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Automation and social policy: Which policy responses do at-risk workers support?

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Abstract

How does automation affect the politics of the welfare state? People whose jobs are at risk of being automated may react by claiming social protection (passive social policy), up-skilling/commodification (active social policy) or both. In this brief contribution, we study this question relying on novel survey data on perceived automation risk and social policy preferences in 8 West European countries. We first estimate the size and profile of the group of voters concerned about their potential substitution by technology and examine how *subjective* perceptions of automation risk compare to widely used *objective* indicators of automation risk. In contrast to a somewhat alarmist public debate, we find that a surprisingly small share of voters feels imminently threatened by automation. We then turn to an assessment of the demand for different kinds of social policy as a response to automation risk and find highly consistent preferences across countries. At-risk workers support and prioritize passive unemployment protection measures, while support for activation, education and labor market reintegration policies is very limited. In other words: progressive automation increases demand for passive, consumption-oriented welfare policies and thereby narrows the support base for an activation/human capital-oriented policy strategy, which technocrats and policy advisers tend to recommend in reaction to automation of production.

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1. Introduction

Automation of routine tasks has been increasing in speed for several decades now. However, it is only in the past few years that the topic has also reached public and political debates, with – sometimes alarmist – interpretations forecasting mass unemployment for ever widening occupational groups of the workforce. A rapidly growing literature studies the political and, especially, electoral repercussions of technological change (Frey et al. 2017; Kurer and Palier 2019; Im et al. 2019; Anelli et al. 2019; Kurer 2020; Gallego et al. 2020). With the politicization of automation risks, the technological change that has been underpinning deindustrialization for a very long time has gained new political relevance by creating a new type of employment risk. These risks are likely to inform political preferences. However, beyond a general link between automation risk and support for a redistributive welfare state, we still know little about *what kind* of social policy threatened workers demand.

Research on (perceived) risk as a determinant of social policy has become a standard factor in micro-level research on welfare preferences over the past decade (e.g. Rehm 2009, 2016; Walter 2010; Schwander and Häusermann 2013; Marx and Picot 2013). These studies have shown that unemployment risk, offshoreability, or atypical employment drive support for social insurance, i.e. the demand for protection from these risks that are not in the individual's command. Hence, a first question we may need to ask is if there is anything specific about the (perceived) risk of automation, which would justify a theoretical distinction between this and other labor market risks. Indeed, one may argue that knowing that the risk of being substituted by machines depends on the cognitive vs. routine type of work tasks, individuals have somewhat more autonomy in shaping the risk they are exposed to. Delocalization or regulatory labor market liberalization are beyond control of individuals, but the risk of ones job being automated can be reduced by training for and selecting into a less substitutable occupation.

Therefore, one may suggest that social policy demands linked to automation risks should differ from those linked to offshoreability or outsiderness risks. More concretely, one could assume that beyond demands for more social insurance, i.e. passive income protection, individuals may ask for more opportunities, i.e. active training opportunities and activation. Studying the implications of automation for the welfare state hence requires distinguishing between the passive, consumption-led policies of the welfare state and social investment (Garritzmann et al. 2018; Busemeyer 2018; Häusermann et al. 2019).

The few existing studies that explicitly link automation risk to social policy preferences have largely neglected this distinction and instead mainly focused on traditional redistributive policies and passive transfers (but see Busemeyer et al. 2020). Thewissen and Rueda (2017) show that general demand for redistribution is stronger among individuals in occupations with higher levels of routineness, which translates into higher susceptibility to automation (Autor et al. 2003). In a similar vein, **?** examine the relationship between automation risk and more specific passive social policies in Italy. In particular, they find consistently positive associations between objective automation risk and support for a general minimum income scheme. In a second step, they also look at unconditional (universal) basic income support. However, in line with other recent contributions (Martinelli 2019; Dermont and Weisstanner 2020), they only find scant evidence of an independent effect of automation risk on preferences for basic income. Im's (2020) recent contribution is a notable exception from the otherwise common focus on passive transfers. His study shows a correlation between occupation-level routineness and support of demanding active labor market policy to punish unemployed workers who voluntarily turn down jobs.

We add to this nascent literature by examining the prevalence of subjective automation risk in eight post-industrial societies and its relation to a variety of potential policy responses. We build on original survey data that allows to differentiate between support for more short-term solutions related to pensions and passive transfers and more long-term approaches related to human capital investment and (re-)activation of labor supply. We find clear-cut evidence that at-risk individuals first and foremost demand traditional passive insurance against the risk of job loss. In contrast, they do not show any sign of support for investment policies that might not be directly beneficial to them. Workers susceptible to automation thus demonstrate rational (short-term) preferences against the backdrop of the automation threat. This pattern of compensation-oriented preference implies that the political support base for human capital-oriented policies commonly recommended in response to technological change does precisely not include those individuals who feel most exposed to the contemporary downsides of technological innovation. However, in light of the relatively small size of the group of people who feels imminently threatened by automation, we conclude that at-risk workers' resistance to a more investment-oriented policy agenda will most likely not carry sufficient political weight to prevent a transformation of the welfare state in exactly that direction.

2. Measuring Automation Risk

To assess our hypotheses, we use original data from a survey conducted in the context of the ERC-project "welfarepriorities" (Häusermann et al. 2020). Data was collected in eight Western European countries with 1500 respondents in each country. The countries were chosen to represent the main welfare regimes in Western Europe: Denmark and Sweden for the social democratic regime, Germany and the Netherlands for the conservative type, Ireland and the United Kingdom for the group of Liberal welfare states, and Italy and Spain as representatives of the Southern regime. They also nicely encompass countries with very different profiles regarding the development towards a knowledge economy, with notably the Southern European countries opposing the Nordic ones (Garritzmann et al. 2021). Fieldwork was done in cooperation with a professional survey institute (Bilendi) using their online panels. The target population was a country's adult population (older than 18 years). The total sample counts 12'501 completed interviews that were conducted between October and December 2018.

Different measures were taken in order to increase the survey's representativeness and to ensure high quality answers. We based our sampling strategy on quota for age, gender, and educational attainment, drawn from national census figures. Age and gender were introduced as crossed quotas, with six age groups (18-25, 26-35, 36-45, 46-55, 56-65, 66 or older) for both female and male respondents. We used a three-group split for educational attainment quotas. The survey includes a wide range of items capturing social policy positions as well as priorities. Hence, survey respondents were well aware that they were to think about their material demands, needs and circumstances, also when answering the question regarding automation risk.

The main independent variable is the *subjective* risk of automation, measured as follows: *"What is the percent likelihood (0-100) that your job will be automated by a robot, new technology, smart software or artificial intelligence in the next 10 years?"*. While a precise estimate of automation risk is certainly a difficult task, we have no indication that the cognitive burden of this specific item is overly high. The number of "don't know" answers is very low (<1%) and comparable to similar but arguably simpler questions on, e.g., future labor market prospects more generally.[1] For obvious reasons, the question on automation risk was asked only to respondents currently in paid employment (N=6'960). Our results hence apply to the active labor force but do not necessarily generalize to the general population. This caveat is particularly relevant when we describe average levels and distributions of automation risk across countries. It is possible that risk perceptions among the full population deviate to some extent from those of the active labor force. Hence, we cannot completely rule out the possibility that our estimates of risk prevalence and especially the political impact of this automation anxiety is somewhat underestimated.[2]

We complement our original survey data with two *objective* measures of automation risk. First, we add occupation-specific values of routine task intensity (RTI) from (Goos et al. 2014). As a second, more future-oriented measure, we add the estimates of an occupation's susceptibility to computerization produced by Frey and Osbourne (2017).

[1] "Don't know" answers are slightly more common among lower educated respondents as well as among younger respondents, which might reflects that employment prospects and automation risk is more difficult to gauge for younger labor market entrants who will remain in the labor force for many more years. There are no differences in the frequency of "don't know" answers between countries.

[2] Another item in our survey asks all respondents a more general question about "personal chances of a good, stable employment relationship until retirement". Comparing groups shows that respondents who are not in paid employment have significantly more pessimistic perceptions of general labor market prospects compared to respondents currently in paid employment.

3. Who and how many feel threatened by automation?

3.1. Cross-national variation

As a first step, we explore the distribution of automation risk across countries and societal groups. The first plot shows country-specific densities of automation risk. The first noteworthy aspect of Figure 1 is the generally high number of people who seem relatively unconcerned by automation. In every country under study, the densities peak at very low numbers of estimated probabilities that respondent's jobs will be replaced by robots or smart software. Across the sample, the mean perceived risk is around 23% probability of replacement, the median value is 10%. However, as noted above, these values result from respondents currently in paid employment. We can only speculate about risk perceptions in the full population. While individuals in the working age population who struggle to enter the labor market are likely more concerned, we would expect that retired respondents largely got rid of worries about employment security.

Taking a closer look at differences between countries reveals some interesting variation. While fear of automation seems very rare in Nordic and Continental knowledge economy countries, especially in Denmark, Sweden and Germany, the distributions are noticeably flatter in Southern Europe and Ireland. Here, a larger share of the respondents seem at least somewhat concerned about their occupational prospects in the light of technological innovation.

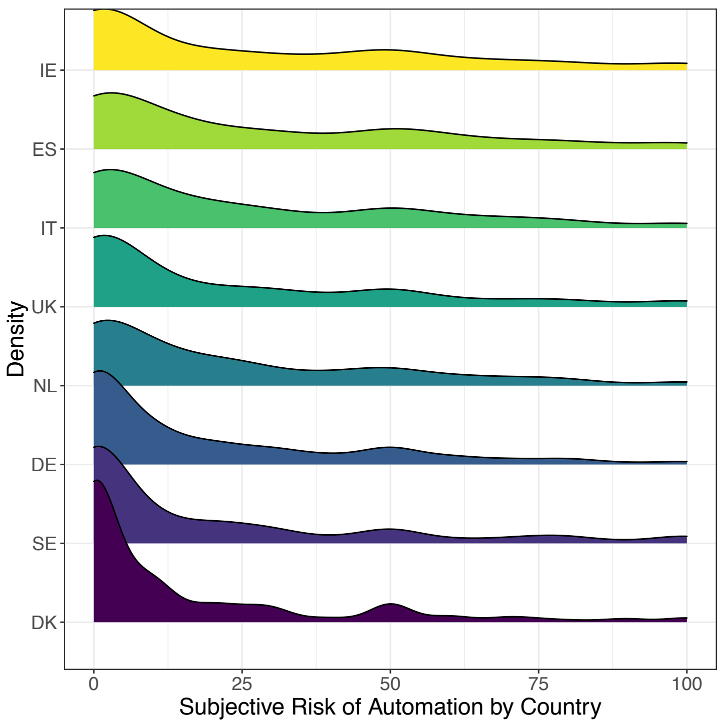


Figure 1: What is the distribution of perceived automation risk?

Figure 2 provides a different illustration of the same distributions to get a more precise idea of the size of the at-risk group. We calculated the country-specific share of respondents who estimate their own risk of being replaced by robots or smart software in the next 10 years to be above 30%, 50% or 90%. Again, people who feel very seriously concerned about automation are relatively rare. In every country, the share of respondents who believe that jobs like theirs will almost certainly disappear is below 5%. However, between around 10%-20% of respondents see a daunting fifty-fifty probability of being replaced and on average 28% of our respondents estimate this probability at 30% or higher. By implication, a sizable majority of the sample feels relatively secure and believes that their jobs are rather unlikely to be automated.

In terms of cross-sectional variation, Figure 2 even more clearly demonstrates that fear of automation is much more pronounced in Ireland and Southern Europe than in Nordic and Continental European countries. Most likely, these differences primarily reflect the distinct composition of the labor market and, thus, our samples, with more developed knowledge economies being dominated by highly skilled and specialized jobs that are – objectively – much less susceptible to automation. More jobs with lower objective risk seems to translate in reasonable ways into national patterns of subjective automation risk.

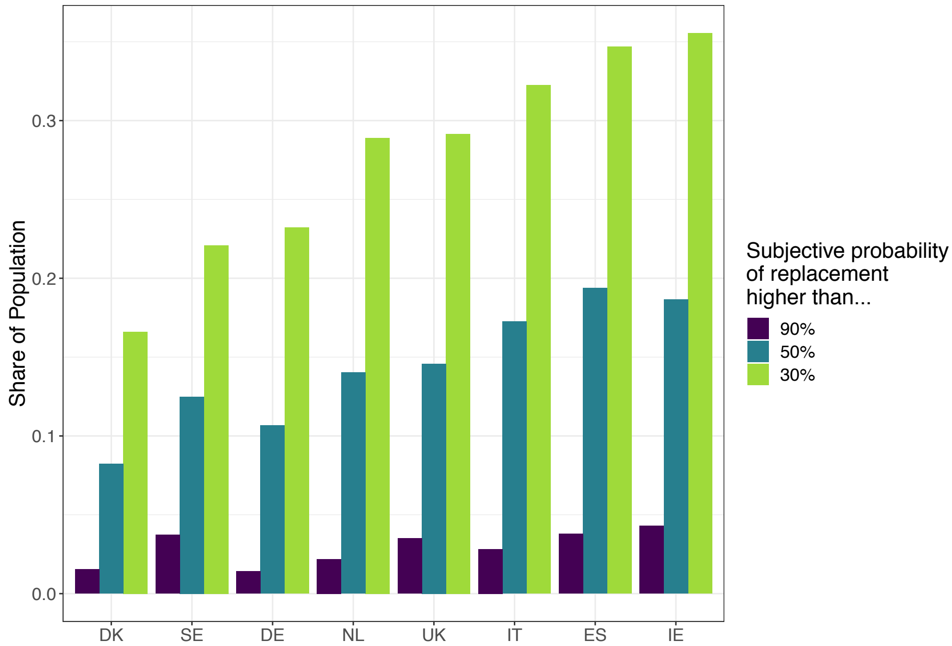
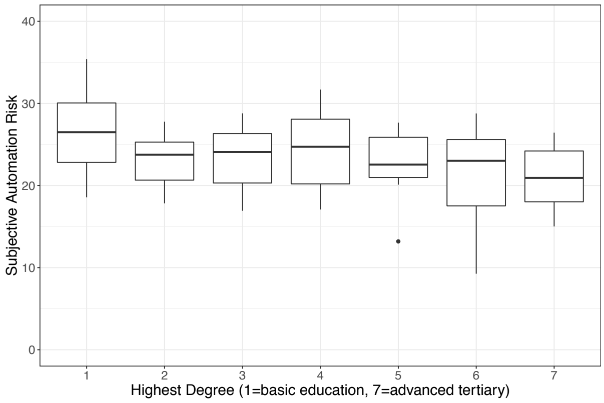


Figure 2: What share of the population feels threatened by automation?

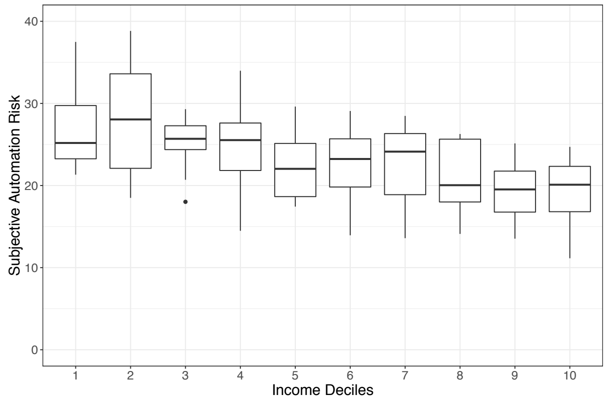
3.2. Individual determinants

We next evaluate some of our priors regarding individual determinants of perceived risk of automation. In general, higher skilled and specialized workers are expected to flourish in the knowledge economy, which should be reflected in lower perceived threat of automation. Figure 3 shows distributions of risk perceptions pooled across countries for different education and income groups. Higher values on both variables, as expected, go hand in hand with lower levels of subjective automation risk. However, it is interesting to see that income seems to be a somewhat stronger predictor. Although higher education does reduce perceived automation risk, a tertiary degree alone does not seem to represent an effective insurance against the subjective risk of technology-induced job loss.

Figure 3: Individual Determinants of Perceived Automation Risk



(a) By Education



(b) By Income Decile

Furthermore, fear of being replaced by technology tends to decrease with age, which is likely to reflect that labor market entrants face much more insecurity about long-term employment prospects compared to respondents closer to retirement age. We do not find significant differences in automation risk perceptions between women and men. Finally, looking at risk perceptions by occupation, service customer clerks[3] (mean risk: 38%) and, especially, machine assemblers[4] (mean risk: 47%) stand out as high-risk groups. These subjective perceptions square exceptionally well with the observation that routine occupations in both blue- and white-collar jobs are particularly threatened by automation (Autor et al. 2003). The task content of a job, much more than formal skill requirements, determines susceptibility to automation and basic administrative work as well as repetitive assembling jobs in manufacturing both belong to the key examples of routine work.

[3]ISCO 42: Customer services clerks deal with clients in connection with money-handling operations, travel arrangements, requests for information, making appointments, operating telephone switchboards, and interviewing for surveys or to complete applications for eligibility for services.

[4]ISCO 82: Assemblers assemble prefabricated parts or components to form subassemblies, products and equipment, according to procedures strictly laid down. The products worked on may be moved from one worker to the next along assembly lines.

3.3. Correlation with objective indicators

We next wish to systematize the comparison between our subjective measure of perceived vulnerability to automation and objective indicators of the same risk. Directly related to the previous discussion on occupation-specific risk, Figure 4 shows how subjective automation risk relates to objective routine task intensity (RTI). RTI relies on detailed occupational dictionaries to quantify the occupation-specific importance of routine tasks vis-a-vis non-routine tasks. The more a job relies on such routine tasks, the more prone is it to be replaced by robots or smart software (see, e.g., Autor et al. 2003; Autor and Dorn 2013; Arntz et al. 2016).

The two measures are consistently correlated in the expected direction, but this correlation is far from perfect. In contrast to the past and present routine task intensity of an occupation, our subjective indicator is a forward-looking measure that explicitly taps into prospective risk of automation (within the next 10 years). RTI hence does a fairly good job in describing vulnerability in typical routine jobs as the ones discussed before. Indeed, the highest levels of subjective risk are found among semi-skilled machine assemblers (RTI: 0.49) and customer service clerks (RTI: 1.41) with reasonably high degrees of routineness. But RTI is only insufficiently capable of capturing the justified and widespread fear of automation among lower-skilled workers, for example in sales or transportation, whose jobs are not particularly routine-heavy but still strongly challenged by current advances in smart software and deep learning.

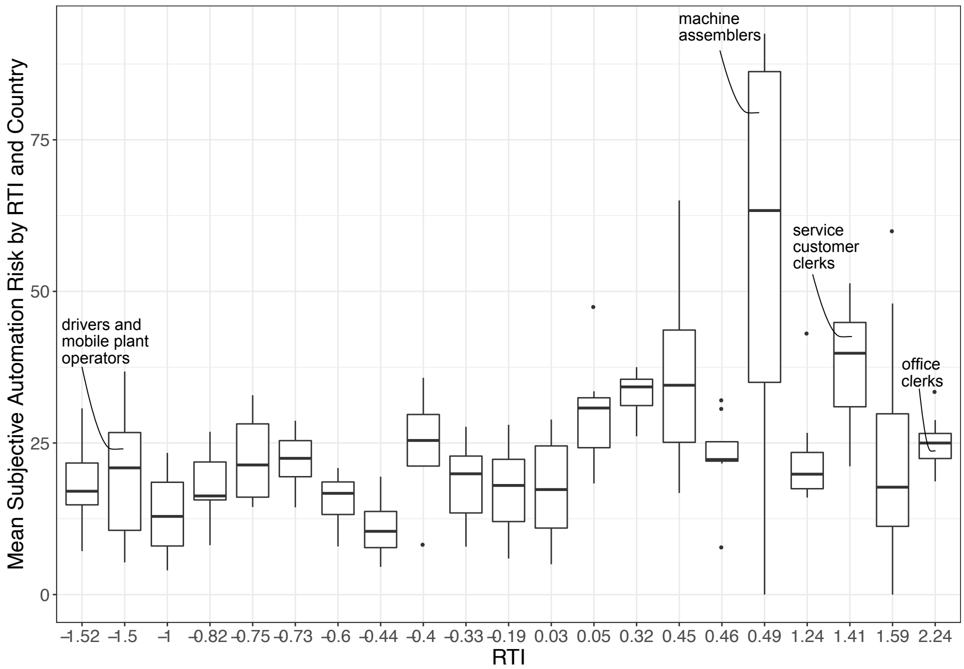
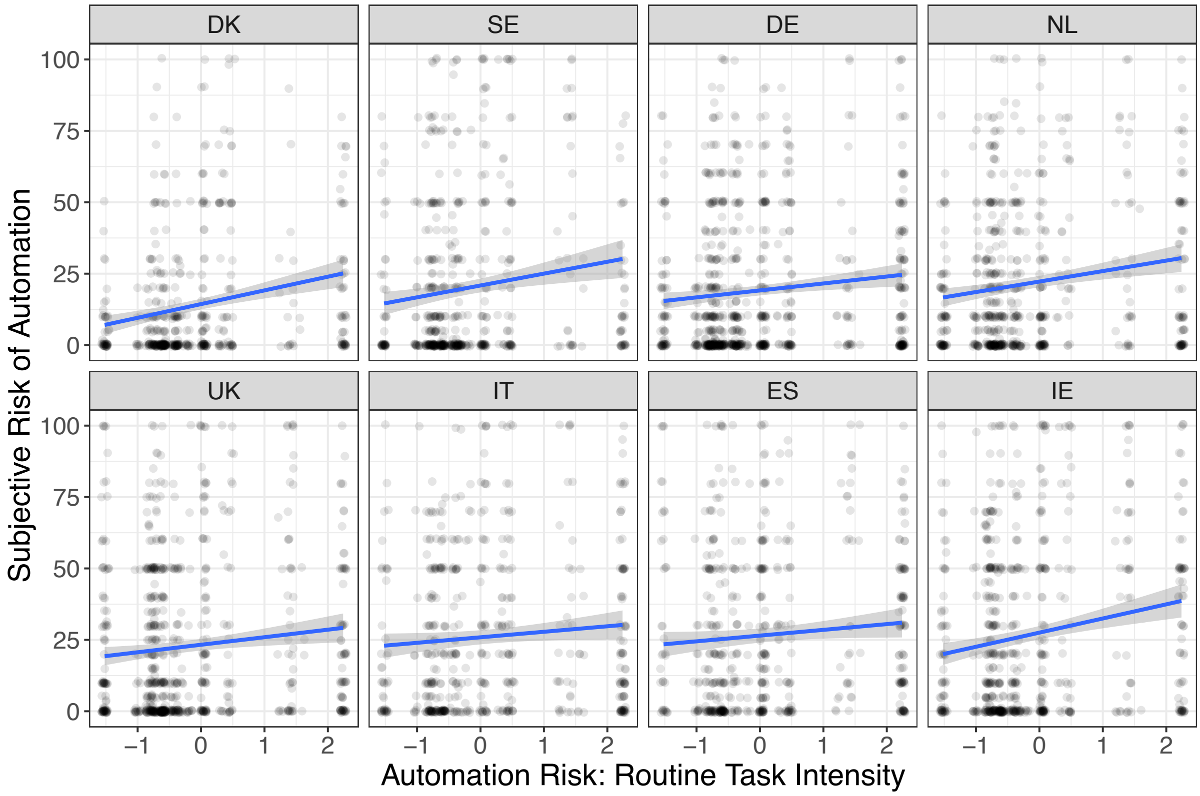


Figure 4: Subjective Automation Risk and Routine Task Intensity (RTI)

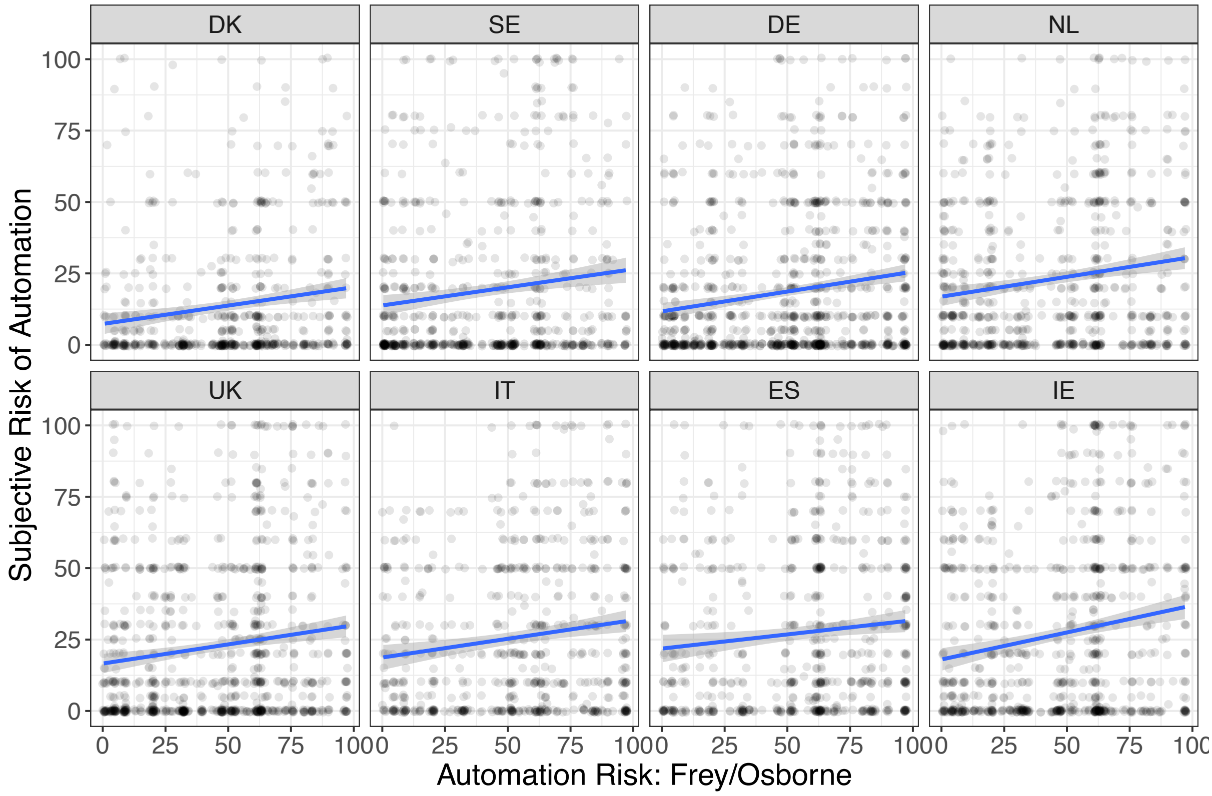
Figure 5 complements this overview with country-specific correlations between our subjective measure and routine task intensity (RTI). While there is some variation in the extent to which subjective automation fear and routine task intensity correlate, the pattern is fairly consistent across countries.

Figure 5: Perceived Automation Risk and Routine Task Intensity by Country



Since RTI insufficiently captures digitalization and recent software developments, we complement our validation exercise with a much more future-oriented indicator of automation risk developed by Frey and Osborne (2017) as a second comparison. This indicator applies a revised task model of substitution that takes into account that recent advances in machine learning and pattern recognition increasingly allow for the replacement of non-routine tasks. Subject to remaining "engineering bottlenecks", Frey and Osborne assume that it will soon be possible to automate almost any task provided sufficient amounts of data. Figure 6 shows correlations between subjective perceptions of risk and this more futuristic approach to automation. Again, there is a consistent yet only moderately positive relationship. Interestingly, this time the bias goes in the other direction. Most respondents are less concerned about automation than Frey/Osborne. This deviation is particularly pronounced in jobs that are doomed to soon and complete extinction according to the Frey/Osborne model, e.g. white-collar office occupations of almost any skill level or elementary occupations like cleaning. The only groups that *over*estimate their risk compared to Frey/Osborne are respondents in highly analytical and thus hard-to-replace managerial and professional jobs.

Figure 6: Perceived Automation Risk and Frey/Osborne Measure by Country



Taken together, the consistently positive relationship to two conceptually different objective indicators of automation risk (see Appendix Figure A.1 for a compact summary) lends credence to the general validity of subjective perceptions of vulnerability. Many respondents seem to be slightly more concerned than the routine-task intensity of their job would suggest but at the same time somewhat less anxious about competition by algorithmic intelligence. In fact, the Frey/Osborne measure has been criticized for offering overly gloomy estimates of labor substitution because most often it is not entire occupations but certain tasks within an occupation that are replaced by technology (Arntz et al. 2016). Hence, our respondents might be right to be slightly less pessimistic about their labor market prospects in times of automation.

4. Automation Risk and Social Policy Preferences

To test how the subjective risk of automation relates to social policy demands, we look at four variables that capture support for passive and active social policy in different ways. Passive social security is measured via pension policy and unemployment benefits; active social policy via support for tertiary education and labor market reintegration measures. Specifically, we asked:

"To what extent do you agree with the following policy reform proposals? The government should..."

- ...increase old age pension benefits
- ...increase unemployment benefits
- ...expand services that help reintegrate the long-term unemployed into the labour market
- ...invest more in education

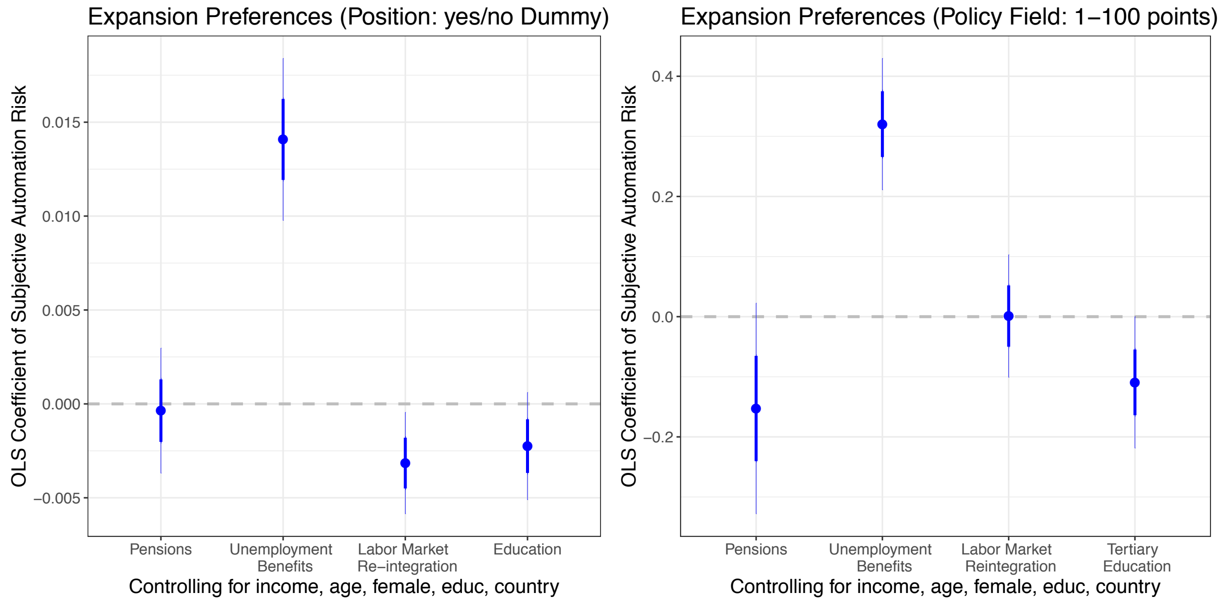
All items have been answered on a 1 (disagree strongly) to 4 (agree strongly) scale and have been dichotomized into a support/oppose dummy variable for the sake of simplicity.

In addition, to measure how much *relative* importance respondents attribute to these different policies, respondents were asked to allocate 100 points to six items, reflecting the relative importance they attribute to different strategies of welfare state expansion. We asked interviewees to distribute 100 points to six social policy fields: old age pensions, childcare, tertiary education, unemployment benefits, labor market reintegration services, services for the social and labor market integration of immigrants. For our analyses here, we use the items relative to pensions, unemployment benefits, labor market reintegration, and education.

Figure 7 visualize the key coefficients of our simple multivariate linear regression analysis. In addition, Table A.1 in the Appendix shows full regression tables for linear and logistic specifications. The result is clear-cut and straightforward: Workers who fear that they will be replaced by smart software or robots in the near future have a higher probability to support an extension of unemployment benefits. This is a rational (short-term) response to unemployment risk. At the same time, they do not show any sign of support for more long-term solutions, in particular policies related to labor market re-integration policies or human capital formation policies, i.e. the key policies of the social investment state. This key result does not depend on whether we look at respondents' policy position or their relative policy preferences. It is even robust to a direct trade-off question that asked respondents if they supported higher unemployment benefits at the cost of lower pensions.

The positive association between automation risk and support for unemployment benefits is consistent across all countries albeit not statistically significant in each and every country. This had to be expected given the reduced N in the split samples (see Table A.2 in the appendix.) In terms of the substantive importance of the coefficient, the magnitude of the effect is relatively small – but so are the effect sizes of other standard predictors. Standardized coefficients (see Figure A.2) show that the effect is comparable in size to the coefficient of respondents' age but somewhat smaller than the coefficient of their income. Education (in the standardized analysis treated as a continuous variable) seems practically irrelevant, perhaps indicating that ideological conflicts within education groups cancel out any overall effect.

Figure 7: Automation Risk and Social Policy Preferences



(a) Expansion Preferences (Position) **(b)** Expansion Preferences (Relative Importance)

Finally, we demonstrate in the appendix that the general pattern of support for passive transfers as opposed to investment-oriented policies also holds when looking at objective rather than subjective indicators of automation risk. The results are even more clear-cut in the sense that respondents with high RTI or high values of risk according to Frey/Osborne not only support unemployment benefits but also the higher pensions, i.e. a different form of passive transfers (see Figure A.3). Just as in the case of subjective automation risk, there is no sign of support for investment-oriented policies among more risk-exposed respondents.

5. Extension: Heterogeneous Preferences by Education?

Previous research on this topic has also drawn our attention to differential incentive structures for higher- and lower status individuals. Specifically, Thewissen and Rueda (2017) show that among higher-income individuals, the link between automation risk and demand for social compensation is even stronger than among lower-income individuals, an effect they ascribe to opportunity costs rising with income. Elsewhere, we (Häusermann et al. 2015) have shown that more highly educated labor market outsiders specifically prefer social investment, whereas less educated outsiders prefer redistribution. We read this effect as showing that more highly educated vulnerable employees have a primary preference for work, i.e. for employment opportunities, over non-work compensation. A similar reasoning may apply when it comes to automation, as one could think that more highly educated respondents who fear the risk of automation substitution would want to invest in upskilling and retraining, whereas low-skilled individuals would prefer income protection.

Figure 8: Subjective Automation Risk and Policy Preferences (Position), by Education

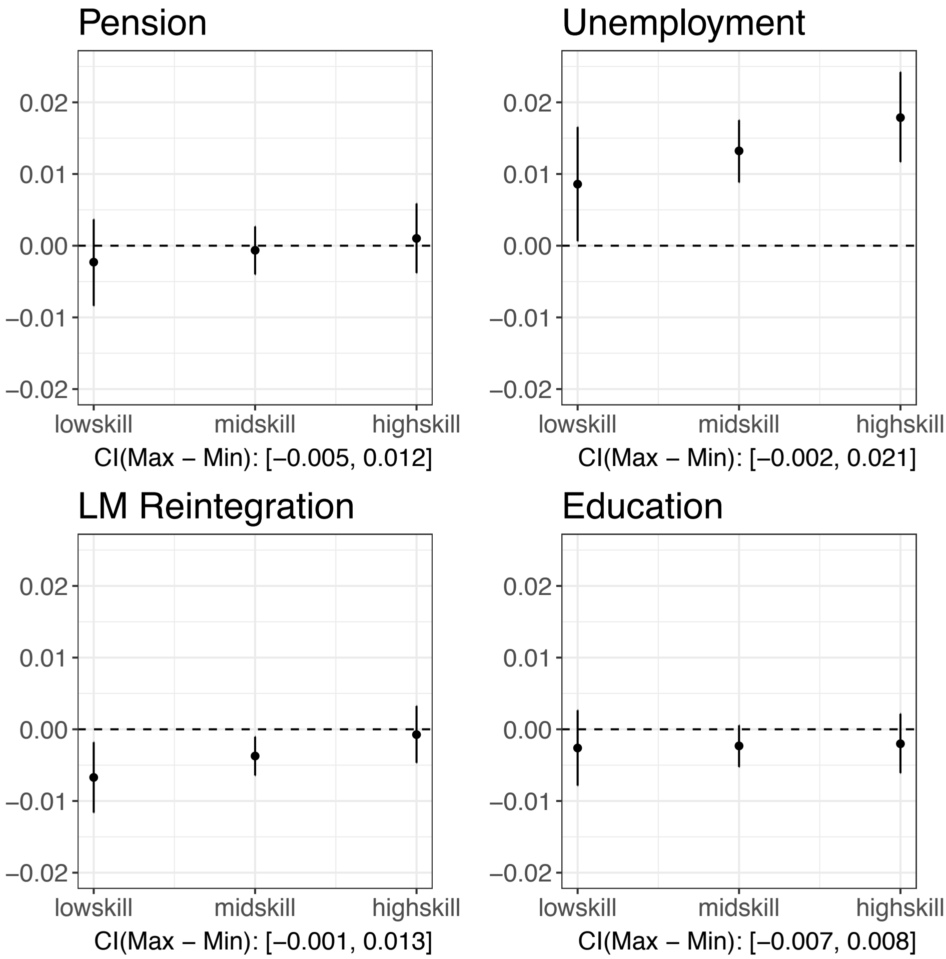


Figure 8 shows that this expectation is not borne out by the data when it comes to the relationship between subjective automation-risk and social policy preferences. In general, the effect of automation risk varies only weakly with education. If anything, education seems to reinforce the pattern shown above. High-skilled respondents who feel threatened by automation have an even more pronounced demand for unemployment benefits than lower-skilled respondents. With regard to investment-oriented policies, they seem a tiny bit less skeptical towards spending for labor market reintegration measures but hardly differ from lower-skilled workers when it comes to supporting investment in education. Lower skilled workers who feel threatened by automation are particularly opposed to measures supporting labor market reintegration, indicating that such ALMP may be perceived more constraining by these respondents than opportunity-enhancing. The pattern is similar and even slightly weaker when we look at the relative importance of policy fields instead (see Figure A.4). Taken together, the strong adherence to passive transfers among the at-risk group largely holds across education groups. Contrary to what one might expect, not even higher skilled respondents who feel susceptible to automation do seem to support more long-term strategies related to activation and investment.

6. Discussion and Conclusion

This chapter has examined the relationship between perceived risk of automation and support for specific social policy preferences. Importantly, our data allows to differentiate between support for passive transfers and more long-term approaches related to human capital investment and (re-)activation of labor supply. We find clear-cut evidence that at-risk individuals primarily demand traditional passive insurance against the risk of job loss but do not show any sign of support for investment policies generally recommended by policy advisers. Our results indicate that the support base for human capital-oriented policies does not include those individuals who feel most exposed to the contemporary downsides of technological innovation.

The political implication of our findings are open to interpretation. Whether such preference differences matter politically depends on several factors, not least on the size of the at-risk group and on their political mobilization. As of now, the group of people who feels imminently threatened seems relatively small. Between roughly 10-15% of our sample are somewhat concerned and see reasonably high probability that jobs like theirs will be automated within the next ten years. This share is considerably higher in countries that have not yet completely transformed into modern knowledge economies that rely heavily on a highly skilled and specialized workforce.

This relatively small size of the group of voters who feels subjectively acutely threatened by automation certainly contrasts with the massive attention the spread and threat of automation gathers in the media and public debate. Part of this discrepancy may result from our question, which asks not about fear in general, but about a concrete expectation of one's job being automatized within one decade. There might be a difference between the egotropic fear and a more socio-tropic worry about where economic development may lead societies. This distinction may also explain a certain gap between the limited political relevance of the at-risk group in our study and the arguments in the literature that expect a more massive electoral fallout of automation. We therefore conclude that the at-risk group's preference for rather short-sighted policy responses is likely to find only limited resonance within the political arena. On their own, the socio-structural group of automation losers - if one can see them as a group in the sociological sense at all - might therefore most likely not be influential enough politically to challenge a transformation of the welfare state towards the social investment model in case mainstream parties, technocrats and policy-advisors agree on orienting policies in this direction.

Two caveats are in order, here, however. First, the demonstrated preference for short-term social protection over long-term social investment among automation losers in fact closely resembles the social policy preferences of right-wing populist voters more generally (??). The claims and priorities of these parties when it comes to welfare are not vague at all but are perfectly in line with the above-shown preferences of individuals who feel susceptible to automation (?). Hence, it seems that right-wing populist parties are in a much better position to mobilize those threatened by automation than liberal-progressive forces that push for education, activation and training.

Second, in the near future, subjective risk of automation may well spread beyond current levels, which would reinforce the political clout of this alliance of national-conservative and economically fearful voters. Our indicator can be interpreted as a conservative estimate because of the narrow time window of the next ten years. However, technological innovation is fast-paced and has certainly not yet reached its peak. In particular, the domains of deep learning and artificial intelligence are evolving rapidly and are increasingly helpful (or threatening) in performing increasingly complex tasks. Indeed, our results show that higher education only weakly attenuates subjective risk perceptions. Even though we believe that high-skilled voters might tend to overestimate their immediate risk of replacement, this aspect of our analysis is important when thinking about prospective welfare state reform. It suggests that the pool of voters who feel susceptible to automation might well reach beyond the usual group of economically disappointed citizens. A lower correlation between risk and income, that is, a situation in which economic disadvantage and economic risk tend to be cross-cutting traits, creates broader and more influential coalitions in favor of a welfare state that *insures* citizens against economic threat (?). If these developments generally lead to stronger support for passive transfers and hesitant support for social *investment*, policy makers might find it challenging to create sufficient public support for a future-oriented policy agenda able to cope with the challenges and reap the benefits of the fourth industrial revolution.

The overall and most important lesson of our chapter for the studies interested in effective responses to economic modernization hence is that automation does not automatically produce support in favor of the investive welfare states envisioned by many experts.

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A. Appendix

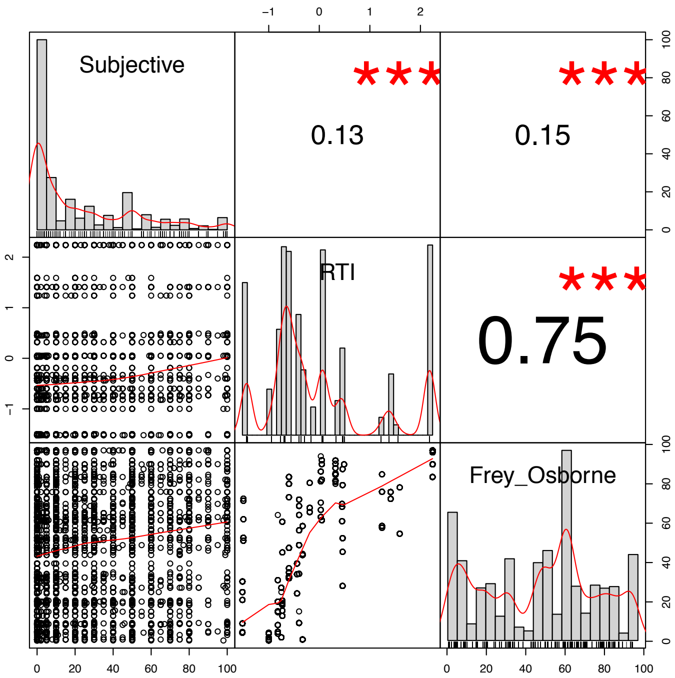


Figure A.1: Subjective vs Objective Indicators

Table A.1: Automation Risk and Social Policy Preferences

	Pension		Unemp		LM Re		Educ	
	lin	logit	lin	logit	lin	logit	lin	logit
AutoRisk	-0.000	-0.002	0.014^{***}	0.062^{***}	-0.003^{*}	-0.034^{*}	-0.002	-0.021
	(0.002)	(0.012)	(0.002)	(0.010)	(0.001)	(0.015)	(0.001)	(0.014)
Female	0.013	0.101	-0.015	-0.069	0.026^{***}	0.288^{***}	0.002	0.024
	(0.009)	(0.067)	(0.012)	(0.051)	(0.007)	(0.083)	(0.008)	(0.077)
Age	0.002^{***}	0.012^{***}	0.003^{***}	0.013^{***}	0.001^{***}	0.016^{***}	0.001^{***}	0.010^{***}
	(0.000)	(0.003)	(0.000)	(0.002)	(0.000)	(0.003)	(0.000)	(0.003)
Income	-0.000	-0.003	-0.023^{***}	-0.101^{***}	-0.001	-0.007	0.003^{*}	0.033^{*}
	(0.002)	(0.013)	(0.002)	(0.010)	(0.001)	(0.016)	(0.001)	(0.015)
Educ (1-8)	yes	yes	yes	yes	yes	yes	yes	yes
Cntry FE	yes	yes	yes	yes	yes	yes	yes	yes
R^2	0.154		0.087		0.022		0.026	
Adj. R^2	0.152		0.085		0.020		0.023	
Num. obs.	6768	6768	6774	6774	6769	6769	6814	6814
RMSE	0.369		0.478		0.300		0.317	
AIC		5947.779		8808.252		4358.432		4782.533
BIC		6077.358		8937.848		4488.014		4912.241

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$. Categorical measure of education included but dropped for sake of compactness of table.

Table A.2: Automation Risk and Unemployment Benefit Preferences by Country

	DE	ES	IT	IE	SE	NL	DK	UK
AutoRisk (0-10)	0.005	0.008	0.011	0.014*	0.026***	0.019**	0.004	0.019***
	(0.006)	(0.005)	(0.007)	(0.006)	(0.006)	(0.006)	(0.008)	(0.005)
R^2	0.069	0.031	0.038	0.047	0.048	0.055	0.028	0.051
Adj. R^2	0.060	0.017	0.024	0.035	0.035	0.041	0.013	0.042
Num. obs.	1095	750	691	886	811	789	751	1001
RMSE	0.484	0.421	0.481	0.487	0.491	0.474	0.490	0.473

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$. Results by country, covariates as in Table A.1.

Figure A.2: Subjective Automation Risk and Position (Extension), Standardized

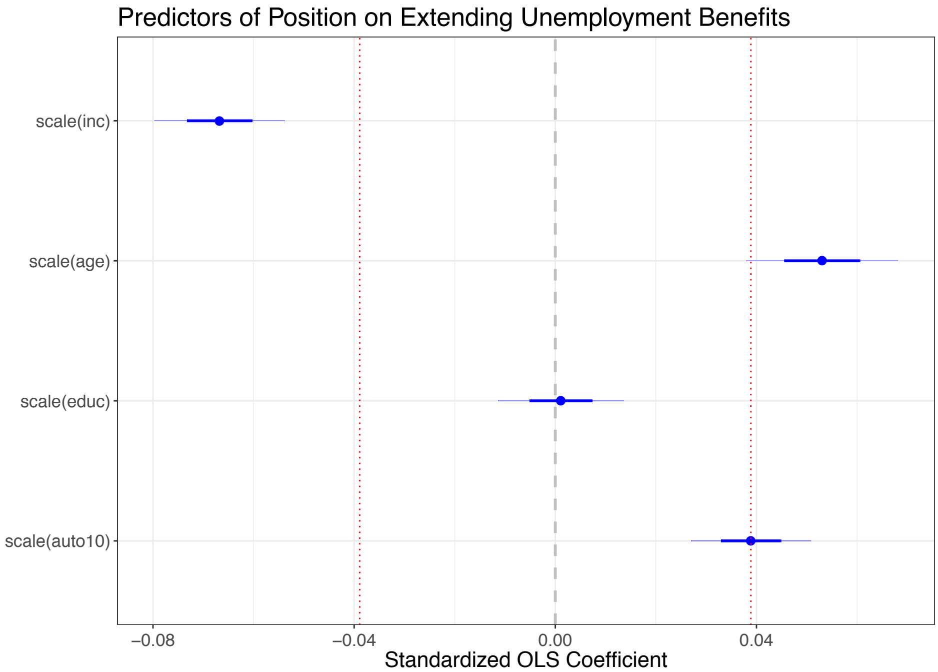
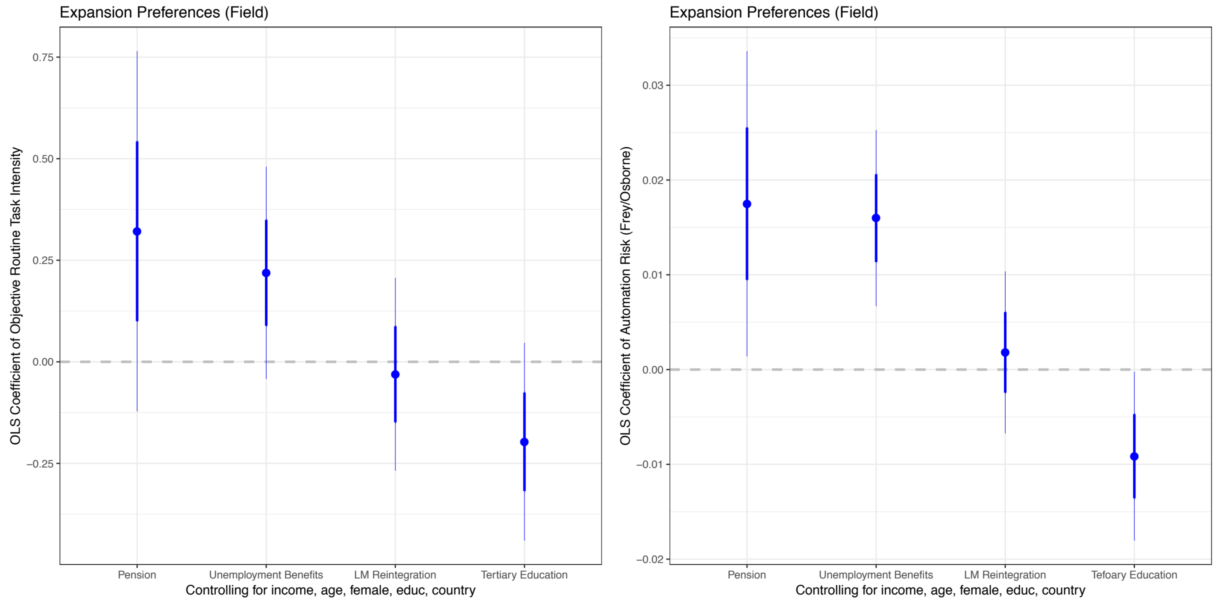


Figure A.3: Automation Risk and Social Policy Preferences



(a) Routine Task Intensity **(b)** Frey/Osborne

Figure A.4: Subjective Automation Risk and Field (Extension), by Education