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Workers support for policies to address digitalization-related risks

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Workers support for policies to address digitalization-related risks

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Abstract

What policies do individuals prefer in response to the labor market risks related to the ongoing processes of digitalization and automation? To what extent does being exposed to different forms of "technological risk" condition such preferences? In this paper, we advance existing research on this topic by distinguishing between three main dimensions of technological risks (general concern about negative impacts, concern about tasks in one's job being automated, and technostress) and preferences for three types of policies related to these risks (compensation, retraining, and protectionist policies intended to slow down or prevent technological change). Using new survey evidence from Spain, we find little evidence that technological risks matter for preferences for compensation or retraining, but they do condition support for protectionist policies. We conclude with implications for politics in the current context of rapid digitalization.

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1 Introduction

The covid-19 pandemic has accelerated existing trends towards digitalization in areas such as teleworking, e-commerce, and the use of big data in Europe (European Commission 2022). Such trends are only likely to deepen because of the combination of the rapid development and roll-out of artificial intelligence (AI) technologies and public investment to accelerate the so-called "digital transition". A coordinated effort involving a mix of policy tools to accelerate digitalization is a key strategic goal of the EU. Of the 723.8 billion euros allocated to the Recovery and Resilience Facility (RRF) of the European Union, the main European Union policy instrument designed to help economies recover after the pandemic (Schram, 2022), 20% will be invested in digital transformation projects, related to areas such as supercomputing, artificial intelligence, cybersecurity, and training of the workforce in advanced digital skills. Indeed, a staggering 127 billion euros had already been approved between 2021 and early 2022.

Institutions and political parties remain adamant about the benefits of digitalization. For instance, the European Commission (EC), recently stated that "there is a broad consensus on the priorities for the European economic growth model, including the green and digital transitions" (EC press release, March 2022). Party manifestos refer overall very positively to digitalization and only discuss as relevant downsides some specific aspects such as cybersecurity or disinformation (Marenco and Seidl 2021; König and Wenzelburger, 2019).

However, the enthusiasm about digitalization is not shared by all experts. Leading economists are increasingly voicing concerns about the uncertain or negative implications of the current wave of digitalization, as seen in Autor (2022) and Acemoglu (2021). A key concern is that the expansion of artificial intelligence (AI) technologies will make large numbers of workers redundant but only increase productivity marginally, and hence will not generate enough jobs or profits to offset losses. AI, a general-purpose technology that uses big data to train algorithms to perform tasks such as machine learning, image and pattern recognition, or customer service, will likely strongly reshape numerous white-collar and skilled occupations, ranging from lab technicians to chemical engineers, epidemiologists, statisticians, credit analysts and accountants (Webb 2020; Felten, Raj and Seamans 2019).

In this context of accelerating digitalization and broadly spread risks, we ask: Do some workers perceive digitalization as a risk? What policies do workers who are concerned about various technology-related risks prefer in response to the ongoing processes of digitalization in the workplace? Specifically, if they see technology as a risk, do they demand compensation, retraining, or protection from change?

Recent studies on the correlation between various measures of risk and policy preferences—such as support for passive redistribution, active redistribution, universal basic income, and active labor market policies—indicate mixed findings about the types of compensatory policies preferred (for reviews, see Weisstanner 2021; Gallego and Kurer 2022). A key shortcoming of this literature is that existing measures of both technology-related risks and policies preferred by citizens are few and indirect, which may explain some of the mixed findings.

Our study advances the literature about attitudes towards digitalization-related policies in two ways. First, we differentiate among three subjective concerns related to technology: generic concern about the consequences of technology in the workplace, self-perceived job displacement (substitution) risk, and "technostress," the stress of keeping up technologically at work. Most existing studies about perceived risk only ask about the probability of being substituted by a machine and find that few workers have egotropic concerns (Heinrich and Witko, 2021). Technostress, or concern about one's ability to learn to use new technologies, may be relevant for workers in occupations that require using computers, but has received little attention in political science so far1. Second, we articulate the distinction between three types of policies that may be demanded by citizens who feel exposed to technology-related labor market risks: compensation, retraining, and protectionist policies intended to slow down or prevent technological change.

The three types of policies have very different efficiency consequences. Labor economists and social policy scholars generally agree that the most efficient, growth-enhancing policy to address labor market risks related to technological change is to help citizens acquire skills that are in high demand in the knowledge economy (for a review of the social investment paradigm, see Hemerijck, 2018). However, recent empirical evidence indicates that workers at risk of automation are less likely to support active labor market policies (Busemeyer and Sahm 2021, Busemeyer et al 2022; Kurer and Häusermann 2021, though see Im, 2020, for contrasting findings). Gallego and Kurer (2022) speculate that retraining is not psychologically appealing because it is costly for individuals -- they must give up social identities and social environments related to their current jobs, learn new skills, and change jobs and sectors, and possibly location. It may be more appealing from the affected worker's point of view to demand protection against change, which would allow preservation of existing jobs, identities, and social environments. Using correlational and experimental methods, Gallego et al. (2022) indeed find that workers at higher risk of displacement are more likely to demand government action to prevent technological change. However, the measures of protectionist policies in that study were fairly limited, as the survey instrument asked generically about policies that "accelerate" or "slow down" technological change, without specifying what such policies would be.

In this paper, we develop new measures of preferences for protectionism, and examine how each technology-related risk is related to preferences for redistribution, retraining, and protection. Our findings come from an original online survey in Spain from July 2021, with 1450 working-age respondents.2 Overall, we find little evidence that any technology-related risk correlates with support for redistribution or retraining. We find a strong correlation between various forms of automation risks and support for "protectionist" policies aimed at slowing down technological change. These results have implications for both the measurement of what worker features matter most for predicting policy preferences, and also what policies parties or governments might propose to gain political traction if current digitalization policies generate a sense of threat among workers, either of being substituted or of not being able to keep up learning. We discuss implications in the conclusions.

2 Relevant literature and theoretical expectations

2.1 Background findings

Given the prioritization of digitalization by European policy-makers and the substantial funding allocated, digitalization-related labor market change is likely to continue and accelerate in the coming years. Whilst this should have a positive impact on overall economic growth, scholars have established that such advances have in the past led to rising job polarization and inequality (e.g. Goos, Manning & Solomons, 2009, 2014; Autor & Dorn, 2013). Gil-Hernández, Vidal & Torrejón (2022) confirm that

[1] The only survey we are aware of that asks respondents about technostress is Busemeyer et al. (2022), but they include this item in a principal component analysis about general perceptions of risk and do not separately test if it correlates with policy preferences.

[2] We have also measured policy preferences and technological risk for a subset of this sample in November 2018, but our focus for this paper is on policy views that were assessed only in wave 2.

this trend is likely to continue in the future, with technological change likely to perpetuate or even exacerbate class differences, with already disadvantaged workers likely to bear 'the most significant negative and substitutive impact of new technologies on their employment relations and life chances' (p.17).

In this context, it is relevant to understand whether workers perceive digitalization as a risk and, in that case, which policies they demand in response. The recent literature about the political consequences of technological change finds that those who economically lose from digitalization are more likely to support populist parties (e.g., Gallego and Kurer, 2022), suggesting that they may not be supporters of digitalization policies. However, there remain few studies about citizens' subjective concerns and their preferred policies.

The broad point of theoretical departure of extant studies on policy preferences adapts various conceptions of occupation-based "displacement" or unemployment risk (e.g., Rehm 2016) to empirically test whether objectively measured automation-based risk correlates with support for forms of redistribution, a policy often noted as an appropriate compensatory policy for such risk. A standard theoretical claim is that objective labor market risk affects preferences for redistribution and compensation because workers at higher risk are at some level aware of their higher probability of unemployment or of potentially longer unemployment spells, and therefore support more generous compensation policies to insure against income loss (Thewissen and Rueda 2019, Weisstanner 2021). 3

In a standard account, awareness of being exposed to a specific structural risk is a basic micro-foundation for the process through which being at risk should lead workers to prefer that governments implement certain policies. "Subjective" concern (or "subjective risk") is therefore a key mechanism linking objective risk and policy preferences (Walter, 2010, applies this logic to the case of international trade). A precise version of this claim is a mediation model in which objective automation risk causes concern about the impact of technological change, and this concern in turn affects support for specific policies. This mediation relationship is often implicitly assumed in existing accounts that focus only on objective risk indicators.4

Most studies that apply this framework specifically to automation risk use objective measures of risk, rather than subjective ones, which are not asked in standard surveys such as the European Social Survey (for a review, see Weisstanner 2021). The most frequent way to measure objective risk is by assigning a "routine task intensity" (RTI) score based on the occupation that respondents report in surveys. RTI is taken from Autor, Levy & Murnane (2003), who estimated the routineness of tasks in US occupations based on occupational dictionaries.

Several limitations of "objective" risk measures used in public opinion surveys have been mentioned: a) the tasks conducted in occupations vary widely over time and across contexts, but the measure is neither time- nor country-specific; b) occupation risk is aggregated at the 1- or 2-digit level and assigned to survey respondents. This conflates workers with very different occupations and makes it unfeasible to add occupation fixed-effects as controls in empirical analyses, hence compromising the interpretation of results as related to technology-related risks vs other occupational characteristics; c) even if a task is routine it is very uncertain whether it will be automated, as this also depends on costs and engineering bottlenecks; d) workers at risk of substitution by AI-related technologies include workers not in classical "routine" occupations, such as translators.

[3] The core theoretical claim is that workers at higher risk of unemployment or losing income should be more likely to support redistributive policies to insure against risk (Moene and Wallerstein 2001, Iversen and Soskice 2001, Rehm 2016).

[4] See Zhang (2019) for further discussion of the assumption that those who are at objective risk may be unaware of these risks.

In this paper, we concentrate on the question of whether subjectively perceived technological risks are associated with different policy demands (we present descriptive statistics and results regarding objective risks in the Supporting Information).5

Previous research is inconclusive on this question. Jeffrey (2021), using UK data, documents a general lack of information or concern about automation risks, and finds that individuals only make the link between such risks and redistributive policies when directly primed6. Gallego, et al. (2022) find that subjective concern for automation increases demand for protection, but not for redistribution. Using original survey data from 8 European countries, Kurer & Häusermann (2021) find that, while support for increasing unemployment benefits correlates with concern about automation, this positive correlation is absent for the other redistribution policies of increasing pensions, expanding retraining programmes for the unemployed, and investing in education.7 Other survey evidence has not found a strong correlation between subjective automation risk and support for "active labor market policies" (Busemeyer & Sahm, 2021; Weisstanner, 2021, Busemeyer et al 2022). This finding is relevant given that active labor market policies are one of the key policy instruments proposed to help workers adapt to and benefit from technological change.

2.2 Hypotheses

Our main expectation is that individuals who are at a higher risk of experiencing substitution should be more supportive of policies to reduce adoption of new technologies in the workplace. We hypothesize that compensation and retraining may be relatively less supported policy choices than protectionism for multiple reasons. First, workers may prefer to keep their occupation and maintain the status quo, as opposed to becoming recipients of state aid. Second, theoretical and empirical studies have shown that support for redistribution measures can be hampered due to sensitivity to tax increases required to pay for redistribution (e.g., Naumann 2018, Citrin 1979). Overall, we hypothesize that "slowing down" workplace technological change may be considered a more effective and direct policy to maintain job security than redistribution, as the latter implies a worker accepting the possibility of job insecurity and receiving uncertain compensation, changing work environments, or accepting being a net payer in case of an unrealized risk.

Thus, whilst the theory would point towards technological risk correlating with the three categories of policies[8], we expect a higher positive correlation between digitalization-related risks and support for protectionist policies to decelerate workplace technological change, relative to support for compensation and retraining.

Of course, the particular relationship between a type of subjective concern and corresponding policy preference may be more pronounced for some sub-groups, as for such groups the particular mechanism for *why* subjective concern measures may differ. In the SI, we consider multiple demographic or attitude moderators for which technological risk should be relevant. In particular, we

[5] Still, we caution that subjective concern is not the only mechanism connecting objective risk to policy preferences, as there are other plausible reasons why indicators of objective risk could affect policy views. For example, workers in occupations threatened by technological change may perceive that their skills are less demanded or valued than in the past, even if they are not aware of the exact cause of this change (for a recent discussion of declining status perceptions see Gidron and Hall, 2020). Alternative mechanisms related to policy views may thus be psychological, such as lower self-esteem; another could be general concern about one's economic prospects. Such mechanisms might operate in the absence of or in addition to subjective concern about workplace technological change.

[6] Jeffrey (2021) uses subjects' self-reported concerns.

[7] Panel evidence on whether unemployment shocks themselves affect long-term policy preferences indicates mixed
results (Margalit 2019, O'Grady 2019).

[8] Even though, as seen above, some recent empirical results have cast doubt on this idea.

focus on several of the most theoretically relevant characteristics. We focus on one natural moderator, consistent with redistribution theories, which is the role of perceived *outside job options*. Our expectation is that for our subjective risk measures, the correlation with support for redistribution in particular should be higher for those who are *both* higher risk on substitution perception *and* pessimistic about finding an alternate job if displaced.

We consider two other sensible moderators. One is *age*. Our general expectation is that for workers closer to retirement age, technological risk should be particularly relevant for support for protectionism, as older workers may feel more incentivized to prevent change. Older workers may on average be less inclined to accept redistribution support; they may have more difficulty retraining than younger workers, and may thus demand different policies to prevent automation displacement. Our final moderator is *job identity*; greater at-risk workers who identify more with their job may be more supportive of technological protectionism and less inclined to support redistribution.

3 Data, Measurement, and Research Design

In order to empirically assess the correlation between objective and subjective risks and whether either is more correlated with policies of compensation, retraining, or protectionism, we present evidence from an online survey administered to workers in Spain in June-July 2021[9]. Our sample size of the working-age population is 1450, nationally representative with quotas by age, gender, educational category (lower secondary or less, secondary, and any university). The participants were selected by the Spanish survey firm Netquest from a large panel of people who have agreed to fill online surveys in exchange for points that can be exchanged as rewards or as tickets in lotteries. Panelists are recruited through websites and ads and then are sent invitations to participate in surveys. The company programmed the questionnaire, which was extensively pretested by the principal investigators of the project. The fieldwork was closely supervised to ensure that all quotas were met and that the data had sufficient quality (e.g. response time, consistency of responses).

Spain is a useful case study for our approach for two main reasons. First, it represents a fairly typical advanced economy in many respects, but Spain was a late industrializer and still retains a relatively high number of routine workers (de la Rica & Gortazar, 2016), allowing for a more complete analysis of their preferences. Second, like its Southern European peers, it has tended to respond differently to the challenges of de-industrialization compared to the more oft-studied Anglo-Saxon and Germanic countries, preferring to accrue government debt and avoiding overly liberalizing the labor market (Boix, 2019). This has led to the creation of a workforce that has at times been highly dualized between protected insiders and temporary workers, but this sharp divide has been weakening in the last years due to a series of labor law reforms.

Next, we discuss measurement, with a focus on the differing notions of "risk" and new measurements of policy preferences.

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[9] By the time of the fieldwork, the most stringent restrictions and disruptions caused by the COVID-19 pandemic in Spain had subsided, though some of the wage loss and unemployment caused by the pandemic endured. Given that, as mentioned above, this is the second wave of a panel study, some indication of the pandemic's effects can be garnered by examining differences between the two waves. Such an exercise is not without its issues, as the first wave was administered in 2018, and thus any changes across waves could be due to longer-term trends occurring between 2018 and 2021 rather than to the pandemic itself. Further, some of the policy preference variables discussed in this paper were not measured in wave 1. In any event, changes across waves are relatively small, with respondents having become slightly more negative about the impact of technology on their careers in the later wave, as well as very slightly more supportive of redistributive policies. More importantly, the occupation-level fixed effects discussed below in the main text should (at least to some extent) help control for the effects of COVID-19, as these were felt disproportionately across occupation categories.

3.1 Subjective risk

We measure subjective risk or concern about technological substitution in a number of ways: a) technological concern, b) job substitution risk, and c) "technostress" (the aforementioned concern about adapting to technological change). Regarding our first category of subjective technological concern, for all respondents, we ask whether they believe that technological advancements in their workplace will have positive or negative consequences for future work opportunities.[10] The five response options were: "Very Positive, Mostly Positive, Neither Negative nor Positive, Mostly Negative, Very Negative." We label this variable self-reported concern and code it categorically with higher values indicating greater concern.

Besides this measure of subjective concern, we also assess the two other measures of technological concern that we think capture worker concern about occupational technological change. We asked individuals to give their best estimate on a scale of 0-100 the percent of their weekly work tasks that could be done by a computer, robot, or algorithm (with higher values indicating greater automation concern); we rescale this variable 0-1 with higher values indicating higher beliefs about substitution risk. To measure "technostress," we ask whether the individual both thinks that learning about technology is relevant in their job, and is also concerned about being able to learn to keep up (coded binary, if the individual believes both as 1, and 0 otherwise). To test the availability of outside options (one of our moderators), we asked how likely it is that respondents will lose their job in the next 5 years and how likely it is that they could find an equivalent or better job (coded binary, if the individual believes both as 1, and 0 otherwise); we finally also ask about how much the respondent identifies with their job on a 0-10 scale; we rescale this variable 0-1 with higher values indicating greater identity attachment to one's job.

3.2 Measures: Policy preferences and other variables

Compensation. We measure support for compensation via a standard measure of support for increased spending on unemployment benefits (even if it implies tax increases), scaled 0-10 with higher values indicating greater support.[11] We recode this into three categories of support to be consistent with our other policy variables, described below.

Retraining. Building on findings that focus on individual support for investment-style policies such as worker retraining (due to unemployment), we measure support for worker retraining (this question was coded on a 3-point Likert scale, with higher values indicating greater support).[12]

Protectionism. We asked two questions that are more precise policies regarding possible government efforts to slow down technological change. They are about giving trade unions more power to prevent firms from substituting workers[13] (even if these policies cause a reduction in salaries or a loss of

[10] Question: "Thinking about your future work opportunities (think of yourself in 5 years' time), do you think that technological advancements in the workplace will have positive or negative consequences?"

[11] We also measure support for general increases in social services (again even if it implies higher taxes). The results with both measures of compensation are similar; we focus in this paper on support for unemployment benefits.

[12] The wording was: "The government should spend more money in offering retraining to the unemployed, even if this means increasing taxes." Response options were strongly oppose to strongly support.

[13] Unfortunately, our dataset does not contain data on union membership. Whilst such a direct control is unavailable to us, the occupation-level fixed effects we introduce in some of the models (see Tables A15-A17 in particular) should at least in part account for this variation, as union membership is to some extent predicted by occupation category.

employment), and about fining firms that replace workers with technology.[14] Response options were coded on a three-point Likert scale with the highest values indicating support.

3.3 Other variables

While objective measures are not our empirical focus, we did measure two main objective measures of automation in this and control for them. The results are presented in Section 1 in the Supporting Information, but our discussion of results in the main paper focuses on subjective risks.

First, we assign a Routine Task Intensity (RTI, Autor, et al. 2003) score to each of our respondents. This measurement is based on the observation that computers and other digital tools are particularly proficient at substituting humans in occupations that mostly require carrying out routine, repetitive tasks (Autor, et al., 2002). While Autor et al. (2003) initially measured RTI for the American context (using 1990s occupational dictionaries), the measurement has since been adapted to the Spanish labor market (Sebastian, 2018). By asking our survey respondents to indicate their occupation[15] at the 2-digit ISCO code level, we then assign them a value based on Sebastian (2018)'s coding. This variable is referred to as RTI in our analyses, and scales from 0-1, with higher values indicating higher automation risk.

We also consider a measurement that is task-based (as tasks that are not especially repetitive can now be carried out by robots or software), as researchers have increasingly focused on producing more detailed measurements based on the automation potential of specific tasks, as opposed to occupations as a whole (see for example Frey & Osborne, 2017; Arntz, et al., 2017; Feng & Graetz, 2020). We specify ten tasks currently coded as less likely to be automatable as defined by the OECD (see Arntz et al., 2017, Nedelkoska & Quintini, 2018) and survey respondents on how often they are required to carry them out at work. By pooling each individual's answers, we assign them a single task-based score, which we then term 'tasks at risk at low risk of automation' (or TLRA). To maintain consistency in coding direction and interpretation, the variable is also scaled 0-1, with higher values indicating higher risk of automation substitution.

We also collected demographic data of female and male gender, age, education, employment status, and income. Male gender is coded as 1, age as nine categories between 18 and 64, education is coded into five categories, employment status into nine[16], and household income is recoded into ten categories.[17] We also use a 3-category broad "occupational class" schema, derived from Oesch (2006)'s 5-class one and based on the respondents' 1-digit ISCO occupational dummy variables.[18]

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[14] Respondents were presented with the statements "'Governments should fine companies that fire workers to replace them with machines, computers or algorithms," and "'Trade unions should have more power to oppose the adoption of new technologies by firms if this causes a reduction in salaries or a loss of employment" and given response options of "strongly disagree" to "strongly agree." Our compensation measures were measured on a 0-10 scale as the 2018 wave measured this support in a similar way; measurement of investment and protectionism support was only undertaken in the 2021 wave.

[15] Those unemployed were asked to describe which ISCO code best described their last profession.

[16] Employed with a long-term contract, employed with a temporary contract or no contract at all, self-employed with employees, self-employed without employees, unemployed, student, pensioner/retired, homemaker, on ERTE (Covid furlough). Most of our analyses focus on the first four categories listed above, as non-workers were filtered out of many of our survey questions.

[17] Missing values for the income variable were imputed using the Amelia II R package (Honaker, King & Blackwell, 2011), using age, gender, education, occupation and employment status as predictor variables. Results are the same when we consider less granular categories of these demographic variables.

[18] In the SI, we display the results with controls for 1-digit ISCO occupational fixed effects, which are broadly similar.

4 Results

4.1 Subjective risk and support for policies: Descriptive Statistics

This section discusses descriptive patterns, then turns to the baseline regression models of the correlates of policy preferences.[19] Regarding our first variable of subjective concern about automation, we observe that a plurality of respondents actually have a positive attitude about the impact of technology on their job (45%), while 34% see it as neither positive nor negative and 22% as negative. Figure 1a below plots the distribution of this technological concern. As pertains to Technostress, on the other hand, figure 1b shows that only around 18% of our respondents reported that learning to use new technology was important and that they were worried about being able to do this. Finally, figure 1c shows the frequencies of responses to the substitution potential question. 75% reported that 40% or less of the tasks they carry out at work could be automated, 13 % that between 40% and 60% could be substituted, and 12% that over 60% could be carried out by a robot, computer or algorithm.

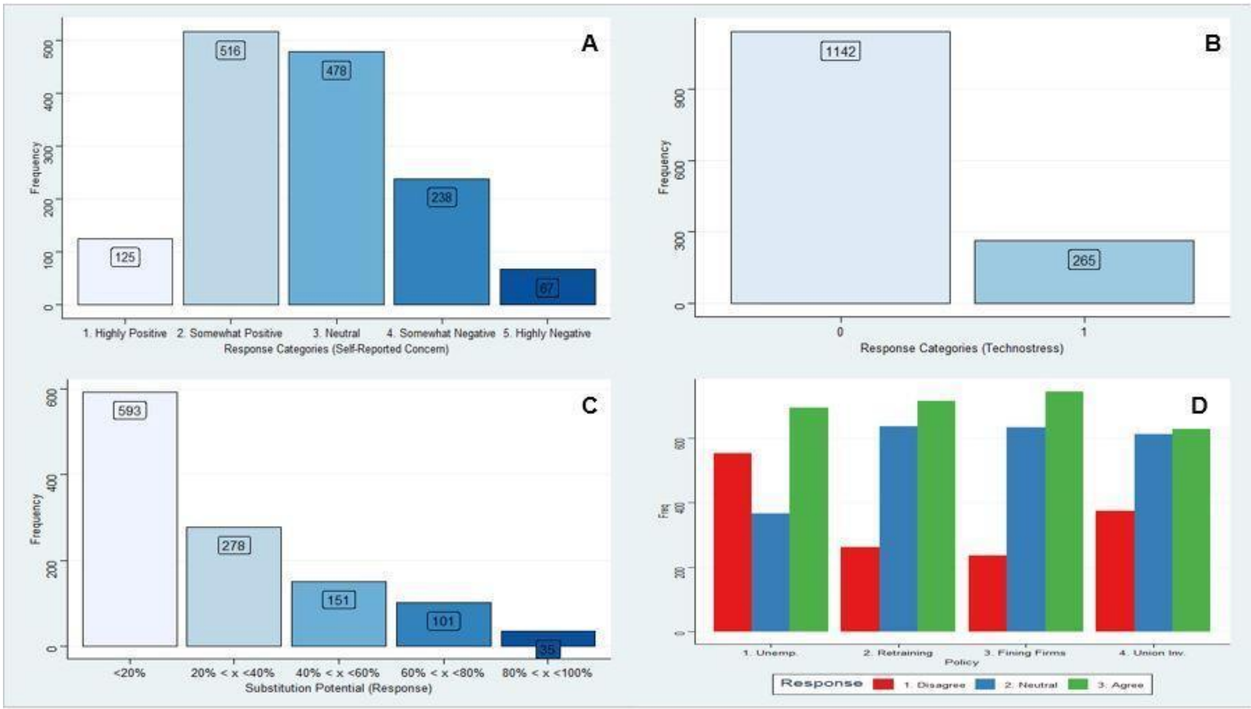
Turning to the policy preferences (Figure 1D), on support for unemployment benefits, using a recoded trichotomous coding of support, we observe that 34% expressed low support for such an increase (0-4 on the original scale), 23% were neutral on the issue (answer 5), and 43% expressed high support (answers 6-10).[20] On the policy of government-sponsored retraining for the unemployed, only 16% of our respondents had negative views of this policy, while a plurality (44%) reacted positively and 40% stayed neutral. In the SI, we present bivariate correlations between all policy measures.

On the first protectionist policy of introducing punitive fines for companies that lay off workers to replace them with machines or software, only 15% of respondents disagreed with this policy, while 39% selected the neutral option and 46% agreed with the statement. On the second policy to empower workers, when asked whether they would support more union involvement in decisions to adopt new labor-substituting technology at the company level, 23% disagreed. 38% selected the neutral option, and a very slight plurality was supportive (39%).

[19] Due to space constraints we do not present discussion on our measurement of objective risks (RTI and TLRA), but they are in the SI for interested readers. In the SI, we demonstrate limited evidence of correlation between these objective risks and our measures of subjective concern (controlling for demographic variables).

[20] Regarding support for funding social services more generally, which is measured on the same 0-10 scale, 21% expressed supported for lower taxes over more social services (answers 0-4 on the original scale), 24% were neutral (answer 5), and 56% support an increase in social services even at the cost of higher taxes (answers 6-10).

Figure 1: Description of subjective concern about automation and policy preference



Note: The figure presents the frequencies of our key variables of interest: self-reported general concern about the implications of technological change on own job prospects (panel A); whether the respondent reports that it is relevant to learn to use new technologies in the job and he or she is concerned that he or she may not be able to learn at the required speed (panel B); the percentage of tasks currently done in a job that could be performed by a computer (panel C); and the four policy preferences (panel D). These are support for expanding unemployment benefits ('Unemp'), support for expanding spending on retraining programs ('Retraining'), support for the government using fines or other instruments to prevent companies from substituting workers ('Fining Firms'), support for unions to have a say in whether technology is adopted in a workplace ('Union Inv.').

4.2 Correlates of policy preferences by types of subjective risks and policies

We now turn to correlations between our measures of subjective risk and policy preferences. We categorize the results by different *types or measures* of risk, examining the correlations across the four broad policies. We report the main results based on core specifications here, but robustness checks and alternate specifications are available in the SI. Unless otherwise noted, all specifications control for demographic variables as noted above, including the 3-class occupational schema based on aggregation of 1-digit occupational codes. Variables are either scaled 0-1 or are entered categorically to ease interpretation of results (with the baseline category set at the lowest level of each variable). We report specifications controlling for our measures of objective automation risk in the SI, but the results are similar when excluding such controls. As a brief preview of our findings, we find overall stronger effects of subjective risks on support for both protectionist policies, and little evidence that any subjective risk is strongly correlated with redistribution or retraining support.

Table 1 presents the results for each of the four dependent variables, where the focus is on the coefficients of each of our three measures of technological risk (general concern, substitution risk, and technostress). We first discuss the results measuring generic self-reported "technological concern"; we then turn to results where we examine the roles of substitution-risk and technostress. Consider first the outcomes of support for both redistribution and retraining (i.e., traditional passive and active labor market policies), presented on Table 1, which show OLS and logistic regression results. With our first measure of subjective concern, we find that it is uncorrelated with support for either increasing unemployment benefits or government-sponsored retraining programmes when we consider the full battery of demographic controls (see Table 1, Panel A, models 1-2).[21]

But technological concern is positively correlated with support for both protectionist policies (see Section 3 in the Supporting Information for alternate specifications). Models 5-8 indicate a positive and significant coefficient for both these variables. As discussed above, the reason why such concern could matter to policy support is unclear. We further delineate two theoretical channels, captured in measures of risks that are more precise than general technological concern. We first consider the specific measure of substitution risk by automation. Recall we measure this by asking about the percent of tasks that are automatable, then reframe this variable so that it ranges from 0 to 1. Panel B of Table 1 displays the results of the same regression models as above, only considering the role of "substitution risk." Models 9-16 indicate that this type of risk does not appear to be correlated with support for these policies.

Finally, the third part of Table 1 focuses on the entire working-age sample to test the specific role of technostress as a correlate of policies, following the same general approach as before. This part of the table shows that this variable (recall it is binary), does not correlate with support for either redistribution or retraining. However, technostress does positively and significantly correlate with support for both fining firms and increasing union power to check workplace technological change. Thus, those who are more concerned about keeping up with technology in the workplace appear less concerned about redistribution and more so about slowing down its adoption.

[21] Across almost all outcomes, we find little evidence that either measure of objective automation risk (RTI or TLRA) is systematically correlated with any of our measures of redistribution and retraining policy preferences. The TLRA measure is not correlated with support for increasing unemployment benefits under any model specification. The RTI coefficient is in one specification negatively correlated with support for increasing unemployment benefits, though imprecisely estimated. Neither TLRA nor RTI are correlated with support for government-sponsored retraining policies under any specification. See SI Tables A4 and A5.

Table 1: Subjective Risk and Policy Preferences (Even-numbered models include Social Class FEs, odd-numbered ones do not)

DV:	Unemp. Benefits		Retraining		Fining Firms		Union Involvement	
Panel A	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Self-Reported Concern	0.080 (0.406)	0.066 (0.412)	-0.404 (0.255)	-0.366 (0.258)	0.906*** (0.262)	0.876*** (0.265)	1.032*** (0.258)	0.971*** (0.261)
Num.Obs.	1090	1073	1090	1073	1090	1073	1090	1073
Log.Lik.	-2751.3	-2711.0	-1101.5	-1083.9	-1047.1	-1027.5	-1114.1	-1091.7
Panel B	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
Substitution Potential	0.528 (0.371)	0.481 (0.382)	0.265 (0.232)	0.297 (0.238)	-0.155 (0.237)	-0.223 (0.244)	-0.031 (0.232)	-0.176 (0.238)
Num.Obs.	1147	1126	1147	1126	1147	1126	1147	1126
Log.Lik.	-2885.1	-2836.6	-1160.6	-1138.8	-1180.0	-1152.6	-1108.3	-1085.2
Panel C	(17)	(18)	(19)	(20)	(21)	(22)	(23)	(24)
Technostress	0.137 (0.239)	0.123 (0.242)	0.062 (0.150)	0.048 (0.151)	0.454*** (0.157)	0.472*** (0.158)	0.503*** (0.151)	0.542*** (0.153)
Num.Obs.	1147	1126	1147	1126	1147	1126	1147	1126
Log. Lik.	-2885.9	-2837.3	-1161.2	-1139.5	-1104.2	-1081.1	-1174.4	-1146.5

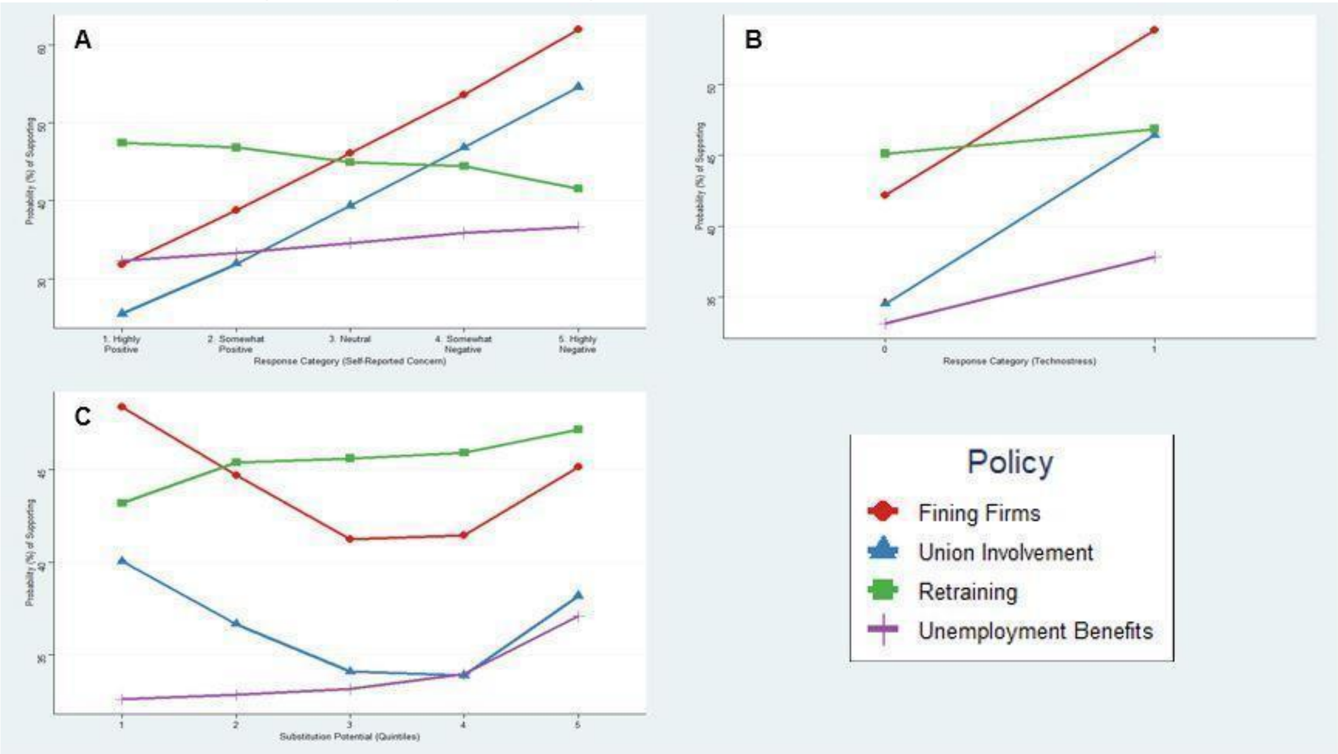
*Note: Models 1-2, 9-10 and 17-18 are OLS, all others are Ordered Logits; Even-numbered models include Social Class FEs, odd numbered ones do not. Demographic Controls included in all models. These are age, gender, education, income and type of contract; Social Class FEs split respondents into 3 categories: Unskilled workers, Skilled Workers and Upper/Middle class; + p < 0.1, * p < 0.05, ** p < 0.01, *** p < 0.001*

Figure 2 displays the predicted probabilities of supporting each of the four policies according to the full models with all controls. As pertains to the self-reported concern measurement of subjective risk (see Figure 3a), an increase in concern regarding workplace technological change from the lowest response category to the highest increases the predicted probability of support for fining firms that automate from roughly 32% to around 62%, and for greater union involvement in firm decisions about technology from roughly 26% to approximately 55%, according to the models with all controls included. Workers professing a generic higher degree of technological concern are not more likely to demand compensation or retraining policies than others. There is clearer evidence that those with higher subjective risk are more likely to demand more protection from technology-related risks by asking governments to fine firms who fire workers due to technological change, and by supporting union approval before firms introduce new technologies.

A similar pattern emerges on the technostress variable (figure 2b), as 'Technostressed' workers are approximately 12 ppts more likely than others to support fining firms that automate (from 42% to 54%) and 11 ppts more likely to support union involvement (from 35% to 46%). The predicted values for retraining and increasing unemployment benefits also show a slightly positive trend, though the differences are much smaller. Finally, figure 3c confirms the lack of an effect of substitution potential on policy preferences.

As mentioned above, we also attempted to tease out the mechanisms linking risk and policy preferences, by creating a variety of interaction models with three theoretically-derived moderators. The results from said models are presented in the SI (section 4) and, whilst there is some limited evidence pointing towards the existence of such moderation effects, this is far too inconsistent for us to draw any solid conclusions.

Figure 2. Subjective technological concern and policy support



Note: The figure presents predicted probabilities of supporting our four policy proposals by response category of each subjective risk measure: self-reported general concern about the implications of technological change on own job prospects (panel A); whether the respondent reports that it is relevant to learn to use new technologies in the job and he or she is concerned that he or she may not be able to learn at the required speed (panel B); the percentage of tasks currently done in a job that could be performed by a computer (panel C). It is important to note that these are not lines of best fit, but rather that they simply connect the different probabilities represented by the points. Furthermore, the plots above are not an exact representation of the models in Table 1, as they reduce the policy preference variables from three categories ('Disagree', 'Neutral', 'Agree') to two ('Disagree/Neutral', 'Agree'). Results with confidence intervals are reported in the appendix on Figures A3-A5.

5 Discussion

This study builds on the growing literature that examines the role of automation risk in policy preferences. Our results overall find limited evidence regarding correlations between many forms of technological risk and support for compensation or retraining, but we find a more consistent relationship between such risk and support for technologically protectionist policies. We find some evidence that such support is more pronounced among individuals who have fewer outside job options and who identify more with their current jobs.

We focus in this conclusion on additional routes for research. First, additional research might consider both alternative arguments for subjective concern about automation, and mechanisms that link objective risks to such concern. If concern is caused by factors other than occupational risk, then policies to address digitalization risk could be insufficient in easing automation or technological anxiety. Relatedly, if there is some overlap in automation and openness concerns, then worries about globalization may dominate given the salience of out-groups associated with this risk (Wu 2021a, 2021b). We believe our distinction of different concepts of technological risk could be built upon to further detail political-economic or psychological connections between levels of such risk and support for even more precise government policies.

Second, we speculate why we do not find posited relationships regarding support for redistribution; there are many plausible explanations that future work should disentangle. In the Spanish context, while there is strong support for inequality reduction generally, there is evidence that individuals vary in how much they benefit from various government redistribution programs or whether individuals perceive that, due to related tax increases, they would be less likely to be net beneficiaries (Fernández-Albertos and Manzano, 2016). As many workers in at-risk jobs are in the middle of the income distribution, tax aversion or eligibility concerns may play a role in skepticism of redistribution.

However, the fact that subjective concern in particular is not strongly correlated with redistribution merits further attention. The finding that workers concerned about automation threats do not necessarily prefer more compensation for potential losses, but more aggressive policies to prevent change in the first place, has relevant policy implications and should be further investigated. Workers might prefer to maintain the status quo, even at the expense of lower economic growth, instead of redistribution. Policy packages addressed to preserving the status quo or even going back to an idealized past are arguably favored by more populist parties (Colantone and Stanig 2018). While such policies would reduce economic growth, they may be desirable for individuals concerned about their capacity to adapt to rapid change.

Anti-technological movements are historically rare, but given the predicted fast pace of technological change it is not implausible that enough individuals become concerned about such change in the near future. Our results seem to indicate that an increase in perceived risk would lead to an increase in demand for protection, but not in demand for redistribution. Thus, it is unclear whether it would benefit parties on the left or on the right of the political spectrum. Further research should investigate if there is a correlation between demand for protection and vote choice, especially if the issue of technological change becomes politicized.

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7 Appendix

Section 1: Correlations between objective and subjective risk

First, we examine the correlations between our three measures of subjective risk (Figure A1). We note that correlations are all positive, though rather weak. Then, we regress them onto the two measures of objective risk discussed in the main paper (Tables A1-A3). Models with Concern as the DV are ordered logits, with Substitution Potential they are OLS and with Technostress are simple binary logits. All continuous variables are reframed to range between 0 and 1 for ease of interpretation. As reported in the main text, the results of these regressions are mixed and heavily dependent on the selected measures of risk, but some pattern of correlation does appear to emerge.

Figure A1. Correlogram between measures of subjective risk

Section 2: Objective and subjective risks

Table A1. Objective and Subjective Risks (No Controls)

DV	Self-Reported Concern		Substitution (0-1)	Potential	Technostress (Binary)	
Model	(1)	(2)	(3)	(4)	(5)	(6)
TLRA (0-1)	1.454*** (0.245)		-0.117** (0.037)		-0.900** (0.345)	
RTI (0-1)		1.255*** (0.174)		0.081** (0.025)		0.051 (0.237)
Num.Obs.	1424	1317	1163	1114	1407	1312
R2			0.009	0.010		
R2 Adj.			0.008	0.009		
F			10.148		6.806	
RMSE	0.34	0.34	0.24	0.24	0.39	0.39

Note: Models 1-2 are Ordered Logits, 3-4 OLS, 5-6 Binary Logits; + p < 0.1, * p < 0.05, ** p < 0.01, *** p < 0.001

Table A2. Objective and Subjective Risks (Demographic Controls only)

DV	Self-Reported Concern		Substitution (0-1)	Potential	Technostress (Binary)	
Model	(1)	(2)	(3)	(4)	(5)	(6)
TLRA (0-1)	0.722** (0.268)		-0.128** (0.040)		-1.471*** (0.375)	
RTI (0-1)		0.759*** (0.205)		0.095** (0.029)		-0.381 (0.285)
Demographic Controls	Yes	Yes	Yes	Yes	Yes	Yes
Social Class FEs	No	No	No	No	No	No
Num.Obs.	1408	1303	1147	1100	1391	1298
R2			0.035	0.041		
R2 Adj.			0.013	0.018		
RMSE	0.33	0.33	0.24	0.24	0.38	0.39

Note: Models 1-2 are Ordered Logits, 3-4 OLS, 5-6 Binary Logits; Demographic Controls include age, gender, education, income and type of contract; Social Class FEs split respondents into 3 categories: Unskilled workers, Skilled Workers and Upper/Middle class; + p < 0.1, * p < 0.05, ** p < 0.01, *** p < 0.001

Table A3. Objective and Subjective Risks (Demographic Controls + Social Class FEs)

DV	Self-Reported Concern		Substitution Potential (0-1)		Technostress (Binary)	
Model	(1)	(2)	(3)	(4)	(5)	(6)
TLRA (0-1)	0.486+ (0.286)		-0.187*** (0.041)		-1.600*** (0.400)	
RTI (0-1)		0.350 (0.278)		-0.001 (0.039)		-0.506 (0.381)
Demographic Controls	Yes	Yes	Yes	Yes	Yes	Yes
Social Class FEs	Yes	Yes	Yes	Yes	Yes	Yes
Num.Obs.	1341	1303	1126	1100	1333	1298
R2			0.070	0.055		
R2 Adj.			0.046	0.031		
RMSE	0.33	0.33	0.24	0.24	0.38	0.39

Note: Models 1-2 are Ordered Logits, 3-4 OLS, 5-6 Binary Logits; Demographic Controls include age, gender, education, income and type of contract; Social Class FEs split respondents into 3 categories: Unskilled workers, Skilled Workers and Upper/Middle class; + $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Section 3: Objective risk and policy preferences

We also examine the correlation between our measures of objective risk and policy preference (Tables A4-A5). Generally, we see weaker results than we do for the subjective concern ones, though both our objective measurements return a positive and significant coefficient for the union involvement variable.

Table A4. Objective Risk (TLRA) and Policy Preferences

DV	Unemployment Benefits (0-10)		Retraining		Fining Firms		Union Involvement	
Model	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
TLRA (0-1)	-0.268 (0.392)	-0.317 (0.428)	-0.259 (0.247)	-0.230 (0.266)	0.066 (0.253)	-0.052 (0.273)	0.712** (0.248)	0.564* (0.268)
Demographic Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Social Class FEs	No	Yes	No	Yes	No	Yes	No	Yes
Num.Obs.	1599	1511	1599	1511	1599	1511	1599	1511
R2	0.034	0.033						
R2 Adj.	0.014	0.012						
RMSE	2.95	2.99	2.00	2.00	1.99	1.99	1.92	1.92

Note: Models 1-2 are OLS, 3-8 Ordered Logits; Demographic Controls include age, gender, education, income and type of contract; Social Class FEs split respondents into 3 categories: Unskilled workers, Skilled Workers and Upper/Middle class; + p < 0.1, * p < 0.05, ** p < 0.01, *** p < 0.001.

Table A5. Objective Risk (RTI) and Policy Preferences

DV	Unemployment Benefits (0-10)		Retraining		Fining Firms		Union Involvement	
Model	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
RTI (0-1)	-0.229 (0.315)	-0.242 (0.425)	-0.152 (0.199)	-0.231 (0.269)	0.397* (0.201)	0.056 (0.272)	0.972*** (0.200)	0.735** (0.266)
Demographic Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Social Class FEs	No	Yes	No	Yes	No	Yes	No	Yes
Num.Obs.	1470	1470	1470	1470	1470	1470	1470	1470
R2	0.035	0.035						
R2 Adj.	0.015	0.013						
RMSE	2.98	2.98	2.00	2.00	1.99	1.99	1.92	1.92

Note: Models 1-2 are OLS, 3-8 Ordered Logits; Demographic Controls include age, gender, income and type of contract; Social Class FEs split respondents into 3 categories: Unskilled workers, Skilled Workers and Upper/Middle class; + p < 0.1, * p < 0.05, ** p < 0.01, *** p < 0.001

Section 4: Correlation between measures of policy preferences

In this section, we report the correlations between our measures of policy preferences (Figure A2). As one would expect, we find much stronger correlations, here, particularly between the two protectionist measures and the two redistributive ones.

Figure A2. Correlogram between measures of policy preferences

Section 5: Alternative specifications

Next, we propose alternative specifications of our main models. First, in Tables A7-A8, we report the results from our main models (Tables 1-3), but without the inclusion of any controls. Tables A9-A14, on the other hand, report the results of our main models including controls for both subjective measures of risk *and* objective ones at the same time. Finally Tables A15-A17 report the results for the models including the more fine-grained occupation fixed effects, rather than the social class ones reported in the main text, whilst Figures A3-A5 show the plots depicted on Figure 2 in the main text, with the addition of 95% level confidence intervals.

Table A7: Subjective technological concern and Support for Redistributive Policies (No Controls)

DV	Unemployment Benefits (0-10)			Retraining		
Model	(1)	(2)	(3)	(4)	(5)	(6)
Self-Reported Concern (0-1)	0.093 (0.321)			-0.328 (0.202)		
Technostress		0.194 (0.204)			0.118 (0.128)	
Substitute (0-1)			0.485 (0.366)			0.152 (0.226)
Demographic Controls	No	No	No	No	No	No
Social Class FEs	No	No	No	No	No	No
Num.Obs.	1424	1407	1163	1424	1407	1163
R2	0.000	0.001	0.002			
R2 Adj.	-0.001	0.000	0.001			
RMSE	3.02	2.99	3.04	2.01	2.00	2.01

Note: Models 1-3 are OLS, 4-6 Ordered Logits; Demographic Controls include age, gender, education, income and type of contract; Social Class FEs split respondents into 3 categories: Unskilled workers, Skilled Workers and Upper/Middle class; + $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table A8: Subjective technological concern and Support for Protectionist Policies (No Controls)

DV	Fining Firms			Union Involvement		
Model	(1)	(2)	(3)	(4)	(5)	(6)
Self-Reported Concern (0-1)	1.118*** (0.207)			1.303*** (0.203)		
Technostress = 1		0.497*** (0.133)			0.508*** (0.129)	
Substitution			-0.082 (0.226)			0.024 (0.221)
Demographic Controls	No	No	No	No	No	No
Social Class FEs	No	No	No	No	No	No
Num.Obs.	1424	1407	1163	1424	1407	1163
RMSE	2.01	2.01	2.00	1.94	1.93	1.92

Note: All models are Ordered Logits; Categories of Substitute compared to baseline 1st Quintile; Demographic Controls include age, gender, education, income and type of contract; Social Class FEs split respondents into 3 categories: Unskilled workers, Skilled Workers and Upper/Middle class; + $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table A9: Self-Reported Concern and Support for Redistributive Policies (Controlling for objective risk)

DV	Unemployment Benefits (0-10)				Retraining			
Model	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Self-Reported Concern (0-1)	-0.161 (0.340)	-0.072 (0.355)	-0.061 (0.359)	-0.050 (0.360)	-0.476* (0.218)	-0.420+ (0.225)	-0.367 (0.228)	-0.378+ (0.228)
TLRA (0-1)	-0.317 (0.430)	-0.348 (0.466)			-0.446 (0.272)	-0.452 (0.290)		
RTI (0-1)			-0.241 (0.336)	-0.154 (0.454)			-0.234 (0.213)	-0.268 (0.288)
Demographic Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Social Class FEs	No	Yes	No	Yes	No	Yes	No	Yes
Num.Obs.	1408	1341	1303	1303	1408	1341	1303	1303
R2	0.038	0.040	0.043	0.043				
R2 Adj.	0.016	0.016	0.019	0.018				
RMSE	2.96	2.99	2.98	2.98	2.00	2.00	2.00	2.00

Note: Models 1-4 are OLS, 4-8 Ordered Logits; Demographic Controls include age, gender, education, income and type of contract; Social Class FEs split respondents into 3 categories: Unskilled workers, Skilled Workers and Upper/Middle class; + $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table A10: Self-Reported Concern and Support for Redistributive Policies (Controlling for objective risk)

DV	Fining Firms				Union Involvement			
Model	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Self-Reported Concern (0-1)	0.795*** (0.224)	0.790*** (0.232)	0.850*** (0.235)	0.828*** (0.236)	1.102*** (0.221)	1.075*** (0.229)	1.140*** (0.233)	1.121*** (0.233)
TLRA (0-1)	0.039 (0.278)	-0.117 (0.297)			0.701* (0.273)	0.551+ (0.293)		
RTI (0-1)			0.395+ (0.214)	-0.028 (0.291)			0.958*** (0.213)	0.674* (0.285)
Demographic Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Social Class FEs	No	Yes	No	Yes	No	Yes	No	Yes
Num.Obs.	1408	1341	1303	1303	1408	1341	1303	1303
RMSE	1.98	1.98	1.98	1.98	1.91	1.91	1.91	1.91

Note: All models are Ordered Logits; Demographic Controls include age, gender, education, income and type of contract; Social Class FEs split respondents into 3 categories: Unskilled workers, Skilled Workers and Upper/Middle class; + p < 0.1, * p < 0.05, ** p < 0.01, *** p < 0.001

Table A11: Technostress and Support for Redistributive Policies (Controlling for objective risk)

DV	Unemployment Benefits (0-10)				Retraining			
Model	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Technostress = 1	0.107 (0.208)	0.096 (0.215)	0.130 (0.215)	0.130 (0.215)	0.094 (0.132)	0.063 (0.135)	0.089 (0.136)	0.090 (0.136)
TLRA (0-1)	-0.551 (0.433)	-0.540 (0.468)			-0.569* (0.273)	-0.528+ (0.293)		
RTI (0-1)			-0.180 (0.331)	-0.150 (0.451)			-0.364+ (0.211)	-0.473+ (0.287)
Demographic Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Social Class FEs	No	Yes	No	Yes	No	Yes	No	Yes
Num.Obs.	1391	1333	1298	1298	1391	1333	1298	1298
R2	0.033	0.034	0.035	0.035				
R2 Adj.	0.012	0.011	0.013	0.011				
RMSE	2.94	2.97	2.97	2.97	1.99	2.00	2.00	2.00

Note: Models 1-4 are OLS, 4-8 Ordered Logits; Demographic Controls include age, gender, education, income and type of contract; Social Class FEs split respondents into 3 categories: Unskilled workers, Skilled Workers and Upper/Middle class; + p < 0.1, * p < 0.05, ** p < 0.01, *** p < 0.001

Table A12: Technostress and Support for Protectionist Policies (Controlling for objective risk)

DV	Fining Firms				Union Involvement			
Model	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Technostress = 1	0.446**	0.447**	0.458**	0.456**	0.501***	0.559***	0.543***	0.543***
	(0.139)	(0.142)	(0.142)	(0.142)	(0.134)	(0.138)	(0.138)	(0.138)
TLRA (0-1)	0.043	-0.130			0.567*	0.431		
	(0.279)	(0.299)			(0.274)	(0.295)		
RTI (0-1)			0.416+	0.037			1.017***	0.699*
			(0.213)	(0.290)			(0.213)	(0.285)
Demographic Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Social Class FEs	No	Yes	No	Yes	No	Yes	No	Yes
Num.Obs.	1391	1333	1298	1298	1391	1333	1298	1298
RMSE	1.98	1.98	1.98	1.98	1.90	1.90	1.90	1.90

Note: All models are Ordered Logits; Demographic Controls include age, gender, education, income and type of contract; Social Class FEs split respondents into 3 categories: Unskilled workers, Skilled Workers and Upper/Middle class; + p < 0.1, * p < 0.05, ** p < 0.01, *** p < 0.001

Table A13: Substitution Potential and Support for Redistributive Policies (Controlling for objective risk)

DV	Unemployment Benefits (0-10)				Retraining			
Model	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Substitute (2nd Quintile)	0.006	-0.016	-0.034	-0.039	0.303+	0.344+	0.335+	0.330+
	(0.288)	(0.292)	(0.294)	(0.295)	(0.181)	(0.182)	(0.184)	(0.184)
Substitute (3rd Quintile)	-0.219	-0.248	-0.272	-0.273	0.234	0.253	0.245	0.245
	(0.291)	(0.296)	(0.298)	(0.298)	(0.181)	(0.183)	(0.185)	(0.185)
Substitute (4th Quintile)	0.034	-0.009	0.008	0.008	0.354+	0.357+	0.325+	0.326+
	(0.291)	(0.295)	(0.296)	(0.297)	(0.181)	(0.182)	(0.184)	(0.184)
Substitute (5th Quintile)	0.202	0.142	0.211	0.208	0.198	0.229	0.276	0.275
	(0.288)	(0.296)	(0.296)	(0.297)	(0.178)	(0.183)	(0.183)	(0.184)
TLRA (0-1)	-0.706	-0.772			-0.618*	-0.589+		
	(0.499)	(0.527)			(0.311)	(0.326)		
RTI (0-1)			-0.105	-0.216			-0.407+	-0.520+
			(0.368)	(0.492)			(0.233)	(0.308)
Demographic Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Social Class FEs	No	Yes	No	Yes	No	Yes	No	Yes
Num.Obs.	1147	1126	1100	1100	1147	1126	1100	1100
R2	0.033	0.033	0.033	0.033				
R2 Adj.	0.007	0.005	0.006	0.004				
RMSE	2.99	3.00	3.00	3.00	2.00	2.00	2.00	2.00

Note: Models 1-4 are OLS, 4-8 Ordered Logits; Categories of Substitute compared to baseline 1st Quintile; Demographic Controls include age, gender, education, income and type of contract; Social Class FEs split respondents into 3 categories: Unskilled workers, Skilled Workers and Upper/Middle class; + p < 0.1, * p < 0.05, ** p < 0.01, *** p < 0.001

Table A14: Substitution Potential and Support for Protectionist Policies (Controlling for objective risk)

DV	Fining Firms				Union Involvement			
Model	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Substitute (2nd Quintile)	-0.301 (0.186)	-0.244 (0.188)	-0.221 (0.190)	-0.223 (0.190)	0.077 (0.181)	0.080 (0.183)	0.047 (0.185)	0.050 (0.185)
Substitute (3rd Quintile)	-0.200 (0.188)	-0.182 (0.190)	-0.141 (0.191)	-0.149 (0.191)	0.126 (0.183)	0.076 (0.185)	0.078 (0.187)	0.073 (0.187)
Substitute (4th Quintile)	-0.257 (0.186)	-0.256 (0.187)	-0.209 (0.188)	-0.217 (0.189)	-0.037 (0.181)	-0.087 (0.182)	-0.070 (0.184)	-0.077 (0.184)
Substitute (5th Quintile)	-0.311+ (0.185)	-0.338+ (0.190)	-0.267 (0.190)	-0.283 (0.191)	-0.055 (0.180)	-0.152 (0.184)	-0.140 (0.184)	-0.154 (0.185)
TLRA (0-1)	-0.268 (0.318)	-0.466 (0.334)			0.329 (0.309)	0.072 (0.326)		
RTI (0-1)			0.417+ (0.234)	0.202 (0.310)			1.014*** (0.232)	0.783* (0.307)
Demographic Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Social Class FEs	No	Yes	No	Yes	No	Yes	No	Yes
Num.Obs.	1147	1126	1100	1100	1147	1126	1100	1100
RMSE	1.97	1.97	1.97	1.97	1.89	1.89	1.89	1.89

Note: All models are Ordered Logits; Categories of Substitute compared to baseline 1st Quintile; Demographic Controls include age, gender, education, income and type of contract; Social Class FEs split respondents into 3 categories: Unskilled workers, Skilled Workers and Upper/Middle class; + p < 0.1, * p < 0.05, ** p < 0.01, *** p < 0.001

Table A15: Concern and Policy Preferences (Occupation fixed effects)

DV:	Unemp. Benefits	Retraining	Fining Firms	Union Involv.
Model:	(1)	(2)	(3)	(4)
Concern	0.130 (0.414)	-0.365 (0.260)	0.910*** (0.267)	0.963*** (0.262)
Demographic Controls	Yes	Yes	Yes	Yes
Occupation FEs	Yes	Yes	Yes	Yes
Num.Obs.	1073	1073	1073	1073
R2	0.037			
R2 Adj.	0.006			
F	1.188			
RMSE	3.02	2.00	1.96	1.89

Note: Model 1: OLS, Models 2-4: Ordered Logits; All models include controls for age, gender, education, income and type of contract; Occupation FEs taken at the 1-digit ISCO level; + p < 0.1, * p < 0.05, ** p < 0.01, *** p < 0.001

Table A16: Technostress and Policy Preferences (Occupation fixed effects)

DV:	Unemp. Benefits	Retraining	Fining Firms	Union Involv.
Model:	(1)	(2)	(3)	(4)
Technostress	0.122 (0.242)	0.063 (0.151)	0.472** (0.159)	0.554*** (0.154)
Demographic Controls	Yes	Yes	Yes	Yes
Occupation FEs	Yes	Yes	Yes	Yes
Num.Obs.	1126	1126	1126	1126
R2	0.036			
R2 Adj.	0.006			
F	1.185			
RMSE	3.00	2.00	1.97	1.89

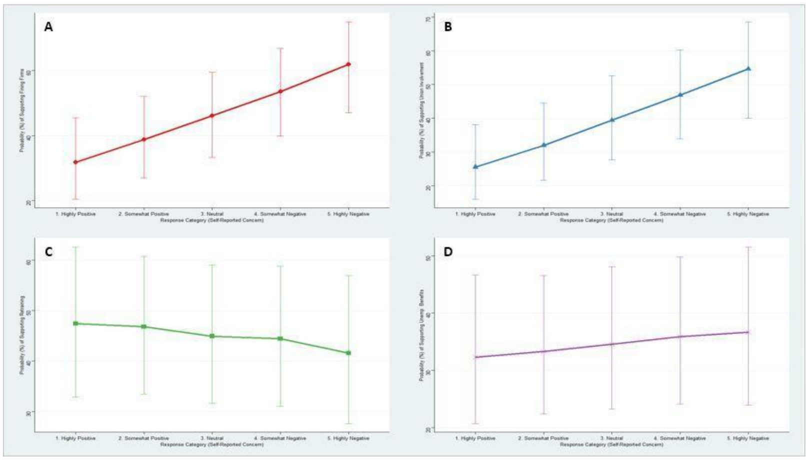
Note: Model 1: OLS, Models 2-4: Ordered Logits; All models include controls for age, gender, education, income and type of contract; Occupation FEs taken at the 1-digit ISCO level; + p < 0.1, * p < 0.05, ** p < 0.01, *** p < 0.001

Table A17: Substitution Potential and Policy Preferences (Occupation fixed effects)

DV:	Unemp. Benefits	Retraining	Fining Firms	Union Involv.
Model:	(1)	(2)	(3)	(4)
Substitution	0.517 (0.384)	0.315 (0.241)	-0.210 (0.245)	-0.176 (0.239)
Demographic Controls	Yes	Yes	Yes	Yes
Occupation FEs	Yes	Yes	Yes	Yes
Num.Obs.	1126	1126	1126	1126
R2	0.037			
R2 Adj.	0.007			
F	1.233			
RMSE	3.00	2.00	1.98	1.89

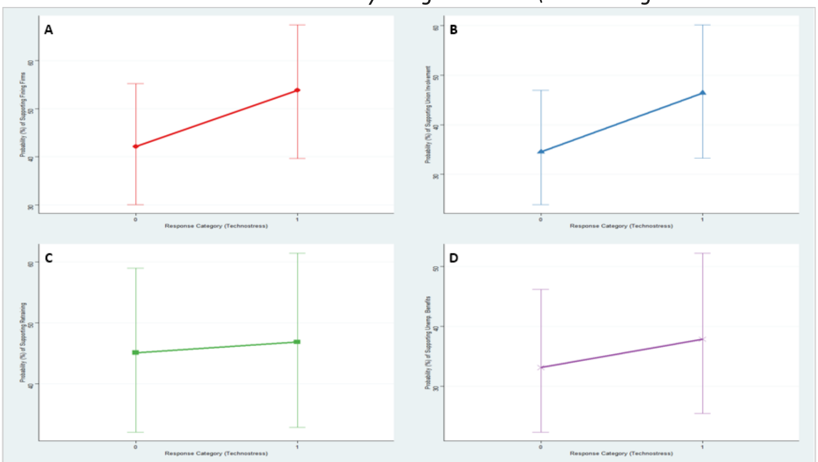
Note: Model 1: OLS, Models 2-4: Ordered Logits; All models include controls for age, gender, education, income and type of contract; Occupation FEs taken at the 1-digit ISCO level; + p < 0.1, * p < 0.05, ** p < 0.01, *** p < 0.001

Figure A3. Concern and Policy Preferences (with confidence intervals)



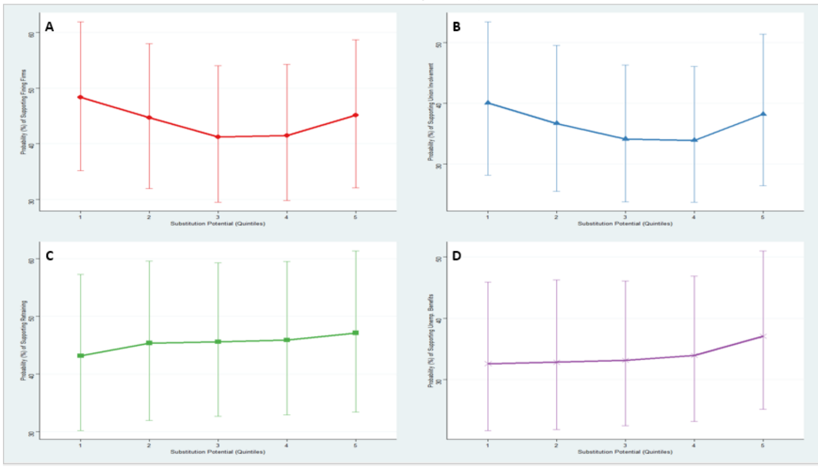
Note: The figure presents predicted probabilities of supporting our four policy proposals by response category of self-reported concern, with 95% Confidence Intervals added in to get an idea of significance. The x-axis represents response categories to the generic concern question for all four panels, whilst the y-axis represents the probability of supporting Fining Firms (panel A), Union Involvement (panel B), Retraining (Panel C) and increasing unemployment benefits (panel D). It is important to note that these are not lines of best fit, but rather that they simply connect the different probabilities represented by the points. Furthermore, the plots above are not an exact representation of the models in Table 1, as they reduce the policy preference variables from three categories ('Disagree', 'Neutral', 'Agree') to two ('Disagree/Neutral', 'Agree').

Figure A4. Technostress and Policy Preferences (with confidence intervals)



Note: The figure presents predicted probabilities of supporting our four policy proposals by response category of self-reported concern, with 95% Confidence Intervals added in to get an idea of significance. The x-axis represents response categories to the Technostress questions for all four panels, whilst the y-axis represents the probability of supporting Fining Firms (panel A), Union Involvement (panel B), Retraining (Panel C) and increasing unemployment benefits (panel D). It is important to note that these are not lines of best fit, but rather that they simply connect the different probabilities represented by the points. Furthermore, the plots above are not an exact representation of the models in Table 1, as they reduce the policy preference variables from three categories ('Disagree', 'Neutral', 'Agree') to two ('Disagree/Neutral', 'Agree'). This should explain why the results in Panels A and B do not appear significant, even though they are highly so in the models (see Table 1). This would indicate that much of the action occurs between the Disagree and Neutral categories.

Figure A5. Substitution Potential and Policy Preferences (with confidence intervals)



Note: The figure presents predicted probabilities of supporting our four policy proposals by response category of self-reported concern, with 95% Confidence Intervals added in to get an idea of significance. The x-axis represents quintiles of substitution potential for all four panels, whilst the y-axis represents the probability of supporting Fining Firms (panel A), Union Involvement (panel B), Retraining (Panel C) and increasing unemployment benefits (panel D). It is important to note that these are not lines of best fit, but rather that they simply connect the different probabilities represented by the points. Furthermore, the plots above are not an exact representation of the models in Table 1, as they reduce the policy preference variables from three categories ('Disagree', 'Neutral', 'Agree') to two ('Disagree/Neutral', 'Agree').

Section 6: Interactions with moderators

We now turn to our three moderators (outside options, age, and job identity) to see if individuals who are older, have fewer outside options, and greater job attachment have distinct preferences, given different levels of the distinct forms of technological risks.

Age. Tables A18-A20 represent the results of the models with interaction by age categories. Recall that while we do not find an average effect of technological risk measured in different ways on demand for compensation and retraining policies, it is possible that such a relationship may be pronounced among specific age groups. We note that older workers in the 50-64 range do seem slightly *more* supportive of unemployment benefits as such subjective risk increases; for them higher concern correlates with higher support for increasing unemployment benefits. This is particularly evident (and significant) when Technostress is considered as the IV, though the same tendency also appears for the generic concern variable.

Age has an inconsistent effect on technological protectionism; with two of our measures, we find suggestive (though imprecisely estimated) evidence that older individuals who report higher substitution risk are more supportive of both protectionist measures. However, we actually find the opposite tendency when generic concern is taken as the IV, as the positive correlation between the latter and fining firms is actually more pronounced among *younger* workers. Overall, we find modest to little evidence in our sample that older workers are much more technologically protectionist, contra our expectations, but, consistent with theories about support for redistribution, older workers at greater perceived risk are slightly more supportive of redistribution.

Table A18: Concern and policy preferences by age category

DV	Unemployment Benefits (0-10)		Retraining		Fining Firms		Union Involvement	
Model	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Concern (Baseline 18-29)	-0.664 (1.020)	-0.322 (1.202)	1.622* (0.661)	1.780* (0.782)	2.223*** (0.662)	2.721*** (0.782)	-0.431 (0.619)	-0.318 (0.724)
Concern: 30-39	-0.239 (1.232)	-0.547 (1.391)	-1.819* (0.805)	-1.954* (0.906)	-2.179** (0.796)	-2.802** (0.899)	-0.070 (0.762)	-0.128 (0.849)
Concern: 40-49	0.189 (1.153)	-0.046 (1.319)	-0.657 (0.748)	-0.809 (0.856)	-0.918 (0.747)	-1.403 (0.856)	-0.040 (0.709)	-0.071 (0.801)
Concern: 50-65	1.518 (1.173)	1.254 (1.341)	-0.646 (0.763)	-0.779 (0.873)	-0.894 (0.762)	-1.450+ (0.871)	-0.106 (0.723)	-0.156 (0.816)
Demographic Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Social Class FEs	No	Yes	No	Yes	No	Yes	No	Yes
Num.Obs.	1408	1341	1408	1341	1408	1341	1408	1341
R2	0.037	0.040						
R2 Adj.	0.018	0.018						
RMSE	2.96	2.99	1.98	1.98	1.91	1.91	2.00	2.00

Note: Models 1-2 are OLS, 3-8 Ordered Logits; Demographic Controls include gender, education, income and type of contract; Social Class FEs split respondents into 3 categories: Unskilled workers, Skilled Workers and Upper/Middle class; + $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table A19: Technostress and policy preferences by age category

DV	Unemployment Benefits (0-10)		Retraining		Fining Firms		Union Involvement	
Model	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Technostress (Baseline 18-29)	-0.944 (0.680)	-0.944 (0.785)	0.224 (0.459)	0.171 (0.524)	-0.264 (0.418)	-0.125 (0.472)	-0.228 (0.409)	-0.326 (0.471)
Technostress1:30-39	1.163 (0.836)	1.147 (0.931)	0.268 (0.569)	0.338 (0.626)	0.965+ (0.533)	0.822 (0.580)	0.234 (0.509)	0.326 (0.562)
Technostress1:40-49	0.891 (0.753)	0.863 (0.851)	0.457 (0.508)	0.491 (0.569)	0.801+ (0.468)	0.690 (0.520)	0.270 (0.461)	0.336 (0.517)
Technostress1:50-65	1.544* (0.766)	1.500+ (0.866)	-0.014 (0.513)	0.078 (0.575)	0.749 (0.475)	0.691 (0.527)	0.617 (0.468)	0.667 (0.525)
Demographic Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Social Class FEs	No	Yes	No	Yes	No	Yes	No	Yes
Num.Obs.	1391	1333	1391	1333	1391	1333	1391	1333
R2	0.033	0.033						
R2 Adj.	0.014	0.012						
RMSE	2.94	2.97	1.98	1.98	1.91	1.90	1.99	2.00

Note: Models 1-2 are OLS, 3-8 Ordered Logits; All other coefficients compared to baseline Technostress:18-29; Demographic Controls include age, gender, income and type of contract; Social Class FEs split respondents into 3 categories: Unskilled workers, Skilled Workers and Upper/Middle class; + p < 0.1, * p < 0.05, ** p < 0.01, *** p < 0.001

Table A20: *Substitution potential and policy preferences by age category*

DV	Unemployment Benefits (0-10)		Retraining		Fining Firms		Union Involvement	
Model	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Substitute (Baseline 18-29)	1.996 (1.376)	2.194 (1.413)	-1.120 (0.874)	-1.261 (0.903)	-0.631 (0.812)	-0.740 (0.837)	-0.406 (0.832)	-0.309 (0.853)
Substitute: 30-39	-1.256 (1.575)	-1.477 (1.618)	0.043 (1.005)	0.033 (1.035)	0.296 (0.938)	0.244 (0.965)	0.841 (0.953)	0.926 (0.978)
Substitute: 40-49	-1.378 (1.491)	-1.637 (1.526)	1.212 (0.947)	1.264 (0.973)	0.419 (0.888)	0.336 (0.911)	0.419 (0.908)	0.365 (0.926)
Substitute: 50-65	-2.144 (1.531)	-2.413 (1.568)	1.555 (0.975)	1.664+ (1.002)	1.248 (0.916)	1.256 (0.939)	0.990 (0.936)	0.791 (0.955)
Demographic Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Social Class FEs	No	Yes	No	Yes	No	Yes	No	Yes
Num.Obs.	1147	1126	1147	1126	1147	1126	1147	1126
R2	0.030	0.030						
R2 Adj.	0.009	0.007						
RMSE	2.99	3.01	1.97	1.97	1.89	1.89	2.00	2.00

Note: Models 1-2 are OLS, 3-8 Ordered Logits; All other coefficients compared to baseline Substitute:18-29; Demographic Controls include age, gender, income and type of contract; Social Class FEs split respondents into 3 categories: Unskilled workers, Skilled Workers and Upper/Middle class; + p < 0.1, * p < 0.05, ** p < 0.01, *** p < 0.001

Outside work options. We find that overall, the correlation between subjective risk of automation and support for union involvement does tend to be more positive among those reporting fewer opportunities to find a new job (should they be made redundant). This is particularly the case when we use substitution potential as our main independent variable. Among those who report that they would be highly unlikely to find a new job should they lose their current one, an increase from the lowest quartile of substitution potential to the highest correlates with a 12 ppt increase in the probability of supporting union involvement in technology decision-making (from 34% to 46%). On the other hand, among those who reported that they would be highly likely to find a new job should they lose their current one, an increase from the lowest quartile of substitution potential to the highest correlates with a 16 ppt *decrease* in the probability of supporting union involvement (from 40% to 24%). The results from the models using "technostress" as the independent variable are similar to the ones above (though coefficients are less precisely estimated), while those with subjective technological concern show a different pattern, with no significant correlations reported and the interaction coefficients tending to have the opposite sign as those for the other two IVs. Overall, the evidence is that lack of outside job options does condition the impact of substitution-risk on support for some forms of technological protectionism, but matters less for our other measures of technological risk.

Table A21. IV = Tech concern DV = See Table; Moderator = Outside Options

DV:	Unemployment Benefits		Retraining		Fining Firms		Union Involvement	
Model:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Tech concern (Baseline H. Unlikely)	0.582 (0.671)	0.475 (0.680)	−0.498 (0.419)	−0.491 (0.423)	1.052* (0.436)	0.938* (0.440)	0.938* (0.424)	0.848* (0.428)
Tech concern:S. Unlikely	0.196 (0.932)	0.347 (0.944)	0.694 (0.587)	0.766 (0.594)	−0.763 (0.600)	−0.637 (0.607)	−0.138 (0.586)	−0.065 (0.592)
Tech concern:S. Likely	−1.293 (1.214)	−1.208 (1.224)	−0.046 (0.751)	−0.032 (0.753)	0.395 (0.782)	0.460 (0.784)	0.134 (0.766)	0.148 (0.769)
Tech concern:H. Likely	−1.909 (1.571)	−1.821 (1.580)	−1.348 (0.980)	−1.309 (0.980)	0.625 (1.035)	0.743 (1.043)	1.114 (1.030)	1.171 (1.040)
Demographic C.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Social Class FEs	No	Yes	No	Yes	No	Yes	No	Yes
Num.Obs.	1090	1073	1090	1073	1090	1073	1090	1073
R2	0.031	0.030						
R2 Adj.	0.014	0.011						
Log.Lik.	−2752	−2712	−1103	−1085	−1048	−1028	−1117	−1094
F	1.828	1.573						
Edf			21.000	23.000	21.000	23.000	21.000	23.000

Note: Models 1-2: OLS, Models 3-8: Ordered Logits; All coefficients compared to baseline Tech concern: H. Unlikely; Interaction term is response categories to the question 'If you lost your job, how likely is it that you find a job similar or better than the current one?'; Demographic Controls include age, gender, education, income and type of contract; Social Class FEs split respondents into 3 categories: Unskilled workers, Skilled Workers and Upper/Middle class; + p < 0.1, * p < 0.05, ** p < 0.01, *** p < 0.001

Table A22. IV = Technostress; DV = See Table; Moderator = Outside Options

DV:	Unemployment Benefits		Retraining		Fining Firms		Union Involvement	
Model:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Technostress1 (Baseline H. Unlikely)	0.689+ (0.396)	0.674+ (0.402)	0.261 (0.251)	0.219 (0.253)	0.311 (0.262)	0.342 (0.265)	0.711** (0.251)	0.759** (0.254)
Technostress1:S. Unlikely	−0.662 (0.556)	−0.660 (0.565)	−0.306 (0.349)	−0.254 (0.353)	0.166 (0.371)	0.173 (0.376)	−0.368 (0.353)	−0.354 (0.359)
Technostress1:S. Likely	−1.429* (0.668)	−1.419* (0.675)	−0.456 (0.418)	−0.429 (0.418)	−0.118 (0.426)	−0.173 (0.429)	−0.438 (0.421)	−0.507 (0.426)
Technostress1:H. Likely	−0.342 (0.925)	−0.331 (0.932)	0.210 (0.598)	0.237 (0.599)	1.308* (0.648)	1.283 (0.650)	−0.031 (0.585)	−0.042 (0.591)
Demographic Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Social Class FEs	No	Yes	No	Yes	No	Yes	No	Yes
Num.Obs.	1147	1126	1147	1126	1147	1126	1147	1126
R2	0.031	0.030						
R2 Adj.	0.015	0.012						
Log.Lik.	-2885.035	-2836.827	-1162.761	-1141.317	-1102.991	-1079.910	-1176.724	-1148.944
F	1.905	1.640						
Edf			21.000	23.000	21.000	23.000	21.000	23.000

Note: Models 1-2: OLS, Models 3-8: Ordered Logits; All coefficients compared to baseline Technostress: H. Unlikely; Interaction term is response categories to the question 'If you lost your job, how likely is it that you find a job similar or better than the current one?'; Demographic Controls include age, gender, education, income and type of contract; Social Class FEs split respondents into 3 categories: Unskilled workers, Skilled Workers and Upper/Middle class; + p < 0.1, * p < 0.05, ** p < 0.01, *** p < 0.001

Table A23. IV = Substitute; DV = See Table; Moderator = Outside Options

DV:	Unemployment Benefits		Retraining		Fining Firms		Union Involvement	
Model:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Substitute (Baseline H. Unlikely)	0.633 (0.614)	0.552 (0.623)	0.112 (0.382)	0.041 (0.384)	0.361 (0.406)	0.328 (0.410)	0.681+ (0.391)	0.577 (0.395)
Substitute:S. Unlikely	0.102 (0.864)	0.102 (0.879)	0.261 (0.535)	0.406 (0.542)	−0.810 (0.561)	−0.889 (0.568)	−1.066* (0.544)	−1.151* (0.551)
Substitute:S. Likely	−1.110 (1.056)	−1.073 (1.076)	0.164 (0.671)	0.399 (0.682)	−0.885 (0.682)	−0.916 (0.691)	−0.783 (0.654)	−0.852 (0.664)
Substitute:H. Likely	1.012 (1.419)	1.099 (1.429)	0.193 (0.926)	0.327 (0.925)	−0.577 (0.901)	−0.660 (0.904)	−2.034* (0.907)	−2.086* (0.908)
Demographic Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Social Class FEs	No	Yes	No	Yes	No	Yes	No	Yes
Num.Obs.	1147	1126	1147	1126	1147	1126	1147	1126
R2	0.031	0.029						
R2 Adj.	0.014	0.011						
Log.Lik.	-2885.347	-2837.332	-1163.143	-1141.192	-1108.149	-1084.994	-1179.492	-1151.957
F	1.872	1.592						
Edf			21.000	23.000	21.000	23.000	21.000	23.000

Note: Models 1-2: OLS, Models 3-8: Ordered Logits; All coefficients compared to baseline Substitute: H. Unlikely; Interaction term is response categories to the question ‘If you lost your job, how likely is it that you find a job similar or better than the current one?’; Demographic Controls include age, gender, education, income and type of contract; Social Class FEs split respondents into 3 categories: Unskilled workers, Skilled Workers and Upper/Middle class; + p < 0.1, * p < 0.05, ** p < 0.01, *** p < 0.001

Job identification. Our final moderator of interest is job identification. All regression results following the same specification and with the same demographic variables are displayed in tables A24-A26. The results indicate that across issues of both pure redistribution and training, job identification does not condition any of the technological risk variables; it does not seem to be the case that technological risks (measured in our three ways) correlate with support for redistribution or retraining among those who have a specific identification level with their jobs.

We find some evidence though that job identification does condition support for technological protectionism. Substantively, among those who identify least strongly with their jobs, moving from the lowest self-reported level of tech concern to the highest correlates with a 27 ppts increase in the predicted probability of supporting fining firms. Among those who identify *most strongly* with their job on the other hand, this increase in probability of supporting fining firms that engage in worker substitution is significantly higher, at 36 ppts.

Similarly, such job identification also conditions the effect of technological substitution risk on support for union retardation of technological adoption, though with smaller magnitudes. Among those who identify least strongly with their jobs, moving from the lowest quartile of substitution potential to the highest coincides with a 6 ppts decrease in the predicted probability of supporting fining firms. But among those who identify *most strongly* with their job on the other hand, the probability increases by 2 ppts.

Table A24. IV = Tech concern (Pessimism); DV = See Table; Moderator = Job ID

DV:	Unemployment Benefits		Retraining		Fining Firms		Union Involvement	
Model:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Concern (Baseline Low JobID)	−0.623	−0.542	−0.579	−0.469	0.039	0.071	0.845	0.796
	(0.802)	(0.844)	(0.522)	(0.542)	(0.534)	(0.555)	(0.518)	(0.542)
Concern: Medium JobID	−0.012	0.035	−0.243	−0.272	0.578	0.556	0.245	0.307
	(1.004)	(1.047)	(0.654)	(0.673)	(0.662)	(0.682)	(0.646)	(0.669)
Concern: High JobID	0.617	0.653	0.292	0.231	1.108+	1.045+	0.392	0.398
	(0.911)	(0.952)	(0.588)	(0.607)	(0.608)	(0.628)	(0.590)	(0.613)
Demographic Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Social Class FEs	No	Yes	No	Yes	No	Yes	No	Yes
Num.Obs.	1408	1341	1408	1341	1408	1341	1408	1341
R2	0.034	0.037						
R2 Adj.	0.020	0.020						
Log.Lik.	-3527.27	-3374.07	-1427.00	-1362.06	-1340.27	-1277.49	-1432.18	-1357.12
F	2.350	2.187						
Edf			23.000	25.000	23.000	25.000	23.000	25.000

Note: Models 1-2: OLS, Models 3-8: Ordered Logits; All coefficients compared to baseline Concern: Low Job ID; Demographic Controls include age, gender, education, income and type of contract; Social Class FEs split respondents into 3 categories: Unskilled workers, Skilled Workers and Upper/Middle class; + p < 0.1, * p < 0.05, ** p < 0.01, *** p < 0.001

Table A25. IV = Technostress; DV = See Table; Moderator = Job ID

DV:	Unemployment Benefits		Retraining		Fining Firms		Union Involvement	
Model:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Technostress1 (Baseline Low JobID)	0.165	0.038	0.040	0.047	0.491	0.452	0.469	0.403
	(0.530)	(0.551)	(0.331)	(0.340)	(0.361)	(0.367)	(0.346)	(0.353)
Technostress1:Medium JobID	−0.148	−0.085	0.238	0.254	−0.317	−0.238	0.061	0.156
	(0.659)	(0.683)	(0.414)	(0.425)	(0.440)	(0.449)	(0.425)	(0.435)
Technostress1:High JobID	0.096	0.252	0.021	−0.052	0.071	0.113	−0.040	0.121
	(0.592)	(0.616)	(0.372)	(0.382)	(0.404)	(0.411)	(0.386)	(0.395)
Demographic Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Social Class FEs	No	Yes	No	Yes	No	Yes	No	Yes
Num.Obs.	1391	1333	1391	1333	1391	1333	1391	1333
R2	0.027	0.028						
R2 Adj.	0.013	0.013						
Log.Lik.	-3479	-3348	-1412	-1354	-1342	-1284	-1429	-1360
F	1.984	1.813						
edf			21.000	23.000	21.000	23.000	21.000	23.000

Note: Models 1-2: OLS, Models 3-8: Ordered Logits; All coefficients compared to baseline Technostress1: Low Job ID; Demographic Controls include age, gender, education, income and type of contract; Social Class FEs split respondents into 3 categories: Unskilled workers, Skilled Workers and Upper/Middle class; + p < 0.1, * p < 0.05, ** p < 0.01, *** p < 0.001

Table A26. IV = Substitute; DV = See Table; Moderator = Job ID

DV:	Unemployment Benefits		Retraining		Fining Firms		Union Involvement	
Model:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Substitute (Baseline Low JobID)	-0.005 (0.938)	0.015 (0.962)	0.097 (0.585)	0.188 (0.602)	-0.534 (0.605)	-0.695 (0.614)	-1.093+ (0.583)	-1.331* (0.596)
Substitute: Medium JobID	0.348 (1.151)	0.243 (1.177)	-0.041 (0.719)	-0.051 (0.737)	0.062 (0.735)	0.138 (0.746)	1.144 (0.715)	1.189 (0.729)
Substitute: High JobID	0.559 (1.065)	0.515 (1.087)	0.267 (0.665)	0.170 (0.680)	0.739 (0.689)	0.854 (0.697)	1.374* (0.665)	1.515* (0.677)
Demographic Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Social Class FEs	No	Yes	No	Yes	No	Yes	No	Yes
Num.Obs.	1147	1126	1147	1126	1147	1126	1147	1126
R2	0.029	0.028						
R2 Adj.	0.014	0.011						
Log.Lik.	-2887	-2838	-1164	-1142	-1109	-1086	-1182	-1154
F	1.949	1.669						
edf			19.000	21.000	19.000	21.000	19.000	21.000

Note: Models 1-2: OLS, Models 3-8: Ordered Logits; All coefficients compared to baseline Substitute: Low Job ID; Demographic Controls include age, gender, education, income and type of contract; Social Class FEs split respondents into 3 categories: Unskilled workers, Skilled Workers and Upper/Middle class; + p < 0.1, * p < 0.05, ** p < 0.01, *** p < 0.001.

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