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# Greenwashing the Talents: attracting human capital through environmental pledges

Wassim Le Lann\*, Gauthier Delozière†, Yann Le Lann‡

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## Abstract

In times of global ecological crisis, the responsibility of large corporations in environmental degradation is increasingly pointed out. As a result, there has been a surge in private organizations' pledges to reduce their environmental impact in recent years. In this paper, we demonstrate that companies with poor environmental responsibility have incentives to take such pledges to maintain their ability to attract high-skilled human capital. Through a case study on a French climate movement which was initiated by elite students who threatened to boycott job offers from polluting employers, we find that environmental pledges can significantly attenuate this selection effect. Using a unique and large survey database on the climate movement participants (n=2307) and machine learning classifiers, we find that individuals who initially intended to refuse a job offer from a polluting employer were, on average, three times less likely to hold such intentions after being exposed to a corporate environmental pledge. This result can be explained by the fact that intentions to refuse to work for polluting companies, and reactions to environmental pledges are driven by different factors. Furthermore, we find substantial heterogeneity in the response to environmental pledges, which is primarily explained by career perspectives, beliefs about the ecological crisis and support for radical political action in the name of ecology.

*JEL Codes:* D91, J24, Q50, M50, M14.

*Keywords:* Climate movement, Greenwashing, Human capital, Organizational behavior, Labor market, Machine learning.

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# 1 Introduction

In times of global ecological crisis, the transformation of organizations into sustainable businesses is crucial. In this process, large corporations are increasingly pointed out for their responsibility in environmental degradation. As a result of this growing pressure, there has been a surge in private organizations' pledges to take environmental action in recent years. More than one-third of the world's largest publicly traded companies now have net-zero targets, 20% of the plastic packaging market is under pledges to achieve a circular economy for plastic, and 55% of the companies most involved in deforestation have pledged to eliminate it by 2025. While some have applauded the integration of nature into business decision-making, many have criticized the gap between voluntary commitments and credible action. This issue has been recently recognized by the United Nations, through the establishment of the High-Level Expert Group on Net-Zero Emissions Commitments, which acknowledges that the current growth in pledges "misleads consumers, investors, and regulators with false narratives, and feeds a culture of climate misinformation and confusion".<sup>1</sup>

These criticisms are founded, as the effectiveness of environmental pledges is far from straightforward. The current boom in corporate voluntary commitments is accompanied by a proliferation of criteria, scope, and benchmarks, some of which are irrelevant for achieving environmental goals (Garrett et al., 2019; LeBaron and Lister, 2021). Furthermore, their implementation is also questionable, as stakeholders often rely on self-reported information to assess companies' environmental impact, with a lack of regulation to punish false claims and hold companies accountable for their commitments. An extensive body of literature demonstrates that these information asymmetries rise corporations incentives to disconnect their environmental communication from their true environmental impact (Lyon and Maxwell, 2011; Delmas and Burbano, 2011), which can lead to a failure to implement environmental commitments (Ramus and Montiel, 2005; Kim and Lyon, 2011).

On the other hand, corporations have strong incentives to make environmental pledges to preserve their reputation. Some of the main benefits include preempting political action (Maxwell et al., 2000), increasing political access (Werner, 2015), facing more lenient regulatory enforcement (Hong et al., 2019), or dampening the adverse consequences of environmental controversies (Barrage et al., 2020). Notably, being perceived as more environmentally responsible can significantly enhance an organization's ability to attract hu-

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<sup>1</sup>Figures on net-zero targets, plastic pollution, and deforestation are retrieved from the Net Zero Tracker, the Ellen MacArthur Foundation, and Forest 500, respectively. For the United Nations' position on climate pledges, see <https://www.un.org/en/climatechange/high-level-expert-group> and the High-Level Group report.

man capital. Early studies on the determinants of employer attractiveness highlight that pro-environmental messaging in recruitment brochures can significantly improve job pursuit intentions (Bauer and Aiman-Smith, 1996; Greening and Turban, 2000). Job seekers with high pro-environmental preferences and seeking meaning through their work are particularly responsive to pro-environmental messaging during the recruitment process (Gully et al., 2013; Jones et al., 2014). On the broader topic of corporate social responsibility (CSR), of which environmental responsibility is a dimension, the recent field experiment of Hedblom et al. (2019) shows that the selection effect resulting from job seekers' perception of a company's CSR has a substantial impact on firm productivity. Other empirical studies show that this increased organizational attractiveness also translates into lower reservation wages for firms perceived as more environmentally and socially responsible (Nyborg and Zhang, 2013; Burbano, 2016; Non et al., 2022; Krueger et al., 2021). Environmental responsibility can, therefore, be used as leverage to attract productive and skilled employees and is already used as a strategic human resources management tool by large corporations (Bhattacharya et al., 2008).

In this paper, we demonstrate that companies exposed to a negative organizational attractiveness shock caused by a poor environmental responsibility have incentives to make environmental pledges to remain attractive to high-skilled human capital. Using a case study on a French climate movement initiated by *Grandes Écoles* elite students threatening to boycott job offers from polluting employers, we show how environmental pledges can significantly dampen this threat and identify key individual characteristics moderating the students' response to corporate environmental pledges. This event provides a unique opportunity to study talent attraction strategies in times of increasing societal pressure for climate action. Indeed, *Grandes Écoles* are elite institutions of higher education parallel to the public university system that admit students through a highly competitive selection process. They play a key role in the social reproduction of French elites (Bourdieu, 1998) and their graduates occupy a significant portion of key decision-making positions in public administration and the private sector (Dudouet and Joly, 2010; Reberieux and Roudaut, 2018).

Furthermore, the climate movement under consideration, which took place in 2018, had significant success in the French higher education system, gathering more than 30,000 participants across 400 institutions and gaining national media coverage. Notably, it was strongly supported by future engineers, with 51% of the participants being enrolled in engineering schools, in a context of high risk of skill shortage in the engineering profession in France and Europe.<sup>2</sup> A large portion of the graduate students involved in this movement also belong to

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<sup>2</sup>In 2016, the engineering profession was ranked in the top five occupations with the highest risk of

the class of workers that seeks meaning through their job (75% of our survey respondents seek a job “useful for society”, 78% a job “compatible with their values”), while recent findings on non-monetary incentives at work suggest that meaning-driven agents can enhance organizational performance (Cassar and Meier, 2018). Lastly, although the manifesto spread to the whole French higher education system, it met considerable success among the most selective and prestigious institutions that traditionally produce future corporate elites. This climate movement, therefore, constitutes a negative shock on polluting companies’ ability to attract high-skilled and productive human capital, thus giving them incentives to address this issue.

Supporting this idea, we find evidence of negative abnormal stock returns among the largest French greenhouse gas (GHG) emitters around a public meeting which gathered organizers of the climate movement, ministers of the French government, and top executives of publicly listed French companies. Furthermore, the climate movement took place during a period of increasing climate pledges made by French multinationals. The French Business Climate Pledge, an initiative supported by the main employer federation launched in 2015, now gathers pledges to take climate action from 102 of the largest publicly listed French companies. Moreover, private organizations have become more engaged with the climate movement, and several multinational companies agreed to meet its organizers to publicly answer questions on their environmental policies.<sup>3</sup> Given the proximity between the *Grandes Écoles* and corporate elites, participants in the climate movement are therefore highly exposed to environmental pledges, raising questions about how such pledges would impact their intentions to refuse to work for polluting companies.

Exploiting a unique anonymized survey database of 2,307 climate movement participants and 127 predictor variables measuring individuals’ education, socio-demographic characteristics, work values, career perspectives, environmental attitudes, and beliefs on the ecological crisis, we investigate the reaction of students intending to boycott polluting employers to environmental pledges. We use a survey experiment with repeated measurement of respondents’ intentions to refuse to work for polluting companies to study their reaction to environmental pledges. Although less conservative than a between-subject experiment, this design has the advantage of increasing the number of independent observations and there-

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skill shortage in Europe (CEDEFOP, 2016). According to the French Employment Office data, engineer was ranked six among the ten professions with the most recruitment projects in 2021 excluding seasonal workers, yet 65.6% of these recruitment projects were judged as difficult to fill by companies. French engineers also benefit from an enhanced work mobility with an unemployment rate more than two times lower than the national average according to surveys from the Society of Engineers and Scientists of France (<https://www.iesf.fr/>). In comparison to the social movement figures, 42800 young engineers graduated in 2019 (<http://www.cdefi.fr/fr/la-cdefi/chiffres-cles>).

<sup>3</sup>See Section 2 for a more detailed discussion.

fore the power of the statistical procedures (Charness et al., 2012). Furthermore, a recent study by Clifford et al. (2021) indicates that repeated measurement designs tend to yield the same results as more conservative designs, but with a substantial increase in the precision of treatment effect estimation.

Our survey experiment consists of measuring respondents' intentions to refuse to work for a polluting employer, and their intentions to refuse to work for a polluting employer making a pledge to improve its environmental impact in the future. While 86% of survey respondents have intentions to refuse to work for polluting employers, this proportion falls to 28% for polluting employers making environmental pledges. We find evidence that the primary mechanism explaining why some respondents are not affected by environmental pledges is skepticism towards the pledge's honesty. To explain this finding and identify drivers of the students' response to corporate environmental promises, we take advantage of our repeated measurement design to compute a measure of the reaction to environmental pledges at the individual level. This quantity, which we refer to as the *reaction*, measures how much less likely an individual is to intend to refuse to work for a polluting employer after being exposed to an environmental pledge. We then estimate this quantity for each individual in our sample using machine learning classifiers. We find that, on average, respondents are more than three times less likely to have intentions to refuse to work for a polluting employer after being exposed to an environmental pledge, with students enrolled in engineering schools being particularly responsive to pledges. We then apply the SHAP interpretability method of Lundberg and Lee (2017) to identify the most important moderators of the reaction and use the reaction measure as a dependent variable in linear regressions to draw inference.

Consistent with previous personnel psychology findings, we find that intentions to refuse to work for polluting companies are primarily driven by one's search for meaning through work and environmental attitudes (Gully et al., 2013; Jones et al., 2014). However, these factors only play a minor role in explaining the reaction to environmental pledges. We find that the most important drivers of the reaction to environmental pledges are whether one integrates large companies into their career perspectives, beliefs on the ecological crisis, and support for radical action in the name of ecology. Quantitatively, these sole factors explain 73% of the variation in the reaction to environmental pledges. The strong effect of pledges can therefore be explained by the fact that the desire to work for an environmentally responsible employer and the reaction to corporate environmental promises are driven by different individual characteristics.

Our analysis indicates that students incorporating large companies into their career perspectives are 31% more sensitive to environmental pledges. One possible reason for that is that students who are interested in working for large companies may assume that their

future employer could have a significant impact on the environment. Therefore, a polluting employer that pledges to improve its environmental impact would be more likely to align with their personal preferences, making it more attractive compared to a polluting employer that does not make such a pledge. As a consequence, the least reactive individuals are the ones switching from traditional career paths. In addition, individuals having a strong disbelief in the ability of the current economic system and technological development to solve the ecological crisis react less to environmental pledges: a one-point increase in our index measuring this disbelief is associated with a  $-5\%$  decrease in the reaction. Support for radical political action in the name of ecology is also associated with a strong decrease in the reaction: believing that society should be changed by revolution is associated with a  $-17\%$  decrease, and a one-point increase in the support of material damage in the name of ecology is associated with a  $-9\%$  decrease.

Our results have several implications. First, while some scholars have argued that the self-selection of talented workers outside of polluting companies could foster businesses' sustainability transition (Brekke and Nyborg, 2008; Brannstrom et al., 2022), their analysis did not take into account the effect of potentially misleading corporate environmental communication. Our results thus highlight that opportunistic environmental pledges could render this channel less effective. Second, past empirical results show that companies increase their prosocial claims to preserve their reputation when threatened by boycott movements (McDonnell and King, 2013). Our results shed new light on this organizational behavior by taking a person-centric approach, and contribute to explaining the surge of corporate environmental pledges that is currently observed. Our findings also contribute to identifying new individual factors moderating the reaction of job seekers to CSR communication. Finally, a number of studies have highlighted the heterogeneity of beliefs on the ecological crisis in the French climate movement (Gaborit, 2020; Le Lann et al., 2021; Alexandre et al., 2021). Our findings show that this heterogeneity has practical consequences regarding individual responses to environmental communication.

The rest of the article is organized as follows. Section 2 reviews the climate movement history and firms' reactions, Section 3 describes the econometric methodology, Section 4 describes the data, Section 5 explains the computation of our dependent variables and the decision-making process, Section 6 presents our empirical results. The last section concludes the paper.

## 2 Climate movement history and firms' reactions

In this section, we review the history of the climate movement and examine how large French companies responded to it.

In March 2018, a group of students from French *Grandes Écoles*<sup>4</sup> launched the “Student Manifesto for an Ecological Awakening”. The petition gathered over 30,000 signatures across 400 institutions and received national media coverage. The call was primarily directed towards political and economic decision-makers who were blamed for not taking action in response to the climate emergency. The largest companies, which are traditionally the main employers of these students upon graduation, were specifically targeted. The climate movement aimed to use the unique position of elite students to accelerate the pace of change among political and economic actors. To exert pressure, one suggested course of action was to integrate environmental criteria into their future career path decisions:

*“As we approach our first job, we realize that the system of which we are part of directs us towards positions often incompatible with our reflections and locks us into daily contradictions. We are determined, but cannot act alone: we can overcome these contradictions only with the active involvement of economic and political decision-makers, whose sole objective must be to serve the general interest in the long term. We, future workers, are ready to question our comfort zone so that society changes profoundly. We want to take advantage of the leeway we enjoy as students by turning to employers whom we deem in accordance with our demands expressed in this manifesto.”* (Student Manifesto for an Ecological Awakening, 2018 pledge)

Highlighting the unique position of *Grandes Écoles* students in the French education system, a general meeting held on March 7, 2019 brought together 180 initiators of the manifesto, top executives from four CAC40 listed companies (Engie, Sanofi, Kering, Schneider Electric), the Secretary of State for Ecological and Inclusive Transition, the Minister of Ecological and Solidary Transition and the Minister of Higher Education, Research and Innovation.<sup>5</sup> Since then, the ecological commitment of *Grandes Écoles* graduates has remained a recurring topic in national media coverage. However, the initiators of the manifesto acknowledge the limited impact the movement had in promoting the transformation of large companies into sustainable businesses, pointing out the lack of concrete action that followed environmental pledges:

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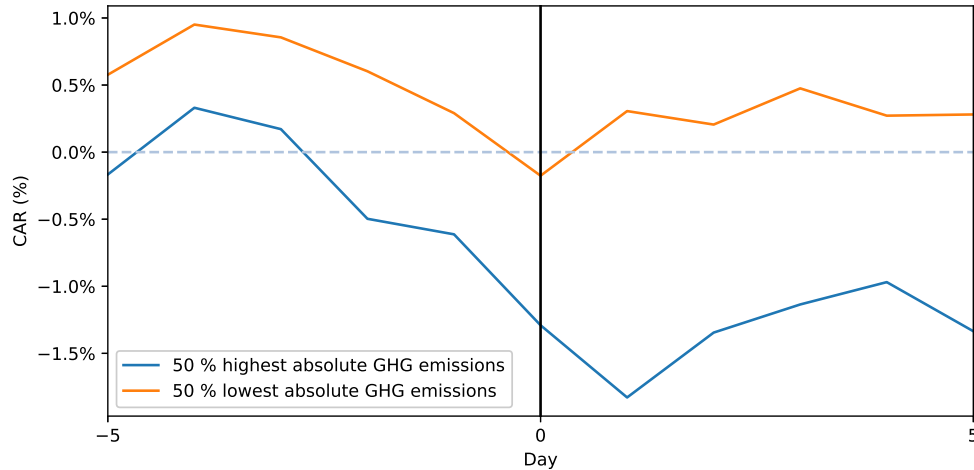
<sup>4</sup>The initiators of the climate movement were from École Polytechnique, HEC Paris, AgroParisTech, ENS Ulm, and CentraleSupélec.

<sup>5</sup><https://escp.eu/news/le-manifeste-etudiant-pour-un-reveil-ecologique-organise-son-grand-debat>



“For more than two years, we have been trying to mobilize companies [...]. We denounce those who limit their efforts to publicity effects, and salute those who, unfortunately much less numerous, have carried out a truly ambitious process of reducing their impact. But we are faced with a largely insufficient result.”  
 (Student Manifesto for an Ecological Awakening, 2022 pledge)

Figure 1: CAR of the SBF120 companies around the 7th March 2019 meeting



*Note:* CAR are calculated using the CAPM and return on the MSCI France index. Day 0 is when the meeting took place. Carbon intensity is computed as Scope 1 plus Scope 2 carbon emissions divided by total assets. We adopt a 255-trading day estimation window ending 46 trading days prior to the event. For each firm, we require a minimum of 40 observations in the estimation window. Data are retrieved from Refinitiv.

On the firm side, the climate movement took place during a period of increasing environmental pledges made by the largest French companies. The MEDEF, the main French employers’ federation, launched the French Business Climate Pledge in 2015, an initiative which encourages firms to make voluntary commitments to take climate action. The first edition gathered 39 companies, while 109 participated in the 2020 edition, and by the end of 2022, 322 companies had signed the pledge. Despite this success, signatories face heterogeneous incentives to take concrete action, as they belong to different industry sectors and are not held accountable for their commitments. As a result, the scope and specificity of commitments vary from abstract statements to quantified targets. In this context of strong environmental communication and due to the proximity between *Grandes Écoles* and corporate elites, corporations have become more involved with the climate movement. The initiators of the manifesto were invited to the 2019 summer meeting of the MEDEF to express their views, and several multinational companies, including 26 companies currently listed on the CAC40 index, agreed to meet with the initiators of the manifesto to publicly answer questions on their environmental policy.<sup>6</sup>

<sup>6</sup><https://pour-un-reveil-ecologique.org/en/les-entreprises-nous-repondent/>

Table 1: SBF120 companies' reaction to 7th March 2019 meeting, by level of carbon dioxide equivalent emissions

Absolute emissions	Window	N	Mean CAR	Neg : Pos	Adjusted BMP	Adjusted Patell
<u>Panel A: Highest emitters</u>						
Top 50 %	[0, 1]	49	-2.57%	41 : 8	-4.8***	-4.823***
	[0, 2]	49	-1.46%	37 : 11	-3.257***	-3.272***
	[0, 3]	49	-1.19%	32 : 16	-2.711***	-2.724***
	[0, 4]	49	-0.41%	30 : 19	-0.587	-0.589
	[0, 5]	49	0.08%	22 : 27	1.003	1.008
Top 25 %	[0, 1]	25	-2.34%	20 : 5	-3.199***	-3.241***
	[0, 2]	25	-1.24%	20 : 5	-1.752**	-1.775**
	[0, 3]	25	-1.04%	17 : 8	-1.411*	-1.429*
	[0, 4]	25	-0.62%	16 : 9	-0.191	-0.193
	[0, 5]	25	-0.25%	12 : 13	0.74	0.75
<u>Panel B: Lowest emitters</u>						
Bottom 50 %	[0, 1]	49	-0.99%	32 : 16	-1.516*	-1.539*
	[0, 2]	49	-0.58%	30 : 18	-0.74	-0.751
	[0, 3]	49	-0.24%	25 : 23	-0.022	-0.022
	[0, 4]	49	0.06%	25 : 24	0.605	0.614
	[0, 5]	49	0.77%	18 : 30	1.823	1.849
Bottom 25 %	[0, 1]	25	-1.05%	16 : 9	-1.086	-1.112
	[0, 2]	25	-0.51%	14 : 10	-0.268	-0.275
	[0, 3]	25	-0.19%	12 : 12	0.226	0.232
	[0, 4]	25	0.29%	13 : 12	0.828	0.848
	[0, 5]	25	0.66%	10 : 14	1.272	1.302

*Note:* Cumulative abnormal returns (CARs) are calculated using the CAPM and the return on the MSCI France index. The event day is labeled as Day 0. The estimation window for the CAR calculation is set at 255 trading days, ending 46 days before the event. A minimum of 40 observations is required for each firm in the estimation window. The sample is divided by absolute total CO2 emissions (Scope 1 + Scope 2 emissions). The “Neg:Pos” column shows the ratio of firms with negative versus positive CARs over the event window. The BMP and Patell tests are used to test the nullity of the mean CAR against the alternative that the mean CAR is negative. Test statistics are corrected for cross-sectional correlation using Kolar and Pynnönen (2010) adjustment. The notations \*, \*\* and \*\*\* indicate significance at the 10%, 5% and 1% levels respectively.

Previous research indicates that climate activism can have a negative impact on the valuation of carbon-intensive companies (Ramelli et al., 2021). To demonstrate that polluting companies have incentives to respond to this negative organizational attractiveness shock, we examine the stock price movements of SBF120 companies around the March 7, 2019 meeting. SBF120 companies are likely to be exposed to this shock as *Grandes Écoles* are the primary recruitment pool of their executives (Reberioux and Roudaut, 2018). We calculate the cumulative abnormal returns (CARs) of the SBF120 companies using the CAPM and returns on the MSCI France index. Following standard practices in the event study literature, we adopt a 255-trading day estimation window ending 46 days prior to the meeting and require a minimum of 40 observations in the estimation window for a firm to be included in the sample. We then partition the sample by level of absolute carbon dioxide equivalent emissions, taking into account Scope 1 and Scope 2 emissions, before computing average

CARs. Figure 1 shows the average CARs of the 50% highest and lowest GHG emitters in a 5-day window surrounding the March 7, 2019 meeting. In Table 1, we observe negative and significant average CARs for up to three days following the meeting for the highest GHG emitters, a pattern that is not present among the lowest emitters. Similar results are displayed in Table C.1 and Table C.2 in Appendix C when the sample is partitioned by absolute Scope 1 and Scope 2 emissions, respectively. These simple tests suggest that a negative organizational attractiveness shock caused by a poor environmental responsibility could adversely affect the valuation of the most polluting companies, thereby increasing their incentives to address this issue.

### 3 Econometric Methodology

In this section, we present our methodology for identifying agents' reactions to corporate environmental pledges and their drivers, assuming a repeated measurement design.

Let  $Y_i$  denote a random variable that takes the value of one if an agent intends to refuse to work for a polluting company and zero otherwise. In the survey, this outcome is captured by measuring respondents' intentions to refuse to work for a fictitious company that they have been informed has a negative environmental impact. Here, the notion of a polluting company can also be taken to mean that the agent has a prior belief that the firm emitting the job offer has a negative impact on the environment. We assume a repeated measurement design in which this outcome variable is observed twice for every agent: once without the polluting company making a pledge to improve its environmental impact and once with the company making such a pledge. We denote the outcome in each state by  $Y_i^{(0)}$  and  $Y_i^{(1)}$ , respectively. We are interested in modeling the conditional probability that an agent intends to refuse to work for a polluting employer in both states. Let  $X_i$  be the random vector of the agent's individual characteristics, and  $D_i$  be an indicator variable that takes the value of one if the agent has been exposed to the environmental pledge and zero otherwise. The probabilities of having intentions to refuse to work for a polluting company given the agent's characteristics in both states are given by:

$$\mathbb{P}\left(Y_i^{(0)} = 1|X_i\right) = \mathbb{P}(Y_i = 1|X_i, D_i = 0), \quad (1)$$

$$\mathbb{P}\left(Y_i^{(1)} = 1|X_i\right) = \mathbb{P}(Y_i = 1|X_i, D_i = 1). \quad (2)$$

Equation (1) represents the conditional probability that an agent intends to refuse to work for a company when they only have knowledge of its negative environmental impact. On the other hand, Equation (2) represents this conditional probability when the agent has

both knowledge of the company’s negative environmental impact and has been exposed to a pledge by the company to improve its impact in the future. Note that in our repeated measurement setting, the treatment is exogenous and received by each agent, implying that both observed and unobserved characteristics do not vary across the two states. Consequently, any difference in the probabilities of having intentions to refuse to work for a polluting company given by Equation (1) and Equation (2) is purely resulting from the exposure of the agent to the environmental pledge. Comparing the value of the two probabilities therefore allows to measure the effect of the environmental pledge on the agents’ intentions. We take advantage of our repeated measurement design to compute a measure of the reaction to the environmental pledge at the individual level:

$$\tau_i = \frac{\mathbb{P}(Y_i = 1 | X_i, D_i = 0)}{\mathbb{P}(Y_i = 1 | X_i, D_i = 1)}. \quad (3)$$

This quantity measures how much less likely an agent is to refuse to work for a polluting company after being exposed to an environmental pledge. In the rest of the paper, we refer to this quantity as *reaction to the environmental pledge* or simply *reaction*. It should be noted that in our setting, this quantity can be estimated for each individual in our database. A reaction greater than one corresponds to the agent being less likely to refuse to work for a polluting company after being exposed to an environmental pledge. A value lower than one corresponds to a backfire of the pledge, with the agent being more likely to refuse to work for the employer. A value equal to one would correspond to the absence of an effect of the environmental pledge. In this study, we find evidence that participants to the climate movement threatening to boycott polluting employers have heterogeneous responses to the environmental pledge. We are therefore interested in identifying individual drivers of this reaction in order to assess why some individuals react while other do not.

To highlight the importance of agents’ reactions to environmental pledges, consider a company subject to a negative shock on its organizational attractiveness due to its poor environmental impact. To mitigate this selection effect, an honest firm can take costly actions to improve its environmental impact and signal its good practices to job seekers. However, an opportunistic firm, knowing the pro-environmental preferences of its recruitment pool, can make an environmental pledge to maintain its organizational attractiveness without taking significant action to improve its impact. In this case, the environmental pledge corresponds to purely opportunistic behavior to shift job seekers’ perceptions of the firm. Extensive literature indicates that both honest and dishonest firms can make environmental commitments (Lyon and Montgomery, 2015), implying that such commitments carry little information regarding a company’s future environmental impact. While honest firms could

provide greater evidence of their efforts, if simple pledges are enough to shift job seekers' selection intentions, it would raise companies' incentives to engage in purely opportunistic behavior. Therefore, the impact of a selection effect caused by a company's poor environmental performance depends not only on job seekers' intentions to avoid companies with a negative environmental impact but also on how they react to corporate environmental promises.

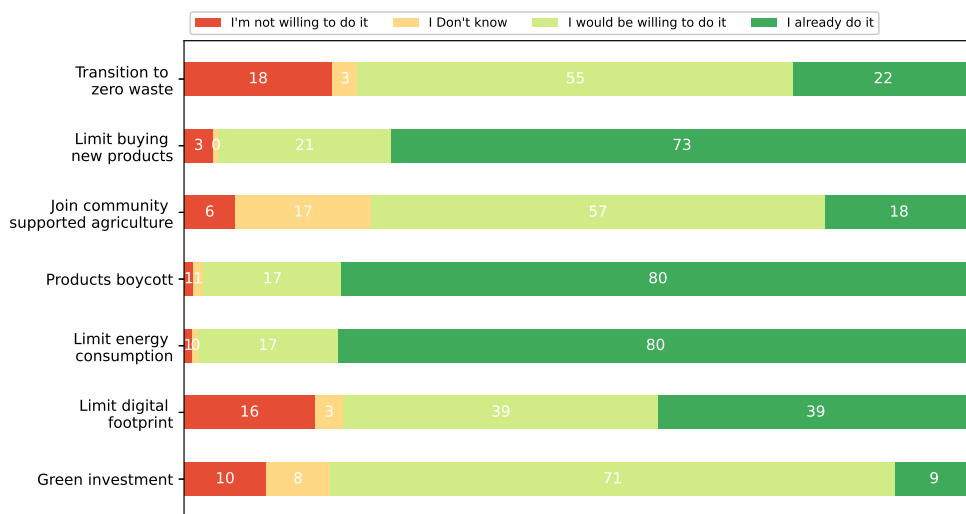
The reaction to the environmental pledge given by Equation (3) is estimated by using plug-in estimators of the conditional probabilities (1) and (2). In empirical applications, these conditional probabilities are estimated jointly by building a classification model of  $Y_i$ , using the vector  $(X_i, D_i)$  as a set of explanatory variables. As previously emphasized, we find evidence that the reaction to environmental commitments is moderated by individual characteristics, as some respondents shift their intentions to refuse to work for a polluting company after being exposed to the commitment whereas others do not react. To account for this, we use semi-parametric estimation of the link function mapping  $(X_i, D_i)$  to  $Y_i$  based on machine learning classifiers that allow interactions between the treatment and individual characteristics. Specifically, we use random forest classifiers (Breiman, 2001) to estimate the conditional probabilities required to compute the reaction. Random forests are an ensemble learning method that generates predictions by averaging the results of many randomized decision trees constructed during a training phase. This procedure has several advantages. First, it has established theoretical properties, including consistency results (Biau and Scornet, 2016). Second, it has shown superior empirical performance over a wide range of classification tasks and data types (Fernández-Delgado et al., 2014). Third, it performs simultaneously model selection and estimation while being robust to the presence of irrelevant features (Chi et al., 2022), which is of primary interest here as we use a large set of explanatory variables, while only a small subset may be driving agents' reactions to corporate commitments.

After estimating the reaction to the environmental pledge using a machine learning classifier, we use Shapley value (SV) decomposition to identify its most important drivers. Methods based on Shapley value decomposition have become standard for explaining the output of black-box models (Lundberg and Lee, 2017), because they enable the computation of the marginal contributions of predictors to model outputs, including non-linear combinations of outputs such as the reaction measure. Therefore, we apply this methodology to identify individual characteristics that drive the reaction to the environmental pledge. Details on how to compute the marginal contributions based on SV decomposition in our framework are provided in Appendix A. In addition, we complement this approach with classic inference by using the reaction measure as a dependent variables in linear regressions.

## 4 Data

The self-administered questionnaire was distributed via the newsletter of the organizers of the “Student manifesto for an ecological awakening” petition. Data collection took place from July to October 2019, and we collected 3607 responses, from which we obtained a complete dataset representing 2,307 manifesto signatories.<sup>7</sup> The questionnaire consists of 54 questions structured into five parts: studies and professional perspectives, ecological commitments and practices, political values and positioning, relation to the manifesto, and socio-demographic characteristics. An English translation of the questionnaire is available in Appendix B. To capture respondents’ representations of a good job, we used the questions from the 2008 wave of the European Values Survey, allowing respondents to select up to five items from the 17 proposed. Socio-demographic characteristics were measured using questions from the European Social Survey. These include variables such as age, gender, religion, mother and father’s socioeconomic status, perceptions of familial financial resources, monthly financial resources, employment status, number of working hours per week, and living situation. To capture respondents’ environmental attitudes and beliefs, we used previous questions from surveys conducted on the French climate movement (Gaborit, 2020; Le Lann et al., 2021; Alexandre et al., 2021). We measured attitudes towards pro-environmental behavior, support for political action and collective mobilization for the ecological cause, and beliefs regarding the causes and solutions to the ecological crisis. Table C.4 in Appendix C displays the questions that were used to measure these factors.

Figure 2: Attitudes towards pro-environmental behavior



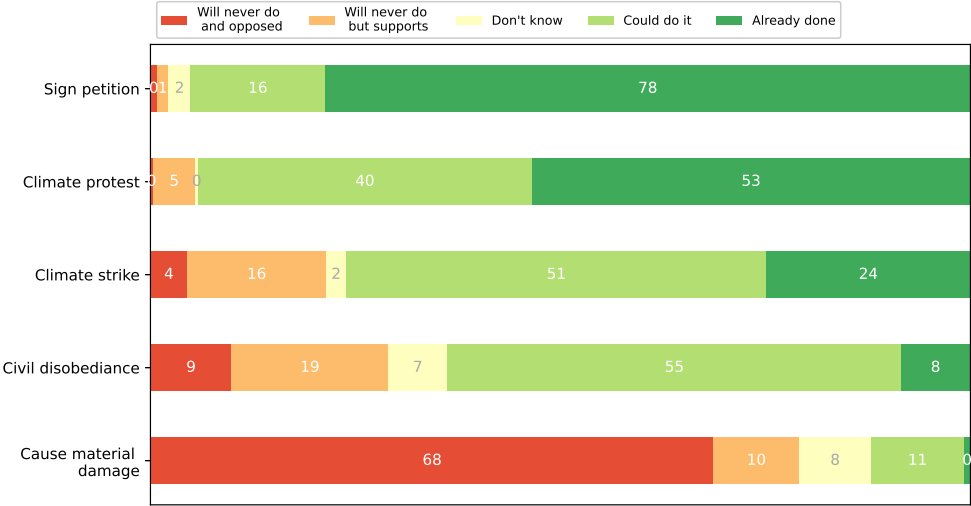
*Note:* This figure displays the distribution of attitudes towards environmentally responsible behavior, as measured on a four-level scale.

We give a description of the average respondent in the following. Women represent 51%

<sup>7</sup>Table C.3 in Appendix C compares our sample relative to the population of signatories.

of our sample and the average age is of 22.1 years old. Most of the respondents are close to their graduation, as 63% of them are at least in fourth year of higher education studies.<sup>8</sup> 53% of them had a job at the time of the study: 14% had a day job and 39% a job related to their educational background (internship or apprenticeship). With regard to parental socioeconomic status, 69% of respondents have at least one parent occupying an executive position or intellectual profession, and 86% perceive their family’s financial resources to be fine or comfortable. *Grandes Écoles* students represent 68% of the sample, with 10% of respondents enrolled in business schools and 58% in engineering schools. Consequently, most respondents are confident regarding their position in the job market: 86% of them believe they will easily find a job in their field of study, with only 4% of them considering unemployment risk in their career perspectives. Respondents are also highly interested in finding meaning through their work: 75% of respondents want a job that is useful for society, and 79% want a job that is compatible with their own values. They have a high level of overall satisfaction with their training, with 83% of them satisfied or very satisfied with the studies they are following. However, a majority of students are dissatisfied with their training on environmental issues, as only 31% of respondents believe that they are well prepared to tackle ecological problems.

Figure 3: Attitudes towards political actions in name of ecology



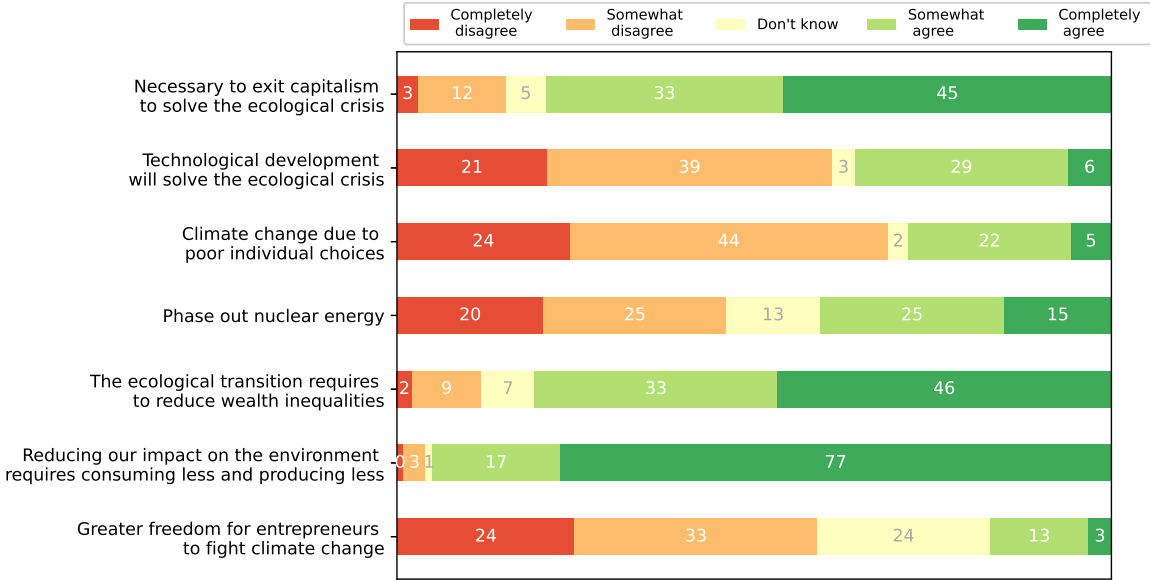
Note: This figure displays the distribution of attitudes towards political action in the name of the ecological cause, as measured on a five-level scale.

Figure 2 displays respondents attitudes towards pro-environmental behavior. Overall, they have highly favorable attitudes towards environmentally responsible behavior and several eco-friendly behavior, such as limiting the purchase of new products or limiting their energy consumption, are already adopted by a majority of the sample. Respondents are also

<sup>8</sup>In France, the junior executive job market usually takes place after five years of post-secondary education.

strongly supportive of taking punitive economic action against environmentally irresponsible products, with 80% of them already boycotting such products and 97% being willing to do so. More involving eco-gestures, such as implementing zero waste or reducing their digital footprint, are less commonly practiced, but a significant portion of respondents perform them, and the large majority has positive attitudes towards them.

Figure 4: Beliefs on the causes and solutions to the ecological crisis



Note: This figure displays the distribution of beliefs regarding causes and solutions to the ecological crisis, as measured on a five-level scale.

Figure 3 shows respondents’ attitudes towards collective mobilization and political actions in the name of ecology. A significant portion of the sample has prior experience in climate activism, with half of the respondents having already participated in a climate protest and one-quarter in a climate strike. Overall, there is strong support for political actions in the name of ecology. However, this support diminishes for riskier and more divisive actions, and it is reversed when considering radical actions such as causing material damage. Figure 4 shows the distribution of beliefs regarding the causes and solutions to the ecological crisis. A large majority of respondents believe that it is necessary to exit capitalism to solve the ecological crisis, that the ecological transition requires reducing wealth inequalities, and that limiting our impact on the environment requires consuming and producing less. However, there is greater heterogeneity among respondents’ beliefs regarding the role of technological development in addressing the ecological crisis, the role of individual responsibility in climate change, and whether we should phase out nuclear energy.

To capture respondents’ overall attitudes and beliefs, we compute indexes by aggregating the answers to multiple questions measuring a similar attribute. By incorporating both indexes and singular attributes in our classification model and utilizing machine learning



Table 2: Indexes computation

Index	Predictors (weight in index)	Predictors values	Measurement	Interpretation
<i>Environmental Attitude Index</i>	Reduce new purchases (1) Limit energy consumption (1) Green investment (1) Limit digital footprint (1) Products boycott (1) Join CSA (1) Zero waste (1)	Four-level scale: Already do (2) Willing to do (1) Don't know (0) Not willing to do (-1)	Overall attitudes towards pro-environmental behavior.	Higher (lower) values correspond to more (less) favorable attitudes towards environmentally responsible behavior.
<i>Political Action Index</i>	Civil disobedience (1) Climate protest (1) Climate strike (1) Sign petition (1) Material damages (1)	Five-level scale: Already done (2) Could do (1) Don't know (0) Will never do it but supports (-1) Will never do it and opposed (-2)	Overall attitudes towards political and collective for ecology.	Higher (lower) values correspond to stronger (weaker) support for political action and collective mobilization for ecology.
<i>Out of System Index</i>	Exit capitalism (1) Exit nuclear (1) Reduce inequalities (1) Reduce production and consumption (1) Technological solution (-1) Individual responsibility (-1) Entrepreneurs freedom (-1)	Five-level scale: Completely agree (2) Somewhat agree (1) Don't know (0) Somewhat disagree (-1) Completely disagree (-2)	Level of skepticism or belief in the ability of a market economy and technological development to solve the ecological crisis.	Higher (lower) values correspond to greater (lesser) skepticism in the ability of a market economy and technological development to solve the ecological crisis.
<i>Work Values CSR Index</i>	People treated equally (1) Compatible values (1) Useful for society (1)	Binary: Yes (1) No (0)	Overall attraction towards organization CSR or seek of meaning through work.	Higher (or null) values correspond to a greater (or no) attraction towards the search for meaning through work.

Note: This table displays the main indexes constructed by aggregating survey questions measuring similar attributes.

classifiers for the automatic selection of relevant information, we capture both global and singular information. We construct four principal indexes: the *Environmental Attitude Index*, the *Out of System Index*, the *Political Action Index*, and the *Work Values CSR Index*. These indexes respectively measure one’s overall attitudes towards pro-environmental behavior, belief in the current economic and political system’s responsibility and ability to solve the ecological crisis, attitude towards collective mobilization in the name of ecology, and attraction towards CSR or search for meaning through work (see Table 2 for details on their computation and interpretation).

## 5 Dependent variables and decision-making process

### 5.1 Dependent variables construction

To evaluate the effect of environmental pledges on respondents’ intentions to boycott job offers from polluting employers, we conducted a survey experiment with repeated measurements of the dependent variable. Although less conservative than a between-subject experiment, this design has the advantage of increasing the number of independent observations and therefore the statistical power of the procedures (Charness et al., 2012). Furthermore, a recent study by Clifford et al. (2021) indicates that repeated measurement designs tend to yield the same results as more conservative designs, but with a substantial increase in the precision of treatment effect estimation. We thus take advantage of this design to gain further insights into the heterogeneity of responses to environmental pledges.

We built our first measure of intentions to refuse to work for a polluting company using responses to the question: “*Would you be willing to give up a job offer in a company that has*

*a negative impact on the environment?*”. This question refers to a fictitious firm for which respondents are only informed about its negative environmental impact. In the survey, this question was asked in the final part of the section relative to work values and professional perspectives. Answers were collected using a five-item scale ranging from *completely willing* to *not at all willing*. Our dependent variable  $Y_i^{(0)}$  measures a respondent intentions to refuse to work for a polluting company and is computed by applying the following binary transformation to the responses:

$$Y_i^{(0)} = \begin{cases} 1 & \text{if respondent } i \text{ survey answer is } \textit{totally willing} \text{ or } \textit{willing}, \\ 0 & \text{otherwise.} \end{cases} \quad (4)$$

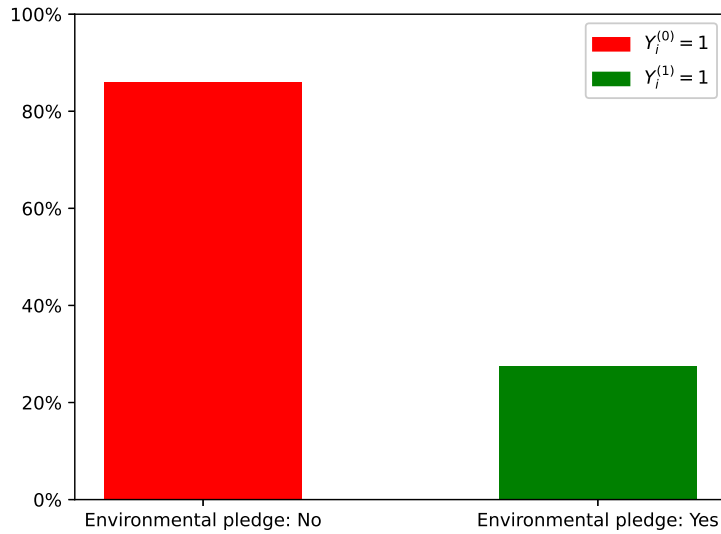
Second, we measured respondents’ intentions to refuse to work for a polluting company that makes a pledge to improve its environmental impact in the future. To do this, we asked a similar question, but referred to the company as “*a company that has a negative impact on the environment but declares to be committed to an ecological transition*”. Answers were also collected using a five-item scale ranging from *completely willing* to *not at all willing*. In contrast to the first question, this second question introduces information regarding the company’s negative environmental impact but also its pledge to improve this impact in the future. As we used a repeated measurement setting, both questions were asked to every respondent. To limit potential carry-over effects, a temporal distance was introduced between the two measures, taking the form of a block of eight questions separating them. Similarly to the first question, a binary transformation was applied to the responses, with the two items associated with the highest level of intentions to refuse to work for polluting employers encoded as a one, and the others as a zero. We denote by  $Y_i^{(1)}$  the resulting dependent variable which measures a respondent intentions to refuse to work for a polluting company making an environmental pledge.

The situation captured by our measures can be illustrated by a graduate student with pro-environmental preferences close to his entry on the job market. While having a negative prior on a potential employer’s environmental impact, the student can be exposed to a corporate commitment at some point of the information acquisition step, leading to a revision of his job pursuit intentions. As our setting allows to control for individual invariant characteristics, it also allows to estimate the causal effect of such corporate commitments on the graduates self-selection intentions.

## 5.2 Decision-making process

An important question to consider is whether exposure to the environmental pledge changed the frequency of intentions to refuse to work for polluting employers, and if so, in which

Figure 5: Frequency of intentions to refuse to work for polluting employers



*Note:* This figure displays the proportion of respondents having intentions to refuse to work for polluting companies with and without being exposed to an environmental pledge.

direction. Figure 5 displays the proportion of individuals who intend to refuse to work for polluting employers, with and without exposure to an environmental pledge. While 86% of respondents have such intentions, this proportion falls to 28% after exposure to the environmental pledge. Given that we are studying a population with a high level of engagement in climate activism, this result suggests that environmental pledges could be a powerful tool for companies seeking to mitigate negative organizational attractiveness shocks due to their poor environmental responsibility.

It may be argued that this major switch in the frequency of intentions to refuse to work for polluting companies could be caused by a lack of true environmental concern. From this perspective, some respondents may not care about working for an environmentally responsible firm due to their personal ethical standards, but rather due to social desirability. In this case, environmental pledges may be merely a way to appear morally cautious. To rule out this possibility, we verified whether respondents who were willing to refuse a job in a polluting company actually cared about their employer’s environmental impact. We measured how respondents evaluated a potential employer’s environmental impact and the importance they gave to this type of information when making their employment decision. First, we found that respondents who had intentions to refuse to work for a polluting company also paid high attention to an employer’s environmental impact: 99% of them deemed at least one information to be “important” or “very important”, and 81% deemed at least four different elements of information to be important.

We compared the importance given to information on an employer’s environmental im-

Table 3: Information on employer’s environmental impact deemed important by respondents.

Information	Weak intentions	Strong intentions
CSR report	39.0%	39.6%
Carbon footprint	67.0%***	74.0%***
Biodiversity impact study	71.5%***	78.7%***
Reason for existence of the company	76.2%***	82.6%***
Reduction strategy for GHG emissions	74.9%	72.1%
Possibilities for action within the company	72.4%	68.1%
Feeling on the company’s environmental policy	84.6%	87.4%

*Note:* This table displays the frequency of responses indicating that information about an employer’s environmental impact is “very important” or “important”. The weak intentions group refers to individuals for whom  $Y_i^{(0)} = 1$  and  $Y_i^{(1)} = 0$  ( $n = 1387$ ). The strong intentions group refers to individuals for whom  $Y_i^{(0)} = 1$  and  $Y_i^{(1)} = 1$  ( $n = 596$ ). A two-sided test of equality of proportions was used. \*\*\*, \*\*, and \* indicate rejection of the null hypothesis of equality of proportions at the 1%, 5%, and 10% nominal level, respectively.

pact between respondents who had intentions to refuse to work for polluting companies but did react to the environmental pledge ( $Y_i^{(0)} = 1, Y_i^{(1)} = 0$ ), which we refer to as the *weak intentions* group, and those who did not react ( $Y_i^{(0)} = 1, Y_i^{(1)} = 1$ ), which we refer to as the *strong intentions* group. Table 3 displays the frequency of the answers *very important* and *important* for seven elements of information about an employer’s environmental impact in the two groups and the results from a two-sided test of equality of proportions. We find that members of the strong intentions group accorded significantly more importance to three measures of environmental impact: carbon footprint, biodiversity impact study, and evaluation of the company purpose. However, the gaps are small between the two groups compared to the magnitude observed in Figure 5: 67% against 74%, 71.5% against 78.7%, 76.2% against 82.6%, respectively. For the other elements of information, we failed to reject the null hypothesis at the 10% nominal level. Overall, this suggests that the magnitude of the treatment effect is unlikely to be explained by a difference in environmental concern between the two groups.

Another important point to note is that respondents assign more importance to their subjective evaluation of a firm’s environmental impact compared to more objective measures such as the company’s level of carbon emissions or its strategy to reduce its emissions. In fact, both groups consider the evaluation of the company’s reason for existence and their subjective feelings towards its environmental policy as the two most important pieces of information. This trend becomes even more apparent when considering the entire sample and the frequency of the answer “very important”: the two most crucial pieces of information are the respondents’ subjective evaluation of the company’s reason for existence (45%) followed by their feelings about its environmental policy (41%). On the other hand, the

reduction strategy of GHG emissions is ranked fifth (28%), while the footprint is ranked second to last (23%).

To further understand why some individuals did not change their intentions to refuse to work for polluting companies even after exposure to the environmental pledges, we asked them the reasons for their choice in an open question. We found that 70% of them did not trust the pledges’ honesty,<sup>9</sup> with 23% of the responses explicitly using the term “greenwashing”. Therefore, the absence of a treatment effect on a part of the sample is first explained by a distrust in the honesty of environmental pledges made by corporations rather than by immediate preferences to work for an environmentally responsible employer.

## 6 Results

This section presents the results of our study on the drivers of reactions to environmental pledges, as defined by Equation (3). To estimate the reaction for each individual in our sample, we jointly estimated the probabilities given by Equations (1) and (2) using a random forest classifier. We used a vector of 128 predictor variables, denoted as  $X_i$ , and the exposure variable  $D_i$  as inputs to the model. The optimal random forest classifier was selected by minimizing the out-of-bag log-loss through a random grid search with 10,000 iterations. Appendix C presents the list of hyper-parameters used in this step and their optimal values. Our analysis reveals that the optimal random forest classifier can effectively distinguish between the two classes. To assess its performance, we randomly divided the original data into ten train-test splits, with each test sample representing 25% of the observations. For each split, we computed the associated AUC score. The average AUC score across the ten splits was 0.87, indicating that the model has a strong ability to differentiate between the two classes. After estimation of the optimal random forest, we use the probabilities predicted by the classifier to calculate the reaction for each individual in the sample.

In our empirical analysis, we use the reaction as the dependent variable in our regressions, and we also directly identify its most important predictors using Shapley value decomposition. We used the KernelShap methodology, which is implemented in the SHAP package Lundberg and Lee (2017), to compute the Shapley values. Appendix A provides details on the computation of the Shapley values in our setting. After computing a Shapley value for each individual and each predictor in our dataset, we aggregate the Shapley values to identify the most important predictors of the reaction. We first average absolute Shapley

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<sup>9</sup>Answers were classified as skeptical if they expressed doubts about the honesty of the pledge, contained the term *greenwashing*, or asked for action rather than words. Examples of such answers include: “I’m afraid of lies as bait”, “I do not want to engage in a firm based on a promise, I want to see facts”, “What are the guarantees that this company is really engaging in an ecological transition?”.

values across groups of variables that measure similar attributes to compute factor importance. We gather the predictors into nine factors: beliefs on the ecological crisis, career perspectives, education, political action for ecology, political positioning, pro-environmental attitude, sociodemographics, work values, and a final factor that includes variables that could not be grouped under the previous factors, such as associative engagement. We also compute predictor importance as measured by the sum of absolute Shapley values associated with a given predictor across all individuals.

## 6.1 Drivers of intentions to boycott polluting employers

Before applying our methodology to identify drivers of the reaction to the environmental pledge, we first identify the drivers of individuals' intentions to refuse to work for polluting companies. Previous personnel psychology research on the determinants of recruitment found that job seekers are more attracted to organizations that better fit their own values (Judge and Bretz, 1992; Chapman et al., 2005). In the specific case of environmental communication to attract job seekers, previous work has found that job seekers with higher pro-environmental attitudes and a desire to have an impact through their work are more attracted to environmentally responsible companies (Gully et al., 2013; Jones et al., 2014).

Table 4: Drivers of intentions to refuse to work for polluting companies

	(1)	(2)	(3)	(4)	(5)
Constant	1.582*** (0.60)	0.207 (0.66)	0.950 (0.65)	1.324** (0.60)	-0.0323 (0.70)
Age	-0.00524 (0.028)	-0.00603 (0.031)	-0.0368 (0.031)	-0.0104 (0.027)	-0.0284 (0.033)
Gender - Man	0.235* (0.12)	0.324** (0.13)	0.455*** (0.13)	0.279** (0.12)	0.478*** (0.13)
Employed	0.170 (0.12)	0.227* (0.13)	0.159 (0.13)	0.192 (0.13)	0.222* (0.13)
Monthly financial resources	0.000110 (0.00011)	0.0000733 (0.00011)	0.0000388 (0.00012)	0.0000737 (0.00011)	0.00000892 (0.00012)
Family financial situation	0.0572 (0.056)	0.0347 (0.059)	0.0349 (0.058)	0.0523 (0.058)	0.0281 (0.060)
Work values CSR Index		0.892*** (0.086)			0.642*** (0.095)
Environmental Attitude Index			0.188*** (0.016)		0.131*** (0.018)
Political Action Index				0.170*** (0.018)	0.0849*** (0.021)
Observations	2307	2307	2307	2307	2307
Pseudo $R^2$	0.005	0.070	0.078	0.053	0.124

*Note:* This table presents the results of estimating Equation (1) using logistic regression. Standard errors robust to heteroskedasticity are reported in parentheses. \*, \*\*, \*\*\* indicate significance at the 10%, 5%, and 1% level, respectively.

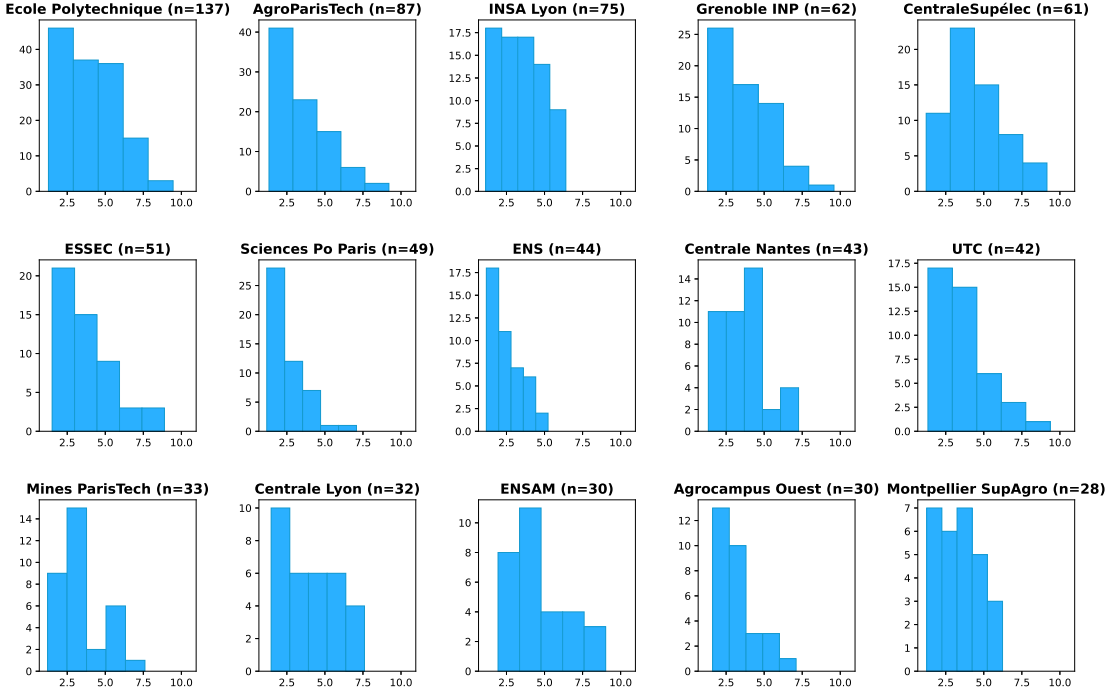
To check for these findings in our sample, we estimate Equation (1) using a logistic

regression. We use socio-demographic characteristics as control variables and include the *Environmental Attitude Index*, the *Political Action Index*, and the *Work values CSR Index* as explanatory variables in our model to proxy for environmental preferences and the search for meaning through work. Results are displayed in Table 4. Consistent with previous research, we find that respondents with higher pro-environmental attitudes, more supportive of political action for ecology, and seeking meaning through their work are significantly more likely to have intentions to refuse to work for polluting companies.

To check that the effect of environmental preferences and search of meaning through work are properly captured by the random forest classifier, we also apply the Shapley value decomposition to the predicted intentions to refuse to work for polluting companies. Factors and predictors' importance to explain the random forest classifiers' prediction of intentions to refuse to work for polluting companies, as measured by average absolute Shapley values, are displayed in Figure C.1 and Figure C.2 in Appendix C. Supporting our previous finding, we find that predictors associated with pro-environmental attitudes, support for political action for ecology, and the search for meaning through work are ranked as the most important predictors of these intentions.

## 6.2 Drivers of the reaction to environmental pledges

Figure 6: Distribution of the reaction by institution

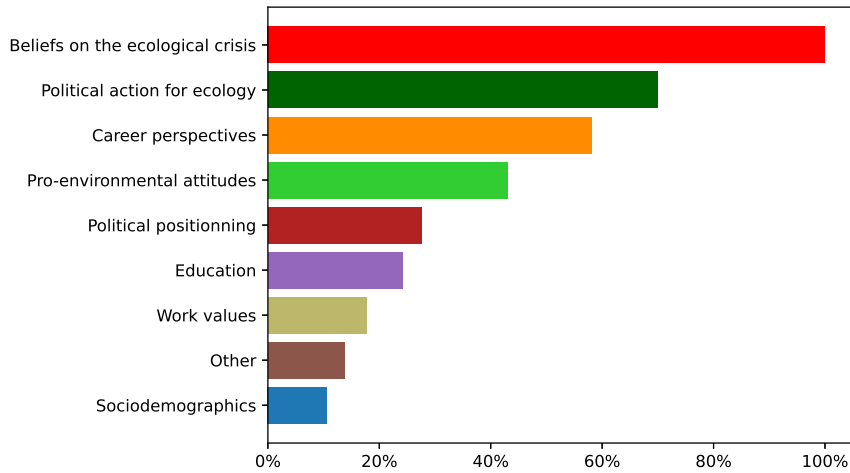


*Note:* This figure shows the distribution of the reaction to the environmental pledge among individuals who initially had intentions to refuse to work for polluting companies ( $n = 1983$ ) in the fifteen most represented institutions in our sample. The reaction is computed using the output of a random forest classifier.

In this section, we aim to identify the factors that influence the reaction to environmental pledges. As a reminder, the reaction, represented by Equation (3), measures of how much less likely an individual is to intend to refuse to work for a polluting employer after being exposed to an environmental pledge. For the rest of our analysis, we consider only those individuals who initially had intentions to refuse to work for polluting employers ( $Y_i^{(0)} = 1$ ), resulting in a sample size of  $n = 1983$ . In our sample, the average reaction is equal to 3.6, indicating that respondents are on average more than three times less likely to intend to refuse to work for a polluting employer after being exposed to an environmental pledge.

Figure 6 displays the distribution of the estimated reaction for the fifteen most represented institutions in our sample. We observe a significant heterogeneity in respondents' reactions depending on their institution of study. Respondents enrolled in Sciences Po Paris and École Normale Supérieure, which are institutions focused on social and political sciences and scientific research, respectively, are less reactive than average. On the other hand, students from top engineering schools, such as CentraleSupélec and ENSAM, are highly responsive to the environmental pledge, with a mean reaction of 4.4 and 4.6, respectively.

Figure 7: Ranking of factors to predict the reaction to the environmental pledge



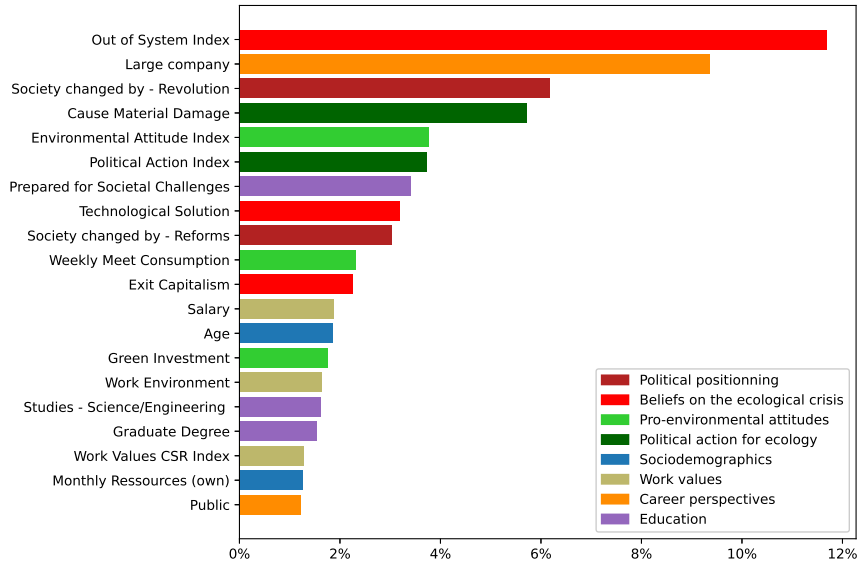
*Note:* This figure displays the importance of factors in predicting the reaction to the environmental pledge, as measured by the mean absolute Shapley value. The reaction, given by Equation (3), is estimated using the output of a random forest classifier. Results are expressed as a percentage of the most important factor.

Figure 7 displays the factor ranking in terms of their ability to explain the reaction to the environmental pledge, as measured by the average absolute Shapley value. The results are expressed as a percentage of the most important factor. We find that the three most critical factors in explaining this reaction are one's beliefs about the ecological crisis, support for political action in the name of ecology, and one's career perspectives. In contrast to the



drivers of intentions to refuse to work for a polluting company, pro-environmental attitudes and work values appear to be less important in explaining the reaction to the environmental pledge.

Figure 8: Top 20 predictors of the reaction to the environmental pledge



*Note:* This figure displays the twenty most important predictors of the reaction to the environmental pledge, as measured by the sum of absolute Shapley values. The reaction, given by Equation (3), is estimated using the output of a random forest classifier. Results are expressed as a percentage of the total sum of absolute Shapley values.

Figure 8 presents the ranking of the top twenty most important predictors in explaining the reaction to the environmental pledge. We observe that the most influential predictors of the reaction are beliefs regarding the causes and solutions to the ecological crisis, as measured by the *Out of System Index*, whether one seeks to work for a large company, and markers of political radicalism, such as believing that society should be changed through revolution or being supportive of causing material damage in the name of ecology. Collectively, these four predictors account for one-third of the total predictor importance.

To draw inference on the drivers of the reaction to environmental pledge, we next estimate the following regression model:

$$\log(\hat{\tau}_i) = \alpha + \beta X_i + \varepsilon_i, \quad (5)$$

where the vector of explanatory variables  $X_i$  includes socio-demographic characteristics, as well as some of the most important predictors that have been identified.

The results are presented in Table 5. We find that the full model has good explanatory power for the reaction, as it accounts for 74% of its variance. Our analysis indicates that incorporating large companies into one's career perspectives is significantly associated with

Table 5: Drivers of the reaction to the environmental pledge

	(1)	(2)	(3)	(4)	(5)
Constant	1.834*** (0.11)	1.790*** (0.091)	1.850*** (0.091)	2.157*** (0.074)	1.832*** (0.065)
Age	-0.0300*** (0.0049)	-0.0248*** (0.0040)	-0.0238*** (0.0041)	-0.0196*** (0.0034)	-0.0168*** (0.0028)
Gender - Man	0.0255 (0.021)	-0.0325* (0.017)	0.0486*** (0.016)	-0.0460*** (0.013)	-0.0327*** (0.011)
Employed	0.0156 (0.021)	-0.0000363 (0.018)	-0.00825 (0.016)	-0.0167 (0.014)	-0.0216* (0.011)
Monthly financial resources	-0.0000616*** (0.000018)	-0.0000641*** (0.000015)	-0.0000396*** (0.000014)	-0.0000233** (0.000012)	-0.0000269*** (0.000095)
Family financial situation	0.0145 (0.0098)	0.0113 (0.0083)	0.0159** (0.0077)	0.00131 (0.0063)	0.00368 (0.0052)
Work values CSR Index		-0.0982*** (0.012)			0.00677 (0.0086)
Career perspectives - Large company		0.490*** (0.019)			0.270*** (0.013)
Environmental Attitude Index			-0.0252*** (0.0026)		-0.0137*** (0.0018)
Political Action Index			-0.0450*** (0.0036)		-0.00345 (0.0028)
Cause Material Damage			-0.137*** (0.0093)		-0.0998*** (0.0063)
Out of System Index				-0.0699*** (0.0019)	-0.0476*** (0.0018)
Society changed by - Revolution				-0.270*** (0.014)	-0.193*** (0.011)
Observations	1983	1983	1983	1983	1983
R <sup>2</sup>	0.031	0.313	0.455	0.609	0.740

Note: This table displays the results of regression (5). The reaction, given by Equation (3), is estimated using the output of a random forest classifier. Standard errors robust to heteroskedasticity are reported in parentheses. \*, \*\*, \*\*\* indicate significance at the 10%, 5%, and 1% level, respectively.

a 31% increase in the reaction to environmental pledges. One possible explanation for this result is that students who are interested in working for large companies may assume that their future employer could have a significant impact on the environment. Therefore, a polluting employer that commits to improving its environmental impact would be more likely to align with their personal preferences, compared to a polluting employer that does not make such a commitment.

We also find that variables measuring political radicalism have an important effect on the reaction, with individuals who are more supportive of radicalism being less reactive to the environmental pledge. Believing that society should be changed by revolution is associated with a -17% decrease in the reaction, while a one-point increase in support for causing material damage in the name of ecology is associated with a -9% decrease. Additionally, being more skeptical towards the ability of a market economy and technological development to solve the ecological crisis, as measured by the *Out of System Index*, is associated with a decrease in the reaction: a one-point increase in the *Out of System Index* is associated with a -5% decrease in the reaction. In comparison, pro-environmental attitudes have a lower effect: while the *Environmental Attitude Index* is significant at the 1% level, a one-point increase in the index is only associated with a -1% decrease in the reaction. Finally, while seeking meaning through work was one of the most important drivers of intentions to

refuse to work for polluting companies, it does not appear to have a significant effect on the reaction to environmental pledges.

As a robustness check for our results, we applied the same methodology using an XGBoost classifier. We found a strong correlation of 83% between the measures of predictor importance, as measured by the average absolute Shapley value, obtained for the XGBoost and random forest classifiers. As a result, the predictor ranking associated with both classifiers is very similar. Appendix C shows Figure C.3 and Figure C.4, respectively displaying the factor and predictor ranking to explain the reaction computed using the output of the XGBoost classifier. We find that seventeen out of twenty predictors belong to both rankings, although in a different order. We then replicate the findings of Table 5 using the reaction computed from the output of the XGBoost classifier. The results are displayed in Table C.6 and yield qualitatively similar conclusions.

In conclusion, our findings suggest that environmental pledges can have a substantial impact in counteracting selection effects caused by a poor environmental responsibility. Although the environmental pledge did not change the intentions of a significant portion of survey respondents, a large majority of them switched their intentions. This finding can be explained by the fact that the drivers of intentions to refuse to work for polluting companies are different from the drivers of the reaction to environmental commitments. While intentions to refuse to work for environmentally irresponsible employers are primarily driven by one's search for meaning through work and high pro-environmental preferences, these factors play a minor role in explaining the reaction. Individuals who react the least to environmental pledges tend to self-select outside of large companies, are skeptical about the capacity of a market economy and technological development to solve the ecological crisis, and are supportive of radical action in the name of ecology. On the contrary, the most reactive individuals include large companies in their career path, have faith in a market economy or technological development to solve the ecological crisis, and are not supportive of political radicalism.

## 7 Conclusion

In this paper, we examine a climate movement initiated by elite French students which had a significant impact on the French higher education system. To hasten the sustainable transition of businesses, participants in the climate movement threatened to boycott job offers from polluting employers. To investigate the credibility of this incentive scheme, we assess the effect of corporate environmental pledges on students' intentions to refuse to work for polluting employers using a survey experiment with repeated measurements.

We employ machine learning classifiers to calculate a measure of the extent to which an individual's intentions to refuse to work for a polluting employer change after being exposed to an environmental pledge. To identify the most important factors moderating students' reactions to environmental pledges, we apply the SHAP interpretability method to this measure and use it in traditional linear regressions to draw inference.

While intentions to refuse to work for polluting companies are primarily explained by one's environmental attitudes and pursuit of meaning through work, these factors play only a minor role in explaining reactions to environmental pledges. As a result, environmental pledges have a strong effect on intentions to refuse to work for polluting employers: respondents initially intending to refuse a job offer from a polluting company are, on average, more than three times less likely to maintain these intentions after exposure to an environmental pledge. However, there is significant heterogeneity in reactions to the environmental pledge, with one-third of respondents maintaining their intentions to refuse a job offer from a polluting employer despite the pledge. We find that the most important drivers of reactions to environmental pledges are career perspectives, beliefs about the ecological crisis, and support for radical action in the name of ecology. Individuals who are not responsive to environmental pledges exclude large companies from their career perspectives, do not believe in the ability of a market economy and technological development to solve the ecological crisis, and support radical action in the name of ecology. In contrast, those who react the most to the pledges include large companies in their career perspectives, are less skeptical about the ability of a market economy and technological development to address the ecological crisis, and do not support radical action.

Our results have important practical implications as they highlight that companies have incentives to strategically use environmental pledges to mitigate the adverse effects of negative organizational attractiveness shocks caused by a poor environmental responsibility. Notably, companies in labor-intensive industries, which rely on a highly qualified workforce and have a high environmental impact, such as the financial industry, may have greater incentives to strategically use environmental pledges. Further research on corporate greenwashing could integrate these factors to better explain variations in firm behavior. Moreover, this study focuses only on the selection effects of environmental pledges. Further research could investigate whether employees with high environmental preferences, who have been attracted by pledges, hold their employers accountable for their commitments.

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# A Shapley value for machine learning interpretability

## A.1 Computation

Consider a random vector  $X_i \equiv (X_{i1}, X_{i2}, \dots, X_{ip})$  that represents the individual characteristics of an agent. The vector is composed of  $p$  predictor variables, and  $x_i \equiv (x_{i1}, x_{i2}, \dots, x_{ip})$  represents the corresponding vector of realizations. Let  $D_i$  be an indicator variable that takes the value one if the agent has been exposed to an environmental pledge and zero otherwise. The probability of intending to refuse to work for a polluting company, conditional on the agent's characteristics and exposure to the environmental pledge, is:

$$\mathbb{P}(Y_i = 1 | X_i, D_i). \quad (6)$$

Let  $\hat{p}_i \equiv \hat{g}(D_i, X_i)$  denote an estimator of (6) from a given classifier, which corresponds to a predictive model of (6). In our setting, we do not treat  $D_i$  as a random variable, as we use a repeated measurement design in which the outcome variable is measured before and after receiving treatment for every individual. Consequently, we denote by  $\hat{p}_{0,i} \equiv \hat{g}(0, X_i)$  and  $\hat{p}_{1,i} \equiv \hat{g}(1, X_i)$  the predicted conditional probability of having intentions to refuse to work for polluting companies in the two states, respectively. Usually, the model prediction for individual  $i$  is obtained by setting the random vector  $X_i$  to its realized value  $x_i$  in  $\hat{p}_i$ . However, the Shapley value (SV) computation proceeds by generating predictions when some predictors are set to their realized values, and others are randomly selected. We introduce the following notations to formalize this computation. Let  $P \equiv \{1, \dots, p\}$  denote the complete set of predictor variable indexes, and  $S \subseteq P$  be a subset of indexes. We define a vector  $X_i^S$ , where the  $k$ -th element of  $X_i^S$  is set to  $x_{ik}$  if  $k \in S$ , and  $X_{ik}$  otherwise. This vector corresponds to  $X_i$  when a subset of predictors, indexed by  $S$ , have been set to their realized value. We denote by  $\hat{p}_{0,i}^S \equiv \hat{g}(0, X_i^S)$  and  $\hat{p}_{1,i}^S \equiv \hat{g}(1, X_i^S)$  the associated predicted conditional probabilities. Here, in contrast to the point prediction associated with individual  $i$ , which sets every component of  $X_i$  to its realized value, the information on predictors not included in  $S$  is treated as unknown.

The SV can be defined using the previous notations. First, consider the intentions to refuse to work for a polluting company without being exposed to an environmental pledge. The SV of predictor  $j$  for individual  $i$ , or the marginal contribution of predictor  $j$  to  $\hat{p}_{0,i}$ , is given by:

$$\phi_{ij} = \sum_{S \subseteq P \setminus \{j\}} \frac{|S|(p - |S| - 1)!}{p!} \left[ \mathbb{E} \left( \hat{p}_{0,i}^{S \cup \{j\}} \right) - \mathbb{E} \left( \hat{p}_{0,i}^S \right) \right], \quad (7)$$

where the expectations are taken with respect to the joint distribution of the predictors

excluded from the indexes subsets.

The SV computation works by averaging the difference between the model predicted probabilities when information on predictor  $j$  is known versus when this information is masked, across all existing subsets of predictors. The term *known* refers to the situation in which the value of predictor  $j$  is set to its observed value for individual  $i$ , while *masked* refers to the situation in which this value is randomly drawn. In other words, for each information subset that excludes predictor  $j$ , formula (7) calculates the change in the predicted probability resulting from adding predictor  $j$  to the information set. These differences are then averaged across all existing information subsets. In practice, the expectations needed for the SV computation are estimated by randomly sampling from the empirical joint distribution of masked predictors. However, this procedure becomes computationally infeasible when the number of predictors exceeds a dozen. As a result, the SV computation typically relies on heuristics such as KernelShap or TreeShap (Lundberg and Lee, 2017; Lundberg et al., 2020).

The previous formula can be adapted to explain a non-linear combination of model outputs. Specifically, our main interest lies in identifying factors that drive the reaction to environmental pledges as described by equation (3). Let  $\hat{\tau}_i = \frac{\hat{p}_{0,i}}{\hat{p}_{1,i}}$  represent the plug-in estimator of (3). To calculate the marginal contribution of the  $j$ -th predictor to  $\hat{\tau}_i$ , we modify equation (7) as follows:

$$\phi_{ij}^* = \sum_{S \subseteq P \setminus \{j\}} \frac{|S|(p - |S| - 1)!}{p!} \left[ \mathbb{E} \left( \hat{\tau}_i^{S \cup \{j\}} \right) - \mathbb{E} \left( \hat{\tau}_i^S \right) \right]. \quad (8)$$

## A.2 Interpretation

Let  $\hat{p}_{k,i}(x_i) = \hat{g}(k, x_i)$  denote the predicted probability associated with individual  $i$ , where the subscript  $k$  denotes that  $D_i$  is set to  $k$ . The efficiency property of the Shapley Value (SV) facilitates its interpretation in terms of deviation from the average (Lundberg and Lee, 2017). Considering the SV given by equation (7), it yields:

$$\sum_{j=1}^p \phi_{ij} = \hat{p}_{0,i}(x_i) - \mathbb{E}(\hat{p}_{0,i}). \quad (9)$$

This property states that the sum of predictors' marginal contributions to  $\hat{p}_{0,i}(x_i)$  is equal to the difference between  $\hat{p}_{0,i}(x_i)$  and the average prediction. Therefore,  $\phi_{ij}$  can be interpreted as the contribution of the  $j$ -th predictor's value to the deviation of the prediction associated with individual  $i$  from the average. A positive (negative) value of  $\phi_{ij}$  corresponds to a predictor associated with an increased (decreased) predicted probability of having

intentions to refuse to work for a polluting company with respect to the average. A greater absolute value of  $\phi_{ij}$  corresponds to a greater marginal contribution. Conversely,  $\phi_{ij} = 0$  would correspond to a predictor having no effect on the model output across all information subsets.

Considering now the SV given by equation (8), let  $\hat{\tau}_i(x_i) = \frac{\hat{p}_{0,i}}{\hat{p}_{1,i}}$  denote the estimated reaction for individual  $i$ . The efficiency property yields:

$$\sum_{j=1}^p \phi_{ij}^* = \hat{\tau}_i(x_i) - \mathbb{E}(\hat{\tau}_i). \quad (10)$$

Interpretations remain similar in this case.

## B Questionnaire

### Studies and professional perspectives

1. What year of study are you in?

First year; Second year; Third year; Fourth year; Fifth year; Sixth year; Seventh year; Eighth year; More than eighth year

2. What is the last degree you obtained?

CAP, BEP; General Baccalaureate (economics and social sciences); General Baccalaureate (science); General Baccalaureate (literature); Technological Baccalaureate; Professional Baccalaureate; BTS, DUT; Bachelor's degree; Master's degree; Doctorate; Other

3. What type of program are you following?

BTS; Preparatory classes for Economics and Business; Preparatory classes for Literature; Preparatory classes for Science; Post-baccalaureate engineering school; Post-preparatory engineering school; School of Public Administration; Post-baccalaureate Business and Management School; Post-preparatory Business and Management School; Agricultural or Halieutic Training School; Artistic Training School; Health and Social Training School; Journalism School; Nursery School; Midwifery School; Veterinary School; École Normale Supérieure (ENS); Higher School of Architecture; Institute of Political Studies (IEP); Institute of Medical Electroradiology Manipulators Training; Institute of Occupational Therapy Training; Institute of Podiatry Training; Nursing School; University Institute of Technology; PACES; University (Faculty of Dentistry); University (Faculty of Economics and Management); University (Faculty of Education); University (Faculty of Computer Science); University (Faculty of Chemistry); University (Faculty of Law and Political Science); University (Faculty of Humanities); University (Faculty

of Mathematics); University (Faculty of Medicine); University (Faculty of Music and Musicology); University (Faculty of Pharmacy); University (Faculty of Physics); University (Faculty of Psychology); University (Faculty of Life and Earth Sciences); University (Faculty of Social and Human Sciences); Other

4. What is the name of your institution?
5. What is the name of the study program or specialty you are following this year?
6. What is your overall satisfaction with the studies you are following?  
Very satisfied; Satisfied; Dissatisfied; Very dissatisfied; PNA (Don't know, don't say)
7. Do you have any comments about this?
8. Do you feel properly prepared by your education to address societal challenges?  
Very well prepared; Well prepared; Poorly prepared; Very poorly prepared; PNA (Don't know, don't say)
9. Do you feel properly prepared by your education to address ecological problems?  
Very well prepared; Well prepared; Poorly prepared; Very poorly prepared; PNA (Don't know, don't say)
10. In your opinion, what elements of your curriculum should be modified to better prepare you to actively participate in the ecological transition?
11. At the end of your studies, do you think you can find a job in your field of specialization...  
Very easily; Quite easily; Quite difficultly; Very difficultly; PNA (Don't know, don't say)
12. What type of organization would you like to work for?
  - (a) in a large company
  - (b) in an intermediate-sized, small or medium-sized company
  - (c) in a startup
  - (d) for the State or local authorities
  - (e) for an international organization (UN, IMF...)
  - (f) for an NGO
  - (g) for an association, a cooperative, or a mutual

(h) other:

13. What job do you want to have after your studies?

14. Here are some traits that can be considered important for a job or professional activity. For you personally, which ones do you consider the most important? Please pick a maximum of five answers...

- |   |  |
|---|--|
| (a) it pays well  | (l) what you do is interesting                     |
| (b) the working atmosphere is good                              | (m) it's a job where you can use your abilities    |
| (c) you're not rushed   | (n) you learn new skills                           |
| (d) you're not at risk of unemployment                          | (o) it's a job that is compatible with family life |
| (e) the working hours are satisfactory                          | (p) you can be heard during important decisions    |
| (f) you have initiative   | (q) it's a job where everyone is treated equally   |
| (g) it's a job that is useful for society                       | (r) it's a job that is in line with my values      |
| (h) there are good vacation days                                |  |
| (i) it allows you to meet people                                |  |
| (j) it's a job that gives the impression of achieving something |  |
| (k) you have responsibilities                                   |  |

15. Would you be willing to give up a job offer in a company that has a negative impact on the environment?

Completely willing; Willing; Not willing; Not at all willing; PNA (Don't know, don't say)

16. (If completely willing/willing for 15.) How important are the following elements in making this decision?

- (a) the CSR report
- (b) the carbon footprint
- (c) a biodiversity impact study
- (d) the company's reason for existence
- (e) the company's strategy for reducing greenhouse gas emissions
- (f) the possibility of taking action within the company (given voice to young graduates, to employees...)

(g) your feelings about the company's environmental policy

Very important; Important; Rather important; Not very important; Not at all important;  
Don't know or not familiar with this information; PNA (Don't know, don't say)

17. (If completely willing/willing to 15.) Free comment, or other important elements for you in making the decision.

18. Furthermore, would you be willing to accept a job offer in a company that has a negative impact on the environment but declares to be committed to an ecological transition?

Completely willing; Willing; Not willing; Not at all willing; PNA (Don't know, don't say)

19. (If not willing/not at all willing to 18.) For what reason(s) ?

20. Do you have any comment to make on this subject ?

### **Ecological commitments and practices**

21. Please check the box or boxes of the following organization categories that you belong to, if any:

- |   |  |
|---|--|
| (a) association in the fields of education, music, or culture | (f) professional or student association    |
| (b) religious organization                                    | (g) humanitarian or charitable association |
| (c) trade union   | (h) consumer association                   |
| (d) movement or political party                               | (i) other groups                           |
| (e) association for the environment, ecology, animal rights   | (j) I am not involved in an organization   |
|   | (k) no answer                              |

22. What is the name of this/these organization(s)?

23. Among the following ecological practices, please tell us which ones you already do, which ones you would be willing to do, and which ones you are not willing to do:

- (a) transition to zero waste
- (b) limit buying new products
- (c) join a community-supported agriculture

- (d) boycott certain brands or products
- (e) limit energy consumption (heating, air conditioning, electrical appliances...)
- (f) limit digital footprint (email storage, video viewing...)
- (g) invest money in ecological funds, green projects, etc.

I already do it; I would be willing to do it; I'm not willing to do it; PNA (Don't know, don't say)

24. Regarding meat, how often do you consume it?  
Never (vegan); Never (vegetarian); Once a week or less; Between 2 and 4 times a week; More than 4 times a week; Every day
25. How many times do you take a plane for leisure per year?  
Zero; 1 round trip; 2 round trips; 3 round trips; 4 round trips; More than 4 round trips

### **Relation to the manifesto**

26. How did you hear about the Student Manifesto for an Ecological Awakening?  
Facebook; Facebook group of my school; Email; Media; Word of mouth; LinkedIn; Other
27. For you, the Student Manifesto for an Ecological Awakening is...
28. Would you be willing to share your commitments with the Student Manifesto for an Ecological Awakening through a post on social (Facebook, Twitter) or professional (LinkedIn) networks?  
Yes; Maybe, if I see that people around me are doing the same; No

### **Political values and positioning**

29. Do you think that the division between the right and the left still makes sense today?  
Yes; No; No answer
30. Where would you place yourself...  
Far-left; Left; Center; Right; Far-right; Neither left nor right; PNA (Don't know, don't say)
31. Which list did you vote for in the 2019 European elections?  
Front National; La République en Marche; Les Républicains; La France Insoumise;

Europe Ecologie les Verts; Place Publique - Parti socialiste - Nouvelle Donne - Parti radical de gauche; Debout la France; Parti communiste français; Generation.s - DiEM25; Union des démocrates et indépendants; Parti animaliste; Urgence écologique; Other; Abstention; Blank vote; Did not have the right to vote; PNA (Don't know, don't say)

32. Some people think that society should be radically changed, others that it should be improved through reforms, others still that it should be protected against change. What is your opinion?

Society should be radically changed through revolutionary action; Society should be gradually improved through reforms; Society should be protected against change; PNA (Don't know, don't say)

33. For the following statements, please indicate whether you completely agree, somewhat agree, somewhat disagree or completely disagree:

- (a) it is necessary to exit the capitalist system to solve the ecological crisis
- (b) the development of current and future technologies will allow us to solve the ecological crisis
- (c) climate change is primarily the consequence of poor individual choices
- (d) it is necessary to phase out nuclear energy
- (e) the ecological transition requires reducing wealth inequalities
- (f) reducing our impact on the environment involves consuming less, and therefore producing less
- (g) the fight against climate change involves giving more freedom to entrepreneurs

Completely agree; Somewhat agree; Somewhat disagree; Completely disagree; PNA (Don't know, don't say)

34. In the name of the ecological cause, which of the following actions have you already done, would be willing to do, or would be willing to support those who do them?

- (a) Sign a petition, such as l'Affaire du Siècle
- (b) sign the Student Manifesto for an Ecological Awakening
- (c) protest in a climate march
- (d) take part in a student strike for the climate
- (e) take part in an act of civil disobedience



(f) cause material damage

Already done; Could do it; Will never do it but supports the action; Will never do it and does not support the action; PNA (Don't know, don't say)

### **Socio-demographics**

35. What is the situation of your father?

Employed; Job seeking; Retired; Invalid; On paternity leave; Other inactive (stay-at-home dad...); Not applicable (unknown father)

36. What is/was your father's profession? (If job seeking or retired, please consider the last occupation held.)

Farmer; Self-employed artisan, self-employed merchant, entrepreneur; Executive or intellectual profession (e.g. sales executive, engineer, teacher, lawyer...); Intermediate profession (e.g. nurse, educator, nursery nurse, supervisor, teacher...); Employee (e.g. police officer, secretary, caregiver, salesperson, cashier, security guard...); Industrial or construction worker (e.g. mechanic, agricultural worker, driver, salaried artisan...); Not applicable (unknown father); Inactive (stay-at-home dad, invalid...)

37. Name of the profession

38. What is the situation of your mother?

Employed; Job seeking; Retired; Invalid; On maternity leave; Other inactive (stay-at-home mom...); Not applicable (unknown mother)

39. What is/was your mother's profession? (If job seeking or retired, please consider the last occupation held.)

Farmer; Self-employed artisan, self-employed merchant, entrepreneur; Executive or intellectual profession (e.g. sales executive, engineer, teacher, lawyer...); Intermediate profession (e.g. nurse, educator, nursery nurse, supervisor, teacher...); Employee (e.g. police officer, secretary, caregiver, salesperson, cashier, security guard...); Industrial or construction worker (e.g. mechanic, agricultural worker, driver, salaried artisan...); Not applicable (unknown mother); Inactive (stay-at-home mom, invalid...)

40. Name of the profession

41. Do you have one or more parents of foreign nationality?

Yes; No

42. (If Yes to 41.) Is it...  
Your father; Your mother; One of your grandparents
43. What is the nationality of this person?
44. Regarding your family's financial resources, which of the following best describes their situation?  
You are comfortable; It's fine; It's tight, you have to be careful; You are struggling;  
No response
45. You are living...  
Alone in an individual housing; As a couple in an individual housing; In a flatshare;  
In student accommodation; With your parents or other family members
46. Do you have a religion?  
Yes; No; No response
47. (If Yes to 46.) Which one?  
Catholic; Protestant; Muslim; Jewish; Other religion
48. (If Yes to 46.) Usually, how often do you go to a place of worship...  
Several times a week; Once a week; Once or twice a month; A few times a year; Less  
than once a year; Never
49. What are your monthly resources? Estimation of financial support from relatives (rental payment, possible registration fees, food expenses assistance, etc...) and own resources (allowances, salary, scholarship...):
- (a) financial support from relatives
  - (b) own resources
50. Do you have a job alongside your studies?  
Yes, a part-time job; Yes, I am on an apprenticeship; Yes, I am doing an internship;  
No
51. If yes, how many hours per week?
52. What is your gender?  
Female; Male; Other
53. What is your nationality?
54. What is your age?

## C Additional Tables and Figures

Table C.1: SBF120 companies' reaction to 7th March 2019 meeting, by level of carbon dioxide equivalent emissions (Scope 1 emissions)

Absolute emissions	Window	N	Mean CAR	Neg : Pos	Adjusted BMP	Adjusted Patell
<u>Panel A: Highest emitters</u>						
Top 50 %	[0, 1]	42	-2.58%	35 : 7	-4.752***	-4.777***
	[0, 2]	42	-1.49%	32 : 10	-3.165***	-3.181***
	[0, 3]	42	-0.95%	27 : 15	-1.788**	-1.797**
	[0, 4]	42	-0.13%	24 : 18	0.145	0.145
	[0, 5]	42	0.4%	18 : 24	1.378	1.386
Top 25 %	[0, 1]	21	-2.37%	17 : 4	-3.704***	-3.743***
	[0, 2]	21	-1.24%	17 : 4	-2.354***	-2.378***
	[0, 3]	21	-0.95%	14 : 7	-1.345*	-1.359*
	[0, 4]	21	-0.52%	13 : 8	-0.074	-0.075
	[0, 5]	21	-0.28%	10 : 11	0.565	0.571
<u>Panel B: Lowest emitters</u>						
Bottom 50 %	[0, 1]	42	-1.25%	28 : 13	-1.725**	-1.749**
	[0, 2]	42	-0.73%	27 : 14	-1.151	-1.167
	[0, 3]	42	-0.6%	23 : 17	-0.882	-0.894
	[0, 4]	42	-0.17%	24 : 18	-0.052	-0.052
	[0, 5]	42	0.5%	17 : 25	1.274	1.292
Bottom 25 %	[0, 1]	21	-0.99%	13 : 8	-0.768	-0.791
	[0, 2]	21	-0.25%	11 : 9	0.133	0.137
	[0, 3]	21	-0.04%	8 : 11	0.443	0.456
	[0, 4]	21	0.53%	10 : 11	1.043	1.074
	[0, 5]	21	0.94%	7 : 14	1.451	1.494

*Note:* Cumulative abnormal returns (CARs) are calculated using the CAPM and the return on the MSCI France index. The event day is labeled as Day 0. The estimation window for the CAR calculation is set at 255 trading days, ending 46 days before the event. A minimum of 40 observations is required for each firm in the estimation window. The sample is divided by absolute Scope 1 CO<sub>2</sub> emissions. The “Neg:Pos” column shows the ratio of firms with negative versus positive CARs over the event window. The BMP and Patell tests are used to test the nullity of the mean CAR against the alternative that the mean CAR is negative. Test statistics are corrected for cross-sectional correlation using Kolari and Pynnönen (2010) adjustment. The notations \*, \*\* and \*\*\* indicate significance at the 10%, 5% and 1% levels respectively.

Table C.2: SBF120 companies' reaction to 7th March 2019 meeting, by level of carbon dioxide equivalent emissions (Scope 2 emissions)

Absolute emissions	Window	N	Mean CAR	Neg : Pos	Adjusted BMP	Adjusted Patell
<u>Panel A: Highest emitters</u>						
Top 50 %	[0, 1]	42	-2.77%	35 : 7	-5.09***	-5.104***
	[0, 2]	42	-1.62%	35 : 7	-3.829***	-3.84***
	[0, 3]	42	-1.3%	29 : 12	-3.065***	-3.074***
	[0, 4]	42	-0.71%	29 : 13	-1.27	-1.273
	[0, 5]	42	-0.16%	21 : 21	0.595	0.596
Top 25 %	[0, 1]	21	-2.53%	17 : 4	-3.046***	-3.086***
	[0, 2]	21	-1.4%	17 : 4	-2.001**	-2.027**
	[0, 3]	21	-1.2%	15 : 6	-1.652**	-1.674**
	[0, 4]	21	-0.85%	14 : 7	-0.796	-0.806
	[0, 5]	21	-0.23%	10 : 11	0.346	0.351
<u>Panel B: Lowest emitters</u>						
Bottom 50 %	[0, 1]	42	-0.98%	28 : 13	-1.186	-1.208
	[0, 2]	42	-0.58%	24 : 17	-0.542	-0.552
	[0, 3]	42	-0.23%	21 : 20	0.081	0.082
	[0, 4]	42	0.4%	19 : 23	0.986	1.004
	[0, 5]	42	1.09%	14 : 28	1.967	2.002
Bottom 25 %	[0, 1]	21	-0.92%	12 : 9	-0.615	-0.634
	[0, 2]	21	-0.47%	11 : 9	-0.078	-0.08
	[0, 3]	21	0.15%	9 : 11	0.551	0.568
	[0, 4]	21	0.81%	10 : 11	1.118	1.153
	[0, 5]	21	1.45%	7 : 14	1.653	1.705

*Note:* Cumulative abnormal returns (CARs) are calculated using the CAPM and the return on the MSCI France index. The event day is labeled as Day 0. The estimation window for the CAR calculation is set at 255 trading days, ending 46 days before the event. A minimum of 40 observations is required for each firm in the estimation window. The sample is divided by absolute Scope 2 CO2 emissions. The “Neg:Pos” column shows the ratio of firms with negative versus positive CARs over the event window. The BMP and Patell tests are used to test the nullity of the mean CAR against the alternative that the mean CAR is negative. Test statistics are corrected for cross-sectional correlation using Kolari and Pynnönen (2010) adjustment. The notations \*, \*\* and \*\*\* indicate significance at the 10%, 5% and 1% levels respectively.

Table C.3: Sample characteristics compared to the signatories population

	Sample	Population
<b>Gender</b>		
Man	0.482	0.485
Woman	0.506	0.515
Other	0.012	
<b>Institution Type</b>		
Business schools	0.105	0.185
Engineering schools	0.583	0.507
IEP, ENS, ENA	0.075	0.090
University	0.139	0.188
Other	0.098	0.030

*Note:* Population statistics were computed using first names and school names from the signatories list obtained from the organizers ( $n = 24365$ ).

Table C.4: Environmental attitudes, support for political action, and beliefs on the ecological crisis

Factor	Questions	Answers
<i>Environmental attitudes</i>	<p>Among the following ecological practices, please tell us which ones you already do, which ones you would be willing to do, and which ones you would not be willing to do.</p> <ul style="list-style-type: none"> <li>• Transitioning to zero waste.</li> <li>• Limiting the purchase of new products.</li> <li>• Joining a local community supported agriculture.</li> <li>• Boycotting certain brands or certain products..</li> <li>• Limiting energy consumption (heating, air conditioning, household appliances...).</li> <li>• Limiting your digital footprint (storage of emails, viewing of videos...).</li> <li>• Investing your money in ecological investment funds, in green projects, etc..</li> </ul>	<p>Four-level scale:                      Already do                      Willing to do                      Don't know                      Not willing to do</p>
<i>Political actions for ecology</i>	<p>In the name of the ecological cause, which of the following actions have you already done, would be willing to do, or would be willing to support those who do them?</p> <ul style="list-style-type: none"> <li>• Signing a petition, such as the 'Affaire du Siècle' for example.</li> <li>• Participating in a climate march demonstration.</li> <li>• Taking part in a student strike for the climate.</li> <li>• Taking part in an act of civil disobedience.</li> <li>• Causing material damage.</li> </ul>	<p>Five-level scale:                      Already done                      Would do it                      Don't know                      Will never do it, but supports the action                      Will never do it and does not support the action</p>
<i>Beliefs on the ecological crisis</i>	<p>For the following statements, please indicate whether you completely agree, somewhat agree, somewhat disagree or completely disagree:</p> <ul style="list-style-type: none"> <li>• It is necessary to exit the capitalist system to solve the ecological crisis.</li> <li>• The development of current and future technologies will allow us to solve the ecological crisis.</li> <li>• Climate change is primarily the consequence of poor individual choices.</li> <li>• It is necessary to phase out nuclear energy.</li> <li>• The ecological transition requires reducing wealth inequalities.</li> <li>• Reducing our impact on the environment involves consuming less, and therefore producing less.</li> <li>• The fight against climate change involves giving more freedom to entrepreneurs.</li> </ul>	<p>Five-level scale:                      Completely Agree                      Somewhat Agree                      Don't know                      Somewhat Disagree                      Completely Disagree</p>

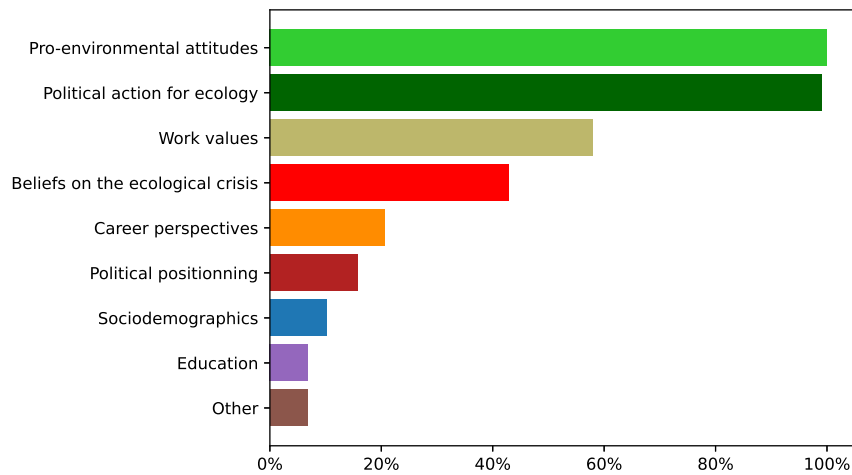
*Note:* This table displays questions and possible answers used to measure respondents' environmental attitudes, support for political action in the name of ecology, and beliefs on the ecological crisis.

Table C.5: Hyperparameters selection

Hyperparameter set	Random Forest	XGBoost
Learning rate		0.01-0.1 (0.05)
Columns subsample ratio		0.025-0.25 (0.225)
Max tree depth	2-30 (16)	1-15 (4)
Number of estimators	50-1000 (350)	50-1000 (200)
Subsample rate	0.5-1 (1)	0.5-1 (1)
Minimum leaf size	1-20 (15)	
Features used for each split	2-40 (40)	

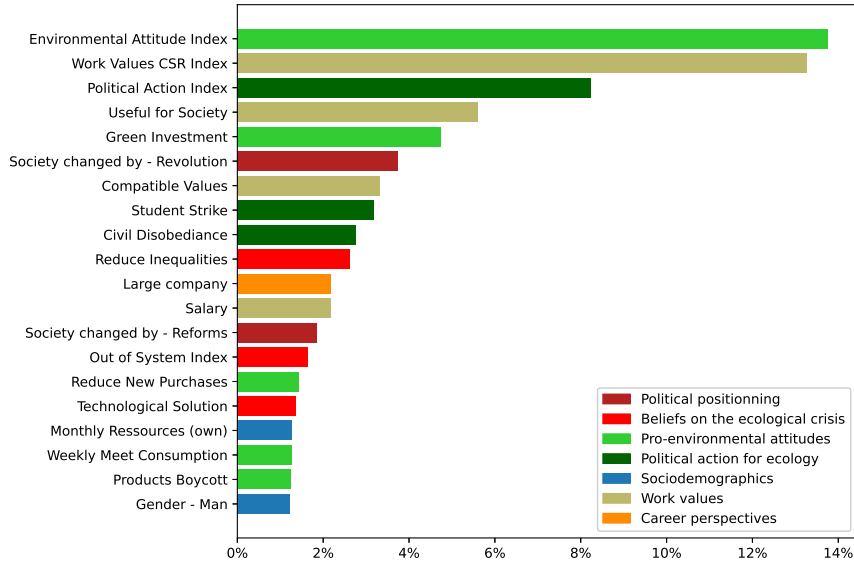
*Note:* This table displays the hyperparameters tuned to calibrate the random forest and XGBoost classifiers. The optimal hyperparameter values are reported in parentheses.

Figure C.1: Ranking of factors to predict intentions to refuse to work for polluting companies



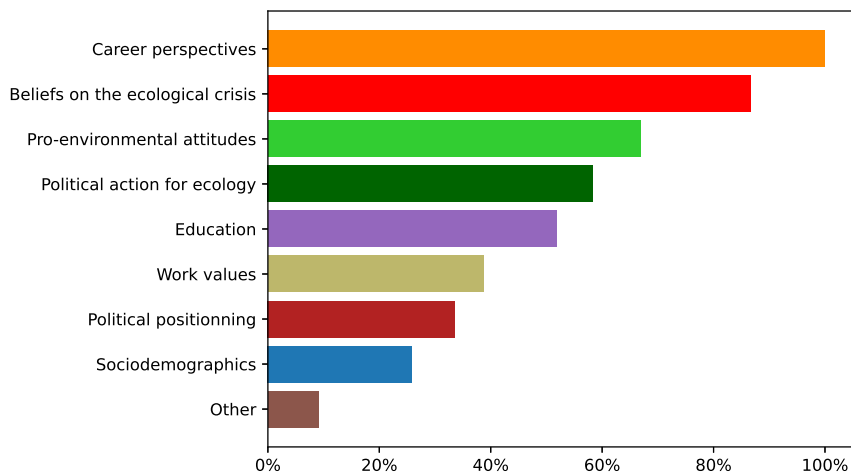
*Note:* This figure displays the importance of factors in predicting intentions to refuse to work for polluting companies, as measured by the mean absolute Shapley value. Intentions to refuse to work for a polluting company, given by Equation (1), are estimated using a random forest classifier. Results are expressed as a percentage of the most important factor.

Figure C.2: Top 20 predictors of intentions to refuse to work for polluting companies



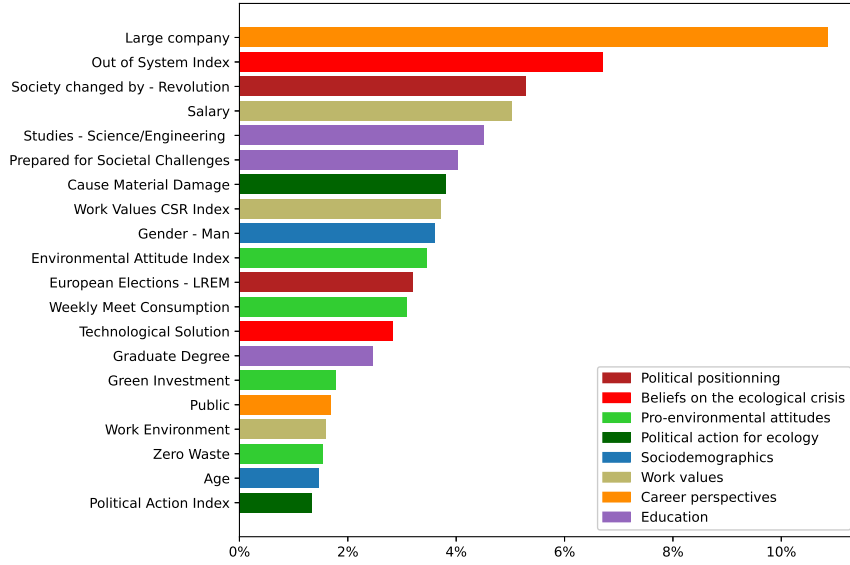
*Note:* This figure displays the twenty most important predictors of intentions to refuse to work for polluting companies, as measured by the sum of absolute Shapley values. Intentions to refuse to work for a polluting company, given by Equation (1), are estimated using a random forest classifier. Results are expressed as a percentage of the total sum of absolute Shapley values.

Figure C.3: Ranking of factors to predict the reaction to the environmental pledge (XGBoost)



*Note:* This figure displays the importance of factors in predicting the reaction to the environmental pledge, as measured by the mean absolute Shapley value. The reaction, given by Equation (3), is estimated using the output of an XGBoost classifier. Results are expressed as a percentage of the most important factor.

Figure C.4: Top 20 predictors of the reaction to the environmental pledge (XGBoost)



*Note:* This figure displays the twenty most important predictors of the reaction to the environmental pledge, as measured by the sum of absolute Shapley values. The reaction, given by Equation (3), is estimated using the output of an XGBoost classifier. Results are expressed as a percentage of the total sum of absolute Shapley values.

Table C.6: Drivers of the reaction to the environmental pledge (XGBoost)

	(1)	(2)	(3)	(4)	(5)
Constant	2.193*** (0.14)	2.246*** (0.11)	2.338*** (0.12)	2.565*** (0.11)	2.354*** (0.088)
Age	-0.0419*** (0.0065)	-0.0346*** (0.0049)	-0.0341*** (0.0056)	-0.0300*** (0.0050)	-0.0258*** (0.0039)
Gender - Man	0.00311 (0.025)	-0.0794*** (0.020)	0.0125 (0.020)	-0.0787*** (0.018)	-0.0875*** (0.014)
Employed	0.0213 (0.026)	-0.00267 (0.020)	-0.00492 (0.020)	-0.0152 (0.018)	-0.0213 (0.014)
Monthly financial resources	-0.0000562** (0.000023)	-0.0000587*** (0.000018)	-0.0000290 (0.000019)	-0.0000120 (0.000017)	-0.0000182 (0.000013)
Family financial situation	0.0148 (0.013)	0.0116 (0.010)	0.0166 (0.010)	-0.000506 (0.0092)	0.00384 (0.0075)
Work values CSR Index		-0.195*** (0.014)			-0.0806*** (0.011)
Career perspectives - Large company		0.650*** (0.022)			0.417*** (0.018)
Environmental Attitude Index			-0.0388*** (0.0033)		-0.0226*** (0.0024)
Political Action Index			-0.0570*** (0.0047)		-0.00545 (0.0037)
Cause Material Damage			-0.128*** (0.012)		-0.0895*** (0.0082)
Out of System Index				-0.0799*** (0.0025)	-0.0465*** (0.0023)
Society changed by - Revolution				-0.318*** (0.019)	-0.226*** (0.015)
Observations	1983	1983	1983	1983	1983
$R^2$	0.033	0.411	0.419	0.542	0.723

*Note:* This table displays the results of regression (5). The reaction, given by Equation (3), is estimated using the output of an XGBoost classifier. Standard errors robust to heteroskedasticity are reported in parentheses. \*, \*\*, \*\*\* indicate significance at the 10%, 5%, and 1% level, respectively.