# The Threat of Automation and Public Support for Environmental Policy

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**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, environmental attitudes, environmental policy, public opinion

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# 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 onset of Covid-19 and widespread adoption of telecommunication and remote working (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 three indices of exposure to automation from information provided by respondents about their occupations (Autor, 2013; Frey and Osborne, 2017; Arntz, Gregory, and Zierahn, 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 negative economic events 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* negative events 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 adverse events 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 adverse event: one where those affected face a permanent loss of income, except if they retrain and change their fundamental skill set. And this 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, and those who undergo displacement due to technological advancements witness a decrease in their earnings exceeding 45 percent (Braxton and Taska, 2023). 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.

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

# 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 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*). A similar trend in Europe has been documented by Jerbashian (2019), who noted a decline in middle-tier job roles and an increase in high-wage positions as IT prices decreased in industries highly reliant on IT. 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. Arntz, Gregory, and Zierahn (2017) reevaluate U.S. job automation risk by considering task variations at the workplace level (job-based approach). Their findings indicate a substantial initial risk of automation, but accounting for job heterogeneity significantly reduces this risk, highlighting a potential upward bias in occupation-level assessments.

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] Chiacchio, Petropoulos, and Pichler (2018) replicate Acemoglu and co-authors' analysis of the US across six European countries and find that the presence of one extra robot per thousand workers leads to a noticeable reduction in the employment rate, especially among individuals with middling education levels and younger age groups, indicating a prominent displacement effect. 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 across European countries. 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

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

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. Anelli, Colantone, and Stanig (2021) examine the impact of automation exposure across European countries and find that those most susceptible to adverse effects of automation tend to express stronger support for far-right ideologies. This aligns with a broader pattern seen in studies linking exposure to technological change with support for radical right parties, often characterized by environmentally skeptical 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).

### 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 theoretical logic, illustrated in Figure 1, that leads to our key hypotheses. Hypothesis 1 focuses on the effect of automation on environmental *concern*. Hypotheses 2 and 3 extend the causal chain to the effect of automation on environmental *policy preference*, distinguish-

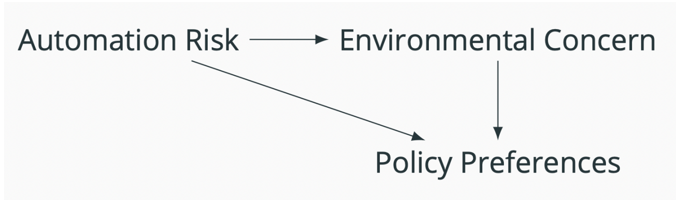


Figure 1: Causal Mechanism

ing 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*).

Occupation-based approaches have faced scrutiny because they may overestimate automation potential, as they often overlook the possibility that workers may specialize in tasks within apparently automatable occupations that are difficult to automate, as discussed by Arntz, Gregory, and Zierahn (2017). Consequently, we also measure exposure to automation by utilizing the 'high risk' job share (with automation potential of 70% or higher), known as the job-based approach.

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 3 shows a positive correlation between fear of automation and occupations (specifically, the RTI index at 1-isco digit). These correlations offer insights into people's awareness of their risk situation. While we do not assert that individuals are fully cognizant of the underlying causes of their risks, they do tend to experience increased feelings of insecurity and job dissatisfaction.[4]

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.

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

[4]Recent research by Kurer and Hausermann (2022) demonstrate a positive correlation between task-based approaches to automation and the subjective measure they propose. However, it's important to note that this correlation is not perfect. Based on the authors' descriptions, it appears that the RTI may not fully capture automation concerns among lower-skilled workers, while the model by Frey and Osborne may overestimate the risk in comparison to subjective perception. Since we employ three different approaches to measure automation risks, we remain vigilant regarding potential biases.

**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 following 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

The empirical implications derived from our theoretical framework are evaluated with two approaches: a repeated 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 $\gamma$ coefficients; where $\mu_{j[i]}$ indicates the hierarchical random intercept by country; and $\epsilon_{it}$ is the error term.

Our theoretical framework predicts that as exposure to automation risks increases, the environmental concerns will decrease. Thus, we expect $\beta_1$ 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 relationship between automation risks and environmental concern is presented in Table 1.[5] 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 es-

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

timates 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.

**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.

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 dummies 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 alternative proxies for our independent variable: RTI index and job-based approach to risk.[6] In this regard, we also estimate models that include controls for occupational classes, as proposed by Kitschelt and Rehm (2014) based on Oesch (2006). Specifically, we add a dummy variable for each occupational class as a sensitivity test, which includes

[6]Tables 8 and 9 in the Appendix for RTI. Table 10 presents the estimations for the independent variable measured as the job-based approach.

classes such as organizational task structure, technical tasks, interpersonal tasks, professionals, and skilled, among others. Table 14 demonstrates that automation risks continue to show a decrease in environmental concern, even after controlling for occupational class.

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.[7] We also investigated whether the risk associated with the green transition, as represented by occupations with high CO2 emissions, moderates the relationship between workers at risk of automation and their level of environmental concern (see Table 13.[8] Our analysis confirms that the results regarding our primary independent variable remain consistent. We do not find evidence to suggest that the threat of automation varies with the level of emissions from a respondent's industry.

Lastly, we account for heterogeneous institutional backgrounds by including additional covariates about public policies and interacting them with automation risk exposure. Table 15 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.

### 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

[7] Tables 11 and 12 in the Appendix.

[8] We operationalized 'high' as having emissions by country and year that exceeded the median emissions.

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**.[9]

[9] Results remain unchanged if we estimate multi-level models clustered by country with several country-level indicators, and adding extra individual level variables (see 24 in Appendix). Results are also robust to the incorporation of a dummy per occupation using ISCO 1-digit code (see Table 25 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 2 displays the results of our causal mediation analysis.[10]

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.

[10] Table 26 reports the sensitivity analysis of these results.

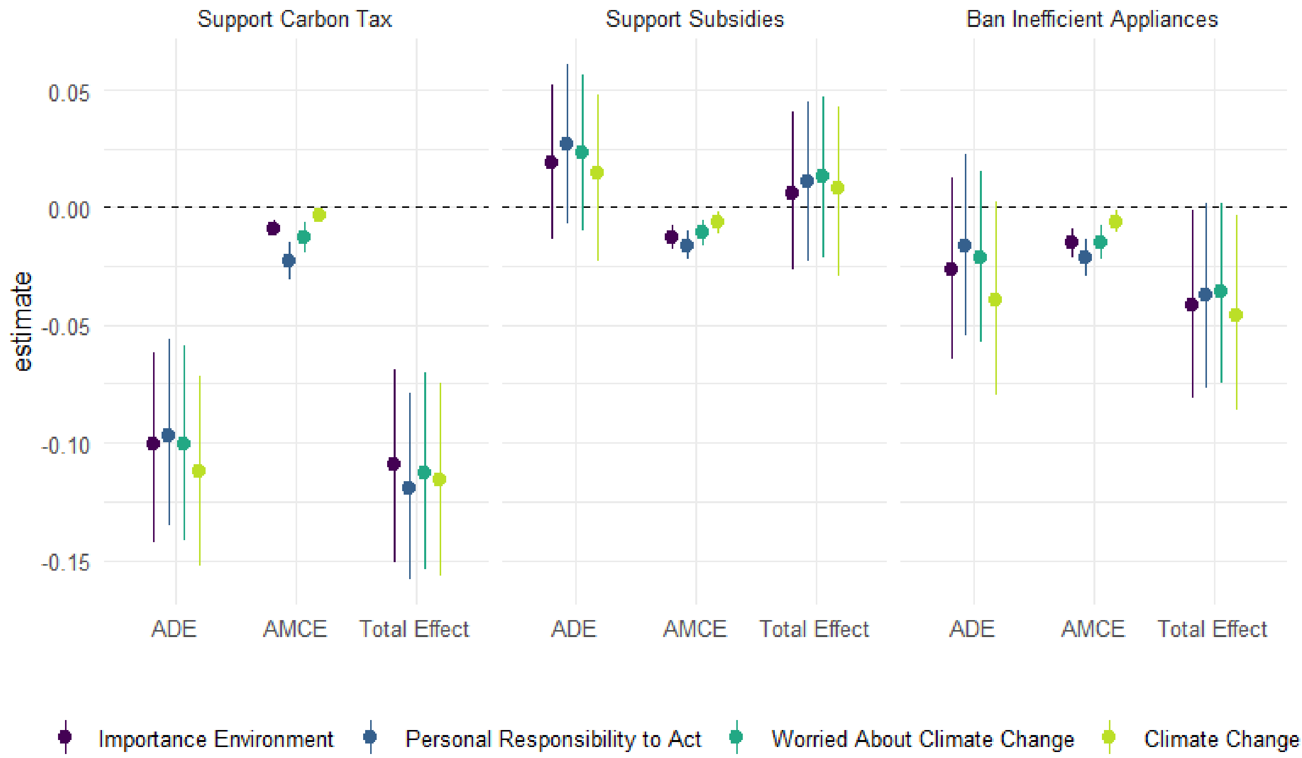


Figure 2: Effect of Automation Risk on Environmental Policy Preferences

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 16 to 23 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.

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# Appendix

# A Figures

## A.1 Preamble

| Probability | Automation Pr = 0 | 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

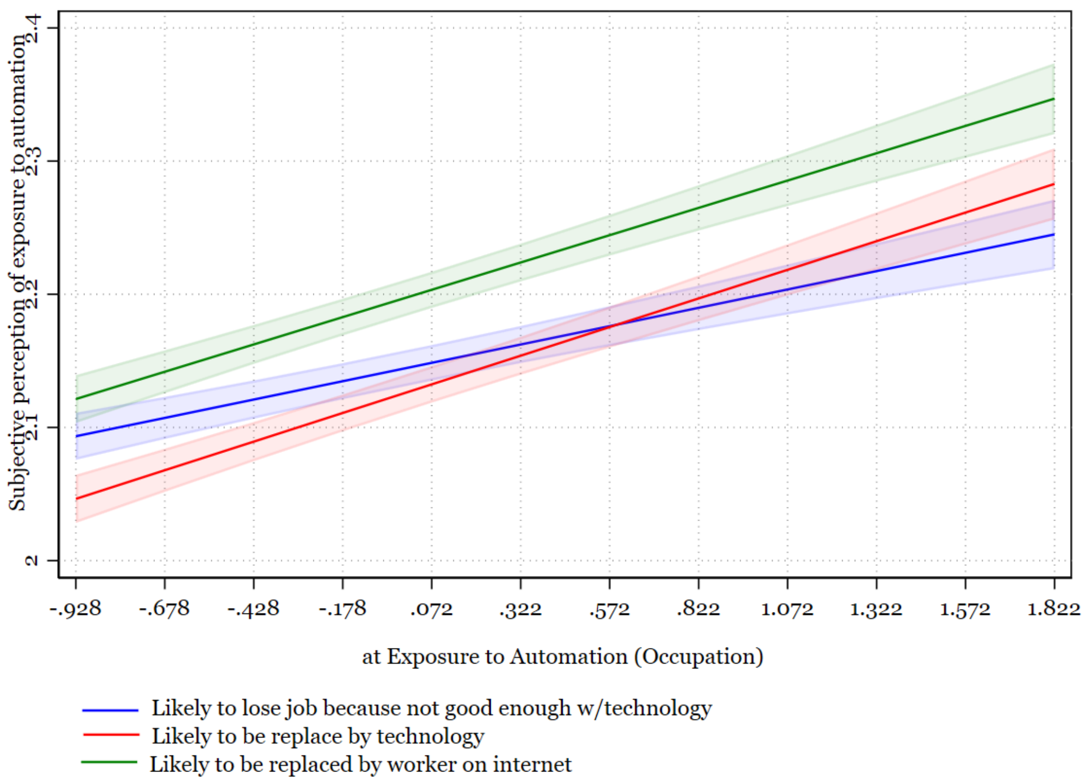


Figure 3: Automation Risks (objective - occupations) and perception to risk (subjective).

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

## A.2 Mediation Analysis

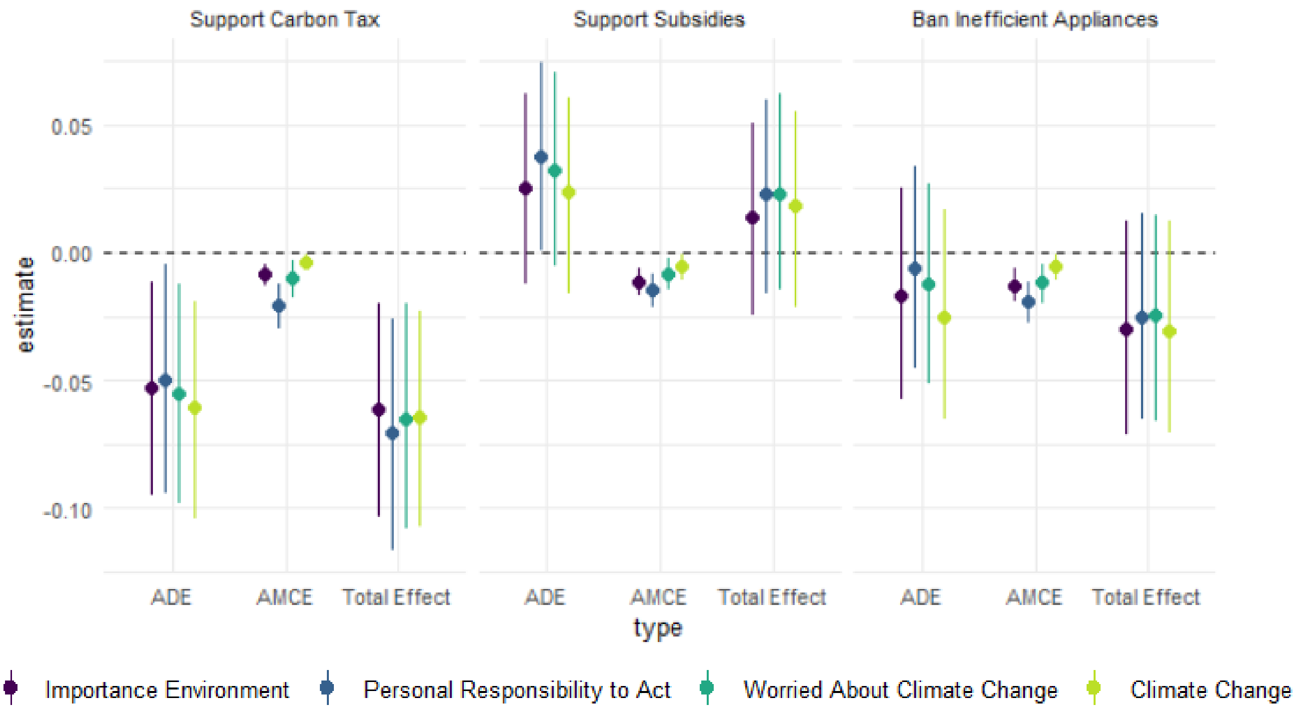


Figure 4: Effect of Automation Risk on Environmental Policy Preferences (w/industry included)

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.

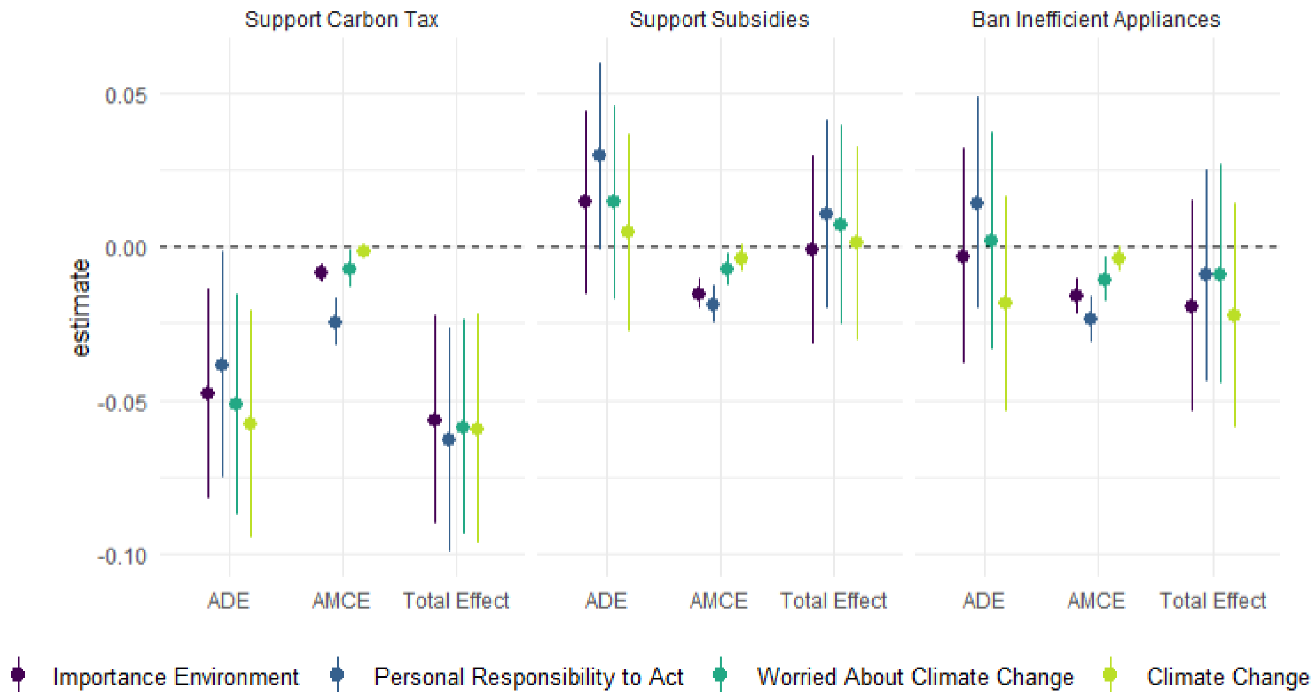


Figure 5: Effect of Automation Risk on Environmental Policy Preferences (w/occupation dummies included)

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) | (2) | (3) | (4) | (5) | (6) | (7) |
|---|---|---|---|---|---|---|---|
| | Risk Only | Demographic | Socio-Eco | Politics | EcoSocial | Industry/Occ | 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.

**Automation Risk Job-Based Approach and Environmental Concerns**

| | (1) RTI Only | (2) Demographic | (3) Socio-Eco | (4) Politics | (5) EcoSocial | (6) Industry | (7) FE |
|---|---|---|---|---|---|---|---|
| Environmental concerns | | | | | | | |
| High risk (Arntz, et al) | -0.470*** | -0.247*** | -0.215*** | -0.205*** | -0.155*** | -0.103*** | -0.100*** |
| | (0.031) | (0.035) | (0.032) | (0.029) | (0.028) | (0.038) | (0.037) |
| Education years | | 0.016*** | 0.017*** | 0.015*** | 0.015*** | 0.014*** | 0.015*** |
| | | (0.002) | (0.001) | (0.001) | (0.002) | (0.002) | (0.002) |
| Gender-male | | -0.092*** | -0.088*** | -0.083*** | -0.075*** | -0.060*** | -0.060*** |
| | | (0.013) | (0.014) | (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 | | 0.017*** | 0.017*** | 0.020*** | 0.022*** | 0.020*** | 0.020*** |
| | | (0.002) | (0.002) | (0.002) | (0.003) | (0.002) | (0.002) |
| Income | | | -0.013** | -0.008* | -0.012* | -0.000 | -0.000 |
| | | | (0.006) | (0.005) | (0.006) | (0.008) | (0.008) |
| Unemployed | | | 0.047*** | 0.043** | 0.061*** | 0.076*** | 0.076*** |
| | | | (0.017) | (0.017) | (0.021) | (0.020) | (0.020) |
| Left-right | | | | -0.035*** | -0.040*** | -0.039*** | -0.039*** |
| | | | | (0.007) | (0.007) | (0.007) | (0.007) |
| Union membership | | | | 0.043*** | 0.033** | 0.028* | 0.027* |
| | | | | (0.014) | (0.015) | (0.015) | (0.015) |
| Social Expenditure | | | | | -0.008* | -0.010* | -0.016*** |
| | | | | | (0.004) | (0.006) | (0.005) |
| Openness | | | | | -0.000 | 0.000 | -0.002* |
| | | | | | (0.001) | (0.001) | (0.001) |
| GDP growth | | | | | -0.000 | -0.006 | 0.002 |
| | | | | | (0.005) | (0.008) | (0.008) |
| Foreign Population | | | | | 0.002 | 0.001 | 0.001 |
| | | | | | (0.002) | (0.003) | (0.003) |
| Industry | | | | | | ✓ | ✓ |
| Year FE | | | | | | | ✓ |
| Observations | 242698 | 241020 | 188375 | 174610 | 122277 | 61521 | 61521 |
| # Countries | 23.000 | 23.000 | 23.000 | 23.000 | 17.000 | 16.000 | 16.000 |

Standard errors in parentheses

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

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). Independent variable: the automation risk is measured following Arntz Gregorym, and Zierahn's job-based approach. 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) | -0.082*** | -0.086*** | -0.080*** | -0.078*** | -0.078*** | -0.078*** |
| | (0.013) | (0.013) | (0.013) | (0.012) | (0.012) | (0.012) |
| Emissions Greenhouse | -0.006*** | | | -0.004 | -0.004 | -0.004 |
| | (0.002) | | | (0.004) | (0.004) | (0.004) |
| Emissions Nitrous oxide | | -0.002 | | 0.005** | 0.005** | 0.005** |
| | | (0.002) | | (0.002) | (0.002) | (0.002) |
| Emissions Particulates | | | -0.007*** | -0.008** | -0.008** | -0.009** |
| | | | (0.002) | (0.003) | (0.003) | (0.003) |
| Manufacture | | | | | | 0.004 |
| | | | | | | (0.012) |
| Demographics | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Socio-econ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Politics | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Year FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Country FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Observations | 138134 | 137887 | 137617 | 137532 | 137532 | 137532 |
| # Countries | 22.000 | 22.000 | 22.000 | 22.000 | 22.000 | 22.000 |

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.

**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 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 (1-8) data.

**Computerization (Frey and Osborne) and its interaction with occupations in high emission industries**

| | (1) | (2) | (3) |
|---|---|---|---|
| Computerization (F& O) | -0.075$^{***}$ | -0.068$^{***}$ | -0.070$^{***}$ |
| | (0.012) | (0.012) | (0.013) |
| High Emissions Greenhouse | -0.033$^{***}$ | | |
| | (0.010) | | |
| Emissions Greenhouse x Computerization | 0.022 | | |
| | (0.016) | | |
| High Emissions Nitrous oxide | | 0.003 | |
| | | (0.011) | |
| Emissions Nitrous oxide x Computerization | | -0.013 | |
| | | (0.017) | |
| High Emissions Particulates | | | -0.025$^{**}$ |
| | | | (0.010) |
| Emissions Particulates x Computerization | | | 0.007 |
| | | | (0.018) |
| Demographics | ✓ | ✓ | ✓ |
| Socio-econ | ✓ | ✓ | ✓ |
| Politics | ✓ | ✓ | ✓ |
| Observations | 156412 | 156412 | 156412 |
| # Countries | 23.000 | 23.000 | 23.000 |

Table 13: 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 Robustness Checks - Oesch Tasks

The baseline of the analysis are interpersonal tasks.

**Automation Risk-Frey and Osborne and Environmental Concerns**

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| Environmental concerns | | | | | | |
| Computerization (F&O) | -0.052*** | -0.049*** | -0.047*** | -0.040*** | -0.031** | -0.028** |
| | (0.013) | (0.012) | (0.011) | (0.011) | (0.012) | (0.012) |
| Organisational task structure | 0.061*** | 0.032*** | 0.024* | 0.024** | 0.024* | 0.022* |
| | (0.012) | (0.011) | (0.013) | (0.012) | (0.013) | (0.013) |
| Technical task structure | -0.046*** | -0.021** | -0.026** | -0.018* | -0.013 | -0.015 |
| | (0.012) | (0.010) | (0.011) | (0.011) | (0.011) | (0.011) |
| Professional authority | 0.155*** | 0.093*** | 0.079*** | 0.073*** | 0.064*** | 0.066*** |
| | (0.018) | (0.017) | (0.015) | (0.016) | (0.018) | (0.018) |
| Assoc prof authority | 0.142*** | 0.101*** | 0.092*** | 0.080*** | 0.076*** | 0.079*** |
| | (0.011) | (0.011) | (0.012) | (0.012) | (0.013) | (0.013) |
| Skilled routine authority | -0.011 | -0.001 | -0.004 | -0.010 | -0.005 | -0.003 |
| | (0.009) | (0.008) | (0.008) | (0.008) | (0.010) | (0.010) |
| Skilled organisational | -0.168*** | -0.123*** | -0.122*** | -0.100*** | -0.114*** | -0.114*** |
| | (0.013) | (0.014) | (0.016) | (0.016) | (0.017) | (0.017) |
| Demographics | | ✓ | ✓ | ✓ | ✓ | ✓ |
| Socio-econ | | | ✓ | ✓ | ✓ | ✓ |
| Politics | | | | ✓ | ✓ | ✓ |
| Societal-Eco | | | | | ✓ | ✓ |
| Year FE | | | | | | ✓ |
| Observations | 213904 | 212439 | 164126 | 151340 | 104717 | 104717 |
| # Countries | 23 | 23 | 23 | 23 | 17 | 17 |

Table 14: 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.5 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 15: 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.6 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 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 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 17: 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 18: 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 19: 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 20: 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 21: 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 22: 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 23: 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.7 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 24: 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 25: 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.8 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 26: Sensitivity analysis ($\rho$)

Note: Table contains values of $\rho$ at which ADE, or ACME are equal to 0, where $\rho$ 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) Ind & Regional | (2) 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 27: 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.