Online Appendix

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This appendix provides supporting information for the article "Dealing with Technological Change: Social Policy Preferences and Institutional Context." The appendix consists of two sections. The first section contains descriptive statistics for each variable in the empirical analysis, as well as descriptive graphs for our dependent variables. The second section reports additional empirical tests and sensitivity analyses that we discuss in the paper without presenting the specific results.

1 Descriptive statistics

Table A1 lists descriptive statistics for the data used in our multivariate linear mixed-effects models. The data are standardized by centering and scaling all continuous variables by two times their standard deviation. Figures A1 to A4 show graphs of the average funding of each policy proposal (excluding the funding for public benefits and service, which is shown by Figure 1 in the main text) across countries. Figure A1 depicts average funding for education and vocational training, Figure A2 for retraining of working-age individuals, Figure A3 for UBI, and Figure A4 for subsidies to firms.

Table A1: Standardized data used in multivariate linear mixed-effects models.

Variable	Minimum	Median	Mean	Maximum	SD
Education	−0.73	−0.08	0.00	2.53	0.50
Retraining	−0.73	−0.04	0.00	2.72	0.50
Benefits	−0.65	0.07	0.00	2.94	0.50
UBI	−0.58	−0.04	0.00	2.10	0.50
Subsidies	−0.63	0.11	0.00	3.07	0.50
TechRisk	−0.63	−0.11	0.00	0.93	0.50
TechUsers	0.00	1.00	0.51	1.00	0.50
Age	−0.96	−0.01	0.00	0.85	0.50
HighEduc	0.00	0.00	0.43	1.00	0.50
Income	−5.05	0.08	0.00	5.24	0.50
Unemployment generosity after one year	−1.12	0.01	0.00	0.74	0.50
Unemployment generosity after two years	−0.87	−0.04	0.00	0.92	0.50

Figure A1: Average funds allocated to education across countries.

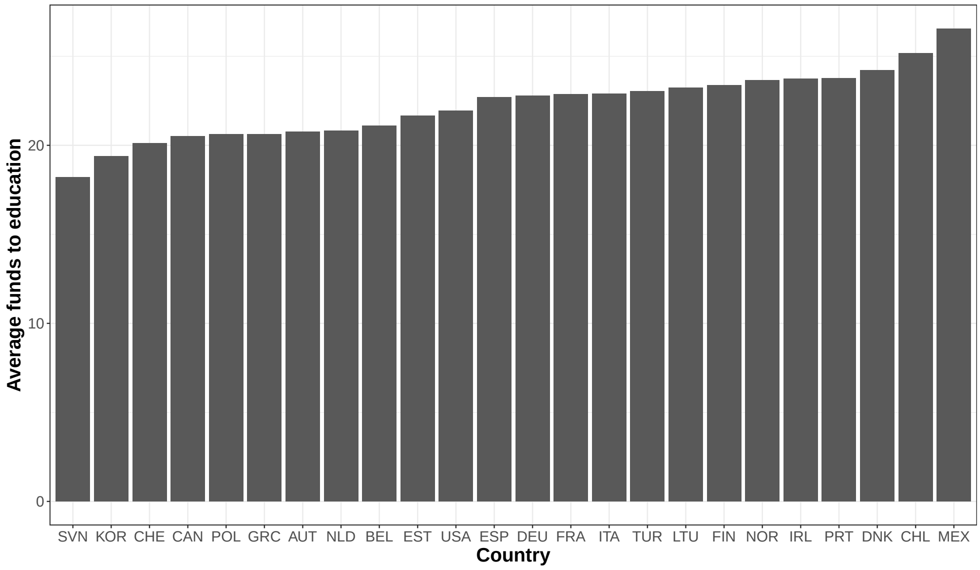


Figure A2: Average funds allocated to retraining across countries.

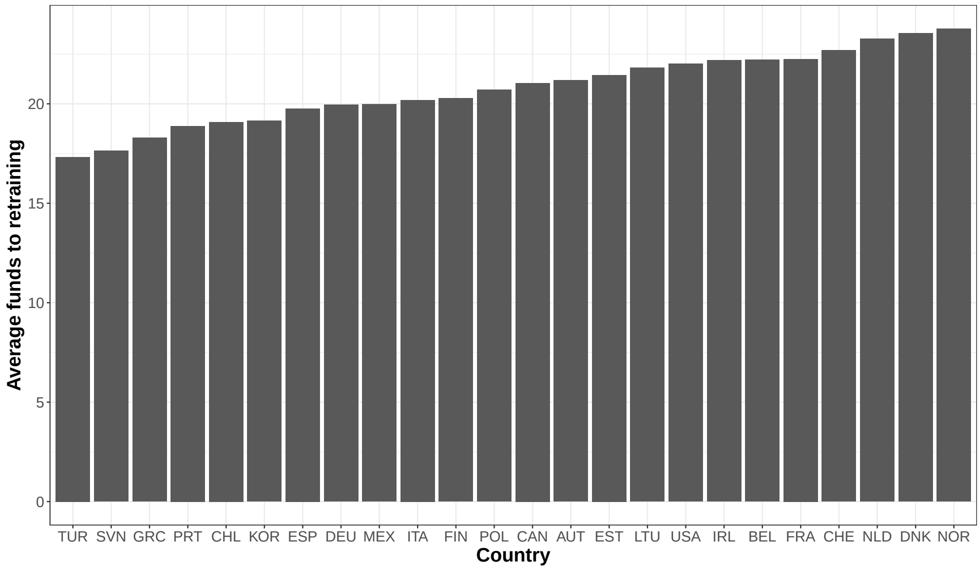


Figure A3: Average funds allocated to UBI across countries.

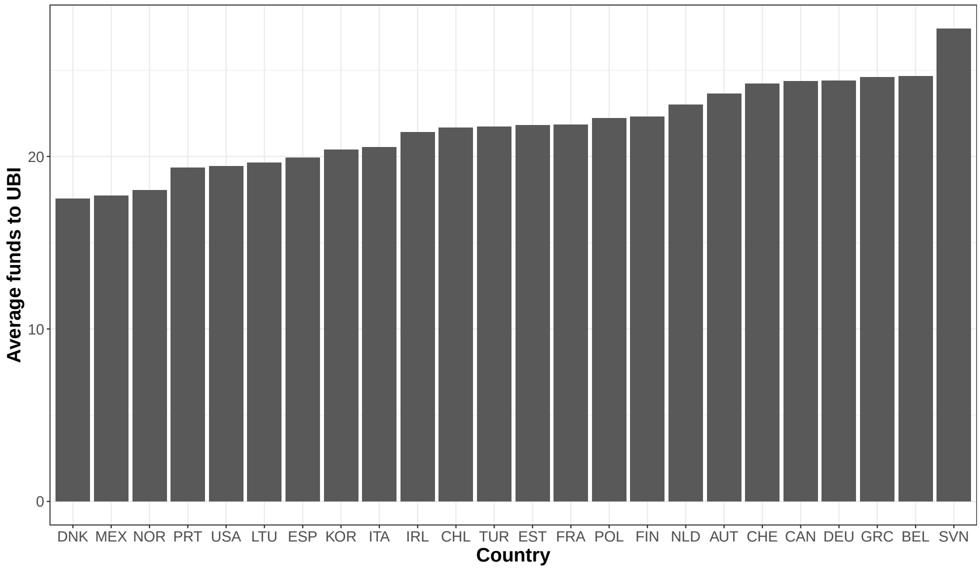


Figure A4: Average funds allocated to subsidies across countries.

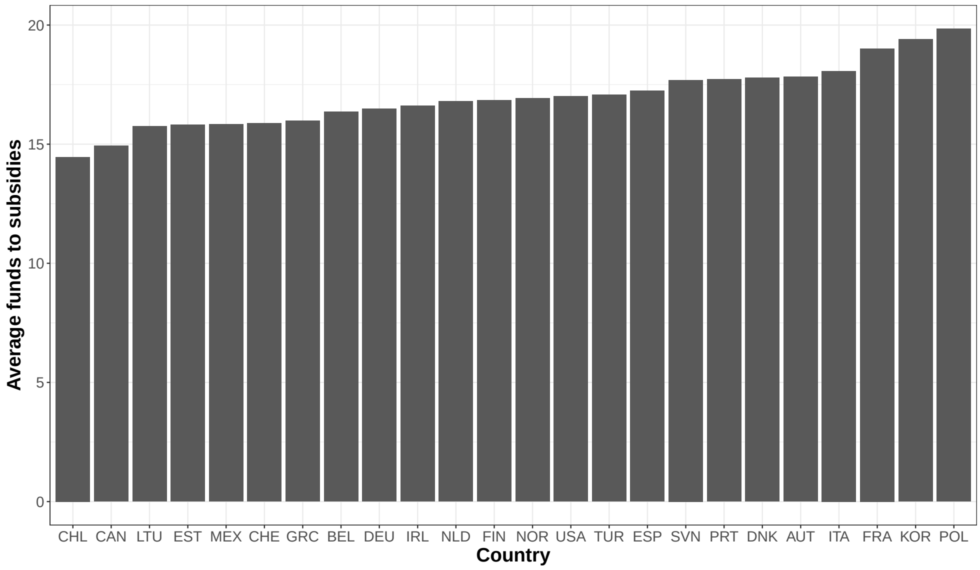
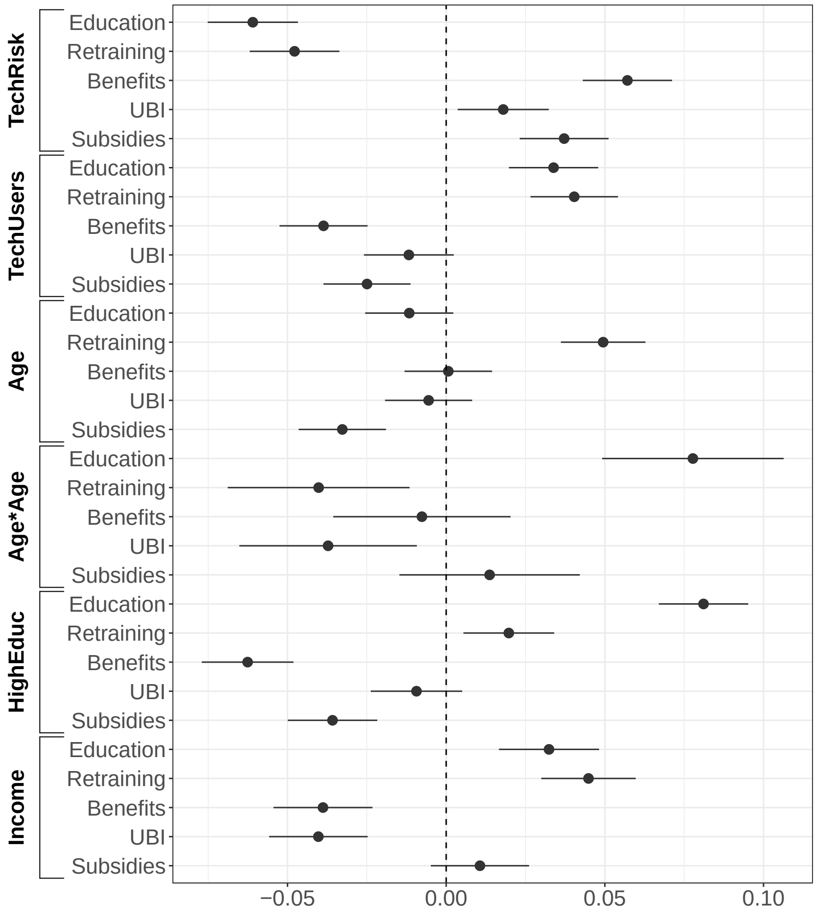


Figure A5: Squared term of age.

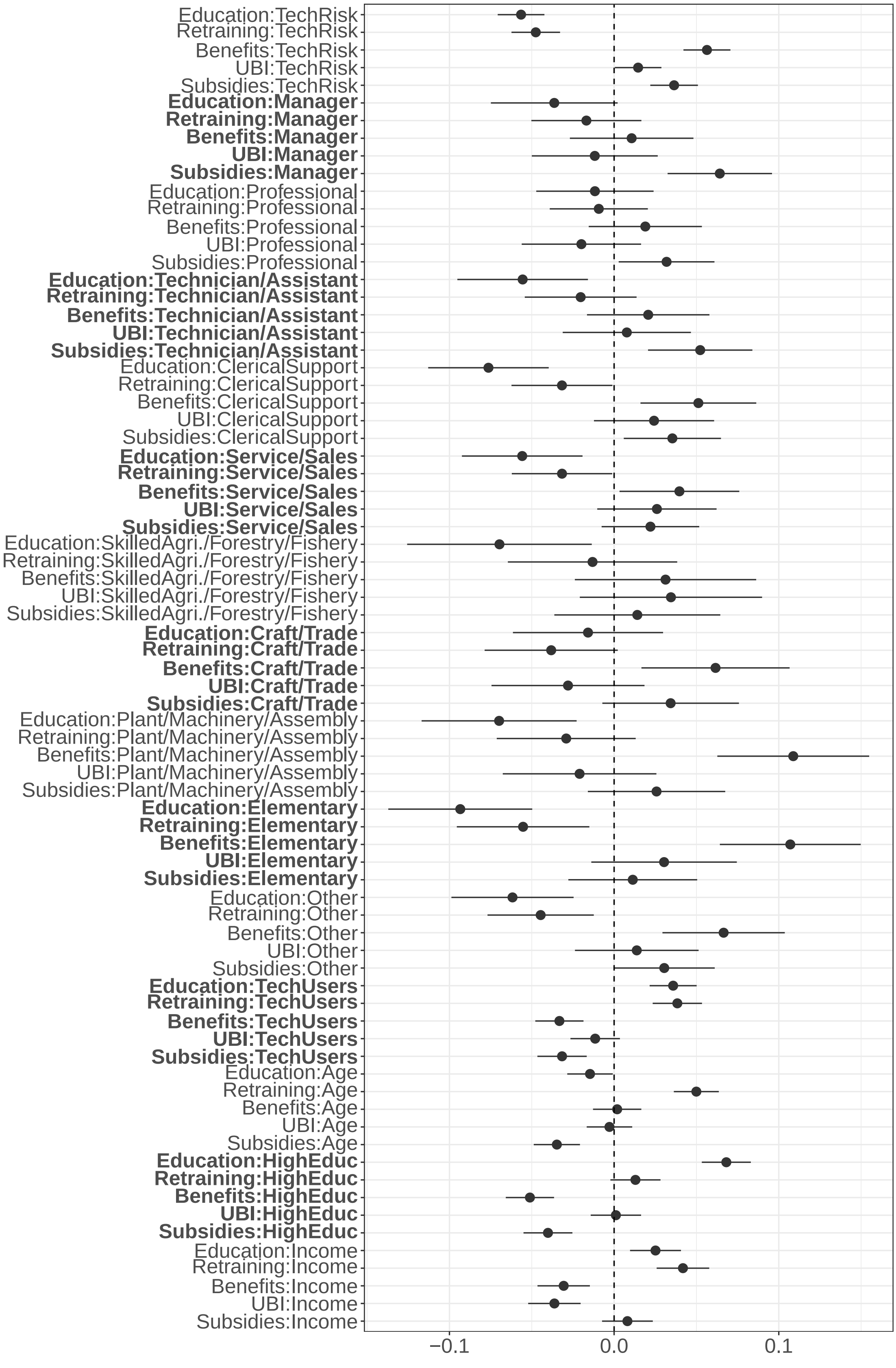


2 Additional empirical results

Including squared term of age reveals nonlinear effect on support for retraining. In Figure A5, we include a squared term of age. The results suggest that the effect of age on support for retraining follows an inverse U-shape, with individuals approaching retirement becoming increasingly opposed to retraining measures. The interpretation of this finding is straightforward: As individuals approach retirement, the labor-market benefits of retraining decline and older individuals increasingly decide to opt-out of the market.

Controlling for occupational groups does not change main findings. To test whether our variable of subjective technological risk captures a type of labor-market risk that is different from other occupational unemployment risks, we include dummy variables for each occupational group as provided in the survey. The estimates for subjective technological risk remain substantially unchanged.

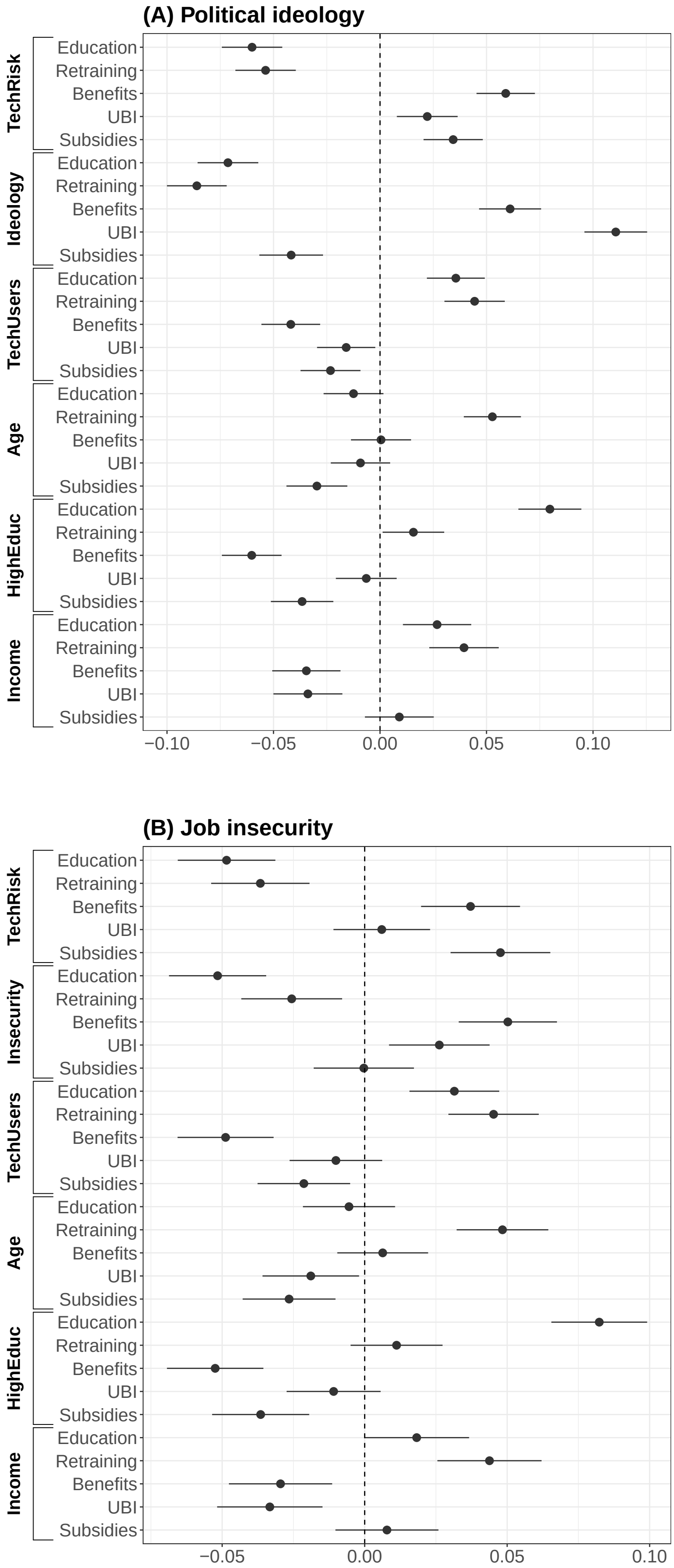
Figure A6: Controlling for occupational groups.



Results are robust to including proxies for ideology and general job insecurity. OECD's Risks that Matter survey does not include a direct measure of political ideology. To proxy for ideology, we use the following survey question: *Do you think the government should be doing less, about the same, or more to ensure your economic and social security and well-being?* Respondents answer this question on a five-point Likert scale ranging from *government should be doing much less* to *government should be doing much more.* While answers to this question will to a certain extent be shaped by an individual's socio-economic position, the broad question wording should also allow for capturing (at least in part) an individual's attitude towards the role of government in general. The results in Panel A of Figure A7 show that respondents who favor a stronger role of government strongly support the introduction of a UBI and, to lesser degree, more public benefits and services. Somewhat surprisingly, the same individuals tend to oppose subsidies to firms, as well as — less surprisingly — education and retraining measures. Most importantly, however, the results for our main variable of interest (TechRisk) remain substantially unchanged.

In an attempt to gauge whether technology-related employment risks differ from general job insecurity, we draw on the following question from the Risks that Matter survey: *How likely do you think it is that you might lose your job or self-employment income in the next 12 months?* The surveyed individuals answer this question on a four-point Likert scale ranging from *very unlikely* to *very likely* (the correlation between this measure and our measure of technology-related risk perceptions is $\rho = 0.36$). The estimates in Panel B of Figure A7 suggest that an increase in the perceived likelihood of job loss in the next 12 months is associated with more support for public benefits/services and a UBI, as well as less support for education and retraining. The coefficients of technology-related risk perceptions largely corroborate our previous findings, with the exception of the estimate of UBI which is no longer statistically significant. However, these results should be treated with caution. The inflated credible intervals across all estimates relative to the base model (leading to an increase in statistically insignificant estimates across all explanatory variables) suggest that the model is likely overspecified in its current form. Thus, in the absence of measures that better distinguish between technology-related and other employment risks, the main take away of this exercise is that technology-related employment risks appear to have an independent effect on social policy preferences relative to other employment risks. Future research should attempt to capture these differences more accurately and in greater detail based on specially tailored measurement and modeling strategies.

Figure A7: Controlling for proxies of political ideology and general job insecurity.



Main findings hold in unconstrained scenario. To test whether our results hold in a scenario in which individuals do not face a budget constraint, we draw on a question in the RTM survey that asks whether respondents support or oppose a certain policy response to technological change. The question includes four of our five policy proposals (subsidies to firms are not included). The question is phrased as follows: *Governments can introduce measures aimed at helping workers and industries cope with the challenges created by digitalization and technological change, such as outdated skills, skills shortages, and possible job loss. Keeping in mind how much they might cost as well as how you and your family might benefit, to what extent would you oppose or support the government taking the following actions as a response to digitalization and technological change?* Respondents answers are coded on a Likert scale ranging from *strongly oppose* to *strongly support*. We recoded these responses such that 1 indicates general and strong support, and 0 indicates otherwise. We than ran Bayesian probit mixed-effects models (100,000 MCMC simulations) on each policy proposal of interest, using the same control variables as in our main model specification. The results are reported in Figure A8. Panels A (without unemployment compensation) and B (with unemployment compensation) corroborate our previous finding that an increase in subjective technological risk is associated with less support for social investment (i.e., education and retraining) and more support for compensation (i.e., public benefits and services as well as UBI). Moreover, Panel B confirms that higher levels of unemployment compensation are associated with lower support for more public benefits and services, both when the generosity of unemployment compensation is measured by income replacement rates after one year (Benefits1) and after two years (Benefits2). In addition, the results of the interaction terms indicate that in more mature welfare states the negative effect of technological risk perceptions on support for social investment policies is stronger than in residual welfare states, which is in line with our previous findings. The interaction terms for the compensatory policies are not statistically significant. To us, this reflects that the unconstrained scenario does not force respondents to think about the trade-off between these different types of social policies and thus the "shock" of perceived technology-related employment risks creates a similarly strong reaction across institutional contexts, which is also reflected by the fact that the unconstrained scenario produces considerably larger effect sizes for the positive impact of subjective technological risk on compensatory policy proposals than the constrained scenario.

Compositional nature of data does not lead to biased results. The compositional structure of our dependent variables entails two potential sources of bias in our estimates. First, since respondents cannot allocate less than zero funds to a policy pro-

Figure A8: Standardized coefficients with 95% credible intervals from probit mixed-effects models.

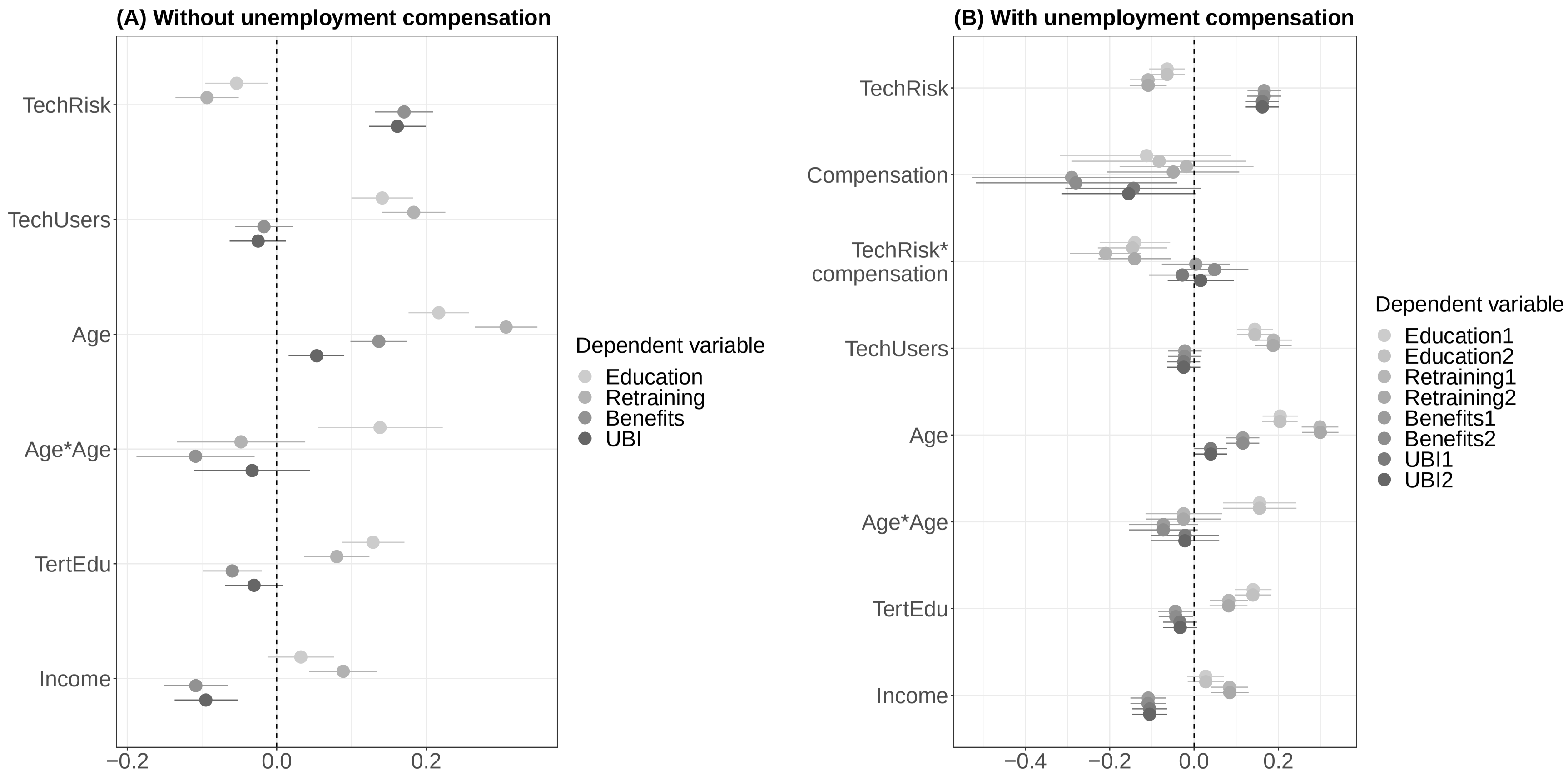


Table A2: Compositional re-estimation of the effect of technological risk.

		Allocation of funds
TechRisk	Education	0.190 [0.185,0.195]
	Retraining	0.193 [0.192,0.194]
	Benefits	0.209 [0.208,0.210]
	UBI	0.201 [0.199,0.204]
	Subsidies	0.207 [0.204,0.210]
Controls		Yes

95% credible intervals in brackets.

posal and the total sum of funds needs to sum up to 100, the data are bounded. Second, the correlation between the individual policy components is by definition negative because allocating more funds to one policy inevitably decreases the total remaining funds of the other policies. This violates the assumption of independence, i.e., zero correlation between the distributed funds. However, Aitchison (1986) has shown that the logarithms of the ratios of the compositional components are unbounded and independent. Thus, we model the funds as a composition ranging between 0 and 1 and calculate the distance-preserving (so-called isometric) log ratios of four of the five policy components, with the last policy component (subsidies) serving as reference category. The transformed policy components can then be used in our MLMM. Finally, we apply the inverse of the (isometric) log transformation to reconstruct the compositions from the estimated parameters (for further detail, see van den Boogaart and Tolosana-Delgado 2013).

Table A2 presents the reconstructed composition for our main variable of interest. The compositional nature of the data is reflected by the fact that all five policy components sum up 1. One way to think about the results is that if technological risk had a uniform effect on all policies, each policy component would be exactly 0.2. However, the policy components deviate from uniformity in ways that corroborate our previous findings. The perception of technology as a risk to one's job reduces the allocation of funds to retraining and education (in increasing order), while simultaneously increasing the amount of funds that go to UBI, firm subsidies, and public benefits and services (in increasing order). Thus, the compositional analysis mirrors exactly our main results.

Interaction between subjective technological risk and welfare state context robust to inclusion of additional macro-level control variables. The first and third column of Table A3 show the regression results underlying the interactive relationship between subjective technological risk and the welfare state context which we delineate graphically — for those social policy components that exhibit statistically significant interaction coefficients (i.e., retraining, public benefits and services, and UBI) — in Figure 6 of the main text.

In the second and fourth column, we include following macro-level controls: gini coefficients as a measure of income inequality (data come from the OECD and are mostly available for the year 2019), the economic dimension of the KOF Globalisation Index (the latest year available is 2019, see Gygli et al., 2019), and the share of respondents who report having confidence in the national government (data come from the OECD and are available for the year 2020). None of these variables have an independent, statistically significant effect on the distribution of funds across our set of policy proposals.[1] Moreover, as shown by Table A3, including these additional macro-level controls does not affect our interactive results for the relationship between subjective technological risk and welfare state context.

Stepwise exclusion does not suggest that results of cross-level interaction are driven by individual countries. In Table A4, we exclude one country at a time from the dataset to test whether the statistically significant interaction coefficients that we present in Table A3 are sensitive to individual countries. We find that this is not the case with two exceptions: Denmark and Turkey. These are the countries with the highest and lowest levels of unemployment generosity, respectively, in our sample. Given that the sample is limited to 22 countries for which we have information on unemployment benefits, it is hardly surprising that further reducing the size and, in particular, the dispersion of the dataset renders a reliable estimation of cross-level interaction effects difficult. Moreover, neither level of unemployment generosity represents extreme values. In the case of Denmark, there are (OECD) countries with comparable levels of generosity, both in and outside (e.g., Bulgaria and Luxembourg) our sample. Turkey is the only case of zero unemployment benefits in the dataset. However, from a global perspective,

[1] Inequality: $\beta_{Education} = 0.05, 0.05$ ($SE = 0.07, 0.06$); $\beta_{Retraining} = 0.03, 0.04$ ($SE = 0.07, 0.5$); $\beta_{Benefits} = 0.04, 0.05$ ($SE = 0.07, 0.06$); $\beta_{UBI} = -0.07, -0.08$ ($SE = 0.06, 0.05$); $\beta_{Subsidies} = -0.03, -0.02$ ($SE = 0.05, 0.04$).

Globalization: $\beta_{Education} = -0.01, 0.00$ ($SE = 0.07, 0.06$); $\beta_{Retraining} = 0.07, 0.07$ ($SE = 0.05, 0.05$); $\beta_{Benefits} = -0.05, -0.05$ ($SE = 0.07, 0.06$); $\beta_{UBI} = 0.02, 0.01$ ($SE = 0.06, 0.04$); $\beta_{Subsidies} = -0.04, -0.04$ ($SE = 0.05, 0.04$).

Trust: $\beta_{Education} = 0.01, 0.02$ ($SE = 0.05, 0.04$); $\beta_{Retraining} = 0.01, 0.01$ ($SE = 0.04, 0.04$); $\beta_{Benefits} = 0.02, 0.01$ ($SE = 0.05, 0.05$); $\beta_{UBI} = -0.01, -0.01$ ($SE = 0.04, 0.03$); $\beta_{Subsidies} = -0.04, -0.03$ ($SE = 0.04, 0.03$).

Table A3: Interaction between subjective technological risk and the generosity of unemployment compensation after one year and two years in unemployment.

		After 1 year		After 2 years	
TechRisk	Education	−0.07*	−0.07*	−0.07*	−0.07*
		(0.01)	(0.01)	(0.01)	(0.01)
	Retraining	−0.05*	−0.04*	−0.05*	−0.05*
		(0.01)	(0.01)	(0.01)	(0.01)
	Benefits	0.06*	0.06*	0.06*	0.06*
		(0.01)	(0.01)	(0.01)	(0.01)
	UBI	0.02*	0.02*	0.02*	0.02*
		(0.01)	(0.01)	(0.01)	(0.01)
	Subsidies	0.04*	0.04*	0.04*	0.04*
		(0.01)	(0.01)	(0.01)	(0.01)
Compensation	Education	0.02	0.06	0.02	0.05
		(0.04)	(0.08)	(0.04)	(0.06)
	Retraining	0.04	0.02	0.04	0.03
		(0.03)	(0.06)	(0.03)	(0.05)
	Benefits	−0.08*	−0.03	−0.06	0.00
		(0.04)	(0.08)	(0.04)	(0.06)
	UBI	0.00	−0.06	−0.02	−0.08
		(0.01)	(0.06)	(0.03)	(0.04)
	Subsidies	0.01	0.03	0.02	0.03
		(0.03)	(0.05)	(0.03)	(0.04)
Interaction	Education	−0.02	−0.02	−0.02	−0.02
		(0.02)	(0.01)	(0.01)	(0.02)
	Retraining	−0.02	−0.02	−0.04*	−0.04*
		(0.02)	(0.01)	(0.01)	(0.02)
	Benefits	0.03*	0.03*	0.04*	0.04*
		(0.01)	(0.01)	(0.02)	(0.01)
	UBI	0.02	0.02	0.03*	0.03*
		(0.01)	(0.02)	(0.02)	(0.01)
	Subsidies	−0.02	−0.02	−0.02	−0.02
		(0.01)	(0.02)	(0.02)	(0.02)
Individual-level controls		Yes	Yes	Yes	Yes
Macro-level controls		No	Yes	No	Yes

* Zero outside the credible interval. Standard errors in brackets.

the absence of an unemployment benefit scheme is the norm and not the exception.[2] In addition, formal outlier-specific tests (Dixon's Q-test, Grubbs test) as well as assessments based on the interquartile range or IQR (where observations 1.5 times outside the IQR are considered outliers) do neither qualify Denmark nor Turkey as outliers in the sample.

[2]See https://blogs.worldbank.org/developmenttalk/its-time-expand-unemployment-protections.

Table A4: Excluding individual countries from interaction between subjective technological risk and the generosity of unemployment compensation after one year and two years.

Excluded country	Retraining (1 year)	Retraining (2 years)	Benefits (1 year)	Benefits (2 years)	UBI (1 year)	UBI (2 years)
Austria	−0.02	−0.04*	0.03*	0.04*	0.02	0.03*
	(0.02)	(0.02)	(0.02)	(0.02)	(0.01)	(0.01)
Belgium	−0.01	−0.03*	0.03*	0.03*	0.02	0.03*
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Canada	−0.01	−0.04*	0.03*	0.04*	0.02	0.03*
	(0.02)	(0.01)	(0.02)	(0.02)	(0.02)	(0.02)
Denmark	−0.03	−0.02	0.02	0.02	0.02	0.03+
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Germany	−0.02	−0.03*	0.03*	0.04*	0.03+	0.03*
	(0.02)	(0.02)	(0.02)	(0.02)	(0.01)	(0.01)
Spain	−0.02	0.04*	0.03*	0.04*	0.03+	0.04*
	(0.01)	(0.02)	(0.01)	(0.02)	(0.01)	(0.02)
Estonia	−0.02	−0.04*	0.03*	0.04*	0.02	0.04*
	(0.01)	(0.02)	(0.01)	(0.02)	(0.01)	(0.02)
Finland	−0.02	−0.04*	0.03*	0.04*	0.02	0.04*
	(0.02)	(0.01)	(0.02)	(0.02)	(0.02)	(0.01)
France	−0.02	−0.04*	0.03*	0.03*	0.02	0.03*
	(0.02)	(0.02)	(0.01)	(0.02)	(0.01)	(0.01)
Greece	−0.02	−0.04*	0.03*	0.04*	0.03+	0.04*
	(0.02)	(0.02)	(0.02)	(0.01)	(0.02)	(0.02)
Ireland	−0.02	−0.04*	0.04*	0.04*	0.02	0.03*
	(0.01)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Italy	−0.02	−0.04*	0.04*	0.04*	0.03	0.03*
	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)	(0.02)
Lithuania	−0.03+	−0.04*	0.04*	0.04*	0.03*	0.04*
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Netherlands	−0.02	−0.04*	0.03*	0.04*	0.03*	0.04*
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Norway	−0.02	−0.03*	0.03*	0.04*	0.02	0.03*
	(0.02)	(0.02)	(0.01)	(0.02)	(0.02)	(0.02)
Poland	−0.02	−0.04*	0.04*	0.04*	0.02	0.03*
	(0.01)	(0.02)	(0.02)	(0.02)	(0.01)	(0.02)
Portugal	−0.02	−0.04*	0.04*	0.04*	0.02	0.03*
	(0.02)	(0.01)	(0.02)	(0.01)	(0.01)	(0.02)
Slovenia	−0.02	−0.04*	0.03*	0.04*	0.02	0.04*
	(0.01)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
South Korea	−0.02	−0.04*	0.03+	0.03*	0.03+	0.04*
	(0.01)	(0.02)	(0.02)	(0.01)	(0.02)	(0.02)
Switzerland	−0.02	−0.04*	0.04*	0.04*	0.03*	0.03*
	(0.01)	(0.01)	(0.02)	(0.01)	(0.02)	(0.01)
Turkey	−0.02	−0.04*	0.02	0.02	0.02	0.03+
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
USA	−0.04*	−0.05*	0.03+	0.03*	0.04*	0.04*
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Remaining variables	Yes	Yes	Yes	Yes	Yes	Yes

* Zero outside the credible interval. + Significant at 10 percent level. Standard errors in brackets.

Table A5: Interaction between subjective technological risk and active labor market policy (ALMP) spending (as a percentage of GDP).

	Explanatory variable		
	TechRisk	**ALMP**	**Interaction**
Education	−0.06*	0.00	−0.06*
	(0.01)	(0.04)	(0.01)
Retraining	−0.05*	0.03	−0.02
	(0.01)	(0.03)	(0.01)
Benefits	0.06*	−0.06	0.03*
	(0.01)	(0.04)	(0.02)
UBI	0.02*	0.00	0.03*
	(0.01)	(0.01)	(0.01)
Subsidies	0.04*	0.03	0.01
	(0.01)	(0.03)	(0.01)

* Zero outside the credible interval. Standard errors in brackets. Controls included.

Using alternative measure of welfare state context does not affect main findings. To test the argument that social investment policies might find stronger support in welfare states that have more experience with these kind of policies, we use active labor market policy spending as a percentage of GDP as an alternative measure of the welfare state context (data come from the OECD and are mostly available for the year 2018). Table A5 shows that the interactive relationship with subjective technological risk closely resembles the previous results based on unemployment compensation. Thus, we conclude that the overall generosity of the welfare state context is more important for technology-related social policy preferences than the relative weight of passive and active policies.

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