Public support for policies that address digitalization-related risks

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Abstract

How concerned are workers about the impact of technological changes on employment, and what policies do they prefer to mitigate potential negative effects of these structural changes? In this paper we address these questions by presenting and testing new analytical distinctions among different types of labor-market concerns. We differentiate among the standard risk of job substitution, "technostress," and general apprehension about the impact of technology in the workplace. In terms of policy responses, we distinguish among worker preferences for job-loss compensation, retraining, and distinct measures of "technological protectionism". Using survey data from Spain and innovative measures of these concepts, our findings reveal that concern about job substitution is modestly correlated with support for some redistribution policies. By contrast, both technostress and general concerns about the negative impact of technology at the workplace significantly increase support for technological protectionist policies but not redistribution. These results contribute to understanding how workers might respond to the labor market effects of new technologies such as artificial intelligence.

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Introduction

The advent of technological change has sparked a debate about the types of policies workers might prefer in response to ongoing and anticipated workplace transformations. A significant portion of this new research agenda in the fields of comparative political economy and behavior examines whether workers at risk of being substituted or displaced by new technologies have distinct policy and partisan preferences. Notably, the literature has established a correlation between technology-related substitution risks and voting for far-right parties (for a review, see Gallego and Kurer 2022). However, there is less consensus regarding how technological change affects workers' preferences for public policies addressing such related labor market risks, with the overwhelming theoretical and empirical focus on compensatory policies such as passive redistribution, active redistribution, universal basic income, and active labor market policies.

In a seminal article advancing this agenda, Thewissen and Rueda (2019) documented a positive correlation between objective occupational risk of substitution (measured as routine-task intensity, or RTI) and support for government action to reduce inequality. However, subsequent analyses have yielded mixed results regarding the correlation between occupational risks and policy preferences, as findings depend on measurement of the risks, the redistribution policies in question, and specifications (for reviews, see Weisstanner 2023; Gallego and Kurer 2022). More recent work has examined how subjective concerns about substitution risk emerge due to technological change (Heinrich and Witko 2021; Kurer and Häusermann 2022; Busemeyer and Tober 2023; Busemeyer et al. 2023). This recent focus on subjective concerns is theoretically crucial, as it addresses the mechanism through which objective occupational exposure to technological risk leads workers to demand compensatory policies (Ahrens 2023).

We advance the existing literature on the connection between subjective concerns about technological risks and policy preferences in two ways. First, we theorize and measure three distinct subjective concerns regarding how new technology impacts the workplace. The few studies that directly measure subjective concerns typically focus on the perceived worker risk of being replaced by technology. However, worker substitution via automation is only one way in which technological change may impact workers. We argue that workers may have more immediate concerns about the impact of technology in the workplace, such as the continuous need to adapt to technological changes. We distinguish and measure three different subjective concerns related to technology: a) the risk of job substitution; b) technostress, or the stress of keeping up with technological advancements at work; and c) overall occupational impact, which may include factors such as autonomy, job satisfaction, interaction, and potential for advancement.

Second, we contribute to this literature by analytically distinguishing among three sets of policies that protect their current jobs over other types of policies, such as passive and active labor market policies. Building on the work of Gallego et al. (2022), Bürgisser (2023), and Weisstanner (2023), we differentiate three types of policies that workers exposed to technology-related labor market risks might demand: compensation, retraining, and protectionist policies designed to slow down or prevent technological change. While most existing research has focused on passive and active labor market policies, there has been less emphasis on measuring preferences for job protection in response to structural change. We explain why protection from labor market risks related to technological change may be an appealing alternative for workers and develop new survey measures to assess preferences for technological protectionism.

Our findings are based on an original online survey conducted in Spain in July 2021, with 1,450 working-age respondents. Spain, with its traditionally high unemployment rates, provides a relevant case for examining concerns about labor market security. Recent legislative changes required by the EU imply that employment protection laws are now relatively typical of other European countries (Eichhorst and Marx 2021).

Overall, we find limited to mixed evidence that perceptions of technology-related risk across our measured dimensions correlate with support for redistribution or retraining policies. However, we document a stronger correlation between various forms of concern about automation and support for protectionist policies designed to slow down technological change. These results have implications for what policies parties or governments might propose to gain political traction if the rapid adoption of new technologies at the workplace generates a sense of threat among workers, either of being substituted or of not being able to maintain their technological skills. We discuss implications in light of recent developments in artificial intelligence in the final section.

Relevant literature and theoretical expectations

New digital technologies have driven economic growth, but they have also contributed to rising job polarization and inequality (e.g., Goos, Manning, & Solomons, 2009, 2014; Autor & Dorn, 2013). There is a consensus that the third industrial revolution benefited highly skilled workers while disadvantaging routine workers. As the fourth industrial revolution progresses, characterized by landmark technologies such as artificial intelligence and robots, the risks appear to be extending to white-collar workers (Webb, 2020; Felten, Raj, & Seamans, 2019). In this rapidly evolving labor-market context, it is crucial to understand whether and how workers perceive digitalization as a risk and what policies they demand in response.

Motivating findings

Thewissen and Rueda (2019) initiated the now burgeoning literature on technological change and policy preferences, building on the foundational argument that occupational risks influence support for redistribution and the welfare state (Iversen and Soskice, 2001; Rehm, 2009; Gingrich and Ansell, 2012; Schwander and Häusermann, 2013). Their work integrates the finding that individuals in routine occupations are more susceptible to displacement by automation (Autor, Levy, and Murnane, 2003) with the standard theoretical framework that posits that income-maximizing workers will become more likely to support redistribution when their objective occupation-based labor market risks increase. This occurs because workers, aware of their probability of unemployment, support more generous compensation policies to safeguard against potential income loss as this risk increases.

Recent studies have expanded on this core finding by noting two key points. First, workers may not be well informed and often remain unaware of the specific risk of losing their job until this actually happens (Ahrens, 2023). Second, workers at high objective risk of displacement fail to recognize automation as a danger, instead misattributing risks to other structural causes, as supported by evidence showing low correlations between objective and subjective risks (Zhang, 2019; Kurer and Häusermann, 2022; Weisstanner, 2023). Ahrens clearly states that, “workers can only act in response to risks they are aware of, that is, their subjective risk. Put simply, one must know about a risk to insure against it” (2023, 8).

Theoretical arguments connecting technological substitution risk to preferred policies

The literature has thus recently focused on theory and measurement of subjective risks regarding technological change. A natural caveat is that, as these are frequently measured via attitudes about risk and technology, it is difficult to causally ascertain the role of such risks, but documenting their potential role is necessary to test this cornerstone family of hypotheses about the origins of policy response. While recent research documents stronger correlations between such subjective risks and various policy preferences, it remains unclear as to *which specific aspects* of technological change concern workers, as few studies measure and assess multiple competing sources of risk.

Existing studies have predominantly focused on one dimension of risk, that of job displacement, and scholars have measured this risk perception in various ways. Busemeyer and Tober (2023) inquire about the perceived likelihood that one's job will be replaced by technology or by someone with better technological skills. Kurer and Häusermann (2022) measure the self-reported percentage of tasks in one's job that may be automated. Both studies find that workers who are more concerned about substitution support passive labor market policies, such as increased spending on unemployment benefits, but not other policies including raising pensions, investing in education, or active labor market policies. This latter finding is particularly relevant since active labor market policies are key instruments proposed to help workers adapt to and benefit from technological change. One possible reason for this lack of support is that workers may be averse to retraining (Gallego and Kurer, 2022).

Analytically, there is a third category of policy response that has received comparatively less attention but is in the menu of possible responses to technological change, that of protection from disruption (Bürgisser 2022, Weisstanner 2023, Gallego, et al. 2022). We argue that policies that protect current jobs from technological disruption are an attractive policy option for individuals who perceive the adoption of technology in the workplace as threatening. Such policies have also been discussed by economists, some of whom have recently advocated for policies to steer or decelerate the adoption of new technologies in the workplace (Acemoglu and Johnsson, 2023). Examples include increased government regulation of technology, tax measures to disincentivize robots or other forms of worker substitution, such as a "robot tax" (Abbott and Bogenschneider, 2018), and the strengthening of worker institutions to better integrate technological change (Dauth et al., 2021). These policies broadly aim to "protect" workers from technological change. While explicitly decelerating technological change is not a current policy priority for most OECD governments, specific actions, such as the ban on Uber and other ride-sharing apps in some European countries, can be seen as distinct protectionist policies. It is entirely plausible for workers concerned about the potential negative implications of technological change to demand such protection.

Protectionist policies have primarily been examined in the context of international trade. For instance, Colantone and Stanig (2018) note that trade policies aimed at preserving the status quo have been seen as more viable and/or politically appealing as welfare states become strained and the limits and costs of redistribution increase. Similarly, protection from technological disruption may be as attractive, if not more so, than redistribution or retraining. Potential losers from technology and artificial intelligence may prefer protection over compensation, even if the former is more economically costly for society, because it allows for the preservation of jobs, identities, and social environments. These workers may prefer to keep their occupation and social networks, maintaining the job status quo, rather than becoming recipients of state aid or accepting that the adoption of new technologies will necessitate investing in new skills and potentially undergoing a job transition. This transition implies uncertainty about their new occupational and relational status.

In summary, we argue that "slowing down" workplace technological change may be seen as a more effective and direct policy for maintaining job security than redistribution or retraining, as the latter require workers to accept the possibility of changing work environments.

The only study we are aware of that focuses on protectionist policies regarding technological change finds that workers who are pessimistic about its negative impacts in the workplace are more likely to support policies to aimed at slowing down its progress (Gallego et al., 2022). This finding suggests that such protectionist policies may garner more support if concerns about job displacement due to technology become more widespread.

Given these arguments and previous findings, we therefore hypothesize the following:

H1: Individuals concerned about being displaced by technology are more likely to support redistributive policies.

H2: Individuals concerned about being displaced by technology are more likely to support protectionist policies that prevent companies from adopting new technologies in the workplace.

Theoretical arguments about other occupational subjective concerns and techno-stress

The subjective risk of being substituted by a computer or algorithm may not be the only or most prominent technology-related risk for workers. Previous research finds that, perhaps surprisingly, only a minority of workers are highly concerned about substitution (Heinrich and Witko, 2021; Gallego et al., 2022; Jeffrey, 2021). In this section, we argue that two other broad subjective risks may be relevant in predicting policy preferences: techno-stress and perceptions about the opportunities (or lack thereof) posed by technological change to one's occupation.

Technostress: We draw on a burgeoning set of theory and findings in the management-studies literature that documents how the continuous necessity, expectation, or demand to learn new technology in the workplace can produce psychological strain for workers. Individuals may simply dislike learning how to use new technologies, perceive themselves as less able than others, or worry that co-workers with more skills may surpass them within their firm or occupation. This problem of aversion to workplace adaptation is known as "technostress." While technostress has received little attention in the political-science discussion of technological change, [1] it has been widely studied in other disciplines, predominantly psychology and management studies (Ayyagari, Groven and Purvis 2011; D'Arcy, Herath and Shoss 2014; Tarafdar, Pullis and Ragu-Nathan 2015). This literature documents the negative psychological and emotional effects of worker concern about their capacity to learn to use new technologies on different outcomes such as job performance, self-efficacy, and satisfaction.

The concept of technostress has broader psychological roots in the extensive literature showing that resistance to change is a common psychological preference for many individuals (Jost, 2015). For those experiencing technostress, policies that protect existing jobs from technological disruption may be particularly appealing because they prevent change and thus shield workers from the strain of continuous retraining. Individuals accustomed to performing

[1] One recent study by political scientists does focus on technostress, but uses the concept as a dependent variable, finding that higher income and a more generous welfare state correlate with lower technostress (Lauterbach et al. 2023). In contrast, we focus on technostress as an independent variable. The only survey we are aware of that asks respondents about technostress as an independent variable is Busemeyer et al. (2023), but they include this a single item in a principal component analysis about general perceptions of risk and do not separately test if it correlates with policy preferences.

their tasks in a certain way may prefer to maintain their current job and workflow rather than having to learn new skills.

We expect that technostress at work can significantly influence an individual's preferences for protectionist policies. However, it is theoretically less clear why technostress alone (not tied to fear of displacement) would shape support for redistributive or active labor market policies. Specifically, we do not anticipate that those experiencing technostress will support increased spending on retraining, as technostress indicates a lack of confidence or an aversion to retraining and upskilling, particularly in relation to technology. Therefore, we hypothesize:

H3: Individuals reporting greater technostress should be more supportive of technologically protectionist policies.

Overall occupational evaluation of the effect of technological change in the workplace: Our final additional conception of technological risk or concern refers to the overall assessment of the impact of new workplace technology. Individuals could consider many dimensions related to the workplace experience regarding technology adoption. One example is autonomy, as many new technologies related to artificial intelligence are being used for workplace surveillance, reducing job satisfaction (Acemoglu and Johnson 2023). Technology, however, can also increase autonomy, for instance by giving workers more ability to select clients. Another example is safety, as technology may increase workplace safety by detecting risks or substituting workers for dangerous tasks, but it may also leave them open to new risks, such as that of being exposed to disturbing images. Yet another example is work-life balance; technology may improve this by enabling work from home and hence decreasing the time devoted to commuting, but it can also worsen it, for instance by increasing availability outside office hours.

While in this study we do not measure all these different dimensions of respondents' assessment of the impact of technology adoption in the workplace, we argue that individuals are able to form an approximate global assessment about whether technology has a positive or a negative impact on their job and occupational opportunities. Gallego et al (2022), measure such generic evaluation about the impact of technological change in the workplace by asking respondents whether it has led to overall positive or negative consequences for them. Using this general question about the implications of technology at the workplace, they find with observational and experimental evidence that this general orientation increases demand for protection, but not for redistribution.

As in the case of technostress, the mechanism or reason may be an overall aversion to change. Again, whether this overall assessment about the effects of technology on one's job should affect attitudes towards redistribution or retraining remains unclear. For these reasons, we hypothesize:

H4: Individuals who believe that the overall impact of technology in the workplace is negative should be more supportive of protectionist policies that prevent companies from adopting new technologies in the workplace.

Data, Measurement, and Research Design

To test our hypotheses about these distinct subjective technological risks for workers and support for policies of compensation, retraining, or protectionism, we gather new data on from an online survey administered by Spanish survey firm Netquest to workers in Spain in June-July 2021[2]. 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).

Spain is an instructive case study to test our hypotheses, as the country was a late industrializer and retained a relatively high number of routine workers until recently (de la Rica & Gortazar, 2016). Like its Southern European peers, Spain has tended to respond differently to the challenges of de-industrialization compared to the more oft-studied Anglo-Saxon and Germanic countries, accruing government debt and resisting liberalization of the labor market (Boix, 2019), and preserving a labor market dualized between protected insiders and temporary workers. Unemployment levels remain comparatively high, making prospects of job displacement due to technological change a credible concern for some workers.

On the other hand, the largest cities of Madrid and Barcelona are economically dynamic and have become regional knowledge economy hubs. Spain is currently at the European median in knowledge economy indicators, such as percentage of the population that has some level of tertiary education, expenditure in research and development as percent of gross domestic product, patents per population and global competitiveness indicators (Širá et al. 2020). In addition, the previously sharp divide between insiders and outsiders has been weakening in the last years due to a series of labor law reforms. Overall, Spain currently combines significant unemployment rates with a modernized economy that in many other respects has converged towards other European countries and currently represents a fairly typical advanced economy.

Subjective Risk

[2] At the time of 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.

In this section, we describe the measurement of our three different types of subjective risks: a) job substitution risk, b) "technostress" (worry about adapting to new workplace technologies), and c) overall occupational concern about the impact of technology.

To measure the first category of risks, we built on the approach from Kurer and Häusermann (2022) and asked individuals to give their best estimate on a scale of 0-100 of the percent of their weekly work tasks that could be done by a computer, robot, or algorithm; we rescale this variable 0-1, with higher values indicating higher beliefs about substitution risk.

To measure "technostress," we asked whether the individual thinks that learning about technology is relevant in her job, and whether she is also concerned or very concerned about being able to learn technological skills to do her job (coded binary, if the individual believes both to be true as 1 and 0 otherwise)[3].

Finally, to measure overall occupational concern about the impact of technology, we asked respondents whether they believe that technological advancements in their workplace will have overall positive or negative consequences for future work opportunities.[4] The response options were: "Very Positive, Mostly Positive, Neither Negative nor Positive, Mostly Negative, Very Negative." We label this variable 'effect of technology' and, for our main analysis, code it categorically, with the "Very Positive" response option as the baseline level.

Measures: Policy preferences and other variables

[3] Question: "How important is learning to use new technologies (such as software, machines or apps) in your line of work?" and: "Do you worry about not being able to learn how to use the new technologies that are being adopted in your profession/job?"
[4] The wording was "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?"

Compensation. Support for compensation is measured via a standard question of support for increased spending on unemployment benefits (even if it implies tax increases), scaled 0-10 with higher values indicating greater support.

Retraining. Building on findings that focus on individual support for investment-oriented policies such as worker retraining as a response to unemployment, we measure support for worker retraining (this question was coded on a 3-point Likert scale, with higher values indicating greater support).[5]

Technological Protectionism. We measure support for two precise policies regarding possible government efforts to protect workers from consequences of technological change. The proposals were giving trade unions more power to prevent firms from substituting workers[6] (even if these policies cause a reduction in salaries or a loss of employment), and fining firms that replace workers with technology.[7] Response options were coded on a three-point Likert scale, with the highest values indicating support.

Other variables

While objective risk measures based on occupations or occupational tasks are not our empirical focus, we also measure two objective measures of technology-related risk and control for them. First, we construct and 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

[5] The wording was: "The government should spend more money in offering retraining to the unemployed, even if this means increasing taxes."

[6] We did not measure union membership. We note that it is possible that union membership is potentially endogenous to some of our policy preferences. The occupation and industry-level fixed effects we introduce in some of the models (see Tables A14-A19 in the SI in particular) should at least in part account for this variation, as union membership is to some extent predicted by occupation category.

[7] The questions read respectively, "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".

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 US context (using 1990s occupational dictionaries), the measurement has since been adapted to the Spanish labor market (Sebastian, 2018). We use the 2-digit ISCO occupation data provided by respondents, and then assign them a value based on Sebastian (2018)'s coding. [8] This RTI variable 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 also 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 (e.g., Frey & Osborne, 2017; Arntz, et al., 2017; Feng & Graetz, 2020). We specified the ten tasks currently coded as least likely to be automatable as defined by the OECD (see Arntz et al., 2017, Nedelkoska & Quintini, 2018) and asked survey respondents how often they are required to carry them out at work. We pool the task frequencies to create 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.

The results using the objective risk variables are presented in Sections 2 and 4 of the Supporting Information, but our discussion of results in the main paper focuses on subjective risks.

We also collected demographic data on female and male gender, age, education, employment status, income and ideology. Male gender is coded as 1, age as nine categories

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

between 18 and 64, education is coded into five categories, employment status into nine [9], household income is recoded into ten, and ideology coded on a 10-point coarse left-right scale where 0 is the most leftwing position and 10 the most rightwing.[10]

Finally, we include two types of fixed effects. First, we use a 3-category broad "occupational class" schema, derived from Oesch (2006)'s 5-class schema and based on the respondents' 1-digit ISCO occupational dummy variables.[11] This control is relevant as an attempt to balance between two considerations. On one extreme, a standard practice in this literature is not to include controls for occupation groups in estimation. The concern with this approach is that our subjective (or objective) risk variables may in fact be capturing differences between occupational groups such as blue-collar workers vs white collar workers that are not captured by education and income alone. At the other extreme, a more stringent approach would be to include the 10 categories of the 1-digit ISCO code as fixed effects, which would capture the variance in objective and subjective risk that is due to differences in occupation and would focus on the variance in these risks within each occupation category. This is in principle more precise, but some of the objective risk variables, notably RTI, are only coded at the 2-digit level in the ISCO classification (in other words, the concept of objective risk is measured with substantial

[9] 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.

[10] 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.

[11] In the SI, we display the results with controls for 1-digit ISCO occupational fixed effects, which are broadly similar (see Tables A14-A16). **We also propose an alternative approach, by controlling for the industry that respondents report working in rather than their ISCO-defined occupations (see Tables A17-A19). Respondents thus sorted themselves as working in 1 of 14 sectors (agriculture, mining, manufacturing, utilities, construction, commerce, transport, hospitality, ICT, finance, real estate, professional, technical and administrative activities, social or personal services, arts and entertainment, with an 'other' option available). Results are unaffected by this control, remaining consistent with our main specifications.**

error). Including 10 occupational fixed-effects would risk absorbing too much of the relevant variance and producing a type II error (false negative). Thus, a reasonable compromise for an occupational control variable is the 3-class scheme as noted above. Second, we also include fixed effects at the level of the province our respondents reside in, i.e. the second-level of administrative division in Spain (there are in 50 in total). This is to account for the ecological effects discussed above, namely the fact that some areas (large cities especially) have benefitted from technological advancements more than others.

Models

With these considerations, our modelling strategy is as follows. We estimate a total of 24 models where each dependent variable *P* represents support for a given policy (these are: increasing unemployment benefits, increasing support for retraining programmes, fining firms that employ displacing technology and increasing union involvement in decision on the implementation of new technology). We regress support of each policy on a given technological risk measure separately. Values are taken at the level of respondent *i* and all models are OLS, though we report results both with (models indicated by an odd number, see tables below) and without (even numbered models) fixed effects at the level of occupational class and province. Standard errors are clustered at the province level. Table 1 below reports the models with substitution concern as the independent variable, Table 2 with technostress and Table 3 with generic concern about the effect of technology. Table 4 reports models where are all three independent variables are included simultaneously. We also include the demographic controls C in all of our models, which include gender, age, education, employment status, income and ideology. Our models can be represented formally as follows:

For Table 1:

(1) $P_{xi} = ß_0 + ß_1Substitution_i + ß_2C_i + \varepsilon$

(2) $P_{xi} = ß_0 + ß_1Substitution_i + ß_2C_i + \alpha Class_i + \gamma Province_i + \varepsilon$

For Table 2:

(3) $P_{xi} = ß_0 + ß_1Technostress_i + ß_2C_i + \varepsilon$.

(4) $P_{xi} = ß_0 + ß_1Technostress_i + ß_2C_i + \alpha Class_i + \gamma Province_i + \varepsilon$

For Table 3:

(5) $P_{xi} = ß_0 + ß_1Effect\_of\_technology_i + ß_2C_i + \varepsilon$.

(6) $P_{xi} = ß_0 + ß_1Effect\_of\_technology_i + ß_2C_i + \alpha Class_i + \gamma Province_i + \varepsilon$

For Table 4:

(7) $P_{xi} = ß_0 + ß_1Substitution_i + ß_2Technostress_i + ß_3Effect\_of\_technology_i + ß_4C_i + \varepsilon$.

(8) $P_{xi} = ß_0 + ß_1Substitution_i + ß_2Technostress_i + ß_3Effect\_of\_technology_i + ß_4C_i + \alpha Class_i + \gamma Province_i + \varepsilon$

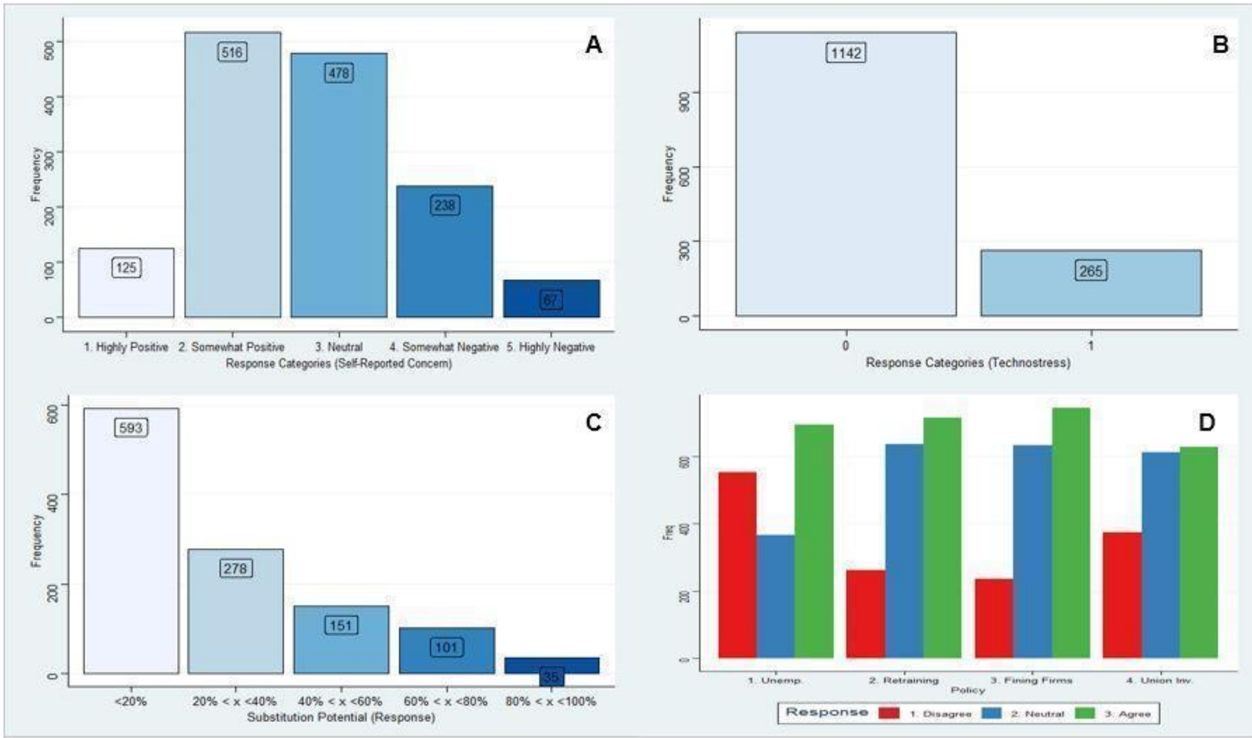
Results

Subjective risk and support for policies: descriptive statistics

We first report key patterns in the data before turning to estimation results. A plurality of respondents have a positive attitude about the overall 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. Regarding technostress, figure 1b shows that around 18% of the sample reported both that learning to use new technology was important in their jobs and that they were worried about being able to do this. 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 a distinct minority of 12% that over 60% could be carried out by a robot, computer or algorithm.

Turning to the descriptive results on policy preferences (Figure 1d), on support for expanding 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). On the policy of government-sponsored retraining for the unemployed, only 16% of our respondents had negative views of this policy, 40% were neutral, and a plurality (44%) support greater spending for such retraining. On the first protectionist policy of introducing punitive fines for companies that dismiss workers to replace them with machines or software, only 15% of respondents disagreed with this policy, 39% selected the neutral option, and 46% agreed with the statement. On the second policy to empower workers to potentially slow down technological adoption, 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 39% supported the policy.

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.').

In the SI (Section 1), we present bivariate correlations between the measures of subjective risk and between policy support. We find no significant relationship within either group. We also report (Tables A3-A7) the mean values of our subjective risk measures according to the various levels of the demographic characteristics. As a brief summary of other demographic correlates of the policies, we note that women appear to suffer from higher levels of technostress, while older respondents tend to score higher on both overall concern about the effect of technology and technostress, but marginally lower on substitution worries. All three of our technological risk variables, on the other hand, appear to be negatively correlated with education levels, as respondents holding a postgraduate degree are the least worried about all three types of risk and those with less education are the most preoccupied. With regard to type of work contract, self-employed individuals are the least affected by all three of our measures of risk, while workers on short-term contracts report higher levels of overall concern about the effect of technology but *lower* concern about substitution potential compared to those on long-term contracts. Finally, as income levels increase, it appears that both overall concern about the effect of technology and technostress decrease, while substitution potential does not appear to vary by income.

Correlates of policy preferences by types of subjective risks and policies

We now turn to the examination of the correlations between our measures of subjective risk and policy preferences. All specifications are OLS and control for demographic variables, with the odd-numbered models including both social class and province-level fixed effects. 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). The SI (Section 3) presents the results without controls and when introducing controls step-wise.

Table 1 presents the results of regressing each of the four policy variables on the measure of substitution concern, testing hypotheses 1-2.

Table 1: Substitution Concern and Policy Preferences

	Unemp. Bens. (0-1)		Retraining (0-1)		Fining Firms (0-1)		Union Inv. (0-1)	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
(Intercept)	0.857*** (0.081)	0.750*** (0.089)	0.583*** (0.120)	0.845*** (0.113)	0.615*** (0.119)	0.628*** (0.128)	0.655*** (0.107)	0.738*** (0.114)

Concern about substitution (0-1)	0.086** (0.033)	0.056 (0.035)	0.044 (0.033)	0.081* (0.035)	-0.010 (0.040)	-0.013 (0.041)	0.018 (0.052)	-0.011 (0.052)
Num.Obs.	1147	1126	1147	1126	1147	1126	1147	1126
R2 Adj.	0.188	0.203	0.011	0.116	0.132	0.142	0.162	0.182
Std.Errors	by: province	by: province	by: province	by: province	by: province	by: province	by: province	by: province
Demographic Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Social Class and Province FEs	No	Yes	No	Yes	No	Yes	No	Yes

OLS regressions with standard errors clustered at the province level; Demographic Controls: age, gender, education, income, ideology and type of contract; Social Class FEs split respondents into 3 categories: Unskilled workers, Skilled Workers and Upper/Middle class; province FEs are dummies indicating which of Spain's 50 provinces R lives in; + p < 0.1, * p < 0.05, ** p < 0.01, *** p < 0.001

Models 1-4 in Table 1 indicate that the subjective perception of job risk by automation substitution is inconsistently correlated with the two policies of redistribution. The coefficient on substitution concern for support for unemployment compensation policy is not precisely estimated when fixed effects by class and province are considered (column 2); however, the coefficient is positive for support for retraining in the more rigorous specification (column 4). The coefficient is not precisely estimated for both of the technological protectionist policies. Thus, we find some limited evidence for hypothesis 1, as such substitution concern is correlated with support for retraining, but none of the other policies.

Next, Table 2 replicates the models when using technostress as the main independent variable, testing hypothesis 3.

Table 2: Technostress and Policy Preferences

	Unemp. Benefits (0-1)		Retraining (0-1)		Fining Firms (0-1)		Union Inv. (0-1)	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)

(Intercept)	0.875*** (0.082)	0.754*** (0.086)	0.801*** (0.100)	0.856*** (0.112)	0.620*** (0.119)	0.604*** (0.137)	0.668*** (0.103)	0.707*** (0.111)
Technostress = 1	0.023 (0.024)	0.013 (0.025)	0.020 (0.025)	0.003 (0.027)	0.078* (0.035)	0.070+ (0.039)	0.103*** (0.023)	0.093*** (0.025)
Num.Obs.	1147	1126	1147	1126	1147	1126	1147	1126
R2 Adj.	0.184	0.201	0.110	0.113	0.138	0.147	0.171	0.190
Std.Errors	by: province	by: province	by: province	by: province	by: province	by: province	by: province	by: province
Demographic Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Social Class and Province FEs	No	Yes	No	Yes	No	Yes	No	Yes

OLS regressions with standard errors clustered at the province level; Demographic Controls: age, gender, education, income, ideology and type of contract; Social Class FEs split respondents into 3 categories: Unskilled workers, Skilled Workers and Upper/Middle class; province FEs are dummies indicating which of Spain's 50 provinces R lives in; + p < 0.1, * p < 0.05, ** p < 0.01, *** p < 0.001

Table 2 shows that technostress does positively and significantly correlate with support for both technological protectionist policies of 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 do not have different views about forms of redistribution, and but are more likely to be concerned about slowing down its adoption via other state instruments.

Finally, Table 3 presents the results when regressing the evaluation of the global impact of technology in the job (with “very positive” as the reference category), testing hypothesis 4. This last measure of technological concern is positively correlated with support for both types of protectionist policies, and the coefficients are not precisely estimated for the outcomes of redistribution support. Models 5-6 and 7-8 indicate a positive and significant coefficient for both these variables.[12]

Table 4 presents the results of models when the three subjective risk variables are included simultaneously. We find the effects to be consistent with those shown when each variable is included individually, providing further corroboration for our contention that there are different types of subjective risk.[13]

Table 3: Generic concern about the effect of technology and Policy Preferences

	Unemp. Benefits (0-1)		Retraining (0-1)		Fining Firms (0-1)		Union Inv. (0-1)	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
(Intercept)	0.897*** (0.100)	0.772*** (0.103)	0.841*** (0.122)	0.913*** (0.130)	0.449** (0.142)	0.467** (0.156)	0.540*** (0.126)	0.637*** (0.129)
Effect of tech: Somewhat Positive	-0.013 (0.036)	-0.017 (0.040)	-0.002 (0.046)	-0.023 (0.045)	0.088** (0.032)	0.093** (0.034)	0.060 (0.040)	0.053 (0.042)
Effect of tech: Neutral	-0.041 (0.042)	-0.041 (0.051)	-0.048 (0.050)	-0.065 (0.052)	0.123** (0.037)	0.127** (0.040)	0.132** (0.043)	0.126** (0.045)
Effect of tech: Somewhat Negative	-0.018 (0.040)	-0.037 (0.044)	-0.030 (0.045)	-0.042 (0.047)	0.130** (0.042)	0.123** (0.045)	0.123** (0.042)	0.103* (0.041)
Effect of tech: Very Negative	0.049 (0.085)	0.040 (0.094)	-0.073 (0.095)	-0.077 (0.101)	0.169* (0.067)	0.156* (0.072)	0.224** (0.069)	0.182* (0.073)
Num.Obs.	1090	1073	1090	1073	1090	1073	1090	1073
R2 Adj.	0.191	0.204	0.113	0.114	0.148	0.158	0.178	0.195
Std.Errors	by: province	by: province	by: province	by: province	by: province	by: province	by: province	by: province
Demographic Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Social Class and Province FEs	No	Yes	No	Yes	No	Yes	No	Yes

OLS regressions with standard errors clustered at the province level; Demographic Controls: age, gender, education, income, ideology and type of contract; Social Class FEs split respondents into 3 categories: Unskilled workers, Skilled

[12] Table A26 and figure A31 in the SI show results when the neutral option is taken as the baseline. The results indicate that it is individuals who are very positive about technological change who are most opposed to both forms of technological protectionist policies. We discuss this in the conclusion.

[13] We thank an anonymous reviewer for this suggestion.

Workers and Upper/Middle class; province FEs are dummies indicating which of Spain's 50 provinces R lives in; + p < 0.1, * p < 0.05, ** p < 0.01, *** p < 0.001

Table 4. Concern about technological change (all variables) and policy preferences

	Unemp. Benefits (0-1)		Retraining (0-1)		Fining Firms (0-1)		Union Inv. (0-1)	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
(Intercept)	0.887*** (0.102)	0.764*** (0.100)	0.830*** (0.126)	0.903*** (0.135)	0.461*** (0.136)	0.449** (0.158)	0.511*** (0.124)	0.615*** (0.127)
Concern about substitution (0-1)	0.073* (0.037)	0.049 (0.039)	0.085* (0.037)	0.097* (0.040)	-0.015 (0.048)	-0.018 (0.051)	-0.046 (0.055)	-0.039 (0.056)
Technostress	0.014 (0.025)	0.008 (0.025)	0.014 (0.025)	-0.006 (0.026)	0.080* (0.036)	0.076+ (0.039)	0.111*** (0.030)	0.101*** (0.030)
Effect of tech: Somewhat Positive	-0.013 (0.036)	-0.017 (0.039)	-0.003 (0.045)	-0.023 (0.044)	0.089** (0.032)	0.093** (0.034)	0.058 (0.042)	0.054 (0.042)
Effect of tech: Neutral	-0.041 (0.041)	-0.041 (0.050)	-0.049 (0.049)	-0.064 (0.052)	0.125** (0.038)	0.129** (0.040)	0.127** (0.045)	0.128** (0.045)
Effect of tech: Somewhat Negative	-0.026 (0.040)	-0.042 (0.044)	-0.040 (0.043)	-0.050 (0.045)	0.125** (0.043)	0.118* (0.046)	0.102* (0.043)	0.098* (0.042)
Effect of tech: Very Negative	0.035 (0.084)	0.032 (0.092)	-0.089 (0.090)	-0.087 (0.095)	0.152* (0.066)	0.139* (0.070)	0.190** (0.071)	0.161* (0.074)
Num.Obs.	1090	1073	1090	1073	1090	1073	1073	1073
R2 Adj.	0.193	0.204	0.115	0.116	0.153	0.162	0.198	0.203
Std.Errors	by: province	by: province	by: province	by: province	by: province	by: province	by: province	by: province
Demographic Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Social Class and Province FEs	No	Yes	No	Yes	No	Yes	No	Yes

OLS regressions with standard errors clustered at the province level; Demographic Controls: age, gender, education, income, ideology and type of contract; Social Class FEs split respondents into 3 categories: Unskilled workers, Skilled Workers and Upper/Middle class; province FEs are dummies indicating which of Spain's 50 provinces R lives in; + p < 0.1, * p < 0.05, ** p < 0.01, *** p < 0.001

We report robustness checks and alternate specifications in Section 3 in the SI. Our results are robust to specifying ordered logistic regression models or OLS; to different specifications adding no controls; including only basic demographic controls; three broad occupational groups at the one-digit level; or alternative specification adding the ten 1-digit occupations or the industry respondents work in as fixed effects. For completeness, we also report results when adding controls for objective measures of risks in the SI. [14] Our core findings remain across specifications and indicate support for most of our main hypotheses that workers concerned about distinct technology-related risks in the workplace support policies that allow governments or trade unions to prevent economic transformations from happening, hence directly sheltering affected workers.

In addition, in Section 6 in the Supporting Information, we consider several theoretically relevant moderators. First, we test whether the correlation between subjective risks and policy preferences is stronger among some age subgroups than others. For instance, we might expect that older workers who have subjective concerns are particularly likely to demand protection of their current jobs. However, we do not find a consistent difference in the relationship between subjective concerns and policy preferences across age groups. Second, we examine outside work options as a moderator. Specifically, we examine whether workers who believe that they would find a similar or better job than their current one if they lost their job and are concerned about technology support different policies than other people. We find inconclusive results. Third, we test whether workers who strongly identify with their current job have different reactions to subjective risks and, again, we do not find consistent results. Finally, we examine the effect of different types of contract (long-term, short-term, self-employed) and of occupational class on the relationship between subjective risks and policy preferences.[15]

[14] The TLRA measure is not correlated with support for increasing unemployment benefits under any model specification. The RTI coefficient in one specification is actually *negatively* correlated with support for increasing unemployment benefits, though imprecisely estimated. Both measures are also negatively correlated with support for retraining policies. See SI Tables A28 and A29.

[15] We find that, for workers on short-term contracts, greater substitution risk is actually negatively correlated with support for retraining policies or for more union involvement (See Table A43).

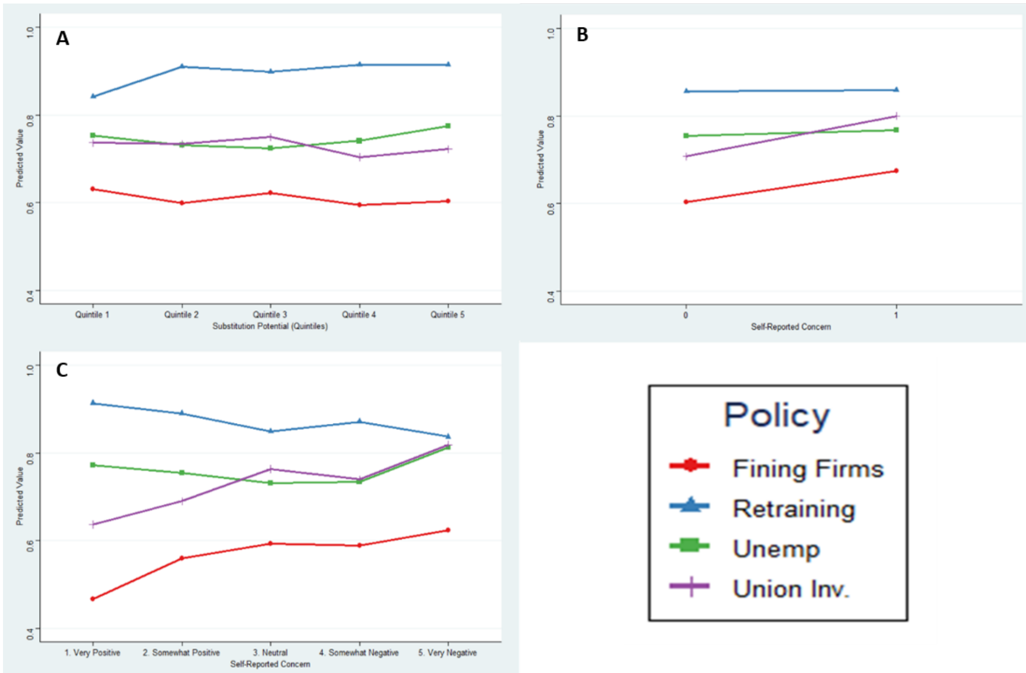
Overall, confirming our expectations, we find stronger correlations of subjective risks with support for both protectionist policies, and little evidence that any subjective risk is strongly correlated with redistribution or retraining support.

Substantive effects

Figure 2 displays the predicted values of support for each of the four policies. Figures 3a-3c display the model plots for the Technostress and Effect of Technology variables to display the substantive effects.[16] Regarding the effect of substitution potential, Figure 2a shows that respondents who worry very little about being replaced are around 7 ppts less supportive of government-funded retraining programmes compared to those who report the highest level of risk. Figure 2b depicts the magnitude of the effect of Technostress on the four policy preference variables. Workers who claim technostress are approximately 7 percentage points more supportive of fining firms that automate and 9 percentage points more likely to support increasing union involvement in technological adoption than other respondents. Finally, for our generic concern measurement of subjective risk (see Figure 2c), an increase in concern about technological change from the lowest response category to the highest increases support for fining firms that automate by around 16 ppts, and for greater union involvement in firm decision by around 18 ppts. Notably, workers professing a higher degree of generic technological concern are *not* consistently more likely to demand compensation or retraining policies than others.

Figure 2. Subjective technological concern and policy support

[16] **We do not plot the results for substitution potential in the main text as they are not significant. The plot can however be found on the SI (Figure A30). The plots are produced using the modelsummary R package (Arel-Bundock, 2022)**



Note: The figure presents predicted values of support for 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 on 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). These lines connect the different predicted values for each category of the various of measures of subjective risk.

Finally, Figures 3-4 display the magnitude of the estimated coefficients and their confidence intervals for the models when substitution potential and technostress (figure 3) or generic concern (figure 4) are taken as the independent variables.

Figure 3. Marginal Effect of Substitution Potential and Technostress on policy preferences

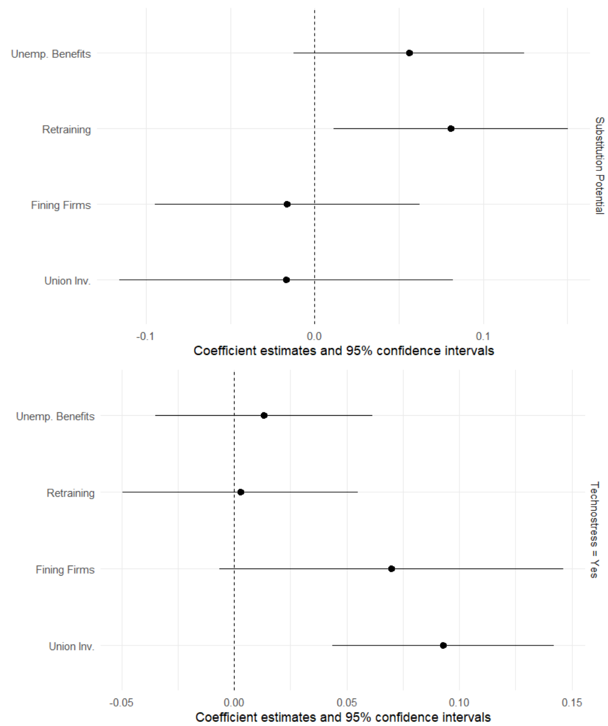
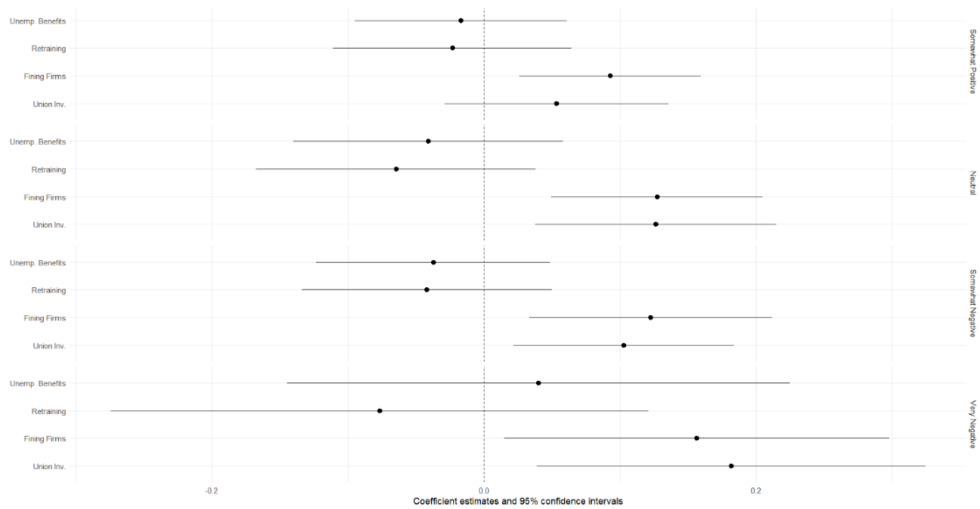


Figure 4. Marginal Effect of levels of generic concern on policy preferences



Note: The figures presents the coefficient estimates and confidence intervals obtained from tables 1, 2 and 3 above for each policy response.

In the case of technostress, we find that those who are more techostressed are more likely to support protectionist policies. In the case of overall concern about the impact of technology in the job, we observe that the results are driven by those who are more optimistic about the impact of technology, as they are less likely to support technologically protectionist policies than any other group. This could indicate that when workers are more confident that the impact of technologies like AI is overall positive, the demand for protection is reduced. Finally, substitution worry has no impact upon support for protectionist policies, but rather correlates with a higher approval for active labor market policies.

Discussion

This study builds on the growing literature that examines the role of automation risk in policy preferences. Our results overall suggest a low correlation between three forms of subjective concern about technological risk and support for compensation or retraining. We document a more consistent relationship between theoretically relevant concerns, such as technostress, and support for technologically protectionist policies.

A key take-away of our results is that workers may perceive multiple concerns and risks, as well as opportunities, regarding technological innovation and automation in the workplace. If such risks have distinct connections with corresponding specific policy preferences, it is important to theoretically define and disentangle *distinct* risks as well as to more precisely define different policies. We have done this by focusing on the relatively ignored role of technostress and technological protectionism. As AI increasingly threatens many different types of occupations across the task spectrum (Webb 2020), honing in on a better understanding and measuring of how these different subjective concerns map onto different policies is a critical task for scholars.

We now turn to additional routes for research building on this core implication. First, scholars might consider what predicts different types of subjective concerns about automation and new workplace technologies. One possibility is that concern is activated by precise objective economic risks, although current studies document a low correlation between objective and subjective risks. If concern is caused by factors *other* than occupational substitution risk, then policies to address digitalization risk in the workplace alone could be insufficient in reducing automation or technological anxiety.

Another possibility is that concern is related to general psychological orientations that are relatively stable (e.g. neuroticism, low openness to experience) which may be activated depending on the context in which the individual is. Recent research points to the importance of 'closed personality', or related traits, in explaining redistributive politics (Johnston, et al. 2017). Exploring such types of traits and their relevance for 'conservative' preferences for the preservation of job status would be worthwhile. Our distinction between different concepts of technological risk could be built upon to generate more detailed predictions for the effects of different types of concern on support for government policies. For instance, in the case of technostress, one reason why it may be related to demand for job protection, but not to support for retraining, is that workers who are averse to change in general or who are lower in openness to experience are more likely to prefer maintaining the status quo and do not necessarily want to learn *new* skills.

Second, we find that those with more concerns are much more pro-protectionist than those who are positive, but the more positively oriented workers are by far the most anti-protectionist. In our view this calls for an agenda to better explore relevant political coalitions against protectionist policies (e.g., Gallego, Kurer & Schöll, 2022).

Third, we speculate as to why we find a less consistent relationship regarding support for redistribution for any of the subjective risks considered. There are several 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 benefit eligibility concerns may play a role in scepticism of redistribution. We caution as well that regarding redistribution, there could be ceiling effects in terms of amount of support.

Fourth, the finding that workers concerned about automation threats do not necessarily prefer more compensation for potential losses, but rather support more aggressive policies to prevent change in the first place has relevant policy implications. Workers might prefer to maintain the status quo, even at the expense of lower economic growth, instead of redistribution. Policy packages aimed at preserving the status quo or even going back to an idealized past are arguably favoured 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. The resulting tension between what is sensible for the individual in the short term and the policies that are better in the long term could be further explored. In particular, protection from automation allows people to keep their current jobs in the short-term, but may negatively affect their long-term survival chances.[17] This question could be further explored in different ways. Workers in the public and private sector may think differently about this trade-off, for instance, if public sector workers feel more sheltered from the long-term consequences of protection.

In this regard, the distinction between ego-tropic and socio-tropic views about the impact of technology may be particularly relevant. Many people may be aware that technologically protectionist policies help incumbent workers in the short term, but may have general negative economic impacts in the long term. To understand how people construct preferences about the optimal pace of technological advancement and the role of government in steering technological change, a better appreciation of how people weigh the personal and social benefits of policies is needed, as well as more fine-grained measures for these ego-tropic and socio-tropic concerns.

Anti-technological movements are historically rare, but given the predicted fast pace of technological change and artificial intelligence it is not implausible that more individuals become

[17] This could be because protection compromises the economic viability of companies or because it makes workers who maintain production in traditional ways less productive compared to other workers, and thus increases incentives for company dismissal.

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.

References

Abbott, R., Bogenschneider, B., 2018. Should Robots Pay Taxes? Tax Policy in the Age of Automation. *Harvard Law & Policy Review.* Volume 12, pp. 145-175.

Acemoglu, D., & Johnson, S., 2023. *Power and Progress: Our Thousand-Year Struggle Over Technology and Prosperity*. Hachette UK.

Ahrens, L. (2023). Labor market risks and welfare preferences: a bounded rationality approach. *Socio-Economic Review*. doi:https://doi.org/10.1093/ser/mwad034

Arel-Bundock V (2022). "modelsummary: Data and Model Summaries in R." *Journal of Statistical Software*, 103(1), 1–23. doi:10.18637/jss.v103.i01.

Arntz, M., Gregory, T. & Zierhan, U., 2017. *The Risk of Automation for Jobs in OECD Countries: A Comparative Analysis,* Paris: OECD Publishing.

Autor, D., Levy, F. & Murnane, R. J., 2002. Upstairs, Downstairs: Computers and Skills on Two Floors of a Large Bank. *ILR Review,* 55(3), pp. 432-447.

Autor, D. H., Levy, F. & Murnane, R. J., 2003. The skill content of recent technological change: an empirical exploration. *The Quarterly Journal of Economics,* 118(4), pp. 1279-1333.

Autor, D. H. & Dorn, D., 2013. The growth of low-skill service jobs and the polarization of the US labor market. *American Economic Review,* 103(5), pp. 1553-1597.

Ayyagari, R., Grover, V., & Purvis, R. 2011. Technostress: Technological antecedents and implications. *MIS quarterly*, 831-858.

Borwein, S., Bonikowski, B., Loewen, P. J., Lee-Whiting, B., & Magistro, B. (2024). Perceived technological threat and vote choice: evidence from 15 European democracies. *West European Politics*, https://doi.org/10.1080/01402382.2023.2297601.

Boix, C., 2019. *Democratic Capitalism at the Crossroads: Technological Change and the Future of Politics.* Princeton, NJ: Princeton University Press.

Bürgisser, R. (2023). Policy Responses to Technological Change in the Workplace. *JRC Working Papers Series on Social Classes in the Digital Age 4, European Commission*.

Busemeyer, M. R., Gandenberger, M., Knotz, C. & Tober, T., 2023. Preferred policy responses to technological change: Survey evidence from OECD countries. *Socio-Economic Review,* https://doi.org/10.1093/ser/mwac015.

Busemeyer, M. R., A. Kemmerling, K. Van Kersbergen, and P. Marx, eds. 2022. *Digitalization and the welfare state*. Oxford University Press.

Busemeyer, M. R., & Tober, T. (2023). Dealing with Technological Change: Social Policy Preferences and Institutional Context. *Comparative Political Studies, 56*(7), 968-999.

Colantone, I. & Stanig, P., 2018. Global Competition and Brexit. *American Political Science Review,* 112(2), pp. 201-218.

D'Arcy, J., Herath, T., & Shoss, M. K. 2014. Understanding employee responses to stressful information security requirements: A coping perspective. *Journal of management information systems*, *31*(2), 285-318.

Dauth, W., Findeisen, S., Südekum, J. & Wößner, N., 2021. The Adjustment of Labour Markets to Robots. *Journal of the European Economic Association,* 19(6), pp. 3104-3153.

de la Rica., S., & Gortazar, L., 2016. *Differences in Job De-Routinization in OECD Countries: Evidence from PIAAC,* IZA Discussion Paper No. 9736.

Eichhorst, W., & Marx, P. (2021). How stable is labour market dualism? Reforms of employment protection in nine European countries. *European Journal of Industrial Relations, 27*(1), 93-110.

Felten, E. W., Raj, M. & Seamans, R., 2019. The Occupational Impact of Artificial Intelligence: Labor, Skills, and Polarization. *NYU Stern School of Business.*

Feng, A. & Graetz, G., 2020. Training Requirements, Automation, and Job Polarisation. *The Economic Journal,* 130(631), pp. 2249-2271.

Fernández-Albertos, J. & Manzano, D., 2016. The Lack of Partisan Conflict over the Welfare State in Spain. In: I. Sánchez-Cuenca & E. Dinas, eds. *Voters and Parties in the Spanish Political Space.* Abingdon, UK: Routledge, pp. 63-85.

Frey, C. B. & Osborne, M. A., 2017. The future of employment: How susceptible are jobs to computerisation?. *Technological Forecasting and Social Change,* Volume 114, pp. 254-280.

Gallego, A., Kuo, A., Fernández-Albertos, P. & Manzano, D., 2022. Technological risk and policy preferences. *Comparative Political Studies,* 55(1), pp. 60-92.

Gallego, A. & Kurer, T., 2022. Automation, Digitalization and Artificial Intelligence in the Workplace: Implications for Political Behavior. *Annual Review of Political Science,* 25, pp. 463-484

Gallego, A., Kurer, T., & Schöll, N. (2022). Neither Left Behind nor Superstar: Ordinary Winners of Digitalization at the Ballot Box. *The Journal of Politics, 84*(1), 418-436.Goos, M., Manning, A. & Salomons, A., 2009. Job Polarization in Europe. *The American Economic Review,* 99(2), pp. 58-63.

Gingrich, J., & Ansell, B. (2012). Preferences in Context: Micro Preferences, Macro Contexts, and the Demand for Social Policy. *Comparative Political Studies, 45*(12), 1624-1654.

Goos, M., Manning, A. & Salomons, A., 2014. Explaining Job Polarization: Routine-Biased Technological Change and Offshoring. *American Economic Review,* 104(8), pp. 2509-2526.

Heinrich, T. & Witko, C., 2021. Technology-Induced Job Loss and the Prioritization of Economic Problems in the Mass Public. *Review of Policy Research,* 38(2), pp. 164-179.

Hiscox, M., J., Hainmueller, J., 2006. Learning to Love Globalization: The Effects of Education on Individual Attitudes towards International Trade. *International Organization.* 60(2), pp. 469-498.

Honaker, J., King, G., & Blackwell, M., 2011. Amelia II: A Program for Missing Data. *Journal of Statistical Software.* 45(7), pp. 3-47.

Iversen, T., Soskice, D., 2001. An Asset Theory of Social Policy Preferences. *American Political Science Review.* 95(4), pp. 875-893.

Jeffrey, K., 2021. Automation and the Future of Work: How Rhetoric Shapes the Response in Policy Preferences. *Journal of Economic Behaviour and Organization,* Volume 192, pp. 417-433.

Johnston, Christopher D., Howard G. Lavine, and Christopher M. Federico. *Open versus Closed: Personality, Identity, and the Politics of Redistribution.* New York: Cambridge University Press. 2017

Jost, J. T. (2015). Resistance to Change: A Social Psychological Perspective. *Social Research, 82*(3), 607-636.

Kurer, T. & Häusermann, S., 2022. “Automation and social policy: Which policy responses do at-risk workers support?” In Busemeyer et al (eds.) *Digitalization and the Welfare State.* Oxford University Press.

Lauterbach, A. S., Tober, T., Kunze, F., & Busemeyer, M. R. (2023). Can welfare states buffer technostress? Income and technostress in the context of various OECD countries. *PLOS ONE, 18*(12). doi:https://doi.org/10.1371/journal.pone.0295229

Margalit, Y., 2019. Political Responses to Economic Shocks. *Annual Review of Political Science.* Volume 22, pp. 277-295.

Moene, K., O., Wallerstein, M., 2001. Inequality, Social Insurance and Redistribution. *American Political Science Review.* 95(4), pp. 859-874.

Nedelkoska, L. & Quintini, G., 2018. *Automation, skills use and Training - OECD Social, Employment and Migration Working Papers, no. 202.* Paris, FR: OECD.

O’Grady, T., 2019. How do Economic Circumstances Determine Preferences? Evidence from Long-run Panel Data. *British Journal of Political Science.* 49(4), pp. 1381-1406.

Oesch, D., 2006.Coming to Grips with a Changing Class Structure: An Analysis of Employment Stratification in Britain, Germany, Sweden and Switzerland. *International Sociology.* 21(2), pp. 263-288.

Owen, E., Johnston, N., P., 2017. Occupation and the Political Economy of Trade: Job Routineness, Offshorability and Protectionist Sentiment. *International Organization.* 71(4), pp. 665-699.

Rehm, P., 2016. *Risk Inequality and Welfare States: Social Policy Preferences, Development and Dynamics.* New York City, NY: Cambridge University Press.

Schwander, H., & Häusermann, S. (2013). Who is in and who is out? A risk-based conceptualization of insiders and outsiders. *Journal of European Social Policy, 23*(3), 248-269.

Sebastian, R., 2018. Explaining job polarisation in Spain from a task perspective. *SERIEs,* Volume 9, pp. 215-248.

Širá, Elena, Roman Vavrek, Ivana Kravčáková Vozárová, and Rastislav Kotulič. "Knowledge economy indicators and their impact on the sustainable competitiveness of the EU countries." Sustainability 12, no. 10 (2020): 4172.

Tarafdar, M., Pullins, E. B., & Ragu-Nathan, T. S. (2015). Technostress: negative effect on performance and possible mitigations. *Information Systems Journal*, *25*(2), 103-132.

Thewissen, S. & Rueda, D., 2019. Automation and the welfare state: Technological change as a determinant of redistribution preferences. *Comparative Political Studies,* 52(2), pp. 171-208.

Webb, M., 2020. The Impact of Artificial Intelligence on the Labor Market. *Stanford Working Paper.*

Weisstanner, David. 2023. ‘Technological Change and Labour Market Policy Preferences’ In Handbook of Labour Market Policy in Advanced Democracies, eds. D. Clegg and N. Durazzi. Cheltenham: Edward Elgar. 132–147.

Zhang, B., 2019. No Rage Against the Machines: Threat of Automation Does Not Change Policy Preferences. *MIT Political Science Department Research Paper No. 2019-25.*