Bryan and Jenkins, 2016; but also see Elff *et al.*, 2021). Given that the number of countries in our sample is relatively small, we assign weakly informative priors on the variance components.[8] Moreover, we center and scale all continuous variables by two times their standard deviation in order to make the resulting coefficients comparable to the coefficients of the unscaled binary indicators (Gelman, 2008). In particular, this allows to directly compare the results of our technology-risk variable with the results of our binary indicators for constant tech users and university-trained individuals.

Figure 4 compares the results of two hierarchical models with individual-level controls based on 100 000 Markov chain Monte Carlo iterations, where the first model uses preferences for social investment policies and the second model uses preferences for compensatory/protective policies as dependent variable.

Looking at our main variables of interest first, the results confirm the expected effect differences. On the one hand, higher risk perceptions reduce preferences for active policy solutions and strongly increase support for compensatory/protective measures, in line with

8 Following Gelman et al. (2006), we use half-Cauchy priors with $t(4, 0, 1)$.

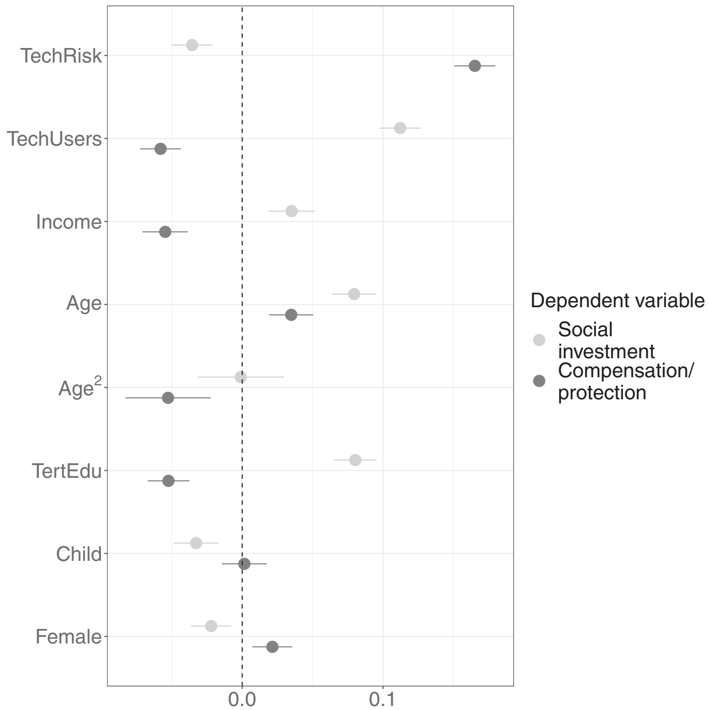

Figure 4 Bayesian hierarchical models with individual-level controls: Standardized coefficients (posterior means) and 95% credible intervals.

Hypotheses 1 and 2. On the other hand, we find the opposite effect for constant technology users, individuals with tertiary education and high-income earners who oppose compensatory/protective measures but prefer social investment policies, confirming Hypothesis 3. The individual-level controls show that higher age is associated with more support for both types of policy. Yet, the squared term of age suggests that these effects follow an inverse u-shape, with individuals who approach retirement becoming increasingly opposed to policy interventions. Moreover, having a child (or children) and/or being female reduces support for active policy solutions to technological change. At the same time, women appear to be more supportive of compensatory/protective measures than men. Figure 5 shows that these findings hold when we include additional macro-level control variables. The macro-level coefficients suggest that higher ALMP spending reduces support for compensatory/protective measures, while higher unemployment increases demand for this kind of policy response to technological change.

To make these effects a bit more tangible, Figure 6 displays conditional effect plots that predict levels of support for social investment (left panels) and compensatory/protective (right) policy measures by our main variables of interest (we hold all other continuous variables at their mean and assign the first level to the remaining factor variables). Starting with the effect of risk perception on support for active policy solutions to technological change (left panel in the first row), the graph suggests that a simulated increase from the lowest

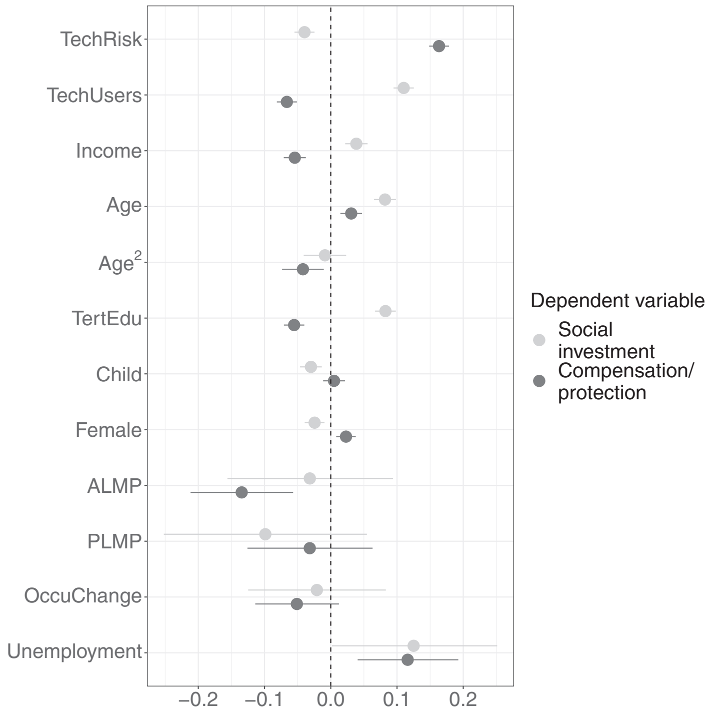

Figure 5 Bayesian hierarchical models with individual- and macro-level controls: Standardized coefficients (posterior means) and 95% credible intervals.

observed value of perceived risk to the highest reduces support for social investment policy measures by roughly 11% of a standard deviation. In contrast, the impact of subjective technology risk on support for compensatory/protective policy solutions is considerably stronger (right panel in the first row). Simulating an increase of perceived technology risk from the lowest to the highest observed value increases support for compensatory and protective policies by about half a standard deviation. The next two rows show that both technology use at work and tertiary education exert a stronger effect on support for social investment than on support for compensation and protection, with the former increasing preferences for social investment policies by about 22% of a standard deviation and the latter by about 16% of a standard deviation (compared to a decline in support for compensatory and protective measures of 12% and 10% of a standard deviation, respectively). Finally, simulating increases in income over the full range of observed values rises support for social investment policies by about 72% of a standard deviation, while reducing support for compensation and protection by more than a standard deviation (113%).

Figure 7 replicates the model with individual-level controls using each individual component of our factor analysis as dependent variable. Focusing again on the variables of interest, the results largely corroborate our previous findings. Subjective technology risk has little effect on support for social investment measures, i.e. education and training for the young, retraining for workers and investment in digital infrastructure. However, high-risk individuals strongly favor compensatory/protective measures in the form of a tax on robots or

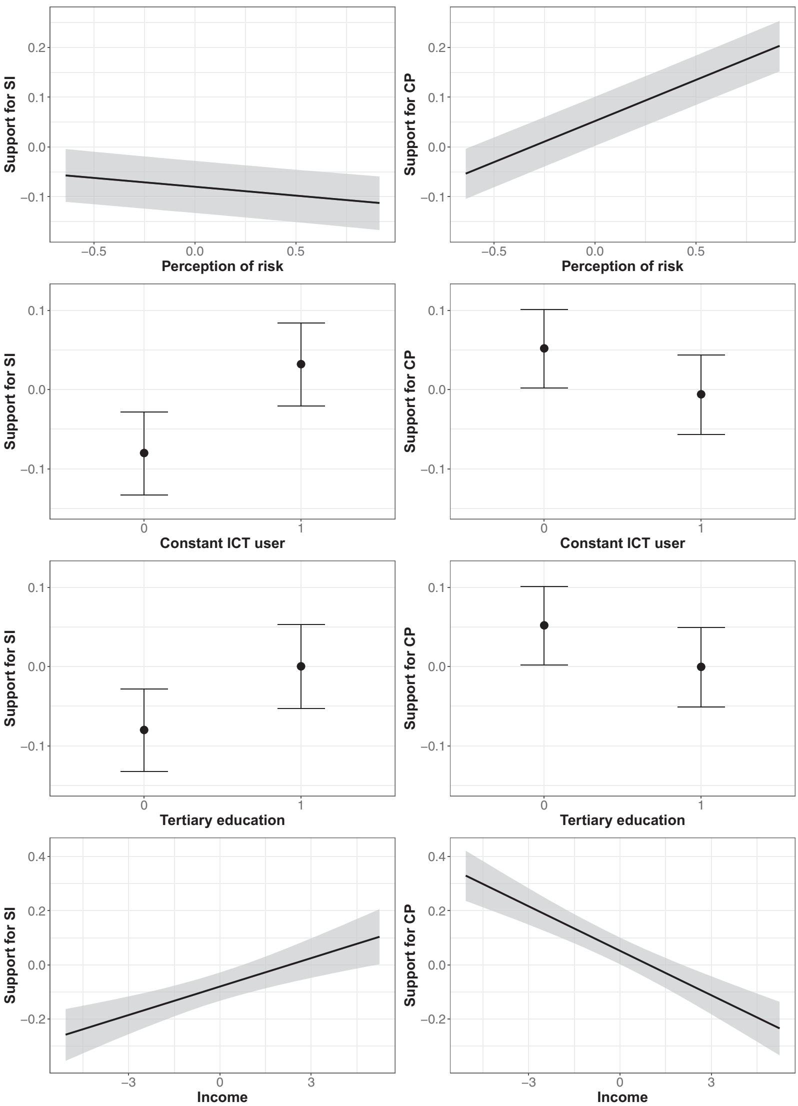

Figure 6 Support for social investment (SI; left panels) and compensation/protection (CP; right panels) predicted by perceived technology risk, constant technology (ICT) usage, tertiary education and income with 95% credible intervals.

technology companies, a limit on working hours to promote work-sharing, social protection through benefits and services and the introduction of an UBI. The picture is largely reversed for technology users, university graduates and high-income earners who generally support social investment policy components and oppose compensatory/protective ones.

Above all, we argue that the subjective technology risk has not only an independent impact on preferred policy solutions, but also moderates the effects of technology usage,

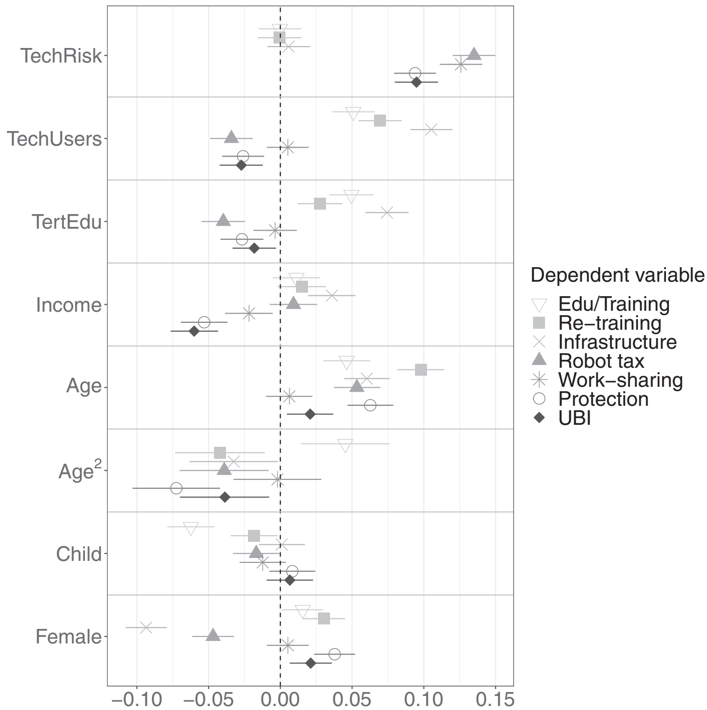

Figure 7 Individual factor components: standardized coefficients (posterior means) and 95% credible intervals.

tertiary education and income. In particular, we predict that the opposition of tech-savvy, university-educated and high-income-earning individuals to compensatory and protective policy measures will decline as perceived levels of technology-related employment risks increase (Hypothesis 4). Figure 8 tests this prediction by plotting the interactive relationship between each of these variables with our measure of risk perception. As annotated in the panels of Figure 8, all underlying interaction terms are highly statistically significant.

The resulting graphs reveal remarkably similar patterns. In the case of support for active policy solutions, constant technology users, university graduates and high-income earners exhibit higher levels of support at low levels of subjective technology risk.[9] However, the difference to non-tech users, individuals with non-tertiary educational attainment and low-income earners becomes significantly smaller as risk perceptions increase. We observe the opposite effect in the case of support for compensatory and protective policy responses to technological change. Here, tech-savvy, university-trained and high-income-earning individuals show lower levels of support than their counterparts when they are less concerned about their jobs being replaced by automation or digitalization. Yet again, as the subjective technology risk increases, the difference between these groups of individuals declines. In

9 We define as low income, a disposable income one standard deviation below the mean; and as high income, a disposable income one standard deviations above the mean.

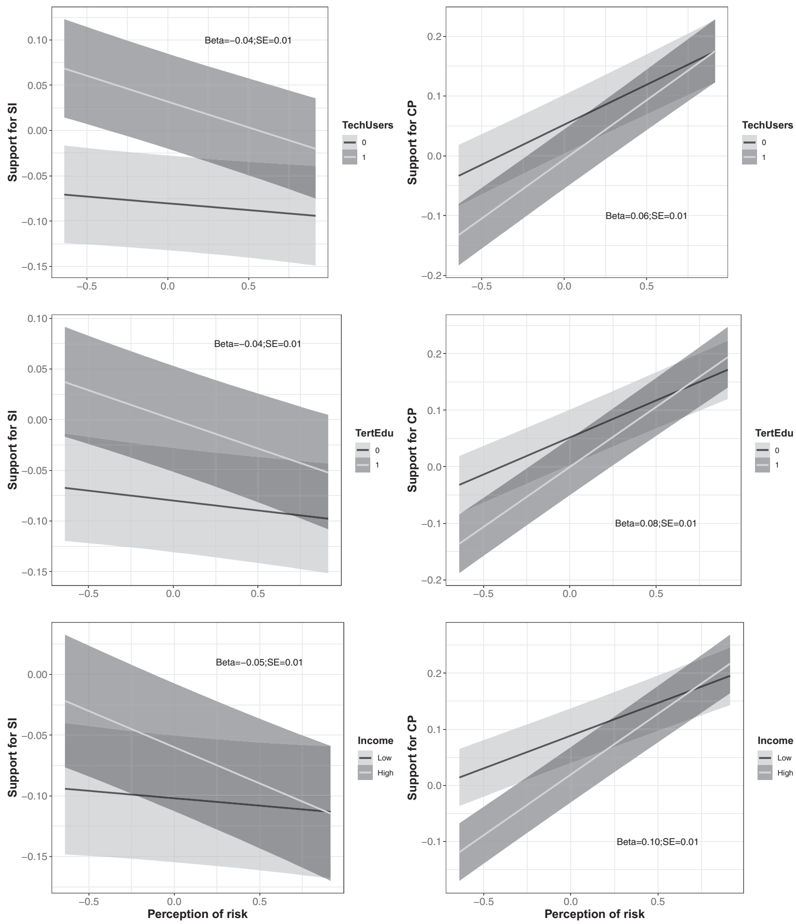

Figure 8 Support for social investment (SI; left panels) and compensation/protection (CP; right panels) predicted by technology usage, tertiary education and income conditional on perceived technology risk with 95% credible intervals. Beta: coefficient of underlying interaction term. SE: standard error of underlying interaction term.

fact, at very high levels of risk perception, support for compensatory and protective measures is virtually identical across all groups, confirming Hypothesis 4.

4. Conclusion

This article has studied the determinants of technology-related social policy preferences with a focus on micro-level associations, while also accounting for the significant cross-national variation in contexts and attitudes. Our core finding is that at-risk individuals are less likely to support investment-type policies. They instead demand short-term compensation and protection, even though social investment policies are arguably more effective instruments for dealing with the challenges of the digital knowledge economy and are therefore typically recommended by policy experts (Colin and Palier, 2015). In this regard, our findings mirror other recent studies which use different data sources (Busemeyer and Sahm, 2021; Kurer and Häusermann, 2021). Our article goes beyond existing work by adopting a broader perspective on the range of policy responses to technological change and by taking into account interaction effects between technology risk and other personal characteristics. Regarding the latter, we find strong evidence for a convergence of preferences toward supporting compensation for high-risk groups, independent of their personal background. In other words, even though highly educated, high-income-earning tech users are generally more supportive of investment-oriented policies, they turn to compensation and protection when faced with concrete labor market risks.

The latter finding has important implications. Discussions about the political consequences of rapid technological change often foreshadow the emergence of new cleavages between the winners and losers of technological change (Palier, 2019). In this context, it is often assumed that demographic and occupational features like the educational background play an increasingly important role in creating and widening this gap (see already Beramendi *et al.*, 2015). Our analysis adds a new perspective to these debates. We show that technology risk (subjectively perceived) as such is not strongly correlated with education, technology use at work or income, but cuts across these characteristics (similar to what Rehm *et al.* (2012) have found for the (non-)association between labor market risk and income). Thus, there are indeed 'high-skilled outsiders' (Häusermann *et al.*, 2015) whose specific background does not prevent them from being worried about their job. However, in contrast to Häusermann *et al.* (2015), our analysis shows that high-skilled at-risk individuals do not demand social investment, but rather prefer short-term compensation and protection. Thus, our analysis suggests that technology risk could become both a source of new cleavages as well as a foundation for new coalitions if at-risk individuals across different occupational boundaries collectively demand compensatory and protective policy responses to technological change. This could pose a challenge for policy-makers, in particular on the left, who may need to decide and prioritize between short-term compensation and long-term social investments against the background of scarce fiscal resources.

An important avenue for future research, which we could only scratch in this article, is the exploration of cross-national variation in attitudes as well as the impact of varying contexts on attitudes and preferences. Our descriptive analyses have revealed a significant degree of cross-national variation, which we included as background controls in our regression analyses. A more detailed examination would explore to what extent preferences are mediated and influenced by this variation, and whether the 'thermostatic' effect we mentioned above holds. A further limitation of this article is that we did not study the relationship between perceived technology risk and attitudes toward 'demanding activation' (or 'workfare') policies, a type of social policy that is distinct from the two types we have studied and which represents a central dimension of welfare state policies (e.g. Rueda, 2015). We can nevertheless point here to a couple of contributions (see Im, 2021; Im and Komp-Leukkunen, 2021) arguing that higher automation risk goes along with greater support for strict activation and workfare policies because workers threatened by automation seek to maintain their relative status in society by 'punching down' on even more vulnerable groups such as the unemployed. Our findings here would suggest that this pattern might not be limited to groups typically seen as vulnerable to automation (such as blue-collar factory workers) but might also be present among some higher educated and better-paid white-collar employees. We suggest this as another hypothesis for future research.

Supplementary material

Supplementary material is available at *SOCECO Journal* online.

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