The Threat of Automation and Public Support for Environmental Policy

Valentina González-Rostani* Liam F. Beiser-McGrath† Michaël Aklin‡

Abstract

The rise of automation has transformed economies around the world. We examine how its effects spill over and affect people's views about environmental issues and policies. We argue that the long-term economic threat posed by automation is expected to reduce environmental concern amongst those affected due to a deprioritization of problems with high levels of uncertainty and that require deep reforms to be addressed. Therefore, we expect automation risk to subsequently reduce support of environmental policy that imposes immediate direct costs, such as carbon taxation. Meanwhile, support for policies with diffuse costs, such as environmental subsidies, will only be affected by automation indirectly, to the extent that it reduces individuals' general environmental concern. Using European Social Survey data from 2002 to 2018 for 23 European countries, our analysis reveals that individuals exposed to automation are less likely to hold environmental concerns and less supportive of carbon taxes that impose immediate visible costs. Mediation analysis suggests that automation reduces support for environmental policies through its negative effect on environmental concern, with this effect being larger for subsidies. Our findings have important implications for understanding how structural transformations in the economy shape individuals' preferences for tackling long-term societal problems like climate change.

Keywords: automation, globalization, environmental attitudes

*Department of Political Science, University of Pittsburgh. Email: mag384@pitt.edu.

†Department of Social Policy, London School of Economics and Political Science. Email: liam@liambeisermcgrath.com.

‡Department of Political Science, University of Pittsburgh. Email: aklin@pitt.edu.

1 Introduction

Automation – the replacement of human labor by machines – has transformed economies around the world over the last decades. Aside from its impact on the labor market, automation has also been found to have broad political consequences, increasing people's hostility toward globalization and paving the way for populist and extremist political regimes (e.g., Frey, Berger, and Chen, 2017; Bisbee et al., 2020; Owen, 2020; Gallego and Kurer, 2022). These structural transformation may have been accelerated with the unexpected Covid-19 and the widespread of telemarketing (e.g., Coombs, 2020).

While there is considerable evidence that automation directly affects economic and political views, it is much less clear whether its effects spillover to indirectly related areas. Notably – and the topic of this paper – we know little about its consequences on individuals' concerns about long-term societal problems such as climate change.

In this paper, we argue that automation has significant impacts upon individuals' environmental concern and support for environmental policies, due to the long-term economic insecurity it implies. In contrast to short-run economic shocks, automation generates considerable long-term economic uncertainty for individuals that ultimately reduces their concern for competing long-term issues such as climate change. Automation therefore is expected to reduce environmental policy support in two ways. First, it does so by generating a generalized lack of concern for the environment. Second, it makes individuals being particularly sensitive to policy options that impose direct visible costs, such as carbon taxation, which compound upon the long-term economic vulnerability individuals face.

We test our hypotheses using data from the European Social Survey (ESS), the International Social Survey Programme (ISSP), and two indices of exposure to automation from information provided by respondents about their occupations (Autor, 2013; Frey and Osborne, 2017). Using a rich set of individual, industry, and country characteristics, as well as a variety of fixed effects we aim to isolate the effect of automation risk upon environmental concern and policy preferences.

Our findings support the empirical implications of our theoretical argument. First, we find that individuals with higher risks of automation are, on average, less concerned about the environment. Second, automation risk is associated with lower support for environmental policies that impose direct immediate costs upon individuals (such as carbon taxes). However, it does not directly reduce support for policies with less visible (diffuse) costs, such as subsidies. Third, using mediation analysis, we find that automation risk reduces support for all environmental policies through its negative impact on environmental concern. However, this effect is much smaller than the direct effect of automation risk upon policy support for carbon taxes, and is offset by a small positive direct effect of automation risk upon policy support for subsidies.

This paper contributes to the lively literature on the effect of economic shocks on environmental attitudes (see, *inter alia*, Elliott, Seldon, and Regens, 1997; Shum, 2012; Scruggs and Benegal, 2012; Mildenberger and Leiserowitz, 2017; Bakaki and Bernauer, 2018; Kolcava, Nguyen, and Bernauer, 2019; Beiser-McGrath, 2022). This literature has typically considered either the role of macro shocks or individual level effects on support in favor of environmental policies. At the macro level, several studies show that unemployment reduces support across the world (Brulle, Carmichael, and Jenkins, 2012; Scruggs and Benegal, 2012; Kenny, 2017). These results stand in sharp contrast with micro-level studies. Bakaki and Bernauer (2018) use data from a survey fielded in Brazil and find neither support for an individual-level nor for a sociotropic effect of the economy on environmental attitudes. Mildenberger and Leiserowitz (2017) use a longitudinal survey fielded in 2008 and 2011 to leverage within-individual variation and find little evidence that adverse conditions affect support for climate action.

Aside from its substantive novelty – little work has so far connected automation to environmental attitudes – we believe our study addresses several limitations of the existing literature. First, past studies tend to use blunt measures of individual vulnerability. Some work focuses on aggregate or regional shocks, such as unemployment. But unemployment rates offer only indirect evidence that a given individual's livelihood is at risk. Permanently-employed bureaucrats, for instance, may not be particularly sensitive to this metric. And subjective assessments of economic hard times – another often used measure – runs the risk of being inaccurately reported. We contribute by offering a tailored and objective measure of exposure to labor market risks at the individual level.

Second, most studies examine the effect of *past* shocks rather than *future* expectations. Consider again the effect of a higher unemployment rate. From the perspective of an individual, this shock has been realized (she is either unemployed or not) and has limited impart about how she perceives the future. But presumably, what may lead individuals to become hostile to environmental regulation is a threat about their future well-being.

Third, most of the shocks examined in the literature tend to be temporary. Generally, the majority of people who lose their job find a new one. In the United States, the share of unemployed individuals who have not found a job after six months has historically been between 10 and 25% and never more than 50%, even during the Great Recession.[1] While the plight of those who are umployed in the long term is indeed dramatic, it represents a minority of the cases. Our study sheds light on a different type of shock: one where those affected face a permanent loss of income, except if they retrain and change their fundamental skill set. And this shock looms large. According to Frey and Osborne (2017), about half of the workforce of a country like the United States is at risk of computerization. The stakes are thus high.

The paper proceeds as follows. In the next section we develop our theoretical logic, that explains why automation leads to a decline in environmental concern and policy support. We additionally distinguish between differential effects of automation for policies with direct versus diffuse costs. The next section then describes our research design and empirical strategy. The results of our empirical analysis, which showcase the correlation between automation risk, environmental concern, and policy support, are presented in a subsequent section. Finally, we provide concluding remarks in the last section.

2 Argument

In this section, we develop our theoretical logic for how automation affects environmental preferences. We start by reviewing the key economic consequences of automation and its significant consequences for individuals' policy preferences. From there, we discuss the literature on the

[1] "Of Total Unemployed, Percent Unemployed 27 Weeks & over," FRED Economic Data, https://fred.stlouisfed.org/series/LNS13025703.

economy-environment trade-off, which generally finds economic conditions to only weakly impact environmental preferences. Finally, we develop our theoretical argument to resolve the potential contradiction between the importance of automation at large and the weak evidence of an economy-environment trade-off. We do so by explaining how the long-term structural nature of automation is qualitatively different from the contemporaneous economic downturns previously examined in the economy-environment trade-off literature. This longer term *prospective* economic risk is thus expected to have a significant impact on environmental preferences. Finally, we explain variation in the direct and indirect effect of automation upon climate policy preferences, differentiating between policies that impose visible direct costs versus uncertain, diffuse costs.

2.1 Automation

Automation and the economy

The risks of automation for the economic prosperity of individuals has received significant attention from researchers in the past decade. While it is not the first time that technological change has impacted employment and the economy, automation has the potential to be far more disruptive and cause greater instability. Two key aspects of automation are noteworthy. First, rather than simply reducing employment in certain industries, automation renders the need for certain skills obsolete. Thus, while in the past low-skilled agricultural workers could relocate to the manufacturing industry and then to the service sector in response to technological change (Floud, McCloskey, and McCloskey, 1994, 100), there are few lateral options resulting from increased automation. Second, automation disrupts the existing low versus high skilled cleavages evident in various industries. High skilled professions, requiring advanced degrees, are at risk if they are susceptible to routinization. Therefore large swathes of high skilled occupations, such as radiologists and geological technicians, amongst others (Frey and Osborne, 2017), are at risk. This widens the scope of the impact of economic change, challenging the nature of traditional interest groups and political coalitions.

Along these lines, our third point is that the consequences of automation are unequally distributed between routine- and capital-biased occupations, which has led to job polarization (e.g, Autor, 2013; Acemoglu and Restrepo, 2018*a*; Dauth et al., 2018; Graetz and Michaels, 2018; Kurer and Gallego, 2019). Routine occupations, mainly middle-skill and middle-wage jobs, prevalent in blue- and white-collar sectors (e.g., manufacturing, administration) are shrinking. Scholars have named this process as *hollowing out the middle*. In the US, for example, the middle four deciles of the income distribution has experienced a decline in their income share from 0.46 in 1980 to 0.4 in 2014 (Milner, 2021*a*). Given the non-trivial role of the middle class as an agent of democratization and policy definitions, understanding the effect of automation matters for politics writ large (e.g, Lipset, 1959; Moore, 1966; Boix, 2003; Acemoglu, Acemoglu, and Robinson, 2006).

The emerging social science literature on the impact of automation started with the identification of which occupations and tasks are at risk. Building upon the task framework outlined in Autor, Levy, and Murnane (2003), the Routine Task Intensity (RTI) index is commonly used to measure any given occupation's risk of being automated (Autor, 2013; Goos, Manning, and Salomons, 2014), with more routine tasks being at risk. Frey and Osborne (2017) also consider routineness to be an important component of automation risk. However, they develop a future orientated measure of automation risk, using subjective expert coding of automation risk and objective data from O*NET, an online service run by the US Department of Labor.

From this point, research began to focus on understanding the economic impact of the forms of automation that have occurred so far. Theoretical work delineates under which conditions we would expect automation to lead to increased unemployment, inequality, and lower incomes. Acemoglu and Restrepo (2018*b*) show that inequality increases during transitions driven both by faster automation and introduction of new tasks, and characterize the conditions under which inequality is increasing or stable in the long run. Acemoglu and Restrepo (2018*b*) emphasize the importance of the form of automation. While low-skill automation increases wage inequality, high skill automation reduces it.

Turning to empirical research in this area, Acemoglu and Restrepo (2017) look at the increased use of industrial robots in the past decades. They find that in US commuting zones that experienced large increases in industrial robot usage, there were significant negative effects upon local employment and wages.[2] This provides evidence that there is indeed cause for concern that the equilibrium impact of automation will be negative. Jobs made redundant by automation will not necessarily be offset with the creation of new jobs.

Automation and policy preferences

Moving beyond this the economic impacts of automation, a recent body of research considers its impact on individuals' political preferences and behavior (Gallego et al., 2022).

First, several studies show that automation affects political and policy preferences. Thewissen and Rueda (2019) focus on how automation affects individuals' policy preferences. Specifically, they argue that individuals in routine occupations, more at risk from automation, will support increased public insurance to protect against the increased threat of future income loss resulting from automation. Using data from the European Social Survey, they find that individuals in more routine occupations are more supportive of government efforts to reduce differences in income levels. Additionally, highly educated individuals are more sensitive to this risk, as they likely have more to lose from automation. Kurer and Häusermann (2021) show that at-risk workers are more likely to support unemployment protection policies, but there are limited changes in the support for education and labor market reintegration policies. Automation effects on redistribution preferences are still in dispute. In a similar spirit, Owen (2020) examines attitudes toward free-trade and whether they depend on risk of automation. Individual with routine-task occupations are expected to be more protectionists. Owen (2020) finds support for this expectation using survey data from ESS and the ISSP. We note that recent studied offer a more ambiguous picture and do not find significant results for the demands for protection (Gallego, Kurer, and Scholl, 2021; Dermont and Weisstanner, 2020).

Second, automation also has consequences for political behavior more broadly. Frey, Berger, and Chen (2017) examine the potential impact of automation on voting. Empirically they find a relationship between the percentage of routine jobs in a congressional district and Trump's vote share in the 2016 US Presidential election. Similarly, studies have shows a connection between

[2] In the US commuting zones are geographical units intended to represent local economic areas, of which there are approximately 700.

exposure to technological change and support for radical right parties – which often run on environmentally skeptic platforms (e.g, Frey, Berger, and Chen, 2017; Owen, 2020; Gingrich, 2019; Im et al., 2019; Kurer, 2020; Milner, 2021*b*; Colantone, Ottaviano, and Stanig, 2021; Anelli, Colantone, and Stanig, 2019).

2.2 The economy-environment trade-off

Having discussed the impact of automation on economic outcomes, and as a result individuals' policy preferences, we now turn to reviewing the economy-environment trade-off. While the changing nature of the economy due to automation is often forward-looking, research on the economy and environmental preferences typically focuses on contemporaneous economic downturns and their consequences.

The original received wisdom of this research, both academically (Kahn and Kotchen, 2011; Scruggs and Benegal, 2012; Shum, 2012; Brulle, Carmichael, and Jenkins, 2012) and in policy circles (Kitcher, 2010; Howell, 2013), is that economic downturns lead to a decline in environmental concern. Green policies are a luxury good (Abou-Chadi and Kayser, 2017), and thus deprioritized when faced with immediate economic problems.

In spite of the intuitive appeal of this logic, empirical evidence is generally inconsistent. At the macro level, several studies conducted across the world show that unemployment reduces support for environmental policies (Brulle, Carmichael, and Jenkins, 2012; Scruggs and Benegal, 2012; Kenny, 2017). These results stand in contrast with micro-level studies. Bakaki and Bernauer (2018) use data from a survey fielded in Brazil and find neither support for an individual-level nor for a sociotropic effect of the economy on environmental attitudes. Mildenberger and Leiserowitz (2017) use a longitudinal survey fielded in 2008 and 2011 to leverage within-individual variation and find little evidence that adverse conditions affect support for climate action. However, recent research on the impact of COVID-19 on the prioritisation of the environment over the economy using within-individual variation does in fact find a deprioritisation of the environment in times of crisis (Beiser-McGrath, 2022).

2.3 Automation and environmental attitudes: hypotheses

How do we resolve the importance of automation for understanding current political economy with the weak evidence for the economy-environment trade-off? Our contention is that *contemporaneous* economic downturns do not have strong effects of environmental concern, as individuals may view them as transient or have already internalized their impact. In contrast, structural economic shifts, as generated by automation, fundamentally change individuals' assessments of *long-run* (expected) economic trajectories which makes individuals less concerned about future-oriented issues such as climate change and the environment.

We now spell out the logic behind our key hypotheses. Hypothesis 1 focuses on the effect of automation on environmental *preferences*. Hypotheses 2 and 3 extend the causal chain to the effect of automation on environmental *policy*, distinguishing between its direct and indirect effects.

Structural economic change and environmental concern

Automation poses a fundamental change the economy that displaces existing occupations' value. As a result affected individuals' likely hold a risk-averse position towards transitions, and thus favor the status quo. The green transition, additionally, poses a fundamental reorganization of economic activity, both in terms of displacing existing industries as well as forms of economic activity within industries. Moreover, recent research finds that low-carbon jobs are fundamentally more skills-intensive (Sato et al., 2023).

In this regard, the green transition is often explicitly linked to technological transitions as a means of achieving more efficient use of scarce resources (World Economic Forum, 2017; Vinuesa et al., 2020). A prominent example often referred to in this context is autonomous vehicles (Hancock, Nourbakhsh, and Stewart, 2019). The under-discussed implication in this case however is that such innovations obviate the need for large classes of workers: those whose tasks and behavior have the potential to be automated. More generally, policy efforts often explicitly involve the use of artificial intelligence and machine learning (Joppa, 2017; Rolnick et al., 2019), tools whose effectiveness rely on reducing the extent of human involvement in decision-making processes by automating routine tasks, thereby rendering large numbers of jobs obsolete.

Overall, then, policies that contribute to and accelerate the secular automation of the economy ought to be rejected by workers at risk of automation. Incidentally, automation has already been shown to offer promising opportunities in green manufacturing and in mining for clean energy materials (Li et al., 2012; Tabor et al., 2018).

Thus individuals' at risk from automation will exhibit less environmental concern. The prospective economic risks from the green transition outweigh any potential benefit, particularly in industrialized economies that are less affected from the immediate consequences of environmental issues such as climate change (Gazmararian and Milner, 2022). As a result individuals' deprioritize the environment as a long term issue to focus on, given the long-term economic risk they face. To the extent that individuals recognize this risk, and feel unable to substitute to alternative professions, they should be opposed to environmental action.

This leads to the following empirical implication:

Hypothesis 1. ***Environmental Concerns****: Individuals at risk from automation will have lower levels of environmental concern.*

Automation's mediated impact on environmental policy preferences

Building upon this, we expect that the impact of automation upon environmental policy support is mediated through this differential concern. To do so, we differentiate between climate policies that impose direct immediate costs to individuals (such as carbon taxes) and those who provide tangible benefits while having diffuse cost structures (such as subsidies).

Individuals who expect future income losses are less supportive of environmental policy that imposes direct immediate costs (Arndt, Halikiopoulou, and Vrakopoulos, 2022). In this case, individuals' are clearly confronted with the costs of dealing with environmental problems, making stark the trade-off between policy action and potential loss of well-being.

Given our previous discussion, we expect that the extent to which automation has a direct and/or indirect effect upon policy preferences depends upon the nature of the policy. For policies with clear immediate costs, such as carbon taxes, automation risk will have a negative direct effect as future economic losses are compounded by the policy instrument. In contrast, for policies with diffuse costs, such as subsidies, automation risk is unlikely to have a significant direct effect. This is both due to the fact that individuals' are less sensitive to the costs imposed and may also believe that they would benefit from the public goods provided by the subsidies.

However, automation risk should have an indirect effect upon support for green policies with diffuse costs, due to the mediating impact of automation risk on environmental concern discussed previously. In this case the reduction in environmental concern generated by automation risk spills over into a lower propensity to support environmental policy in general.

This leads to the following empirical implications:

Hypothesis 2. ***Direct Effect****: The direct effect of risk from automation upon environmental policy support will be stronger for carbon taxation than for subsidies.*

Hypothesis 3. ***Indirect Effect****: Support for subsidies will be reduced by the indirect effect of automation via its reduction of environmental concern more than support for carbon taxation.*

3 Research Design

We test our core hypotheses against two sets of surveys, the ESS and the ISSP. We include all available waves of the ESS. For ISSP, we include the subset of surveys that include questions that are relevant for us, as discussed next.

3.1 Data

Descriptive statistics for all variables are reported in Tables 4 (ESS 1-8), 5 (ISSP), and 6 (ESS 8).

Exposure to technological change

Our key independent variable is an individual's exposure to automation, which we approach using two different measures. First, we consider an influential measure developed by Frey and Osborne (2017) for the US case (*Frey-Osborne index*). Second, we use the routine task intensity (*RTI*) index developed by Goos, Manning, and Salomons (2014) for European countries. We discuss each of these variables next, but first note that these two measures are based on the 'task' approach Autor, Levy, and Murnane (2003); Autor (2013, 2015), by which individual occupations and tasks have important consequences for workers' exposure to risks and economic well-being. This approach assumes that occupation characteristics determines whether workings will be harmed by (or benefit from) automation.

The measure developed by Frey and Osborne (2017) utilizes expert assessments, and machine learning to create their forward looking measure of automation risk. This measure provides the probability of computerization for the US Department of Labor's dictionary of occupations. It predicts the potential (current and future) risks of technological change based on routineness and the predictability of non-routine tasks that can be replaced given the development of artificial intelligence and robotics.

The RTI index also relies on the task approach developed by Autor, Levy, and Murnane (2003); Autor (2013, 2015). This index provides measures susceptibility to automation based upon the degree of routineness of a task. The more routine a task, the easier and thus greater likelihood it will be automated. This is calculated by logging the routine task score per occupation, and subtracting the manual and abstract components of the task (Goos, Manning, and Salomons, 2014). The more routine a task is, the easier it is for a machine to execute it, and thus the more likely it will be replaced by a robot. The index ranges from -1.5, the typical score for managers of small enterprises, to 2.2, as in the case of office clerks.

The Frey-Osborne and RTI indices are thus similar, but not identical. First, the measurement approach differs between the two. RTI focuses explicitly on the routineness of tasks as being the main risk from automation, whereas Frey and Osborne (2017) model the potential for exposure to automation spreading to non-routine domains too (e.g, given the development of artificial intelligence). The measures also differ in their typical geographical usage. The Frey-Osborne index was developed for the case of the US using O*NET data, while the RTI has mainly been used to measure exposure to automation across European countries (see for example, Thewissen and Rueda, 2019; Gingrich, 2019; Milner, 2021*b*).

To link automation scores, we rely on information provided by the surveys about the occupation of each respondent. The ESS reports detailed information about respondents' occupations. We use the variable that contains the International Standard Classification of Occupations (ISCO-08 and ISCO-88) to build our independent variable. The RTI index is defined using two-digit of the ISCO-88. Since occupations are coded using ISCO-08 from the 6th ESS wave onward, we standardize this occupation to the classification using ISCO-88.[3] Likewise, the Frey-Osborne index uses the Standard Occupational Classification (SOC) 2010. We build the latter using a conversion from SOC to ISCO-88 following Thewissen and Rueda (2019).

Before discussing our outcomes of interest, we want to discuss two challenges for our analysis. First, one may wonder whether individuals are aware of how exposed to automation they are. To validate the use of the two objective measures we use, we correlate them with subjective perceptions of job insecurity, job dissatisfaction, how hard it is to find a job, and how concerned respondents are to lose their job. Table 3 reports that these measures are related, showing the increase at the extremes of the distribution of risks (these variables are positively and significantly correlated). This is further supported by data from the OECD Risks That Matter project, Figure 2 shows a positive correlation between fear of automation and occupations (specifically, the RTI index at 1-isco digit). People know that they are at risk.

Second, as noted by Busemeyer and Tober (2022), we are aware that the standardized measured based on occupations lose a relevant proportion of the proportion of variation between individuals. However, we expect this lack of variation to create a downward bias for our estimates.

Environmental Concern and Policy Preferences

The first stage of our analysis involves estimating the association between automation and environmental concern, using Waves 1-8 of ESS. For sake of space, we leave the analysis of ISSP data to the appendix, but note that the two provide very similar findings (in magnitude and statistical significance). Our outcome question captures respondents' self-reported concerns regarding the environment. The survey asks respondents whether they agree or disagree with the follow-

[3]The harmonization comes from Thewissen and Rueda (2019).

ing statements “people should care for nature” and whether “looking after the environment is important to her/him.” Respondents should posit themselves on a 6-point scale ranging from 1 (not like me at all) to 6 (very much like me). This question is the only one available about pro-environmental attitudes for all the survey waves.

The second stage of our analysis involves estimating the association between automation and policy preferences, and exploring whether this is mediated by environmental concern. For this analysis, we rely on individual-level data from the 8th wave of ESS (2016). This is the first wave to contain a module with a large number of items covering public attitudes to climate change, energy security, and energy preferences. This wave, therefore, allows us to explore mechanisms connecting automation to environmental policy.

We operationalize policy preferences in three ways. The first outcome measures an environmental policy with clear direct costs for individuals: whether respondents favor increasing *taxes on fossil fuels* to reduce climate change or not. Our second outcome measures an environmental policy with less visible (or diffuse) costs for individuals (*subsidies*). We use a question about whether respondents favor subsidizing renewable energy to reduce climate change. Finally, ESS also includes an item on *appliance bans* which asks respondents whether they favor banning the sale of least energy-efficient household appliances to reduce climate change. We consider this outcome to be in the middle of the direct-diffuse cost continuum.

To measure environmental concern (our mediator), we use four variables. The first is the same as in the first step of the analysis. The last three are derived from the 8th wave of ESS. These are the following. First, *personal responsibility to reduce climate change*, which ranges from 1 “not at all” to 5 “to a great deal.” Second, whether *climate change has a good or bad impact across the world*, ranging from 1 “extremely good” to 5 “extremely bad.” Third and finally, we study responses to *how worried about climate change they are*, which range from 1 “not at all worried” to 5 “extremely worried.”.

Finally, we replicate our analysis with data from the ISSP, which contains several questions in different waves (1993, 1996, 2000, 2010, 2016). The surveys from 1993, 2000, and 2010 include questions about their willingness to protect the environment by supporting two fiscal instruments with direct costs for respondents: paying higher prices or higher taxes. Then, the surveys from 1996 and 2010 contain a question that asks about respondents' willingness to support higher government spending to protect the environment. These variables go from 1 "strongly disagree" to 5 "strongly agree."

Potential confounders

The literature on political behavior discusses several other factors that may affect individuals' political preferences. Drawing from this work, we include in the model individual demographic controls for age, sex, years of education, an indicator for being a religious believer, union membership, and whether the respondent was unemployed (e.g. Frey, Berger, and Chen, 2017; Gingrich, 2019; Thewissen and Rueda, 2019). These variables were also included by Demski et al. (2018) as individual socio-economic determinants of environmental policy preferences.

We also control for variables at the country level. The data come from the OECD database. Based on economic hardship literature, we expect lower GDP growth to lead to lower environmental concerns. We also include social spending as a percentage of GDP, and we expect it to correlate with environmental concerns positively. Finally, we incorporate economic and institutional control variables, such as openness from the Comparative Political Data Set (CPDS) and the foreign-born rate. These variables allow us to include some proxy for economic crises and globalization. We expect them to be negatively related to environmental concerns.

Finally, in our robustness tests we use fixed effects at the industry and year level to partial out unobserved industry characteristics that are associated with our automation measures and exposure to common shocks.

3.2 Models

Our theoretical framework will be evaluated with two models: a cross-sectional analysis with multiple years and countries; and a causal mediation analysis linking automation and support for environmental regulations.

First, we test whether automation risks shape individuals' environmental concerns (**Hypothesis**

1). For that, we exploit cross-sectional variation on all waves available of the ESS. The data has a multi-level structure with individuals are nested within countries. We employ a hierarchical model that includes a random intercept by countries to account for this structure. This model allows us to model the impacts of individual and contextual factors on environmental concerns.

Second, to better understand the mechanisms behind the link between automation risk and environmental policy preferences (**Hypotheses 2 and 3**), we conduct causal mediation analyses proposed by Imai et al. (2011).

Automation risk and environmental concerns

In order to evaluate the empirical relationship between automation risks and environmental concerns (**Hypothesis 1**) we estimate a linear regression model that takes the following form:

$$Y_i = \beta_0 + \beta_1 \text{Automation Risk}_i + \beta_3 X_i + \gamma Z_{j[i]} + \mu_{j[i]} + \epsilon_{it} \quad (1)$$

where Y_i captures the environmental concerns of the respondent i. *Automation Risk*$_i$ is the index of computerization based on Frey and Osborne (2017). X_{it} is a vector which captures various individual-level control variables, whereas $Z_{j[i]}$ is a vector of country-level predictors of environmental concerns. The impact of the country-level predictors is measured by the γ coefficients; where $\mu_{j[i]}$ indicates the hierarchical random intercept by country; and ϵ_{it} is the error term.

Our theoretical framework predicts that as exposure to automation risks increases, the environmental concerns will decrease. Thus, we expect β_1 to be positive.

Exploring mechanisms: automation risks and environmental policy preferences

We explore the mechanism linking automation risks and the support for environmental policies. We use the approach to causal mediation analysis proposed by Imai et al. (2011); Imai and Yamamoto (2013); Imai, Tingley, and Yamamoto (2013). The causal mediation analysis allows us to estimate two relevant quantities: i) average causal mediation effect (ACME) and ii) average direct effect (ADE). Jointly, the ACME and ADE constitute the average treatment effect (ATE) or total effect of the treatment on the outcome of interest. The ATE is the difference in expectations of the average outcomes of treated individuals and untreated. The ACME is the portion of the treatment's effect that goes through mediators. The remaining treatment effect is ADE.

To test **Hypotheses 2 and 3** we use data from the 8th wave of the ESS. We use the same outcomes (taxes, subsidies, and appliance bans) and primary treatment (automation risk). We use four indicators as plausibly capturing our mediator (environmental concerns): i) importance of the environment, ii) personal responsibility to act against climate change, iii) concerns about climate change, and iv) expected negative impact of climate change.

4 Results

4.1 Environmental concern

The effects of automation risks on environmental concerns are presented in Table 1.[4] All the models contain standard errors clustered by country. Column 1 presents the bivariate model between automation risks and environmental concerns. Columns 2 to 3 incorporate individual-level predictors of environmental concerns. Column 5 includes country-level predictors. Column 6 addresses potential heterogeneous effects by industry and occupation (using ISCO 1-digit indicators). Finally, column 7 accounts for possible temporal trends by incorporating year fixed effects.

These relationships are significant and substantively in line with our theoretical expectations. Automation risks are positively associated with a decrease in environmental concerns. These estimates imply that a one-unit increase in automation risks (which corresponds approximately to one standard deviation) leads to 0.16 standard deviation decrease in an individual's environmental concern. The relationship is robust across all specifications. These results, therefore, provide empirical support for our **Hypothesis 1** that at-risk individuals are less concerned about looking after the environment.

Our results are also robust to additional model specifications. First, one concern that may emerge is about the standardized measures of automation, and how much what we are capturing is specific to the exposure to risk or industry and occupations dynamics. Thus, we add dum-

[4]See the complete Table with control variables in Appendix Table 7.

Frey-Osborne and environmental concerns

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Environmental concerns							
Computerization (F&O)	-0.155***	-0.099***	-0.091***	-0.081***	-0.060***	-0.044*	-0.044*
	(0.012)	(0.012)	(0.010)	(0.010)	(0.011)	(0.024)	(0.023)
Demographics		✓	✓	✓	✓	✓	✓
Indiv. Econ			✓	✓	✓	✓	✓
Politics				✓	✓	✓	✓
Societal Socio-econ					✓	✓	✓
Industry						✓	✓
Occupations (1 digit)						✓	✓
Year FE							✓
Observations	246160	244441	190634	174658	121077	63661	63661
# Countries	23	23	23	23	17	16	16

Table 1: Standard errors in parentheses * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$
Dependent variable: level of disagreement with the statement "strongly believes that people should care for nature." Answers range from "Not like me at all" (= 1) to "Very much like me" (= 6). Country random effects included but not reported. Standard errors clustered by country. Source: ESS (1-8) data.

mies at the industry level using NACE Rev. 2, and dummies per occupation group using ISCO 1-digit. Second, using a different operationalization of automation risk does not affect our results. We replicate the analysis with RTI index as our independent variable.[5] Third, we incorporated industry-level determinants of pollution (greenhouse emissions, N20 emissions, particulates emissions) using data from Eurostat. None of these industry-level pollution predictors have statistically significant effects on individual levels of environmental concerns in our analysis and our key results remain unchanged.[6]

Lastly, we account for heterogeneous institutional backgrounds by including additional covariates about public policies and interacting them with automation risk exposure. Table 12 from the appendix shows that the results remain unchanged. Our results echo those of Gingrich (2019), indicating that the expansion of public services and regulation of the labor market have limited effect compensating the increased risk of automation.

[5]Tables 8 and 9 in the Appendix.
[6]Tables 10 and 11 in the Appendix.

4.2 Environmental policy preferences

We now turn to examining how this affects environmental policy preferences. We start our analysis by estimating the association between automation risk and environmental concern (the mediators) as well as environmental policy preferences (the outcomes).

The results are reported in Table 2. The first four columns (1-4) show the relationship between automation risks and environmental concerns (the mediators). We find that individuals with more exposure to automation risks are less concerned about the environment. All estimated coefficients are negative and statistically significant except for column 1, which is positive but substantively the same (larger values mean fewer concerns). Therefore, we have further empirical evidence in line with **Hypothesis 1** across a broader set of measures of environmental concern.

The last three columns (5-7) show the relationship between automation risks and policy preferences for environmental regulations. In line with **Hypothesis 2**, we find that automation risk primarily reduces support for policies that impose direct costs. We find a statistically significant negative relationship between automation risks and support for higher carbon taxation (Column 5). In contrast, we do not find a statistically nor substantively significant relationship between automation risk and support for subsidies (Column 6). Interestingly, support for inefficient appliance bans are found to be significantly lower amongst those at risk from automation (Column 7), but not to the same degree as support for carbon taxation. This likely reflects that such bans are in the middle ground of direct vs. indirectness of costs faced by individuals.

This initial evidence suggests that automation risk impacts the political feasibility of policies aimed to increase the cost of emissions through taxes and product bans rather than the instruments to fund the adoption of renewable. Thus, it sheds preliminary empirical support for **Hypothesis 2**.[7]

[7] Results remain unchanged if we estimate multi-level models clustered by country with several country-level indicators, and adding extra individual level variables (see 21 in Appendix). Results are also robust to the incorporation of a dummy per occupation using ISCO 1-digit code (see Table 22 in Appendix).

Automation risks, environmental concerns and support for environmental policies.

	Mediators				Policies		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Env Concerns	Responsability	Worry	Climate Change	Carbon Tax	Subsides	Ban
Computerization	-0.072***	-0.175***	-0.062***	-0.045***	-0.102***	-0.024	-0.053**
(F&O)	(0.019)	(0.020)	(0.017)	(0.016)	(0.022)	(0.019)	(0.021)
Demographics	✓	✓	✓	✓	✓	✓	✓
Indiv. Econ	✓	✓	✓	✓	✓	✓	✓
Industry	✓	✓	✓	✓	✓	✓	✓
Observations	35406	34048	34610	33499	34536	34995	34760
# Countries	22	22	22	22	22	22	22
R^2	0.030	0.041	0.020	0.012	0.032	0.016	0.011

Table 2: Standard errors in parentheses * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$
Dependent variables comes from ESS 8. Dependent variables in Columns 1-4 are the mediators: Importance of environment, which comes from the level of disagreement with the statement "strongly believes that people should care for nature." Answers range from "Not like me at all" (= 1) to "Very much like me" (= 6); Climate change has bad impact, which range from (= 1) "extremely good" to (= 5) "extremely bad"; personal responsibility to act, which range from (= 1) "not at all" to (= 5) "to a great deal"; worried about climate change, which range from (= 1) "not at all worried" to (= 5) "extremely worried".
Dependent variables in Columns 5-7 are the primary outcomes: *support for carbon tax* (ranges from 'against' (= 1) to 'great support' (= 5)); *support for subsidies* (range from 'against' (= 1) to 'great support' (= 5)); *support for banning inefficient appliances* (ranges from 'against' (= 1) to 'great support' (= 5)).

We now turn to examining whether automation's impact on policy preferences is mediated through its impact upon environmental concern (**Hypothesis 3**). Figure 1 displays the results of our causal mediation analysis.[8]

Looking at the total effect, our estimates suggest that the treatment (automation risks) decreases the support for carbon taxation policies and for banning inefficient appliances. The negative impact is larger for carbon taxation, as we expect. Moreover, we fail to reject the hypothesis of no effect of automation on subsidies.

What is driving these effects? Our mediation analysis highlights two important findings. First, automation reduces support for all policies via its effect on environmental attitudes. However, that mediated effect is generally quite small (in absolute terms). Second, the effect of automation is primarily a direct one that operates, presumably, via the cost effect of policies. The direct effect (ADE) is negative and large for carbon taxes, negative but small and indistinguishable from zero for appliance bans, and positive (and insignificant) for subsidies.

[8]Table 23 reports the sensitivity analysis of these results.

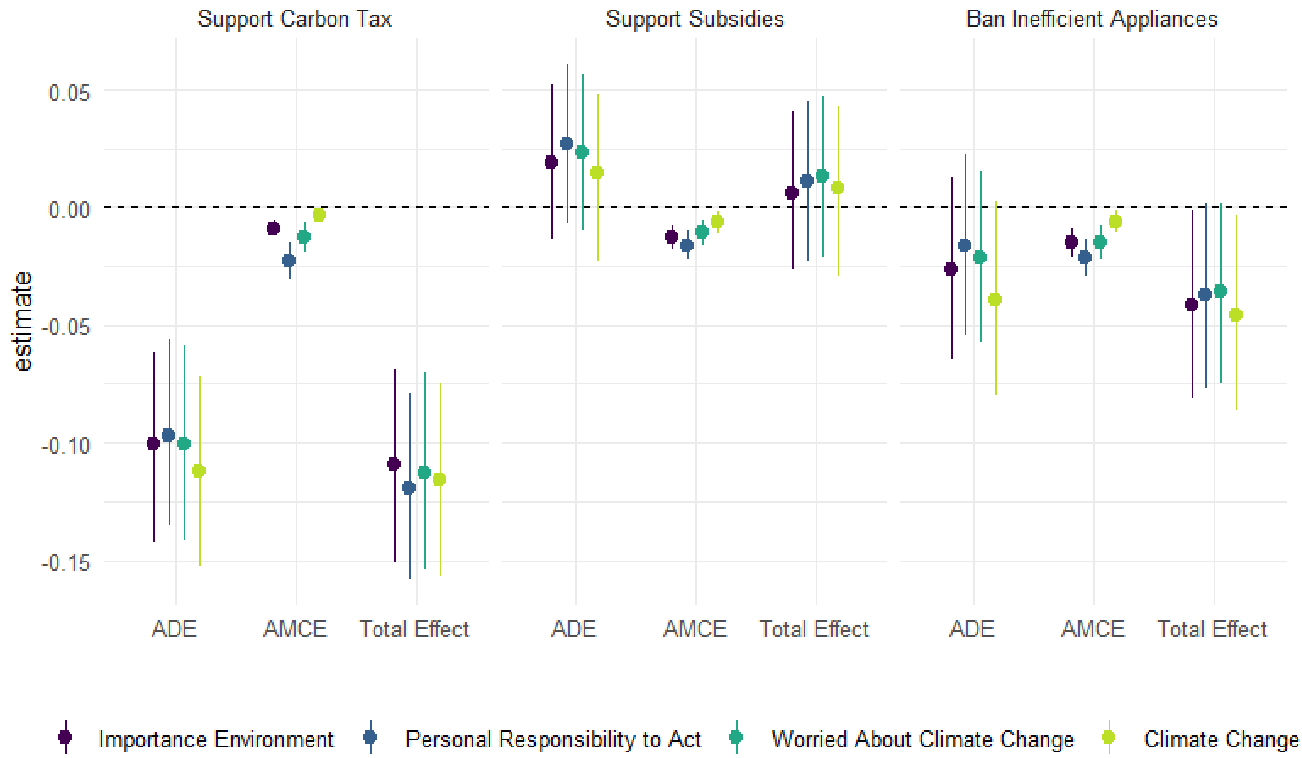

Figure 1: Effect of Automation Risk on Environmental Policy Preferences

Mediators: Importance of environment, which comes from the level of disagreement with the statement "strongly believes that people should care for nature." Answers range from "Very much like me" (= 1) to "Not like me at all" (= 6); Climate change has bad impact, which range from (= 1) "extremely good" to (= 5) "extremely bad"; personal responsibility to act, which range from (= 1) "not at all" to (= 5) "to a great deal"; worried about climate change, which range from (= 1) "not at all worried" to (= 5) "extremely worried".The treatment variable is exposure to automation approached following Frey and Osborne (2017). Data comes from the 8th wave of the ESS. The points indicate the estimated effect of automation risks, with lines displaying 95% confidence intervals generated through simulation from a robust variance-covariance matrix.

These results provide evidence consistent with our hypotheses. **Hypothesis 2** states that the direct effect of risk from automation upon environmental policy support should be stronger for carbon taxation than subsidies because the former policy imposes direct, immediate costs on individuals. Moreover, we also find empirical support for **Hypothesis 3**, which suggests that the support for subsidies will be only reduced by the indirect effect of automation risks. To put it differently, the decline of environmental concerns will explain the reduction in support for subsidies rather than automation directly.

Substantively, we see an interesting pattern that emerges when comparing these three policies. The null effect for automation risk on preferences for renewables subsidies seems to arise due to two oppositely signed effects. The direct effect of automation risk upon support for subsidies is positive when accounting for the mediating impact of personal responsibility. However, this effect is counteracted by automation risk weakening an individual's environmental concern.

This finding further suggests that policy instruments focused on green investment, such as renewable energy do not themselves generate backlash from those at risk. However, for them to be accepted politically they have to overcome the generalized lack of concern for the environment that is generated by economic dislocation. This is in contrast to market-based instruments that incentivize emissions reductions through increasing costs. There the negative impacts on policy support are primarily driven by opposition to the policy itself, rather than declining environmental concern. By failing to provide new options for those potentially left behind explicitly, such instruments create new constituencies against environmental policy. The implicit catalyzing effect that is increasing the cost of CO2 consumption is supposed to generate, appears to be insufficient to avoid a backlash in environmental support among those at risk.

Finally, we test for the robustness of our results on policy preferences by replicating the analysis using data for the ISSP survey. Unfortunately, the survey only contains preferences for policies to protect the environment rather than measuring environmental concerns. Also, the questions are all associated with policies that impose direct, immediate effects on citizens, such as paying higher prices or taxes and supporting higher government spending. Thus we could only estimate regressions between automation and policy preferences in multiple years using hierarchical models with random effects by country. Tables 13 to 20 show the estimation of the relationship between automation risks and direct environmental policies. Our estimates again show a negative and statistically significant association for different specifications of the independent variable and including several control variables.

5 Conclusion

Does the fourth Industrial Revolution threaten the support for policies regulating the environment? While an emerging and growing group of scholars has investigated the political consequences of automation of labor tasks on policy preferences for redistribution (Kurer and Häusermann, 2021; Thewissen and Rueda, 2019; Gallego et al., 2022; Dermont and Weisstanner, 2020) and how at-risk individuals react against the status quo supporting far-right populist parties (Im et al., 2019; Milner, 2021*b*; Kurer, 2020; Owen, 2020; Gingrich, 2019), we have limited knowledge thus far about the mechanisms linking automation risks and these broader social preferences. We do not know how exposure to automation risks affects long-term societal problems like climate change.

Utilizing comprehensive data sets of post-industrialized countries, we have shown that the exposure to the risk of automation affects both individuals' environmental concern and support for environmental policies. In particular, policies that impose clear direct costs upon individuals (such as carbon taxes), receive significantly less support amongst those at risk from automation. Automation risk also indirectly affects all policy types, due to its association with reduced environmental concern (an important predictor of policy support).

These findings have important implications for understanding the political economy of environmental policy efforts. First, in response to insufficient mitigation policies, academics and policy experts have championed technological solutions as means to bypass political conflict and gridlock. The findings in this paper suggest that technological solutions are no silver bullet. Those with a high risk of losing their jobs from automation are more likely to oppose policies to mitigate climate change. Technological solutions to climate change thus have the potential to broaden further a potential new constituency of individuals opposed to ambitious climate policy the more widespread they are used.

Second, it is not pre-determined that environmental policy will generate a backlash from those "left behind" by technological innovation. The findings suggest that focusing on investment and subsidies in green industries may avoid a backlash among those with higher job risks. This echoes an emerging body of research that has examined how revenue usage from carbon pricing (Kotchen, Turk, and Leiserowitz, 2017; Beiser-McGrath and Bernauer, 2019; Dolšak, Adolph, and Prakash, 2020) and the pairing of social and environmental policies (Bergquist, Mildenberger, and Stokes, 2020) affects the political feasibility of ambitious environmental policy. In contrast, policies imposing tangible and direct costs on the consumer, such as carbon taxes and product bans, generate opposition amongst those at risk from continuing technological change. Recognizing these potential grievances, magnified by technological solutions to climate change, and responding with appropriate policy designs, will likely ensure old political conflicts over climate policy are not simply replaced by newer ones.

While our analysis has provided much-needed insight into how structural economic changes such as automation affect the support for environmental policies, several areas remain for future research. First, so far, we have only focused our analysis on policy preferences. A natural future step is to explore whether the decline of environmental concerns also mediates individual vote choices, such as negatively affecting green parties or increasing the support for far-right populist parties with anti-climate change rhetoric. Second, this analysis is limited to citizens, and the supply side of politics is also an essential part of the puzzle. Future work could unpack whether political leaders from areas with higher regional exposure to automation risks are less likely to emphasize environmental policies with direct costs for individuals. Third, our analysis is limited to industrialized countries, and future works should be expanded to developing countries.

References

Abou-Chadi, Tarik, and Mark A Kayser. 2017. "It's not easy being green: Why voters punish parties for environmental policies during economic downturns." *Electoral Studies* 45: 201–207.

Acemoglu, Daron, and Pascual Restrepo. 2017. "Robots and Jobs: Evidence from US Labor Markets." NBER Working Paper 23285.

Acemoglu, Daron, and Pascual Restrepo. 2018*a*. "Low-skill and high-skill automation." *Journal of Human Capital* 12 (2): 204–232.

Acemoglu, Daron, and Pascual Restrepo. 2018*b*. "The Race Between Man and Machine: Implications of Technology for Growth, Factor Shares and Employment." *American Economic Review* .

Acemoglu, Professor Daron, Daron Acemoglu, and James A. Robinson. 2006. *Economic Origins of Dictatorship and Democracy*. Cambridge University Press.

Anelli, Massimo, Italo Colantone, and Piero Stanig. 2019. "We Were the Robots: Automation and Voting Behavior in Western Europe." Working Paper.

Anelli, Massimo, Italo Colantone, and Piero Stanig. 2021. "Individual vulnerability to industrial robot adoption increases support for the radical right." *Proceedings of the National Academy of Sciences* 118 (47).

Arndt, Christoph, Daphne Halikiopoulou, and Christos Vrakopoulos. 2022. "The centre-periphery divide and attitudes towards climate change measures among Western Europeans." *Environmental Politics* 0 (0): 1–26.

Autor, David. 2013. The" task approach" to labor markets: an overview. Technical report National Bureau of Economic Research.

Autor, David. 2015. "Why are there still so many jobs? The history and future of workplace automation." *Journal of economic perspectives* 29 (3): 3–30.

Autor, David H., Frank Levy, and Richard J. Murnane. 2003. "The Skill Content of Recent Technological Change: An Empirical Exploration." *The Quarterly Journal of Economics* 118 (4): 1279–1333.

Bakaki, Zorzeta, and Thomas Bernauer. 2018. "Do economic conditions affect public support for environmental policy?" *Journal of Cleaner Production* 195: 66–78.

Beiser-McGrath, Liam F. 2022. "COVID-19 led to a decline in climate and environmental concern: evidence from UK panel data." *Climatic Change* 174 (3): 31.

Beiser-McGrath, Liam F., and Thomas Bernauer. 2019. "Could revenue recycling make effective carbon taxation politically feasible?" *Science Advances* 5 (9): eaax3323.

Bergquist, Parrish, Matto Mildenberger, and Leah C. Stokes. 2020. "Combining climate, economic, and social policy builds public support for climate action in the US." *Environmental Research Letters* 15 (5): 054019. Publisher: IOP Publishing.

Bisbee, James, Layna Mosley, Thomas B. Pepinsky, and B. Peter Rosendorff. 2020. "Decompensating domestically: the political economy of anti-globalism." *Journal of European Public Policy* 27 (7): 1090–1102.

Boix, Carles. 2003. *Democracy and Redistribution*. Cambridge University Press.

Brulle, Robert J, Jason Carmichael, and J Craig Jenkins. 2012. "Shifting public opinion on climate change: an empirical assessment of factors influencing concern over climate change in the US, 2002–2010." *Climatic change* 114 (2): 169–188.

Busemeyer, Marius R., and Tobias Tober. 2022. "Dealing with Technological Change: Social Policy Preferences and Institutional Context." *Comparative Political Studies* p. 00104140221139381.

Colantone, Italo, Gianmarco IP Ottaviano, and Piero Stanig. 2021. "The backlash of globalization.".

Coombs, Crispin. 2020. "Will COVID-19 be the tipping point for the Intelligent Automation of work? A review of the debate and implications for research." *International Journal of Information Management* 55: 102182.

Dauth, Wolfgang, Sebastian Findeisen, Jens Suedekum, and Nicole Woessner. 2018. "Adjusting to Robots: Worker-Level Evidence.".

Demski, Christina, Wouter Poortinga, Lorraine Whitmarsh, Gisela Böhm, Stephen Fisher, Linda Steg, Resul Umit, Pekka Jokinen, and Pasi Pohjolainen. 2018. "National context is a key determinant of energy security concerns across Europe." *Nature Energy* 3 (10): 882–888.

Dermont, Clau, and David Weisstanner. 2020. "Automation and the future of the welfare state: basic income as a response to technological change?" *Political Research Exchange* 2 (1): 1757387.

Dolšak, Nives, Christopher Adolph, and Aseem Prakash. 2020. "Policy design and public support for carbon tax: Evidence from a 2018 US national online survey experiment." *Public Administration* 98 (4): 905–921.

Elliott, Euel, Barry J Seldon, and James L Regens. 1997. "Political and economic determinants of individuals' support for environmental spending." *Journal of Environmental Management* 51 (1): 15–27.

Floud, Roderick, Deirdre Nansen McCloskey, and Donald N McCloskey. 1994. *The economic history of Britain since 1700*. Vol. 1 Cambridge university press.

Frey, Carl Benedikt, and Michael A. Osborne. 2017. "The future of employment: How susceptible are jobs to computerisation?" *Technological Forecasting and Social Change* 114: 254–280.

Frey, Carl Benedikt, Thor Berger, and Chinchih Chen. 2017. "Political machinery: Automation anxiety and the 2016 US presidential election." *University of Oxford* .

Gallego, Aina, Alexander Kuo, Dulce Manzano, and José Fernández-Albertos. 2022. "Technological Risk and Policy Preferences." *Comparative Political Studies* 55 (1): 60–92.

Gallego, Aina, and Thomas Kurer. 2022. "Automation, digitalization, and artificial intelligence in the workplace: implications for political behavior." *Annual Review of Political Science* 25: 463–484.

Gallego, Aina, Thomas Kurer, and Nikolas Bahati Scholl. 2021. "Neither Left-Behind nor Superstar: Ordinary Winners of Digitalization at the Ballot Box." *The Journal of Politics* p. 714920.

Gazmararian, Alexander F., and Helen V. Milner. 2022. "Political Cleavages and Changing Exposure to Global Warming." *Working Paper* .

Gingrich, Jane. 2019. "Did state responses to automation matter for voters?" *Research & Politics* 6 (1): 2053168019832745.

Goos, Maarten, Alan Manning, and Anna Salomons. 2014. "Explaining job polarization: Routine-biased technological change and offshoring." *American economic review* 104 (8): 2509–26.

Graetz, Georg, and Guy Michaels. 2018. "Robots at Work." *The Review of Economics and Statistics* 100 (5): 753–768.

Hancock, P. A., Illah Nourbakhsh, and Jack Stewart. 2019. "On the future of transportation in an era of automated andautonomous vehicles." *Proceedings of the National Academy of Sciences* 116 (16): 7684–7691.

Howell, Lee. 2013. Global risks 2013. World Economic Forum.

Im, Zhen Jie, Nonna Mayer, Bruno Palier, and Jan Rovny. 2019. "The "losers of automation": A reservoir of votes for the radical right?" *Research & Politics* 6 (1): 2053168018822395.

Imai, Kosuke, Dustin Tingley, and Teppei Yamamoto. 2013. "Experimental designs for identifying causal mechanisms." *Journal of the Royal Statistical Society: Series A (Statistics in Society)* 176 (1).

Imai, Kosuke, Luke Keele, Dustin Tingley, and Teppei Yamamoto. 2011. "Unpacking the Black Box of Causality: Learning about Causal Mechanisms from Experimental and Observational Studies." *American Political Science Review* 105 (4): 765–789.

Imai, Kosuke, and Teppei Yamamoto. 2013. "Identification and Sensitivity Analysis for Multiple Causal Mechanisms: Revisiting Evidence from Framing Experiments." *Political Analysis* 21 (2): 141–171.

Joppa, Lucas N. 2017. "The case for technology investments in the environment." *Nature* 552: 325–328.

Kahn, Matthew E, and Matthew J Kotchen. 2011. "Business cycle effects on concern about climate change: the chilling effect of recession." *Climate Change Economics* 2 (03): 257–273.

Kenny, Michael. 2017. "Back to the populist future?: understanding nostalgia in contemporary ideological discourse." *Journal of Political Ideologies* 22 (3): 256–273.

Kitcher, Philip. 2010. "The Climate Change Debates." *Science* 328 (5983): 1230–1234.

Kolcava, Dennis, Quynh Nguyen, and Thomas Bernauer. 2019. "Does trade liberalization lead to environmental burden shifting in the global economy?" *Ecological Economics* 163: 98–112.

Kotchen, Matthew J., Zachary M. Turk, and Anthony A. Leiserowitz. 2017. "Public willingness to pay for a US carbon tax and preferences for spending the revenue." *Environmental Research Letters* 12 (9): 094012.

Kurer, Thomas. 2020. "The Declining Middle: Occupational Change, Social Status, and the Populist Right." *Comparative Political Studies* p. 0010414020912283.

Kurer, Thomas, and Aina Gallego. 2019. "Distributional consequences of technological change: Worker-level evidence." *Research & Politics* 6 (1): 2053168018822142.

Kurer, Thomas, and Silja Häusermann. 2021. "Automation and social policy: Which policy responses do at-risk workers support?". Working Paper.

Li, Jingshan, James R Morrison, Mike Tao Zhang, Masaru Nakano, Stephan Biller, and Bengt Lennartson. 2012. "Automation in green manufacturing." *IEEE Transactions on Automation Science and Engineering* 10 (1): 1–4.

Lipset, Seymour Martin. 1959. "Some Social Requisites of Democracy: Economic Development and Political Legitimacy." *American Political Science Review* 53 (1): 69–105.

Mildenberger, Matto, and Anthony Leiserowitz. 2017. "Public opinion on climate change: Is there an economy–environment tradeoff?" *Environmental Politics* 26 (5): 801–824.

Milner, Helen V. 2021*a*. "Is Global Capitalism Compatible with Democracy? Inequality, Insecurity, and Interdependence." *International Studies Quarterly* 65 (4): 1097–1110.

Milner, Helen V. 2021*b*. "Voting for Populism in Europe: Globalization, Technological Change, and the Extreme Right." *Comparative Political Studies* p. 0010414021997175.

Moore, Barrington. 1966. *Social Origins of Dictatorship and Democracy: Lord and Peasant in the Making of the Modern World*. Beacon Press.

Owen, Erica. 2020. "Firms vs. Workers? The Political Economy of Labor in an Era of Global Production and Automation." Working Paper.

Rolnick, David, Priya L. Donti, Lynn H. Kaack, Kelly Kochanski, Alexandre Lacoste, Kris Sankaran, Andrew Slavin Ross, Nikola Milojevic-Dupont, Natasha Jaques, Anna Waldman-Brown, Alexandra Luccioni, Tegan Maharaj, Evan D. Sherwin, S. Karthik Mukkavilli, Konrad P. Kording, Carla Gomes, Andrew Y. Ng, Demis Hassabis, John C. Platt, Felix Creutzig, Jennifer Chayes, and Yoshua Bengio. 2019. "Tackling Climate Change with Machine Learning." https://arxiv.org/abs/1906.05433.

Sato, Misato, Leanne Cass, Aurélien Saussay, Francesco Vona, and Leo Mercer. 2023. "Skills and wage gaps in the low-carbon transition: comparing job vacancy data from the US and UK." *Working Paper* .

Scruggs, Lyle, and Salil Benegal. 2012. "Declining public concern about climate change: Can we blame the great recession?" *Global Environmental Change* 22 (2): 505–515.

Shum, Robert Y. 2012. "Effects of economic recession and local weather on climate change attitudes." *Climate Policy* 12 (1): 38–49.

Tabor, Daniel P., Loïc M. Roch, Semion K. Saikin, Christoph Kreisbeck, Dennis Sheberla, Joseph H. Montoya, Shyam Dwaraknath, Muratahan Aykol, Carlos Ortiz, Hermann Tribukait, Carlos Amador-Bedolla, Christoph J. Brabec, Benji Maruyama, Kristin A. Persson, and Alán Aspuru-Guzik. 2018. "Accelerating the discovery of materials for clean energy in the era of smart automation." *Nature Reviews Materials* 3 (5): 5–20.

Thewissen, Stefan, and David Rueda. 2019. "Automation and the Welfare State: Technological Change as a Determinant of Redistribution Preferences." *Comparative Political Studies* 52 (2): 171–208. Publisher: SAGE Publications Inc.

Vinuesa, Ricardo, Hossein Azizpour, Iolanda Leite, Madeline Balaam, Virginia Dignum, Sami Domisch, Anna Felländer, Simone Daniela Langhans, Max Tegmark, and Francesco Fuso Nerini. 2020. "The role of artificial intelligence in achieving the Sustainable Development Goals." *Nature Communications* 11 (1): 233.

World Economic Forum. 2017. *Harnessing the Fourth Industrial Revolution for the Earth*.

Appendix

A Figures

A.1 Preamble

Probability	Automation Pr = 0	Automation Pr = 1	Variation
Worried about losing job	0.048	0.060	25%
Difficult to find a new job	0.907	0.924	2%
Job dissatisfaction	0.825	0.838	2%
Job security	0.206	0.220	7%

Table 3: Automation Risks (objective - occupations) and perception to risk (subjective).
Data comes from ISSP

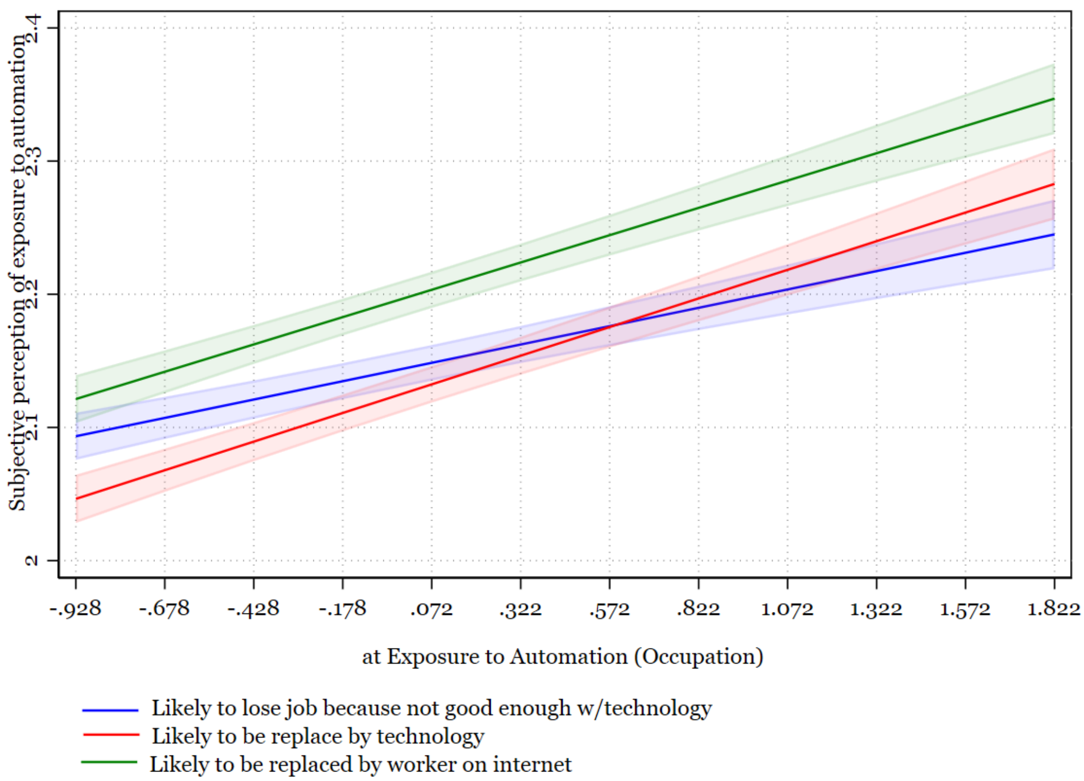

Figure 2: Automation Risks (objective - occupations) and perception to risk (subjective).

Data comes from OECD Risks That Matter 2020. RTI aggregated following Busemeyer and Tober (2022)

A.2 Mediation Analysis

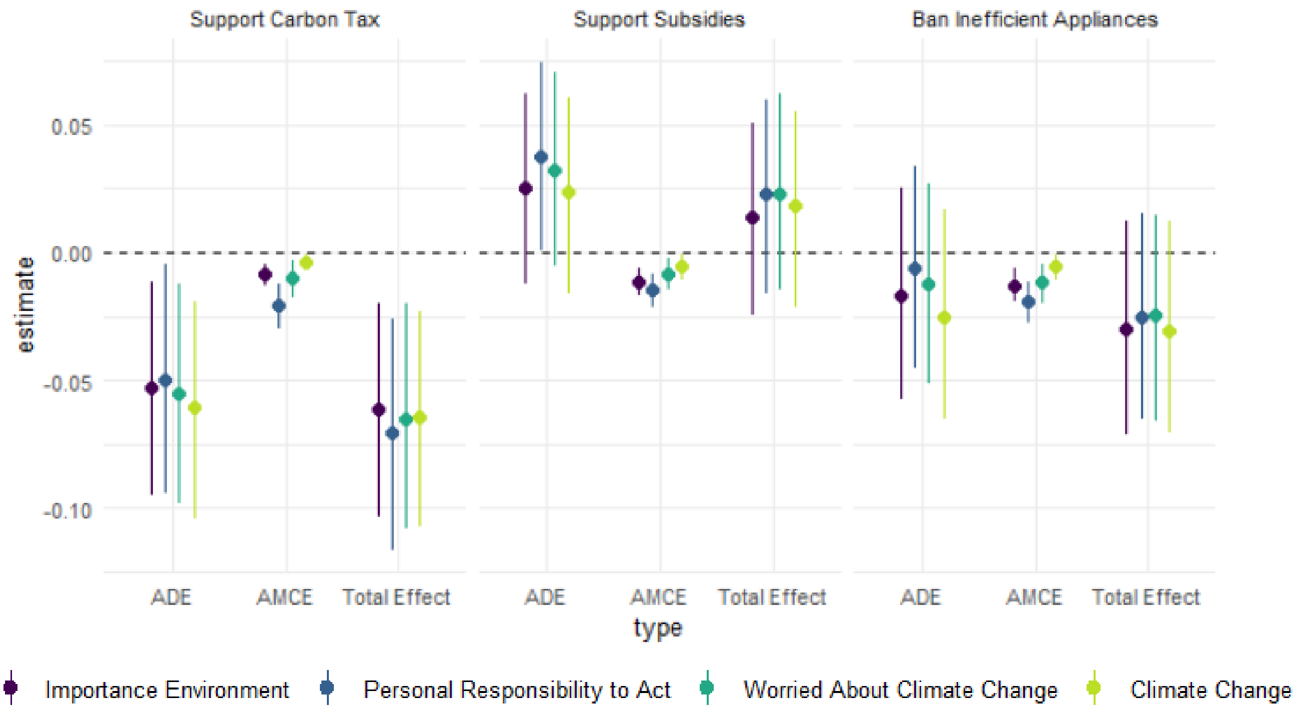

Figure 3: Effect of Automation Risk on Environmental Policy Preferences (w/industry included)

Mediators: Importance of environment, which comes from the level of disagreement with the statement "strongly believes that people should care for nature." Answers range from "Not like me at all" (= 1) to "Very much like me" (= 6); Climate change has bad impact, which range from (= 1) "extremely good" to (= 5) "extremely bad"; personal responsibility to act, which range from (= 1) "not at all" to (= 5) "to a great deal"; worried about climate change, which range from (= 1) "not at all worried" to (= 5) "extremely worried".The treatment variable is exposure to automation approached following Frey and Osborne (2017). Data comes from the 8th wave of the ESS. The points indicate the estimated effect of automation risks, with lines displaying 95% confidence intervals generated through simulation from a robust variance-covariance matrix.

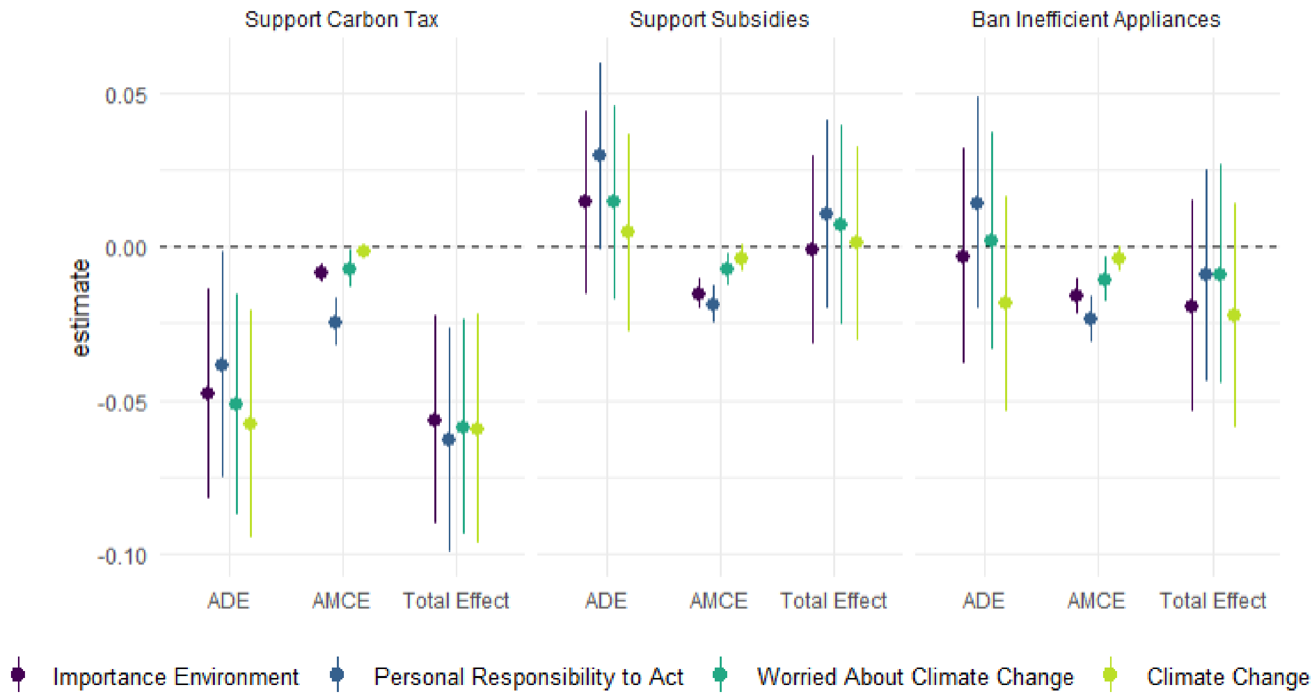

Figure 4: Effect of Automation Risk on Environmental Policy Preferences (w/occupation dummies included)

Mediators: Importance of environment, which comes from the level of disagreement with the statement "strongly believes that people should care for nature." Answers range from "Not like me at all" (= 1) to "Very much like me" (= 6); Climate change has bad impact, which range from (= 1) "extremely good" to (= 5) "extremely bad"; personal responsibility to act, which range from (= 1) "not at all" to (= 5) "to a great deal"; worried about climate change, which range from (= 1) "not at all worried" to (= 5) "extremely worried".The treatment variable is exposure to automation approached following Frey and Osborne (2017). Data comes from the 8th wave of the ESS. The points indicate the estimated effect of automation risks, with lines displaying 90% confidence intervals generated through simulation from a robust variance-covariance matrix.

B Tables

B.1 Summary Statistics

Descriptive statistics

	Mean	Median	S.D.	Min.	Max	Obs.
Environmental concerns	4.90	5.00	1.01	1	6	315157
Routine (RTI)	-0.05	-0.33	0.98	-2	2	264628
Computerization (F&O)	0.55	0.64	0.33	0	1	254754
Education years	12.63	12.00	4.24	0	25	327329
Gender-male	0.47	0.00	0.50	0	1	327197
Age	49.28	49.00	17.94	18	99	327329
Religious	4.59	5.00	3.04	0	10	324813
Income	1.00	0.85	0.73	0	48	246855
Unemployed	0.04	0.00	0.19	0	1	327329
Left-right	5.09	5.00	2.15	0	10	290094
Union membership	0.42	0.00	0.49	0	1	323932
Social Expenditure	22.38	22.23	4.43	13	32	327329
Openness	102.98	86.95	44.76	48	281	297286
GDP growth	2.21	2.19	2.28	-5	10	327329
Foreign Population	9.21	7.98	7.75	0	74	221073
Unemployment	7.96	7.41	3.96	2	25	327329
Manufacture	0.18	0.00	0.38	0	1	293831
Greenhouse emissions	12385353.53	1668376.18	29408965.67	0	362122633	227383
N2O emissions	2092.26	47.50	9032.49	0	123313	227383
Particulates emissions	2784.05	228.17	7749.00	0	110683	227383

Table 4: Summary statistics of all variables used in this study.
Source: ESS (1-8) data.

Descriptive statistics ISSP

	Mean	Median	S.D.	Min.	Max	Obs.
Protect environment: taxes/govmnt spending	2.28	2.00	1.07	0	4	43326
Govmnt spend: environment	2.58	3.00	0.88	0	4	17904
Protect enviro: pay much higher prices	1.80	2.00	1.18	0	4	25615
Protect enviro: pay much higher taxes	2.07	2.00	1.14	0	4	25422
RTI index	-0.08	-0.40	1.01	-2	2	170702
Computerization (F & O)	0.50	0.56	0.32	0	1	127483
Gender-male	0.50	1.00	0.50	0	1	220804
Age	42.74	43.00	11.74	21	65	220823
Education years	13.11	13.00	4.65	0	97	211141
Religious	4.70	5.00	1.49	1	6	176484
Unemployed	0.15	0.00	0.36	0	1	220823
Union membership	0.49	0.00	0.50	0	1	211166
Left-right	3.17	3.00	2.04	0	10	186881
Social Expenditure	23.73	24.66	4.64	13	34	220823
Openness	83.91	73.27	33.58	38	191	220823
GDP growth	1.80	1.87	2.06	-8	10	220823
Foreign Population	9.24	7.71	6.18	1	55	174795

Table 5: Summary statistics of all variables used in this study. Source: ISSP data (1993, 1996, 2000, 2010 and 2016).

Descriptive statistics ESS 8

	Mean	Median	S.D.	Min.	Max	Obs.
RTI index	-0.13	-0.44	0.95	-2	2	35511
Computerization (F&O)	0.51	0.51	0.33	0	1	40499
Education	14.88	14.00	7.83	1	27	44170
Age	49.14	49.00	18.61	15	100	44232
Gender-female	0.53	1.00	0.50	0	1	44378
Economic Insecurity	1.97	2.00	0.90	1	4	40612
Environmental concerns	4.82	5.00	1.05	1	6	43628
Personal Responsability	3.23	3.40	1.09	1	5	41927
Worried about Environment	3.01	3.00	0.93	1	5	42654
Impact Climate Change	3.69	3.80	0.88	1	5	41232
Support Carbon Tax	2.77	3.00	1.23	1	5	42401
Support Subsides	3.94	4.00	1.07	1	5	42983
Ban Inefficient Appliances	3.53	4.00	1.17	1	5	42699

Table 6: Summary statistics of all variables used in this study. Source: ESS (8) data.

B.2 Main results with control variables and RTI

Multilevel-Analysis IV - Frey and Osborne

	(1) RTI Only	(2) Demographic	(3) Socio-Eco	(4) Politics	(5) EcoSocial	(6) Industry/Occ	(7) FE
Environmental concerns							
Computerization (F&O)	-0.155***	-0.099***	-0.091***	-0.081***	-0.060***	-0.044*	-0.044*
	(0.012)	(0.012)	(0.010)	(0.010)	(0.011)	(0.024)	(0.023)
Education years		0.017***	0.018***	0.016***	0.016***	0.016***	0.016***
		(0.002)	(0.002)	(0.002)	(0.002)	(0.003)	(0.003)
Gender-male		-0.080***	-0.075***	-0.073***	-0.065***	-0.053***	-0.052***
		(0.013)	(0.013)	(0.014)	(0.016)	(0.016)	(0.016)
Age		0.008***	0.009***	0.009***	0.009***	0.010***	0.010***
		(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Religious		0.018***	0.017***	0.021***	0.022***	0.021***	0.021***
		(0.002)	(0.002)	(0.002)	(0.003)	(0.003)	(0.003)
Income			-0.010	-0.006	-0.009	0.003	0.003
			(0.007)	(0.006)	(0.007)	(0.009)	(0.009)
Unemployed			0.047***	0.039**	0.061***	0.080***	0.080***
			(0.017)	(0.016)	(0.017)	(0.022)	(0.021)
Left-right				-0.032***	-0.036***	-0.036***	-0.035***
				(0.006)	(0.007)	(0.007)	(0.007)
Union membership				0.050***	0.044***	0.036***	0.035***
				(0.014)	(0.015)	(0.013)	(0.013)
Social Expenditure					-0.009**	-0.011*	-0.016**
					(0.005)	(0.006)	(0.007)
Openness					-0.000	0.000	-0.002
					(0.001)	(0.001)	(0.001)
GDP growth					-0.001	-0.006	0.003
					(0.005)	(0.009)	(0.009)
Foreign Population					0.000	0.002	0.002
					(0.002)	(0.002)	(0.002)
Industry						✓	✓
Occupations (1-digit)						✓	✓
Year FE							✓
Observations	246160	244441	190634	174658	121077	63661	63661
# Countries	23	23	23	23	17	16	16

Table 7: Standard errors in parentheses * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$
Dependent variable: level of disagreement with the statement "strongly believes that people should care for nature." Answers range from "Not like me at all" (= 1) to "Very much like me" (= 6). Source: ESS (1-8) data.

RTI and environmental concerns

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Environmental concerns							
Routine (RTI)	-0.012***	-0.011***	-0.009***	-0.010***	-0.005**	-0.030***	-0.029***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.010)	(0.010)
Demographics		✓	✓	✓	✓	✓	✓
Socio-econ			✓	✓	✓	✓	✓
Politics				✓	✓	✓	✓
Societal-Eco					✓	✓	✓
Industry						✓	✓
Occupations (1-digit)						✓	✓
Year FE							✓
Observations	255507	253749	197056	180636	126537	63734	63734
# Countries	23	23	23	23	17	16	16

Table 8: Standard errors in parentheses * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$
Dependent variable: level of disagreement with the statement "strongly believes that people should care for nature." Answers range from "Not like me at all" (= 1) to "Very much like me" (= 6). Country random effects included but not reported. Standard errors clustered by country. Source: ESS (1-8) data.

RTI and environmental concerns

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	RTI Only	Demographic	Socio-Eco	Politics	EcoSocial	Industry/Occ	FE
Environmental concerns							
Routine (RTI)	-0.012***	-0.011***	-0.009***	-0.010***	-0.005**	-0.030***	-0.029***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.010)	(0.010)
Education years		0.018***	0.018***	0.016***	0.016***	0.016***	0.016***
		(0.002)	(0.002)	(0.002)	(0.002)	(0.003)	(0.003)
Gender-male		-0.079***	-0.076***	-0.074***	-0.063***	-0.052***	-0.052***
		(0.013)	(0.015)	(0.015)	(0.017)	(0.015)	(0.015)
Age		0.009***	0.009***	0.009***	0.010***	0.010***	0.010***
		(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Religious		0.018***	0.018***	0.021***	0.022***	0.022***	0.022***
		(0.002)	(0.002)	(0.002)	(0.003)	(0.003)	(0.003)
Income			-0.007	-0.003	-0.007	0.001	0.001
			(0.006)	(0.005)	(0.006)	(0.009)	(0.009)
Unemployed			0.044**	0.040**	0.059***	0.077***	0.077***
			(0.018)	(0.018)	(0.020)	(0.024)	(0.023)
Left-right				-0.031***	-0.036***	-0.035***	-0.035***
				(0.006)	(0.007)	(0.007)	(0.007)
Union membership				0.043***	0.035**	0.030**	0.029**
				(0.014)	(0.015)	(0.014)	(0.014)
Social Expenditure					-0.009**	-0.010*	-0.017***
					(0.005)	(0.006)	(0.006)
Openness					-0.001	0.000	-0.002
					(0.001)	(0.001)	(0.001)
GDP growth					0.001	-0.004	0.004
					(0.005)	(0.009)	(0.009)
Foreign Population					0.001	0.004*	0.004*
					(0.001)	(0.002)	(0.002)
Industry						✓	✓
Occupations (1-digit)						✓	✓
Year FE							✓
Observations	255507	253749	197056	180636	126537	63734	63734
# Countries	23	23	23	23	17	16	16

Table 9: Standard errors in parentheses * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$
Dependent variable: level of disagreement with the statement "strongly believes that people should care for nature." Answers range from "Not like me at all" (= 1) to "Very much like me" (= 6). Country random effects included but not reported. Standard errors clustered by country. Source: ESS (1-8) data.

B.3 Robustness Checks - Emissions

Frey and Osborne and environmental concerns

	(1)	(2)	(3)	(4)	(5)	(6)
Environmental concerns						
Computerization (F&O)	-0.086***	-0.088***	-0.087***	-0.087***	-0.086***	-0.085***
	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)
Greenhouse emissions	-0.000			-0.000	-0.000	0.000
	(0.000)			(0.000)	(0.000)	(0.000)
N2O emissions		0.000		0.000	0.000	0.000
		(0.000)		(0.000)	(0.000)	(0.000)
Particulates emissions			-0.000	-0.000	-0.000	-0.000
			(0.000)	(0.000)	(0.000)	(0.000)
Manufacture						-0.022**
						(0.010)
Demographics	✓	✓	✓	✓	✓	✓
Socio-econ	✓	✓	✓	✓	✓	✓
Politics	✓	✓	✓	✓	✓	✓
Year FE					✓	✓
Country FE					✓	✓
Observations	138951	138951	138951	138951	138951	138951
# Countries	22	22	22	22	22	22

Table 10: Standard errors in parentheses * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$
Dependent variable: level of disagreement with the statement "strongly believes that people should care for nature." Answers range from "Not like me at all" (= 1) to "Very much like me" (= 6). Country random effects included but not reported. Standard errors clustered by country. Source: ESS (1-8) data.

RTI and environmental concerns

	(1)	(2)	(3)	(4)	(5)	(6)
Environmental concerns						
Routine (RTI)	-0.010***	-0.011***	-0.011***	-0.010***	-0.010***	-0.009***
	(0.004)	(0.003)	(0.004)	(0.004)	(0.004)	(0.003)
Greenhouse emissions	-0.000			-0.000	-0.000	-0.000
	(0.000)			(0.000)	(0.000)	(0.000)
N2O emissions		0.000		0.000**	0.000***	0.000**
		(0.000)		(0.000)	(0.000)	(0.000)
Particulates emissions			0.000	0.000	0.000	0.000
			(0.000)	(0.000)	(0.000)	(0.000)
Manufacture						-0.021**
						(0.009)
Demographics	✓	✓	✓	✓	✓	✓
Socio-econ	✓	✓	✓	✓	✓	✓
Politics	✓	✓	✓	✓	✓	✓
Year FE					✓	✓
Country FE					✓	✓
Observations	142448	142448	142448	142448	142448	142448
# Countries	22	22	22	22	22	22

Table 11: Standard errors in parentheses * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$
Dependent variable: level of disagreement with the statement "strongly believes that people should care for nature." Answers range from "Not like me at all" (= 1) to "Very much like me" (= 6). Country random effects included but not reported. Standard errors clustered by country. Source: ESS (1-8) data.

B.4 Interactions

Exposure to Automation and Safety nets

	(1)	(2)	(3)	(4)	(5)	(6)
Environmental concerns						
Computerization (F&O)	-0.089***	-0.086***	-0.117***	-0.079***	-0.113*	-0.206***
	(0.014)	(0.013)	(0.025)	(0.020)	(0.060)	(0.034)
Expenditure Job Creation	-0.114					
	(0.146)					
Exp*Job Creation	0.032					
	(0.132)					
Expenditure Early Retirement		-0.134**				
		(0.064)				
Exp*Early Retirement		0.035				
		(0.022)				
Labor market programs			-0.063***			
			(0.013)			
Exp*LM Programs			0.016			
			(0.012)			
Expenditure for unemployment				-0.080***		
				(0.018)		
Exp*Unemp Spending				-0.002		
				(0.013)		
Social Expenditure					-0.008	
					(0.006)	
Exp*Soc Spending					0.001	
					(0.002)	
Education Spending						-0.005
						(0.038)
Exp*Edu Spending						0.023***
						(0.005)
Demographics	✓	✓	✓	✓	✓	✓
Socio-econ	✓	✓	✓	✓	✓	✓
Politics	✓	✓	✓	✓	✓	✓
Observations	148385	140195	182676	167106	218209	159837
# Countries	23	20	22	23	23	22

Table 12: Standard errors in parentheses * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$
Dependent variable: level of disagreement with the statement “strongly believes that people should care for nature.” Answers range from “Not like me at all” (= 1) to “Very much like me” (= 6). Country random effects included but not reported. Standard errors clustered by country. Source ESs surveys (1-8).
Safety nets variables comes from OECD data. Job creation: public and private mandatory expenditure on direct job creation as a % of GDP; public and private mandatory expenditure on early retirement for labour market; labor market programs: total expenditure as a percentage of GDP; expenditure for unemployment benefits as a percentage of GDP; social expenditure as a percentage of GDP; education expenditure as a percentage of GDP.

B.5 Robustness Checks - ISSP data

RTI and willingness to pay higher prices/government spending to protect environment

	(1)	(2)	(3)	(4)	(5)
Protect env.: prices/govmnt spending					
RTI index	-0.046***	-0.026***	-0.027***	-0.026***	-0.035***
	(0.011)	(0.007)	(0.007)	(0.008)	(0.009)
Demographics		✓	✓	✓	✓
Socio-econ			✓	✓	✓
Politics				✓	✓
Societal-Eco					✓
Observations	30708	17518	17518	14719	12789
# Countries	14	14	14	14	13

Table 13: Standard errors in parentheses * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$
Dependent variable: comes from ISSP surveys years 1993, 1996, 2000, 2010, 2016. It combines a question whether respondents will be willing to protect the environment by paying higher prices (1993, 2000 and 2010) and another one about government spending (1996 and 2016). From 0 (strongly disagree) to 4 (strongly disagree).

Frey and Osborne and willingness to pay higher prices/government spending to protect environment

	(1)	(2)	(3)	(4)	(5)
Protect env.: prices/govmnt spending					
Computerization (F & O)	-0.332***	-0.224***	-0.232***	-0.244***	-0.256***
	(0.037)	(0.038)	(0.036)	(0.034)	(0.039)
Demographics		✓	✓	✓	✓
Socio-econ			✓	✓	✓
Politics				✓	✓
Societal-Eco					✓
Observations	23520	13239	13239	10989	9273
# Countries	14	14	14	14	13

Table 14: Standard errors in parentheses * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$
Dependent variable: comes from ISSP surveys years 1993, 1996, 2000, 2010, 2016. It combines a question whether respondents will be willing to protect the environment by paying higher prices (1993, 2000 and 2010) and another one about government spending (1996 and 2016). From 0 (strongly disagree) to 4 (strongly disagree).

RTI and willingness to pay more taxes/government spending to protect environment

	(1)	(2)	(3)	(4)	(5)
Protect env.: taxes/govmnt spending					
RTI index	-0.016***	-0.020***	-0.022***	-0.020**	-0.029***
	(0.005)	(0.008)	(0.007)	(0.008)	(0.009)
Demographics		✓	✓	✓	✓
Socio-econ			✓	✓	✓
Politics				✓	✓
Societal-Eco					✓
Observations	30550	17365	17365	14602	12670
# Countries	14	14	14	14	13

Table 15: Standard errors in parentheses * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$
Dependent variable: comes from ISSP surveys years 1993, 1996, 2000, 2010, 2016. It combines a question whether respondents will be willing to protect the environment by paying more taxes (1993, 2000 and 2010) and another one about government spending (1996 and 2016). From 0 (strongly disagree) to 4 (strongly disagree).

Frey and Osborne and willingness to pay more taxes/government spending to protect environment

	(1)	(2)	(3)	(4)	(5)
Protect env.: taxes/govmnt spending					
Computerization (F & O)	-0.180***	-0.221***	-0.232***	-0.237***	-0.267***
	(0.028)	(0.042)	(0.039)	(0.035)	(0.038)
Demographics		✓	✓	✓	✓
Socio-econ			✓	✓	✓
Politics				✓	✓
Societal-Eco					✓
Observations	23354	13092	13092	10874	9157
# Countries	14	14	14	14	13

Table 16: Standard errors in parentheses * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$
Dependent variable: comes from ISSP surveys years 1993, 1996, 2000, 2010, 2016. It combines a question whether respondents will be willing to protect the environment by paying more taxes (1993, 2000 and 2010) and another one about government spending (1996 and 2016). From 0 (strongly disagree) to 4 (strongly disagree).

RTI and willingness to support higher government spending to protect environment

	(1)	(2)	(3)	(4)	(5)
Govmnt spend: environment					
RTI index	-0.033***	-0.025***	-0.026***	-0.026***	-0.023**
	(0.007)	(0.008)	(0.008)	(0.008)	(0.009)
Demographics		✓	✓	✓	✓
Socio-econ			✓	✓	✓
Politics				✓	✓
Societal-Eco					✓
Observations	13986	12515	12515	10447	9011
# Countries	10	10	10	10	9

Table 17: Standard errors in parentheses * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$
Dependent variable: comes from ISSP surveys years 1996 and 2016. It refers to the question whether respondents will be willing to support higher government spending to protect the environment. From 0 (strongly disagree) to 4 (strongly disagree).

Frey and Osborne and willingness to support higher government spending to protect environment

	(1)	(2)	(3)	(4)	(5)
Govmnt spend: environment					
Computerization (F & O)	-0.293***	-0.218***	-0.222***	-0.231***	-0.218***
	(0.031)	(0.035)	(0.034)	(0.034)	(0.040)
Demographics		✓	✓	✓	✓
Socio-econ			✓	✓	✓
Politics				✓	✓
Societal-Eco					✓
Observations	10352	9264	9264	7609	6345
# Countries	10	10	10	10	9

Table 18: Standard errors in parentheses * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$
Dependent variable: comes from ISSP surveys years 1996 and 2016. It refers to the question whether respondents will be willing to support higher government spending to protect the environment. From 0 (strongly disagree) to 4 (strongly disagree).

RTI and willingness to pay higher prices to protect environment

	(1)	(2)	(3)	(4)	(5)
Protect enviro: pay much higher prices					
RTI index	-0.064***	-0.036**	-0.035**	-0.036**	-0.048**
	(0.010)	(0.016)	(0.016)	(0.018)	(0.020)
Demographics		✓	✓	✓	✓
Socio-econ			✓	✓	✓
Politics				✓	✓
Societal-Eco					✓
Observations	16722	5003	5003	4272	3778
# Countries	14	11	11	11	10

Table 19: Standard errors in parentheses * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$
Dependent variable: comes from ISSP surveys years 1993, 2000 and 2010. It refers to the question whether respondents will be willing to pay higher prices to protect the environment. From 0 (strongly disagree) to 4 (strongly disagree).

Frey and Osborne and willingness to pay higher prices to protect environment

	(1)	(2)	(3)	(4)	(5)
Protect enviro: pay much higher prices					
Computerization (F & O)	-0.422***	-0.291***	-0.293***	-0.299***	-0.302***
	(0.047)	(0.060)	(0.060)	(0.063)	(0.065)
Demographics		✓	✓	✓	✓
Socio-econ			✓	✓	✓
Politics				✓	✓
Societal-Eco					✓
Observations	13168	3975	3975	3380	2928
# Countries	14	11	11	11	10

Table 20: Standard errors in parentheses * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$
Dependent variable: comes from ISSP surveys years 1993, 2000 and 2010. It refers to the question whether respondents will be willing to pay higher prices to protect the environment. From 0 (strongly disagree) to 4 (strongly disagree).

B.6 Direct Relationship of Automation Risks, Mediators and Outcomes

Automation risks, environmental concerns and support for environmental policies with country-level control variables.

	Mediators				Policies		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Env Concerns	Responsability	Worry	Climate Change	Carbon Tax	Subsides	Ban
Computerization	-0.065***	-0.072***	-0.099***	-0.110***	-0.141***	-0.057	-0.093***
(F&O)	(0.019)	(0.012)	(0.032)	(0.028)	(0.038)	(0.035)	(0.033)
Demographics	✓	✓	✓	✓	✓	✓	✓
Indiv.Econ	✓	✓	✓	✓	✓	✓	✓
Politics	✓	✓	✓	✓	✓	✓	✓
Societal Socio-Eco	✓	✓	✓	✓	✓	✓	✓
Industry	✓	✓	✓	✓	✓	✓	✓
N	15708	15465	15592	15834	15624	15694	15626
# Countries	14	14	14	14	14	14	14

Table 21: Standard errors in parentheses * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$
Dependent variable: comes from the ESS 8. Column 1 - 4 are the mediators: Importance of environment, which comes from the level of disagreement with the statement "strongly believes that people should care for nature." Answers range from "Not like me at all" (= 1) to "Very much like me" (= 6); Climate change has bad impact, which range from (= 1) "extremely good" to (= 5) "extremely bad"; personal responsibility to act, which range from (= 1) "not at all" to (= 5) "to a great deal"; worried about climate change, which range from (= 1) "not at all worried" to (= 5) "extremely worried".
Columns 5 - 6 are the outcomes: support for carbon tax, which range from (= 1) "against" to (= 5) "great support"; support for subsidies, which range from (= 1) "against" to (= 5) "great support"; support for banning inefficient appliances, which range from (= 1) "against" to (= 5) "great support".

Automation risks, environmental concerns and support for environmental policies with FE by occupation group.

	Mediators				Policies		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Env Concerns	Responsability	Worry	Climate Change	Carbon Tax	Subsides	Ban
Computerization (F&O)	-0.087***	-0.117***	-0.042**	-0.033**	-0.081***	-0.009	-0.014
	(0.019)	(0.020)	(0.017)	(0.017)	(0.023)	(0.019)	(0.022)
Demographics	✓	✓	✓	✓	✓	✓	✓
Indiv.Econ	✓	✓	✓	✓	✓	✓	✓
Occupation (1 digit)	✓	✓	✓	✓	✓	✓	✓
Observations	35505	34099	34668	33553	34602	35064	34832
# Countries	22	22	22	22	22	22	22
R^2	0.026	0.029	0.010	0.007	0.023	0.008	0.007

Table 22: Standard errors in parentheses * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$
Dependent variable: comes from the ESS 8. Column 1 - 4 are the mediators: Importance of environment, which comes from the level of disagreement with the statement "strongly believes that people should care for nature." Answers range from "Not like me at all" (= 1) to "Very much like me" (= 6); Climate change has bad impact, which range from (= 1) "extremely good" to (= 5) "extremely bad"; personal responsibility to act, which range from (= 1) "not at all" to (= 5) "to a great deal"; worried about climate change, which range from (= 1) "not at all worried" to (= 5) "extremely worried".
Columns 5 - 6 are the outcomes: support for carbon tax, which range from (= 1) "against" to (= 5) "great support"; support for subsidies, which range from (= 1) "against" to (= 5) "great support"; support for banning inefficient appliances, which range from (= 1) "against" to (= 5) "great support".

B.7 Mediation Analysis

	Support Carbon Tax		**Support Subsidies**		**Ban Inefficient Appliances**	
	ACME	**ADE**	**ACME**	**ADE**	**ACME**	**ADE**
Importance of Environment	0.1	-0.7	0.2	0.1	0.2	-0.5
Personal Responsibility	0.2	-0.4	0.2	0.2	0.2	-0.1
Worried About Climate Change	0.2	-0.7	0.2	0.2	0.2	-0.4
Climate Change Has Bad Impact	0.1	-0.9	0.1	0.2	0.1	-0.8

Table 23: Sensitivity analysis (ρ)

Note: Table contains values of ρ at which ADE, or ACME are equal to 0, where ρ refers to how severe the violation of the sequential ignorability assumption should be for the ACME and ADE to be biased.

Importance of Environment using Anelli, Colantone, and Stanig (2021) measure: Individual and regional exposure

	(1)	(2)
	Ind & Regional	IV
Automation Risk (Ind & Δ robots)	-0.042***	-0.061***
	(0.012)	(0.018)
Education (Years)	0.022***	0.021***
	(0.001)	(0.002)
Gender-female	0.083***	0.083***
	(0.008)	(0.008)
Demographics	Yes	Yes
NU FE	Yes	Yes
Country-Year FE	Yes	Yes
Observations	150163	150163
R^2	0.067	0.067
AIC	4.3e+05	4.3e+05

Standard errors in parentheses, clustered by region-year.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 24: Regression of exposure to automation on importance of environment.
Dependent Variable: comes from the ESS 1-7, importance of environment, which comes from the level of disagreement with the statement "strongly believes that people should care for nature." Answers range from "Not like me at all" (= 1) to "Very much like me" (= 6).
Independent Variable: Individual and regional exposure to automation measure by Anelli, Colantone, and Stanig (2021), and its IV.