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Labor Market Risk Shapes Individuals' Environmental Attitudes and Policy Preferences

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Abstract

In an era of increasing economic precarity and labour market polarization, meaningful efforts to mitigate climate challenges face a fundamental political challenge. We examine how indviduals' long-term labour market risk shapes their environmental attitudes and support for green policies. We argue that long-term labour market risk 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 labour market risk to subsequently reduce support of environmental policy that imposes immediate direct costs, such as carbon taxation. Using European Social Survey data from 2002 to 2018 and several waves of the International Social Survey Programme across European countries, our analysis reveals that individuals' facing long-term labour market risks are less likely to hold environmental concerns and less supportive of carbon taxes that impose immediate visible costs. 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

1. Introduction

A longstanding concern in the area of climate policy and environmental politics is whether meaningful progress can be made in the aftermath of adverse economic shocks. In an era marked by increasing economic precarity and a polarization of the labour market, this question becomes even more relevant to understanding the political backlash to net-zero policies seen in many countries. This backlash, evident from the failure of environmental referenda in the United States and Switzerland to the Gilets Jaunes protests, underscores how economic concerns have led to a stalling of climate policy and deprioritisation of the environment.

While existing research has elucidated factors influencing support and resistance to climate action (e.g. Bechtel and Scheve 2013; Carattini, Carvalho, and Fankhauser 2018; Cooper, Kim, and Urpelainen 2018; Klenert et al. 2018; Gaikwad, Genovese, and Tingley 2022; Beiser-McGrath 2022; Mildenberger et al. 2022; Vona 2023), there remains a significant gap in theoretical and empirical understanding concerning how people form their preferences about what climate policies are preferred. Increasingly this body of research has centered on economic drivers on climate policy preferences, with the distribution of costs and benefits being key to understanding the nascent green backlash (Aklin 2021; Colantone et al. 2023; Beiser-McGrath and Bernauer 2024; Beiser-McGrath and Busemeyer 2024; Gazmararian 2024; Voeten 2024; Gazmararian and Milner 2025; Aklin 2025).

As we observe significant changes in labour market structures and a rise in economic precarity, economic insecurity is increasingly playing a role in shaping contemporary political economy. In this paper, we argue that a particular form of economic insecurity, long-term labour market risk, has significant impacts upon individuals' environmental concern and support for environmental policies. 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.[1] The channels linking the two, which we explore in greater details in the theoretical section, include skills and human capital that are tied to a carbon economy as well as increased polarization over the valuation of green public goods (e.g., Autor, Levy, and Murnane 2003; De Sario, Marin, and Sacchi 2023). Individuals' long-term labour market risk 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

1. Recent public opinion surveys reveal that most US adults consider that AI will decrease job opportunities, workers' hours and wages (Ballard 2024).

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) and the International Social Survey Programme (ISSP).[2] Leveraging a rich set of individual, industry, and country characteristics, as well as a variety of fixed effects we aim to isolate the effect of long-term labour market risk in the form of occupational risk from automation[3] upon environmental concern and policy preferences.

Our findings support the empirical implications of our theoretical argument. First, we find that individuals with higher long-term labour market risks are, on average, less concerned about the environment. Second, long-term labour market risk is associated with lower support for environmental policies that impose direct immediate costs upon individuals (such as carbon taxes or paying higher prices to protect the environment). However, it does not directly reduce support for policies with less visible (from workers' perspective) and diffuse costs, such as subsidies. Third, using mediation analysis, we find that long-term labour market risk decreases 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.

Our results speak 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; Drews, Antal, and van den Bergh 2018; Drews, Savin, and van den Bergh 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)

2. The ESS is a biennial, cross-national survey conducted since 2002 that measures public attitudes, beliefs, and behaviors across several European countries. The ISSP, initiated in 1985, is an annual cross-national survey covering diverse social science topics, such as work, government, family, and the environment, with modules periodically repeated across various countries.

3. We define "automation" theoretically as production automation—machines displacing human labor. Empirically, we rely on pre-Gen AI proxies, such as Frey and Osborne (2017) probability-of-computerisation, which assesses susceptibility to automation via computer-controlled systems—historically including industrial robots, machine learning, advanced algorithms, mobile robotics, and data analytics. Because these proxies predate the generative AI surge post-2020, they likely underestimate the capabilities of cutting-edge 2025 models (e.g., large-language and diffusion models).

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.

We contribute to this literature in several ways. First, we use a tailored and objective measure of exposure to labour market risks at the individual level, and show that even general risks of that kind – job automation – affect political attitudes toward the environment (e.g., Colantone et al. 2023; Gazmararian 2024; Voeten 2024; Aklin 2025).

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.[4] While the plight of those who are unemployed 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.

Our work has significant implications for the understanding of green policy support and labour market risks. First, by demonstrating that general labour market risks, such as automation, can impact support for pro-environmental policies beyond those that directly displace specific workers (e.g., oil displacement), we identify current and potential sources of backlash against green policies. Additionally, our findings suggest that policies with more diffuse costs are more likely to gain public support, as opposition coalitions are less likely to form around these policies. Finally, we contribute

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

to the literature on the economic and political consequences of one of the major drivers of structural change in the labour market—automation—by highlighting the broader policy effects of these economic shocks, particularly among those left behind by such changes.

2. Theoretical Argument

In this section, we develop our theoretical logic for how long-term labour market risks affects environmental preferences. First, we discuss how our theoretical argument resolves the potential contradiction between our focus on the importance of long-term labour market risk and the mixed evidence of an economy-environment trade-off in previous research. We do so by explaining how the long-term structural nature of labour market risk we examine 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. From there we review the key economic consequences of the form of long-term labour market risk we explore, automation, and its significant consequences for individuals' policy preferences. Finally, we explain variation in the direct and indirect effect of long-term labour market risk upon climate policy preferences, differentiating between policies that impose visible direct costs versus uncertain, diffuse costs.

2.1 The economy-environment trade-off

The economy-environment trade-off follows the intuitive idea that in hard economic times the economy takes precedence over all other issues. 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 Mark A Kayser 2017a), 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).

As noted previously, there could be several reasons for these conflicting findings. One is that economic shocks, as generally measured, are temporary and of various severity. Thus, estimated effects are likely to vary considerably depending on the way shocks are measured and the context in which they take place. The threat from long-term labour market risks, in contrast, may plausibly affect individuals in a permanent manner, absent the acquisition of new skills. Therefore, in subsequent sections we discuss the key features of long-term labour market risk in the form of automation and how it differs from conventional economic risks.

2.2 Long-Term labour Market Risk

Automation and the economy

Our analysis does not rest on the premise that automation will have uniformly positive or negative aggregate effects; the net impact remains debated (Aghion et al. 2023). Rather, we examine how certain groups experience negative effects depending on their skills, tasks, and available alternatives (Lim, Aklin, and Frank 2023).

A defining feature of the current wave of automation is the limited lateral mobility for displaced workers. Historically, technological disruptions enabled relatively smooth labor transitions—from agriculture to manufacturing and subsequently to services (Floud, McCloskey, and McCloskey 1994, 100). The current wave differs fundamentally. Automation not only reduces employment in routine manual manufacturing occupations but generates substantial spillover effects into high-skilled roles across diverse sectors, including business and professional services, retail, and construction (Sarto, Tabellini, and Faber 2025), and affects non-routine jobs (Frey and Osborne 2017). Even sectors previously viewed as absorptive capacity for displaced workers, such as services, face disruption (Mann and Püttmann 2023). Unlike narrowly targeted disruptions such as Chinese import competition—which primarily impacted manufacturing—automation triggers broader societal responses with long-term consequences, including internal migration (Sarto, Tabellini, and Faber 2025). These widespread disruptions blur traditional labor market boundaries and are likely to reshape political coalitions, interest groups, and individuals' long-term policy priorities.

Moreover, emerging roles following task obsolescence demand entirely different skill sets. Zhang, Lai, and Gong 2024 suggest workers must either enhance specific cognitive abilities, such as creativity, or develop broader competencies combining social-cognitive and sensory-physical skills. Retraining opportunities, however, remain unevenly distributed, constrained by time, costs, and barriers disproportionately affecting disadvantaged workers. Workers displaced by automation struggle to shift into emerging roles, particularly because many job losses in routine occupations occur during economic downturns with little subsequent recovery even when the economy rebounds (Jaimovich and Siu 2020). Fully capitalizing on automation's opportunities thus requires proactive human capital investment at both individual and policy levels.

Empirical research substantiates these structural concerns. Acemoglu and Restrepo (2017) find that US commuting zones experiencing large increases in industrial robot usage saw significant negative effects on local employment and wages.[5] Chiacchio, Petropoulos, and Pichler (2018) replicate this analysis across six European countries, finding that one additional robot per thousand workers produces noticeable employment rate reductions, especially among individuals with middling education levels and younger age groups. While young workers might retrain and secure new employment, certain positions—notably entry-level roles—face permanent elimination. Dario Amodei, CEO of Anthropic, recently forecasted that AI could eliminate approximately half of all entry-level white-collar jobs, potentially spiking unemployment rates by 10–20% within five years (Montgomery 2025). Such permanent shifts underscore automation's profound long-term implications for economic stability and, consequently, social attitudes, including pro-environmental stances.

The broader diffusion of automation typically occurs gradually rather than through sudden shocks,[6] yet incremental changes significantly reshape labor market structures. As Acemoglu and Restrepo (2018a) note, "the adjustment of an economy to the rapid rollout of automation technologies could be slow and painful." Persistent labor market frictions—including lengthy job searches, skill mismatches, labor shortages, and retraining requirements—substantially delay workers' realloca-

5. US commuting zones are geographical units representing local economic areas, of which there are approximately 700.
6. For a comprehensive review, see Filippi, Bannò, and Trento (2023).

tion into new sectors and tasks, exacerbating structural unemployment (Danzer, Feuerbaum, and Gaessler 2024; Groiss and Sondermann 2024). Gradual but persistent technological transformations deepen wage stagnation and regional inequalities, especially when investments in human capital and institutional adaptations fail to keep pace (Acemoglu and Restrepo 2020; Koch, Manuylov, and Smolka 2021). These structural changes and persistent economic uncertainty influence long-term career expectations and shift policy priorities, potentially prioritizing short-term job security over addressing abstract, future-oriented challenges such as environmental protection.

The consequences of automation are unequally distributed between routine- and capital-biased occupations, a pattern extensively documented in foundational theories linking technological innovation to polarization in employment and wages (e.g., Krusell et al. 2000; Autor, Levy, and Murnane 2003; Autor 2013; Acemoglu and Autor 2011; Acemoglu and Restrepo 2018b; Dauth et al. 2018; Graetz and Michaels 2018; Kurer and Gallego 2019). Capital-biased technological change disproportionately substitutes capital for routine tasks typically performed by mid-skill workers while complementing tasks at both ends of the skill distribution (Autor, Levy, and Murnane 2003; Acemoglu and Autor 2011). Consequently, routine occupations—middle-skill and middle-wage jobs prevalent in manufacturing and administration—are shrinking, a process scholars term hollowing out the middle. In the US, the middle four deciles of the income distribution experienced a decline in their income share from 0.46 in 1980 to 0.4 in 2014 (Helen V Milner 2021a). Jerbashian (2019) document a similar European trend, noting a decline in middle-tier job roles and an increase in high-wage positions as IT prices decreased in IT-reliant industries. Given the middle class's role in democratization and policy formation (e.g., Lipset 1959; Moore 1966; Boix 2003; Acemoglu, Acemoglu, and Robinson 2006), and its linkage to political engagement and institutional trust (Gonzalez-Rostani 2024; Boix 2019), these shifts carry substantial implications for post-material policies such as environmental protection.

2.3 *Automation and environmental attitudes: empirical implications*

How do we reconcile the importance of long-term labour market risks such as automation for political economy with the weak evidence for an economy-environment trade-off? *Contemporaneous* economic downturns do not strongly affect environmental concern; individuals may view them as transient or have already internalized their impact. Structural economic shifts generated by automation, however, fundamentally alter assessments of *long-run* expected economic trajectories, reducing concern for future-oriented issues like climate change. This echoes research finding that environmental issues are deprioritized when competing with present-day distributional concerns, short-term policy costs, and other long-term policy priorities (e.g. Sommestad 2011; Armingeon and Bürgisser 2021; Busemeyer and Beiser-McGrath 2024).

Automation fundamentally displaces existing occupations' value, prompting affected individuals to adopt risk-averse positions favoring the status quo. The green transition similarly requires fundamental economic reorganization, displacing existing industries and economic activities within industries. Recent research finds that low-carbon jobs are fundamentally more skills-intensive (Sato et al. 2023). The green transition is often explicitly linked to technological change as a means of achieving efficient resource use (World Economic Forum 2017; Vinuesa et al. 2020)—autonomous vehicles being a prominent example (Hancock, Nourbakhsh, and Stewart 2019). The under-discussed implication is that such innovations obviate the need for workers whose tasks can be automated. Policy efforts explicitly involving artificial intelligence and machine learning (Joppa 2017; Rolnick et al. 2019)—technologies designed to automate tasks—increasingly reduce human involvement, rendering numerous jobs obsolete. Automation has already shown promise in green manufacturing and mining for clean energy materials (Li et al. 2012; Tabor et al. 2018).

Research demonstrates that green policies induce economic disruption, increasing the salience of labour-market risk that tempers enthusiasm for decarbonization. Stricter air-quality rules in the United States resulted in sizeable employment and earnings losses in pollution-intensive plants, costs borne disproportionately by displaced workers (Greenstone 2002; Walker 2013). Higher local energy prices depress employment in energy-intensive manufacturing and prompt firms to relocate to cheaper or laxer jurisdictions (Kahn and Mansur 2013). Environmental policies are often skill-biased, favoring technicians and engineers while eroding demand for routine manual occupations (Vona et al. 2018; Marin and Vona 2019). Workers whose jobs depend on the carbon economy' may possess skills in lower demand in a decarbonized world. Vintage' human capital and skills that translate poorly to a greener economy accentuate these dynamics (Chari and Hopenhayn 1991; Violante 2002; Autor, Levy, and Murnane 2003; De Sario, Marin, and Sacchi 2023). These distributional impacts magnify the negative effect of economic shocks upon demands for climate action, particularly when workers associate climate policy with "job-killing" narratives (Vona 2019; Weber 2020).

Labour market risk also connects to post-material values in shaping climate concern. From a post-materialist perspective, climate concern attenuates when economic security is jeopardized. Climate and environmental issues function as "luxury goods" whose salience rises only after basic economic needs are met (Inglehart 1977; Abou-Chadi and Mark A. Kayser 2017b). Heightened job loss prospects crowd out post-material values and refocus attention away from the long-run implications of climate change.

Macro-level research on economic inequality and emissions trajectories reinforces this dynamic. Models accounting for non-homothetic green preferences—allowing the income elasticity of demand for environmental quality to vary with income and development—predict that inequality and economic insecurity dampen green preferences in rich societies while having opposite effects in poor ones (Vona and Patriarca 2011; Berthe and Elie 2015; Nicolli, Gilli, and Vona 2025; Bez et al. 2023). In advanced economies facing technological change automating routine jobs, these non-homothetic preferences challenge climate concern by shrinking the pool of voters willing to bear decarbonization costs and the "pioneer consumer" demand that stimulates the green transition.

Individuals at risk from automation thus face prospective economic risks from the green transition that outweigh potential benefits, particularly in industrialized economies less affected by immediate environmental consequences (Cruz and Rossi-Hansberg 2023; Gazmararian and Milner 2025). These individuals deprioritize the environment as a long-term issue given the long-term economic risk they face, as environmental action is crowded out when compared to social policy action (Busemeyer and Beiser-McGrath 2024). To the extent individuals recognize this risk and feel unable to substitute to alternative professions, they will oppose environmental action.

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

Automation's impact on environmental policy preferences

Automation risk also affects environmental policy support. Policies differ substantially in their distributional consequences and impacts (e.g. Metcalf 1999; Fullerton 2011; Rausch, Metcalf, and Reilly 2011; Cronin, Fullerton, and Sexton 2019; Vona 2023).[7] We differentiate between climate policies imposing direct, immediate costs (carbon taxes) and those providing tangible benefits with

7. For further discussion of climate policy perception and design, see Drews and Bergh (2016).

diffuse cost structures (subsidies).[8]

Individuals expecting future income losses are less supportive of environmental policies imposing direct immediate costs (Arndt, Halikiopoulou, and Vrakopoulos 2022). Such policies confront individuals starkly with the trade-off between policy action and potential welfare loss. Research demonstrates that cost implications shape climate policy preferences: Bechtel and Scheve (2013) and Beiser-McGrath and Bernauer (2019a) find that global climate agreements with lower costs gain more public support, while Kotchen, Turk, and Leiserowitz (2017) document that U.S. citizens are less supportive of green policies involving income or payroll tax reductions.

Research on carbon taxes specifically finds that expectations and beliefs about costs significantly drive acceptance (Beiser-McGrath and Bernauer 2019b; Douenne and Fabre 2020, 2022; Beiser-McGrath and Busemeyer 2024). As the relative salience of costs increases under economic insecurity, climate policies with front-loaded visible cost structures are more susceptible to backlash than indirect, less visibly costly policies like subsidies.

Automation's effect on policy preferences depends on policy design. For policies with clear immediate costs (carbon taxes), automation risk exerts a negative direct effect as future economic losses compound with the policy instrument. For policies with diffuse costs (subsidies), automation risk is unlikely to have a significant direct effect, as individuals are less sensitive to imposed costs and may believe they would benefit from provided public goods.

Hypothesis 2 ***Green Policy Preferences****: The direct effect of risk from automation upon green policy support will be stronger for carbon taxation than for subsidies.*

3. Research Design

3.1 Data

We test our core empirical implications 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. Descriptive statistics for all variables are reported in Tables 6 (ESS 1-8), 7 (ISSP), and 8 (ESS 8).

8. Subsidies and tax-based policies have other relevant characteristics, such as opportunity costs of investment and revenue use (e.g. Metcalf 1999; Rausch, Metcalf, and Reilly 2011; Beiser-McGrath and Bernauer 2019b; Cronin, Fullerton, and Sexton 2019; Bergquist, Mildenberger, and Stokes 2020; Vona 2023; Beiser-McGrath and Bernauer 2024). Our empirical analysis does not examine within-instrument design variation.

Exposure to technological change

Our key independent variable is an individual's exposure to automation, which we approach using different measures. First, we consider an influential measure developed by Frey and Osborne (2017) for the US case (*Frey-Osborne index*), from now on, we will refer to it as *Automation Risk*. Second, we use the routine task intensity (*RTI*) index developed by Goos, Manning, and Salomons (2014) for European countries. These two measures are based on the 'task' approach Autor, Levy, and Murnane (2003) and 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 occupations' characteristics determine whether workers will be harmed by (or benefit from) automation. Third, we use the job-based approach by Arntz, Gregory, and Zierahn (2017).

The measure developed by Frey and Osborne (2017) utilizes expert assessments and machine learning to create its forward-looking measure of automation risk. This measure provides the probability of computerization for the US Department of Labor's Dictionary of Occupational Titles. 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.[9] Rather than reflecting an actual shock, the measure represents potential risks faced by workers from technological advancements.

The RTI index also relies on the task approach developed by Autor, Levy, and Murnane (2003) and Autor (2013, 2015). This index provides measures susceptibility to automation based upon the degree of routineness of a task. 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 index ranges from -1.5, typical for managers of small enterprises (indicating low routineness), to 2.2, as observed in office clerks (where tasks could be more easily executed by machines).[10]

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

9. This measure models automation broadly: it captures computer-controlled machinery, artificial intelligence, machine learning, advanced algorithms, mobile robotics, and big-data analytics—covering both industrial robots and advanced digital technologies.

10. 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; Helen V. Milner 2021b).

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.[11] 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 5 reports that these measures are related, showing the increase at the extremes of the distribution of risks (these variables are positively and significantly correlated). This is further supported by data from the OECD Risks That Matter project, Figure 2 shows a positive correlation between fear of automation and occupations (specifically, the RTI index at 1-isco digit). 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.[12]

Second, standardized measures based on occupations may induce bias. On the one hand, as noted by Busemeyer and Tober (2022), we are aware that these measures lose a relevant proportion of the proportion of variation between individuals. On the other hand, measures based on current occupations might be affected by prior trends in automation (Anelli, Colantone, and Stanig 2021), stemming from both direct displacement (where individuals are moved out of roles susceptible to

11. The harmonization comes from Thewissen and Rueda (2019).

12. Recent research by Kurer and Häusermann (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.

automation) and indirect displacement (where automation leads to a decrease in job opportunities in automatable fields). To address these challenges, we employ an approach to exposure to automation as developed by Anelli, Colantone, and Stanig (2021), leveraging individual variation to more accurately capture the potential effects of automation on individuals' attitudes.

The approach of Anelli et al. is based on historical data from the labour market before the automation shock in the early 1990s from the European Labor Force Survey. They estimate the predicted probabilities of employment in each occupation during this period. These probabilities are then applied to individuals in the ESS survey who have similar characteristics (age, gender, education) but are in the post-shock period (2000-2016). Additionally, these predictions are adjusted by the rate of robot adoption in each country-year in the previous three years. Incorporating this robot exposure provides valuable insight into automation's effects, leveraging national variations in technological adoption that are plausibly exogenous to individual characteristics. Thus, this method enables an understanding of technological change both as an incremental process and as region-specific shocks resulting from accelerated technology adoption.[13]

Environmental Concern and Policy Preferences

We are interested in the association between automation and environmental concerns and policy preferences, using Waves 1-8 of ESS and ISSP. 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 is the only available measure of pro-environmental attitudes across all ESS waves. Additionally, we incorporate three alternative proxies from the 8th wave of the ESS, which is the first to include an extensive module on public attitudes toward climate change, energy security, and energy preferences. These proxies include: (1) personal responsibility for reducing climate change, (2) an assessment of whether climate change has a positive or negative global impact, and (3) the level of concern about climate change. While this question only captures attitudes toward the environment, it is a first step in understanding political

13. To obtain these measures, we merge our database with Anelli et al. replication data based on the round of the ESS countries and the identification number of each individual. Our analysis when using these measures limits to the ESS 1-7 (sample used by Anelli, Colantone, and Stanig). Note that regional-level measures of robot adoption have been widely utilized in prior research (e.g., Acemoglu and Restrepo 2020).

behavior. Previous scholars have shown similar questions to be important determinants of public opinion regarding green policies (Bergquist et al. 2022; Drews and Bergh 2016; Ejelöv and Nilsson 2020).

To explore policy preferences beyond attitudes, we operationalize environmental policy preferences from the 8th wave of the ESS in three distinct ways. The first outcome focuses on a policy with clear and direct costs for individuals: whether respondents support increasing *taxes on fossil fuels* as a measure to combat climate change. The second outcome captures preferences for a policy with less visible or more diffuse costs: whether respondents favor providing *subsidies* for renewable energy to mitigate climate change. Lastly, the ESS includes an item on *appliance bans*, which asks respondents whether they support banning the sale of the least energy-efficient household appliances. We consider this outcome to occupy a middle ground between policies with direct and diffuse costs.

We replicate our analysis using data from the ISSP, which spans several waves (1993, 1996, 2000, 2010, 2016) and focuses exclusively on policy preferences rather than attitudes toward the environment. Notably, these questions pertain to policies with direct financial implications for individuals. The 1993, 2000, and 2010 surveys ask respondents about their willingness to protect the environment by supporting two fiscal measures that impose direct costs: paying higher prices or higher taxes. Meanwhile, the 1996 and 2016 surveys inquire about respondents' willingness to support increased government spending to protect the environment.

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 partially out unobserved industry characteristics that are associated with our automation measures and exposure to common shocks.

3.2 Models

We test whether automation risks shape individuals' environmental concerns (**Hypothesis** 1) exploiting the cross-sectional variation on all waves available of the ESS. The data has a multi-level structure with individuals 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. We estimate a linear regression model that takes the following form:

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

where Y_i captures the environmental concerns of the respondent i. *Automation Risk*$_i$ is the index of computerization. X_{it} is a vector which captures various individual-level control variables, whereas $Z_{j[i]}$ is a vector of country-level predictors of environmental concerns. The impact of the country-level predictors is measured by the γ coefficients; where $\mu_{j[i]}$ indicates the hierarchical random intercept by country; and ϵ_{it} is the error term. Our theoretical framework predicts that greater exposure to automation risks reduces environmental concern, implying that β_1 should be negative.

When the dependent variable (Y_i) refers to support for climate policies, we consider three cases: (1) endorsement of higher fossil-fuel taxes, (2) support for renewable energy subsidies, and (3) backing for bans on energy-inefficient household appliances. For taxation, we expect higher automation risks to lower support, so $\beta_1 < 0$. For policies with diffuse costs, such as subsidies, we anticipate weaker or statistically insignificant effects.

In examining the link between political attitudes and exposure to automation, prior research has emphasized the need to look beyond current occupations and consider the availability of automation technologies (Anelli, Colantone, and Stanig 2021). Robots, in particular, have been a major driver of recent automation, with significant implications for labor markets and political behavior (Acemoglu and Restrepo 2020; Anelli, Colantone, and Stanig 2021). To capture this, we follow Anelli, Colantone, and Stanig's approach, which measures exposure by interacting the pace of robot adoption with individual-level risk. Rather than relying on current occupations (as in Frey and Osborne), which capture contemporaneous risks but may be biased by occupational choices already influenced by automation, Anelli, Colantone, and Stanig (2021) develop a measure that predicts exposure risk from pre-treatment characteristics (gender, education, and age) using labor force data from the early 1990s. This measure reduces bias from occupational sorting and, in practice, assigns greater automation exposure to individuals who—based on their historical profile—were more likely to enter highly automatable occupations and who live in regions with faster robot adoption.

A further concern is that robot adoption itself may be endogenous, as deployment often accelerates during economic upturns. This can bias ordinary least squares estimates, especially if economic cycles also shape environmental attitudes. To address this, we adopt an instrumental variables strategy, instrumenting national robot adoption with adoption in other countries (excluding the respondent's own), following Acemoglu and Restrepo (2020) and Anelli, Colantone, and Stanig (2021). In this specification, the instrument is defined as the change in foreign adoption between $t-1$ and $t-3$, interacted with either the vulnerability index or current occupational risk. The identifying assumption is that foreign robot adoption shifts domestic automation exposure but has no direct effect on environmental attitudes, operating only through the treatment.

4. The Effect of Exposure to Labor Market Risk on Environmental Attitudes

The relationship between automation risks and environmental concern is presented in Table 1. 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 addresses potential heterogeneous effects by industry. Finally, column 6 accounts for possible temporal trends by incorporating year-fixed effects.

These relationships are significant and substantively in line with our theoretical expectations. Automation risks are positively associated with a decrease in environmental concerns. These estimates imply that a one-unit increase in automation risks (which corresponds approximately to one standard

Table 1. Frey-Osborne and environmental concerns

	(1)	(2)	(3)	(4)	(5)	(6)
Environmental concerns						
Automation Risk	-0.155***	-0.099***	-0.091***	-0.081***	-0.058***	-0.057***
	(0.012)	(0.012)	(0.010)	(0.010)	(0.012)	(0.012)
Demographics		✓	✓	✓	✓	✓
Socio-econ			✓	✓	✓	✓
Politics				✓	✓	✓
Industry					✓	✓
Year FE						✓
Observations	246160	244441	190634	174658	102852	102852
# Countries	23	23	23	23	22	22

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. The independent variable *Automation Risk* is the probability of computerization, an occupation-based measure from Frey and Osborne. Full table with control variables reported in Appendix Table 9.

deviation) leads to 0.16 standard deviation decrease in an individual's environmental concern. The relationship is robust across all specifications. These results, therefore, provide empirical support for our **Hypothesis** 1 that at-risk individuals are less concerned about looking after the environment.

Our results are also robust to additional model specifications. First, one concern that may emerge is about the standardized measures of automation and how much of what we are capturing is specific to the exposure to risk or industry. Thus, we add dummies at the industry level using NACE Rev. 2, and the results remain consistent (Column 5). 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. Tables 10 and 11 in the Appendix for RTI, and Table 12 presents the estimations for the independent variable measured as the job-based approach by Arntz, Gregory, and Zierahn 2017. For instance, considering the job-based approach, we find a decline of about 0.5 SD on concerns if we compare those with low and high risk.

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 classes such as organizational task structure, technical tasks, interpersonal tasks, professionals, and skilled, among others. Table 16 demonstrates that automation risks continue to show a decrease in environmental concern, even after controlling for occupational class. Similarly, the results are robust to including dummies per occupation group using ISCO 1-digit (see Table 17).

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.[14] 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 15.[15] 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.

Fourth, we account for heterogeneous institutional contexts by including covariates such as openness, foreign population, GDP growth, and social expenditure (see Table 18). Additionally, when examining the effects of specific social spending and labour market policies and interacting these with automation risk exposure, our main findings remain consistent. As shown in Table 19 in the Appendix, the results are robust to these interactions. Our findings align with those of Gingrich (2019), suggesting that the expansion of public services and labour market regulations has limited capacity to offset the increased risk posed by automation.

Finally, to address potential biases from reliance on current occupations (Frey and Osborne 2017; Goos, Manning, and Salomons 2014; Arntz, Gregory, and Zierahn 2016), we use alternative proxies for automation exposure in our regression estimates. These proxies are derived from Anelli, Colantone, and Stanig's predictions about individual vulnerability and robot adoption rates. The authors estimate the likelihood of job automation impacts for individual-level proxies by assessing occupational risks with data from pre-automation shock periods and demographic characteristics (age, gender, education). This method assigns each individual a probability of automation risk, independent of their current occupation, which may have already experienced automation-related displacement. Instead, the risk is estimated based on demographic traits associated with high-risk occupations. They then multiply this individual-level exposure by the pace of robot adoption (nationally or regionally).

14. Tables 13 and 14 in the Appendix.
15. We operationalized 'high' as having emissions by country and year that exceeded the median emissions.

To account for endogeneity concerns, the latter measure is instrumented using robot adoption rates in other EU countries, following the approach of Anelli, Colantone, and Stanig (2021).[16]

Table 2 displays a range of robustness specifications, employing both OLS and IV estimators for robot adoption. Across these models, we consistently find a negative correlation between environmental attitudes and automation exposure.[17] Columns 1 to 4 of the table apply proxies for individual exposure proposed by Anelli, Colantone, and Stanig 2021, including individual vulnerability and the national pace of robot adoption, along with our proxy for Automation Risk based on current occupations (Columns 3–4). Columns 5 to 8 focus on individual vulnerability and regional robot adoption,[18] with the final two columns also incorporating current occupation for additional robustness.[19] To facilitate interpretation, once we categorize environmental concerns as a binary variable representing strong pro-environmental attitudes. Our analysis reveals that a one-SD rise in automation exposure corresponds to a 2.6 percentage-point decline in the likelihood of holding strong pro-environmental views. In the dummy specification, the baseline probability of reporting the strongest pro-environmental attitude is about 46 percent. Thus, a one–SD increase in automation exposure reduces this probability to roughly 43 percent, equivalent to a relative decline of about 6 percent.[20]

16. The *national* pace of robots refers to $\Delta R_{ct} = \frac{R_c^{t-1} - R_c^{t-3}}{L_c^{pre-sample}}$.

17. Refer to the Appendix for the full model Table 20.

18. Here, the national growth of robots is replaced with regional exposure to automation, where the pace is proxied by the change in the operational stock of industrial robots between years $t-1$ and $t-3$ in country c and industry j, normalized by the pre-sample number of workers employed in the same country and industry: $RegionalExposure_{crt} = \sum_j \frac{L_{crj}^{pre-sample}}{L_{cr}^{pre-sample}} \times \frac{R_{cj}^{t-1} - R_{cj}^{t-3}}{L_{cj}^{pre-sample}}$.

19. The F-statistic reported in Table 2 is comfortably high when the IV is based on national robot adoption, and lower when the IV is based on regional exposure (i.e., country–industry variation within each region), though still above the conventional weak-instrument threshold.

20. See the estimation with a dummy in the Appendix Table 21.

Table 2. Individual vulnerability to industrial robot adoption and environmental concerns

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	OLS	IV	OLS	IV	OLS	IV	OLS	IV
National robots individual exposure	-0.047**	-0.063***	-0.037*	-0.043*				
	(0.020)	(0.024)	(0.019)	(0.024)				
Automation Risk			-0.060***	-0.059***			-0.061***	-0.062***
			(0.012)	(0.011)			(0.012)	(0.012)
Regional robots individual exposure					-0.034**	-0.028***	-0.035***	-0.021*
					(0.012)	(0.009)	(0.011)	(0.013)
Demographics	✓	✓	✓	✓	✓	✓	✓	✓
Socio-econ	✓	✓	✓	✓	✓	✓	✓	✓
Politics	✓	✓	✓	✓	✓	✓	✓	✓
Industry	✓	✓	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓	✓	✓
Observations	108531	108531	86108	86108	108531	108531	86108	86108
# Countries	13.000	13	13	13	13	13	13	13
Kleibergen-Paap rk Wald F		50.826		47.970		10.102		10.504

Standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

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). Standard errors clustered by country. Independent variables: all measures can be read as one-SD increase in exposure to attitudes toward environmental concerns; A) Individual Exposure refers to the proxy based on individual characteristics (age, gender, education) and the predictions of vulnerability based on pre-treatment occupations multiplied by regional exposure developed by Anelli, Colantone, and Stanig (2021).; B) Automation Risk, refers to the probability of computerization, an occupation-based measure by Frey and Osborne; C) Individual Regional Exposure, uses only regional robot adoption, comes from Anelli, et al. Source: ESS (1-7) data.

5. The Effect of Exposure to Labour Market Risk on Green Policy Preferences

Thus far, our analysis has focused on structural economic drivers of environmental attitudes. Yet, the literature has provided some evidence on the role of economic shocks on green policy preferences, too (e.g, Brulle, Carmichael, and Jenkins 2012; Scruggs and Benegal 2012; Beiser-McGrath 2022). Thus, we turn to explore how long-lasting labour market risks affect green policy preferences.

Table 3 presents our analysis with three key environmental policies from the 8th ESS: endorsing higher taxes on fossil fuels, supporting renewable energy subsidies, and advocating for bans on the least energy-efficient household appliances to mitigate climate change. Our results indicate a significant negative correlation between automation risk and support for increased carbon taxation (Column 1). In contrast, Column 2 shows no statistically significant relationship between automation risk and support for renewable energy subsidies. Column 3, however, presents significant evidence of support for banning inefficient appliances, though this correlation is weaker compared to that for carbon taxation.[21][22]

Table 3. Automation risks and support for environmental policies, ESS.

	(1) Carbon Tax	(2) Subsides	(3) Ban
Automation Risk	-0.104***	-0.021	-0.041*
	(0.022)	(0.019)	(0.021)
Demographics	✓	✓	✓
Indiv. Econ	✓	✓	✓
Industry	✓	✓	✓
Observations	34536	34995	34760
# Countries	14	14	14

Standard errors in parentheses * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$
Dependent variables comes from ESS 8: *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)).

To ensure the robustness of our findings, we replicate the analysis using data from the ISSP, which includes multiple years of questions focused on direct-cost environmental policies. The results remain consistent, as shown in Table 4, which confirms a negative correlation between the probability of computerization and support for costly green policies. For instance, we observe a 0.26 standard deviation decline in support for government spending to protect the environment when comparing groups with low and high exposure to automation risk. Further details and alternative proxies for the dependent variable are presented in Appendix section 9.12.

21. Results remain unchanged if we estimate multi-level models clustered by country with several country-level indicators, and adding extra individual level variables (see 23 in Appendix). Results are also robust to the incorporation of a dummy per occupation using ISCO 1-digit code (see Table 24 in Appendix).
22. Tables 25 to 32 replicates the analysis with data from the ISSP survey.

Table 4. Automation risks and support for environmental policies, ISSP.

	(1) Spending/Prices	(2) Spending/Taxes	(3) Gov-Spending
Automation Risk	-0.244***	-0.237***	-0.231***
	(0.034)	(0.035)	(0.034)
Demographics	✓	✓	✓
Socio-econ	✓	✓	✓
Politics	✓	✓	✓
Observations	10989	10874	7609
# Countries	14	14	10

Standard errors in parentheses * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$
Dependent variables come from ISSP, and they go from 0 (strongly disagree) to 4 (strongly agree), greater values refer to pro-green policy support: *Spending/Prices* combines a question of 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); *Spending/Taxes* combines a question of 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); *Gov-Spending* refers to whether respondents will be willing to support higher government spending to protect the environment (1996 and 2016).

Overall, the previous analysis provides evidence in support of **Hypothesis** 2, which posited that individuals exposed to automation risks are less likely to support costly environmental policies, such as paying higher taxes or prices to protect the environment. We also find that when costs are more diffuse, such as in the case of subsidies, the decline in support is less pronounced or null. These heterogeneous effects may be attributed to individuals' perceptions of the financial burden associated with addressing environmental challenges. Consistent with prior research, individuals who anticipate future income losses are more likely to oppose environmental policies that impose direct and immediate costs (Arndt, Halikiopoulou, and Vrakopoulos 2022). In our analysis, carbon taxes—where the costs are most transparent—generate the strongest negative effect, followed by appliance bans. In contrast, the costs associated with subsidies are less visible, leading to weaker opposition.

6. How Do Automation Exposure and the Subsequent Decline in Pro-Environmental Attitudes Affect Policy Preferences?

Our analyses thus far have demonstrated that exposure to long-term labour market risks, such as automation, influences environmental concerns and a decline in support for green policies perceived as costly for workers. However, we could not reject the null hypothesis for policies with more diffuse costs. Previous research has established that one of the strongest predictors of public support for climate policies is concern for the environment (e.g., Bergquist et al. 2022). This leads us to ask: Does the risk of automation affect support for green policies with diffuse costs by shaping pro-environmental attitudes? To investigate this indirect relationship, we employ mediation analysis, clearly distinguishing between the average causal mediation effect (ACME)—the portion of automation's effect transmitted through changes in pro-environmental attitudes—and the average direct effect (ADE), the effect of automation independent of these attitudinal shifts. Together, these components represent the total effect of automation exposure on policy preferences. Given the strong assumptions that underlie this approach (Bullock and Green 2021; Pirlott and MacKinnon 2016; Imai et al. 2011), our results remain exploratory rather than causal.

Environmental concerns reflect the extent to which individuals are aware of environment-related issues, and these attitudes may lead to a greater inclination to support relevant policies and actions.[23] Therefore, it is reasonable to believe that automation risks may affect policies through changes in individual awareness of these issues. Figure 1 presents the results of our causal mediation analysis. We adopt the approach outlined in Imai et al. (2011) to estimate the mediated effect.[24] This approach explicitly distinguishes between mediated and direct effects, enabling us to unpack the mechanisms behind these changes in policy preferences. We proxy environmental concern using four items from the 8th ESS: 1) importance of the environment, 2) personal responsibility in climate change action, 3) concerns about climate change, and 4) anticipated adverse effects of climate change. Table 22 confirms the associations between automation and these proxies of environmental concerns.

Our mediation analysis clearly underscores a significant indirect pathway: automation reduces support for all green policies through its detrimental effect on environmental attitudes. Although modest in size, this indirect effect consistently remains statistically significant across all policy instruments we examined. In contrast, total and direct effects independent of attitudinal shifts frequently fail to reach statistical significance. Specifically, the direct effect of automation is notably negative and substantial for carbon taxes, minor and negligible for appliance bans, and subsidies. These findings align with our hypotheses. **Hypothesis** 2 expects that automation's direct impact on support for environmental policies will be stronger for carbon taxation than for subsidies, given the immediate

23. For instance, previous research has shown that awareness and environmental concerns significantly influence the propensity to purchase environmentally friendly goods, such as organic products (e.g., Asif et al. 2018; Molinillo, Vidal-Branco, and Japutra 2020; Amatulli et al. 2019).

24. The mediation effect is causally identified only if the sequential ignorability assumption holds. This assumption is untestable, but Table 33 provides a sensitivity analysis of these results to any violation of this assumption.

and direct costs associated with carbon taxes.

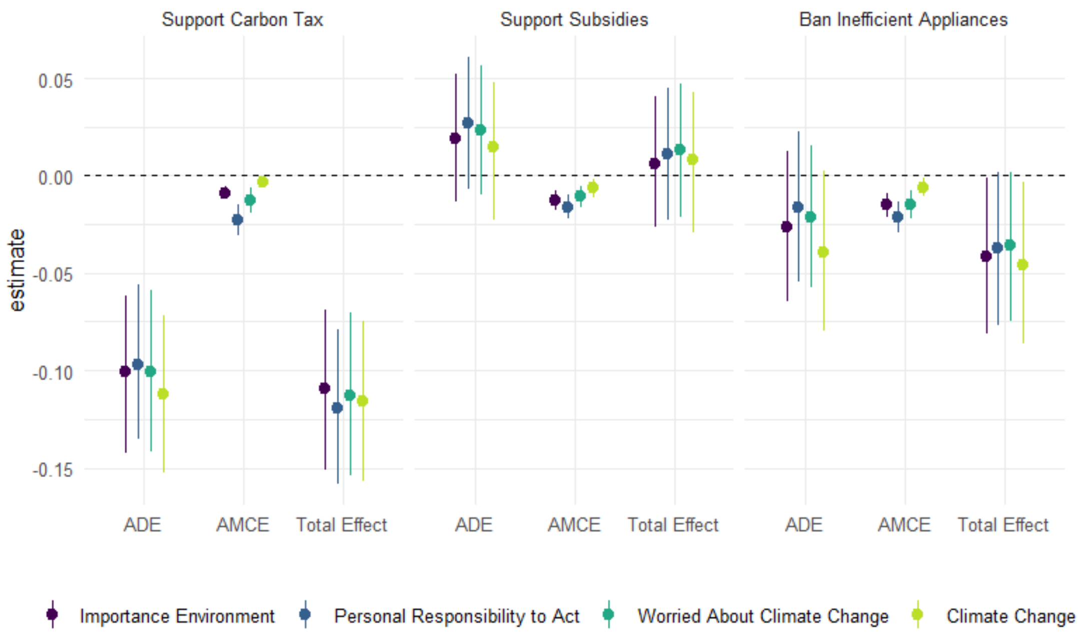

Figure 1. Effect of Automation Risk on Environmental Policy Preferences

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

The evidence just discussed 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.

7. Conclusion

Do long-term labour market risks threaten the support for policies regulating the environment? While previous research on the economy-environment trade-off finds mixed evidence for the negative impact of contemporaneous economic shocks, we argue that long-term labour market risks are different. Specifically, long-term structural nature of labour market risk fundamentally changes individuals' assessments of *long-run* (expected) economic trajectories which makes individuals less concerned about future-oriented issues such as climate change and the environment. This longer term *prospective* economic risk is thus expected to have a significant impact on environmental preferences, unlike transient economic shocks.

Utilizing comprehensive data sets of post-industrialized countries, we have shown that long-term labour market risks, in the form 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. Our exploratory mediation analysis suggests that labour market risk also indirectly affects support for all policy types, due to its negative effect upon 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 2019b; Dolšak, Adolph, and Prakash 2020; Beiser-McGrath and Bernauer 2024) 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. Our findings, thus, suggest a pathway for policymakers aiming to enact green policies without facing opposition from at-risk workers by focusing on policies that have more diffuse costs.

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 work should be expanded to developing countries.

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Appendix

8. Figures

8.1 Preamble

Table 5. Automation Risks (objective - occupations) and perception to risk (subjective).

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

Data comes from ISSP

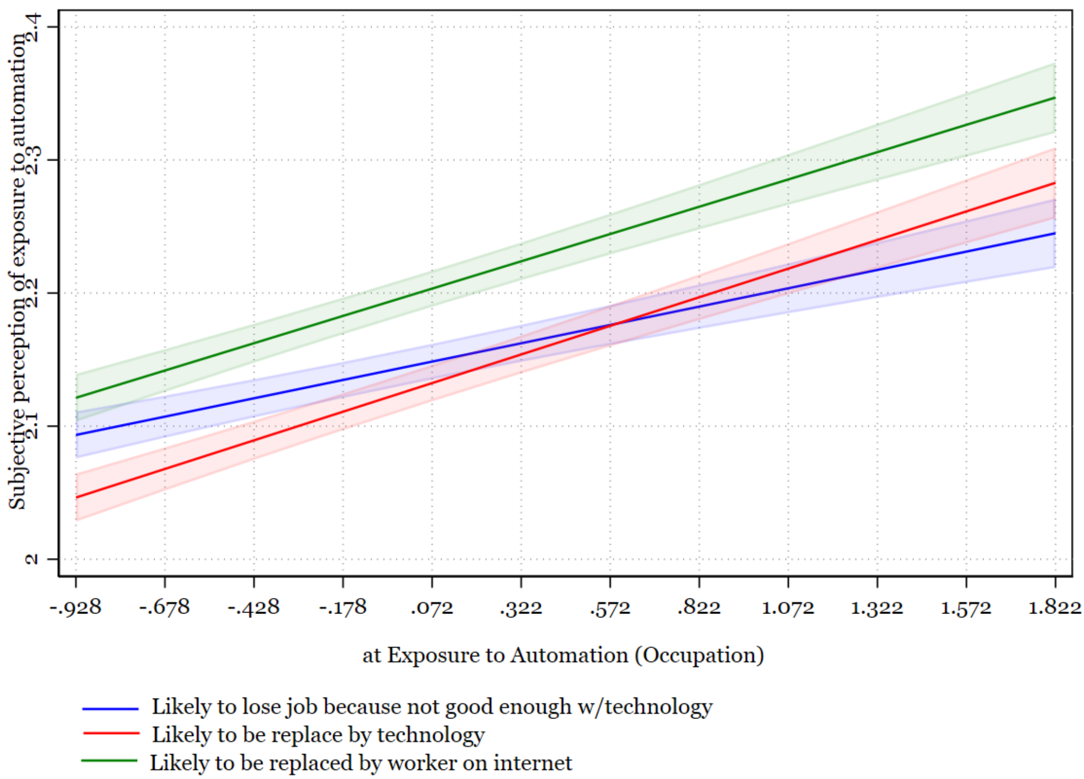

Figure 2. Automation Risks (objective - occupations) and perception to risk (subjective). Data comes from OECD Risks That Matter 2020. RTI aggregated following Busemeyer and Tober (2022)

8.2 *Mediation Analysis*

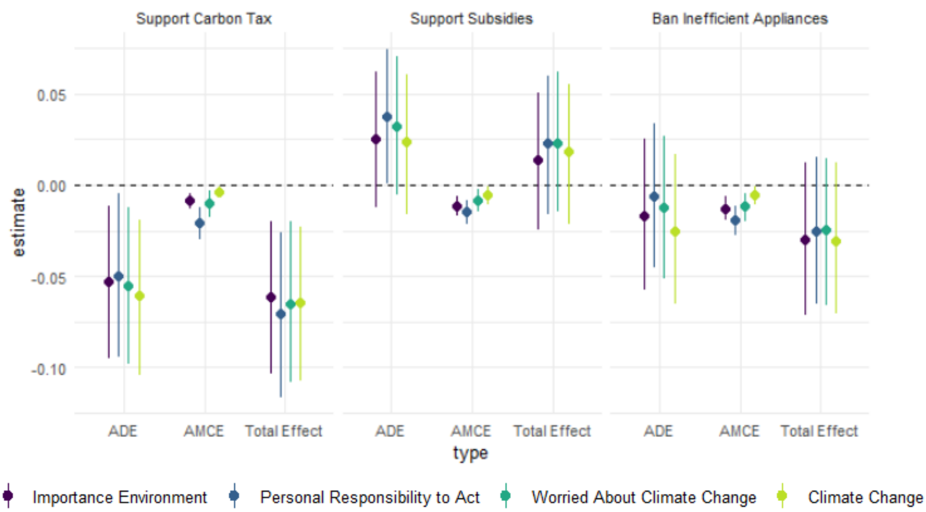

Figure 3. Effect of Automation Risk on Environmental Policy Preferences (w/industry included). Mediators: Importance of environment, which comes from the level of disagreement with the statement "strongly believes that people should care for nature." Answers range from "Not like me at all" (= 1) to "Very much like me" (= 6); Climate change has bad impact, which range from (= 1) "extremely good" to (= 5) "extremely bad"; personal responsibility to act, which range from (= 1) "not at all" to (= 5) "to a great deal"; worried about climate change, which range from (= 1) "not at all worried" to (= 5) "extremely worried".The treatment variable is exposure to automation approached following Frey and Osborne (2017). Data comes from the 8th wave of the ESS. The points indicate the estimated effect of automation risks, with lines displaying 95% confidence intervals generated through simulation from a robust variance-covariance matrix.

Figure 4. Effect of Automation Risk on Environmental Policy Preferences (w/occupation dummies included). Mediators: Importance of environment, which comes from the level of disagreement with the statement “strongly believes that people should care for nature.” Answers range from “Not like me at all” (= 1) to “Very much like me” (= 6); Climate change has bad impact, which range from (= 1) “extremely good" to (= 5) “extremely bad"; personal responsibility to act, which range from (= 1) “not at all" to (= 5) “to a great deal"; worried about climate change, which range from (= 1) “not at all worried" to (= 5) “extremely worried".The treatment variable is exposure to automation approached following Frey and Osborne (2017). Data comes from the 8th wave of the ESS. The points indicate the estimated effect of automation risks, with lines displaying 90% confidence intervals generated through simulation from a robust variance-covariance matrix.

9. Tables

9.1 Summary Statistics

Table 6. Summary statistics of all variables used in this study.
Source: ESS (1-8) data.

Descriptive statistics

	Mean	Median	S.D.	Min.	Max	Obs.
Environmental concerns	4.89	5.00	1.01	1	6	255507
Routine (RTI)	-0.05	-0.33	0.98	-2	2	264628
Automation Risk (F&O)	0.57	0.66	0.32	0	1	230030
Education years	12.65	12.00	4.03	0	25	264628
Gender-male	0.49	0.00	0.50	0	1	264528
Age	49.27	49.00	17.20	18	99	264628
Religious	4.48	5.00	3.01	0	10	262754
Income	1.01	0.86	0.74	0	48	204353
Unemployed	0.04	0.00	0.19	0	1	264628
Left-right	5.09	5.00	2.14	0	10	237100
Union membership	0.45	0.00	0.50	0	1	262332
Social Expenditure	22.39	22.25	4.47	13	32	264628
Openness	103.24	87.62	44.16	48	281	239847
GDP growth	2.22	2.20	2.24	-5	10	264628
Foreign Population	9.49	8.25	7.87	0	72	196422
Unemployment	7.85	7.33	3.90	2	25	264628
Manufacture	0.20	0.00	0.40	0	1	257146
Greenhouse emissions	12673239.24	1678843.16	30526758.36	0	362122633	199845
N2O emissions	1262.97	50.11	5617.60	0	123313	199845
Particulates emissions	2685.21	242.87	7640.91	0	110683	199845

Table 7. Summary statistics of all variables used in this study. Source: ISSP data (1993, 1996, 2000, 2010 and 2016).

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

Descriptive statistics ESS 8

	Mean	Median	S.D.	Min.	Max	Obs.
RTI index	-0.13	-0.44	0.95	-2	2	35511
Automation Risk (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

9.2 Main results with control variables

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). Source: ESS (1-8) data.

Multilevel-Analysis IV - Frey and Osborne

	(1)	(2)	(3)	(4)	(5)	(6)
	RTI Only	Demographic	Socio-Eco	Politics	Industry	FE
Environmental concerns						
Automation Risk	-0.155***	-0.099***	-0.091***	-0.081***	-0.058***	-0.057***
	(0.012)	(0.012)	(0.010)	(0.010)	(0.012)	(0.012)
Education years		0.017***	0.018***	0.016***	0.015***	0.015***
		(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Gender-male		-0.080***	-0.075***	-0.073***	-0.062***	-0.063***
		(0.013)	(0.013)	(0.014)	(0.014)	(0.014)
Age		0.008***	0.009***	0.009***	0.009***	0.009***
		(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Religious		0.018***	0.017***	0.021***	0.019***	0.019***
		(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Income			-0.010	-0.006	0.004	0.005
			(0.007)	(0.006)	(0.006)	(0.006)
Unemployed			0.047***	0.039**	0.057***	0.060***
			(0.017)	(0.016)	(0.018)	(0.017)
Left-right				-0.032***	-0.031***	-0.031***
				(0.006)	(0.006)	(0.006)
Union membership				0.050***	0.040***	0.041***
				(0.014)	(0.014)	(0.013)
Industry					✓	✓
Year FE						✓
Observations	246160	244441	190634	174658	102852	102852
# Countries	23	23	23	23	22	22

Standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

9.3 Main results replicated with RTI instead of Frey & Osborne measures

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

RTI and environmental concerns

	(1)	(2)	(3)	(4)	(5)	(6)
Environmental concerns						
Routine (RTI)	-0.012***	-0.011***	-0.009***	-0.010***	-0.011***	-0.011***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Demographics		✓	✓	✓	✓	✓
Socio-econ			✓	✓	✓	✓
Politics				✓	✓	✓
Industry					✓	✓
Year FE						✓
Observations	255507	253749	197056	180636	102388	102388
# Countries	23	23	23	23	22	22

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

RTI and environmental concerns

	(1) RTI Only	(2) Demographic	(3) Socio-Eco	(4) Politics	(5) Industry	(6) FE
Environmental concerns						
Routine (RTI)	-0.012***	-0.011***	-0.009***	-0.010***	-0.011***	-0.011***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Education years		0.018***	0.018***	0.016***	0.015***	0.015***
		(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Gender-male		-0.079***	-0.076***	-0.074***	-0.063***	-0.063***
		(0.013)	(0.015)	(0.015)	(0.014)	(0.014)
Age		0.009***	0.009***	0.009***	0.009***	0.009***
		(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Religious		0.018***	0.018***	0.021***	0.020***	0.020***
		(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Income			-0.007	-0.003	0.003	0.004
			(0.006)	(0.005)	(0.006)	(0.006)
Unemployed			0.044**	0.040**	0.058***	0.061***
			(0.018)	(0.018)	(0.019)	(0.019)
Left-right				-0.031***	-0.030***	-0.030***
				(0.006)	(0.006)	(0.006)
Union membership				0.043***	0.032**	0.033***
				(0.014)	(0.013)	(0.013)
Industry					✓	✓
Year FE						✓
Observations	255507	253749	197056	180636	102388	102388
# Countries	23	23	23	23	22	22

Standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

9.4 Main results replicated with Job-Based Approach instead of Frey & Osborne measures

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). 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.

Automation Risk Job-Based Approach and Environmental Concerns

	(1) RTI Only	(2) Demographic	(3) Socio-Eco	(4) Politics	(5) Industry	(6) FE
Environmental concerns						
High risk (Arntz, et al)	-0.470***	-0.247***	-0.215***	-0.205***	-0.136***	-0.130***
	(0.031)	(0.035)	(0.032)	(0.029)	(0.035)	(0.034)
Education years		0.016***	0.017***	0.015***	0.013***	0.012***
		(0.002)	(0.001)	(0.001)	(0.002)	(0.002)
Gender-male		-0.092***	-0.088***	-0.083***	-0.063***	-0.063***
		(0.013)	(0.014)	(0.015)	(0.014)	(0.013)
Age		0.009***	0.009***	0.009***	0.009***	0.009***
		(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Religious		0.017***	0.017***	0.020***	0.019***	0.019***
		(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Income			-0.013**	-0.008*	0.002	0.003
			(0.006)	(0.005)	(0.005)	(0.005)
Unemployed			0.047***	0.043**	0.067***	0.070***
			(0.017)	(0.017)	(0.016)	(0.016)
Left-right				-0.035***	-0.034***	-0.034***
				(0.007)	(0.007)	(0.007)
Union membership				0.043***	0.033**	0.033***
				(0.014)	(0.013)	(0.013)
Industry					✓	✓
Year FE						✓
Observations	242698	241020	188375	174610	98985	98985
# Countries	23.000	23.000	23.000	23.000	22.000	22.000

Standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

9.5 Robustness Checks - Emissions

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.

Frey and Osborne and environmental concerns

	(1)	(2)	(3)	(4)	(5)	(6)
Environmental concerns						
Automation Risk (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 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.

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 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 (1-8) data.

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

	(1)	(2)	(3)
Automation Risk (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	23	23

9.6 *Robustness Checks - Oesch Tasks*

The baseline of the analysis are interpersonal tasks.

Table 16. 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-Frey and Osborne and Environmental Concerns

	(1)	(2)	(3)	(4)	(5)	(6)
Environmental concerns						
Automation Risk (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

9.7 *Robustness Check - Occupation one digit*

Adding fixed effects by occupation code at one digit level

Table 17. 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. DV: RTI, Frey & Osborne and Arntz

Automation Risk and Environmental Concerns

	(1)	(2)	(3)
	RTI	F&O	Arntz
Environmental concerns			
Routine (RTI)	-0.005*		
	(0.003)		
Automation Risk (F&O)		-0.058***	
		(0.010)	
High risk (Arntz, et al)			-0.072**
			(0.032)
Education years	0.014***	0.015***	0.014***
	(0.002)	(0.002)	(0.001)
Gender-male	-0.069***	-0.069***	-0.073***
	(0.014)	(0.013)	(0.013)
Age	0.009***	0.008***	0.009***
	(0.001)	(0.001)	(0.001)
Religious	0.021***	0.021***	0.020***
	(0.002)	(0.002)	(0.002)
Income	-0.008*	-0.009	-0.010**
	(0.004)	(0.005)	(0.005)
Unemployed	0.044***	0.042***	0.045***
	(0.017)	(0.016)	(0.017)
Left-right	-0.032***	-0.032***	-0.035***
	(0.006)	(0.006)	(0.007)
Union membership	0.044***	0.050***	0.044***
	(0.014)	(0.015)	(0.014)
Occupation 1 digit	✓	✓	✓
Observations	180636	174658	174610
# Countries	23	23	23

9.8 Robustness Check - Institutional Context

9.8 Robustness Check - Institutional Context

Adding control variables for the institutional context.

Table 18. 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. DV: RTI, Frey & Osborne and Arntz

Automation Risk and Environmental Concerns

	(1) RTI	(2) F&O	(3) Arntz
Environmental concerns			
Routine (RTI)	-0.008*		
	(0.004)		
Computerization (F&O)		-0.042***	
		(0.015)	
High risk (Arntz, et al)			-0.100***
			(0.037)
Education years	0.017***	0.017***	0.015***
	(0.003)	(0.003)	(0.002)
Gender-male	-0.057***	-0.057***	-0.060***
	(0.016)	(0.016)	(0.015)
Age	0.010***	0.010***	0.010***
	(0.001)	(0.001)	(0.001)
Religious	0.021***	0.021***	0.020***
	(0.003)	(0.003)	(0.002)
Income	0.003	0.004	-0.000
	(0.009)	(0.009)	(0.008)
Unemployed	0.074***	0.078***	0.076***
	(0.024)	(0.021)	(0.020)
Left-right	-0.035***	-0.035***	-0.039***
	(0.007)	(0.007)	(0.007)
Union membership	0.030**	0.036***	0.027*
	(0.014)	(0.013)	(0.015)
Social Expenditure	-0.017***	-0.017**	-0.016***
	(0.006)	(0.007)	(0.005)
Openness	-0.002*	-0.002	-0.002*
	(0.001)	(0.001)	(0.001)
GDP growth	0.004	0.003	0.002
	(0.009)	(0.009)	(0.008)
Foreign Population	0.001	-0.000	0.001
	(0.002)	(0.002)	(0.003)
Industry	✓	✓	✓
Year FE	✓	✓	✓
Observations	63734	63661	61521
# Countries	16	16	16

Standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

9.9 Interactions

Table 19. 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; labour 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.

Exposure to Automation and Safety nets

	(1)	(2)	(3)	(4)	(5)	(6)
Environmental concerns						
Automation Risk (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

9.10 Robustness Check Anelli et al's

Table 20. 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). Standard errors clustered by country. Independent variables: all measures can be read as one-SD increase in exposure to attitudes toward environmental concerns; A) Individual Exposure refers to the proxy based on individual characteristics (age, gender, education) and the predictions of vulnerability based on pre-treatment occupations multiplied by regional exposure developed by Anelli, et al.; B) Computerization (F&O) refers to occupation-based measure by Frey and Osborne; C) Individual Regional Exposure, uses only regional robot adoption, comes from Anelli, et al. Source: ESS (1-7) data.

Individual vulnerability to industrial robot adoption and environmental concerns

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	OLS	IV	OLS	IV	OLS	IV	OLS	IV
National robots individual exposure	-0.047**	-0.063***	-0.037*	-0.043*				
	(0.020)	(0.024)	(0.019)	(0.024)				
Automation Risk			-0.060***	-0.059***			-0.061***	-0.062***
			(0.012)	(0.011)			(0.012)	(0.012)
Regional robots individual exposure					-0.034**	-0.028***	-0.035***	-0.021*
					(0.012)	(0.009)	(0.011)	(0.013)
Gender-male	-0.066***	-0.066***	-0.070***	-0.070***	-0.067***	-0.067***	-0.071***	-0.071***
	(0.016)	(0.015)	(0.015)	(0.014)	(0.016)	(0.015)	(0.015)	(0.014)
Age	0.009***	0.009***	0.009***	0.009***	0.009***	0.009***	0.009***	0.009***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Union membership	0.055***	0.055***	0.054***	0.054***	0.056***	0.056***	0.054***	0.054***
	(0.014)	(0.013)	(0.012)	(0.012)	(0.013)	(0.013)	(0.012)	(0.012)
Religious	0.025***	0.025***	0.025***	0.025***	0.025***	0.025***	0.025***	0.025***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Unemployed	0.057*	0.057**	0.057**	0.057***	0.057*	0.057**	0.058***	0.058***
	(0.027)	(0.026)	(0.019)	(0.018)	(0.027)	(0.026)	(0.019)	(0.018)
Constant	3.978***	4.217***	4.043***	4.189***	3.921***	4.178***	3.996***	4.166***
	(0.057)	(0.057)	(0.059)	(0.063)	(0.047)	(0.049)	(0.053)	(0.057)
Demographics	✓	✓	✓	✓	✓	✓	✓	✓
Socio-econ	✓	✓	✓	✓	✓	✓	✓	✓
Politics	✓	✓	✓	✓	✓	✓	✓	✓
Industry	✓	✓	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓	✓	✓
Observations	108531	108531	86108	86108	108531	108531	86108	86108
# Countries	13	13	13	13	13	13	13	13
Kleibergen-Paap rk Wald F		50.826		47.970		10.102		10.504

Standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 21. 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). Standard errors clustered by country. Independent variables: all measures can be read as one-SD increase in exposure to attitudes toward environmental concerns; Individual Exposure refers to the proxy based on individual characteristics (age, gender, education) and the predictions of vulnerability based on pre-treatment occupations multiplied by regional exposure developed by Anelli, et al. Source: ESS (1-7) data.

Individual vulnerability to industrial robot adoption and environmental concerns

	(1) OLS	(2) IV
National robots individual exposure	-0.022*	-0.026*
	(0.010)	(0.013)
Demographics	✓	✓
Socio-econ	✓	✓
Politics	✓	✓
Industry	✓	✓
Year FE	✓	✓
Observations	111890	111890
# Countries	13	13
Kleibergen-Paap rk Wald F		52.369

Standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

9.11 *Direct Relationship of Automation Risks, Mediators and Outcomes*

Table 22. 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)).

Automation risks, environmental concerns and support for environmental policies.

	Mediators				Policies		
	(1) Env Concerns	(2) Responsability	(3) Worry	(4) Climate Change	(5) Carbon Tax	(6) Subsides	(7) Ban
Automation Risk	-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 23. 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 country-level control variables.

	Mediators				Policies		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Env Concerns	Responsability	Worry	Climate Change	Carbon Tax	Subsides	Ban
Automation Risk	-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
Automation Risk (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

9.12 Robustness Checks - ISSP data

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."

Table 25. 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 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 26. 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					
Automation Risk (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 27. 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 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 28. 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					
Automation Risk (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 29. 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 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 30. 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					
Automation Risk (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 31. 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).

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 32. 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 of whether respondents will be willing to pay higher prices to protect the environment. From 0 (strongly disagree) to 4 (strongly agree).

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

	(1)	(2)	(3)	(4)	(5)
Protect enviro: pay much higher prices					
Automation Risk (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

9.13 *Mediation Analysis*

Table 33. Sensitivity analysis (ρ)

	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

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