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**CORSO DI LAUREA MAGISTRALE IN APPLIED ECONOMICS: ENVIRONMENTAL ECONOMICS AND GREEN FINANCE**

**TESI DI LAUREA**

# "ESTIMATING THE CAUSAL IMPACT OF ENVIRONMENTAL CONSCIOUSNESS ON INDIVIDUAL PRO-ENVIRONMENTAL BEHAVIOR"

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# 1. Introduction

As of today, the green transition and the fight against climate change have become more urgent and relevant than ever before. Numerous challenges and pressing issues are being faced by international institutions, national governments, communities, families, and individuals alike, all striving to mitigate the devastating effects of climate change and the increasing frequency and intensity of natural disasters. In this context, the role of institutions is crucial. They are responsible for designing and implementing effective policies and regulatory frameworks that both industries and households must adhere to in order to drive meaningful environmental change. However, for these policies to be truly effective, they must be grounded in a thorough understanding of individuals their values, attitudes, and behaviors. In other words, the change must begin from the bottom up. This thesis aims to explore and evaluate the underlying mechanisms and relationships that individuals have with the environment. Specifically, it investigates whether and to what extent individuals' environmental awareness translates into concrete, proactive behaviors that support environmental sustainability, or whether these attitudes remain merely as abstract concerns or intentions without being followed by action. While it may be tempting to assume certain relationships as intuitively obvious or logically direct, such assumptions can often be misleading. Human reasoning is prone to cognitive biases and false causal inferences, especially in complex domains such as environmental behavior. The core objective of this research is therefore to measure individuals' levels of environmental consciousness and assess whether and how these levels are associated with environmentally responsible actions. In addition to exploring the existence of such a relationship, the study also seeks to estimate the magnitude of this effect, offering insights into the strength and consistency of the link between awareness and action.

The focus of this research is located in the European Union, by exploiting a the information of a dataset that collects all data from across Europe to find a result that can be further generalized. While a growing body of literature has explored the relationship between environmental awareness and sustainable behavior, most existing studies have relied on small, localized samples or have targeted very specific demographic groups, often within a single country or sector. These studies, while valuable, suffer from limited generalizability and often fail to capture the full complexity of individual-environment dynamics at scale.

This thesis sets itself apart by leveraging a large-scale, pan-European dataset encompassing tens of thousands of individuals across multiple countries, cultures, and socio-economic backgrounds. To the best of the author's knowledge, this is the first attempt to estimate a causal relationship between environmental consciousness and pro-environmental behavior using such a broad and comprehensive sample. This unprecedented scope allows for a more robust and generalizable understanding of the mechanisms linking awareness to action.

The remainder of this thesis is structured as follows: a vast literature review to exploit the existing relevant research on the topic and use it a starting point and reference to structure our study. A section dedicated to the methodology of this research, how the model is intended to be structured, and the logic behind statistical processes that will be used. A vast data exploration to understand deeply how the data is distributed among this sample and if there are some peculiar characteristics to take into account. Then the actual model itself and the analysis will be brought out and explained as thoroughly as possible followed by the explanation of the results that arose. To conclude the implication of the results will be analysed and contextualize in order to understand where this research can be positioned in the literature and to whom can be particularly helpful and informative.

# 2. Literature Review

This literature review aims to explore how environmental consciousness can be conceptually framed, measured, and understood in relation to the various psychological, social, and contextual factors that shape it. By reviewing theoretical models and empirical findings, the objective is to identify key determinants and mediators of environmental consciousness that will later serve as guiding principles for the analytical design of the thesis. In particular, understanding how awareness translates into behavior, and under what conditions, can inform a more effective causal identification strategy when estimating the impact of environmental consciousness on individual pro-environmental actions. Moreover, insights from the literature also guide the selection of control variables to ensure coherence between theoretical expectations and empirical modelling, helping to isolate the effect of environmental awareness from potential confounding influences.

## 2.1 Defining and Measuring Environmental Consciousness

The concept of environmental consciousness has attracted growing academic interest over the past decades but remains theoretically and empirically heterogeneous. It generally refers to the set of cognitive, affective, and behavioral predispositions that influence an individual's awareness of, concern for, and actions toward environmental problems. A foundational contribution on the conceptual side is provided by Sanchez, Guardiola and Lafuente (2010) in their report "Defining and Measuring Environmental Consciousness", where the authors propose a multidimensional and behaviorally oriented definition. They argue that environmental consciousness must not be treated as a purely attitudinal or declarative trait, but rather as a composite index that integrates environmental values, beliefs, and concrete behavioral dispositions. Their work, based on survey data from the Ecobarómetro de Andalucía, provides an operational structure that includes both internal (e.g., environmental concern, perceived responsibility) and externalized (e.g., declared behavior, behavioral intention) dimensions, and offers an empirical test of internal consistency and construct validity.
Similarly, in the article "The link between green purchasing decisions and measures of environmental consciousness", authored by Bodo B. Schlegelmilch and Greg M. Bohlen (1996), the authors empirically demonstrate that environmental consciousness scales are more predictive of environmentally responsible consumer behavior than traditional socio-demographic variables. Their study contrasts general environmental concern with specific purchasing behavior across five green product categories, showing that environmental consciousness is a stronger predictor of action than age, income, or education alone.

Further support for this multidimensional interpretation comes from recent work by Cellini et al. (2023), who in their article "Health consciousness and pro-environmental behaviors in an Italian representative sample: A cross-sectional study", find a significant association between health consciousness and pro-environmental behaviors. Their analysis, based on a representative Italian sample, suggests that people who are more health-conscious are also more inclined to act pro-environmentally highlighting an important interconnection between self-care and environmental care. This study also reinforces the idea that environmental attitudes are deeply embedded in broader lifestyle choices and may manifest in behavioral domains not traditionally classified as "green." Lastly, Yang et al. (2020), in the article "An institutional perspective on consumers' environmental awareness and pro-environmental behavioral intention: Evidence from 39 countries", published in Business Strategy and the Environment, use a six-item index to measure environmental awareness within a massive cross-national dataset of over 42,000 individuals from 39 countries. Their findings confirm that higher environmental awareness is associated with stronger pro-environmental behavioral intention, but they also show that this relationship is moderated by institutional factors, such as cultural values (e.g. individualism/collectivism) and national environmental policies. This underscores the necessity of situating environmental consciousness within its broader sociocultural and institutional context and more in general with state specific characteristics. Taken together, these studies demonstrate that environmental consciousness is not a unidimensional construct, nor can it be reduced to demographic profiling. Rather, it is a complex and context-sensitive disposition, influenced by values, health beliefs, purchasing norms, and societal institutions. For this reason, the present study adopts a multidimensional operationalization of environmental consciousness, aiming to estimate its influence on actual pro-environmental behaviors across a large European sample.

## 2.2 Theoretical Frameworks and Empirical Findings

Although environmental consciousness is widely recognized as a key antecedent to pro-environmental behavior, the relationship between awareness and action is not always direct or straightforward. A consistent theme in the literature is the presence of a so-called "intention-behavior gap", where individuals express concern for the environment but fail to act accordingly. This discrepancy is at the center of many theoretical frameworks in environmental psychology and behavioral sciences. The most widely applied model in this field is the Theory of Planned Behavior (TPB) (Ajzen, 1991), which posits that behavior is determined by intention, which in turn is shaped by three key components: attitude toward the behavior, subjective norms, and perceived behavioral control. However, TPB has been critiqued for its limited ability to account for emotional, motivational, and contextual variables that often influence environmental action. An important extension of the TPB is offered in the study by Kim and Lee (2023), titled "Environmental Consciousness, Purchase Intention, and Actual Purchase Behavior of Eco-Friendly Products: The Moderating Impact of Situational Context". The authors investigate how environmental consciousness relates not only to the intention to purchase green products, but also to actual purchasing behavior, introducing situational moderators such as eco-label credibility and ease of purchase. Notably, their findings indicate that while environmental knowledge and perceived consumer effectiveness positively affect purchase intention, environmental interest alone does not. This underscores that awareness must be actionable, supported by trust and accessibility, to translate into behavior. A similar approach is adopted by Si, Jiang, and Meng (2022) in their article "The Relationship between Environmental Awareness, Habitat Quality, and Community Residents' Pro-Environmental Behavior, Mediated Effects Model Analysis Based on Social Capital". Using data from Chinese urban communities, they propose a mediated model in which social capital (trust, participation, reciprocity) acts as a bridge between awareness and behavior. Their results confirm that environmental awareness alone is insufficient unless embedded within a supportive social network that fosters collective environmental engagement. The role of knowledge and social capital is further emphasized by Xing, Li, and Liao (2022) in "Trust, Identity, and Public-Sphere Pro-Environmental Behavior in China: An Extended Attitude-Behavior-Context Theory". Their findings suggest that environmental knowledge and trust-based community interactions independently contribute to pro-environmental actions, but their interaction amplifies the effect, confirming the multidimensionality of the awareness action relationship. Finally, the study by Yang et al. (2020), "An Institutional Perspective on Consumers' Environmental Awareness and Pro-Environmental Behavioral Intention: Evidence from 39 Countries", provides large-scale empirical evidence that the relationship between environmental awareness and pro-environmental intention is systematically moderated by institutional factors. Specifically, normative (social expectations) and cognitive (cultural values like individualism) dimensions play a significant role in strengthening or weakening this link. In societies with stronger individualistic values, the effect of awareness on intention is greater, while in normatively "green" countries, the marginal effect of personal awareness decreases, possibly due to the already high baseline of environmental norms. In sum, the literature consistently shows that while environmental consciousness is a necessary condition for pro-environmental behavior, it is not sufficient. Its effect is mediated or moderated by factors such as knowledge, social capital, cultural norms, institutional frameworks, and situational constraints. This calls for robust, large-scale analyses such as the one presented in this thesis that can identify and quantify these effects across diverse contexts.

## 2.3 Contribution and Placement of This Study

Existing literature has extensively documented the conceptual complexity of environmental consciousness and its conditional role in driving pro-environmental behavior. Prior studies have emphasized the relevance of psychological constructs (e.g., attitudes, perceived control), social factors (e.g., trust, participation), and institutional or situational moderators (e.g., policy context, product accessibility). However, most contributions remain either theoretical or limited in scope, often focusing on specific behaviors (e.g., green purchasing) or national case studies. What is still lacking is a robust, large-scale empirical investigation that combines a multidimensional operationalization of environmental consciousness with a rigorous causal identification strategy. This study addresses that gap by constructing a synthetic index of environmental consciousness using principal component analysis (PCA), applying a two-stage least squares (2SLS) instrumental variable approach to address endogeneity, and using a large, geographically diverse European dataset that allows for heterogeneity analysis across demographic and regional subgroups. In doing so, this thesis not only tests the validity of claims in the existing literature but also provides new empirical evidence on the causal pathways linking environmental awareness to individual behavioral engagement.

# 3. Data Description

To ensure the robustness and relevance of the analysis, all data used in this study had to meet three essential criteria: completeness, accuracy, and credibility of source. The core of the individual-level data comes from the European Social Survey (ESS), a reputable cross-national survey designed to capture attitudes, behaviors, and socio-demographic characteristics across European countries. However, to enrich the analysis and account for regional and contextual heterogeneity, the ESS data were systematically integrated with additional sources. In particular, data from Eurostat were used extensively to obtain regional-level indicators crucial for understanding the socio-economic background which provided standardized measures of environmental and regional indicators distribution across European regions. These complementary datasets allowed the construction of a more nuanced and comprehensive framework, combining both micro-level behavioral information and macro-level structural factors. The integration of these datasets was carefully handled to preserve data quality and alignment across sources, ensuring consistency in regional identifiers and time frames. This multi-source strategy significantly strengthens the explanatory power of the analysis and enhances its validity in exploring the relationship between environmental consciousness and pro-environmental behavior in a European context.

All datasets employed in this study are structured according to the Nomenclature of Territorial Units for Statistics (NUTS), specifically at the NUTS2 level. The NUTS classification, developed by Eurostat, provides a standardized hierarchical system for dividing up the economic territory of the EU for statistical purposes. NUTS2 regions represent basic regions for the application of regional policies and are commonly used for statistical and policy-making purposes across the European Union. By utilizing data at the NUTS2 level, the study ensures a consistent regional framework across all datasets, facilitating accurate integration and comparison of regional indicators. This alignment allows for a detailed examination of regional disparities and the assessment of regional policy impacts, thereby enhancing the granularity and relevance of the analysis. The use of NUTS2-level data is particularly valuable for understanding how regional contexts influence social phenomena, such as cultural values, political attitudes, and public health outcomes (Eurostat, 2021, Glossary: Nomenclature of territorial units for statistics NUTS). The Nomenclature of Territorial Units for Statistics (NUTS) is a hierarchical system developed by Eurostat to standardize regional divisions across the European Union for statistical and policy-making purposes. It comprises three levels: NUTS 1 (major socio-economic regions), NUTS 2 (basic regions for the application of regional policies), and NUTS 3 (small regions for specific diagnoses). In this study, the NUTS 2 level is utilized as it offers an optimal balance between granularity and data availability. NUTS 2 regions typically have populations between 800,000 and 3 million, making them suitable for capturing regional variations without compromising the comparability and reliability of data (European Parliament, 2021, Common classification of territorial units for statistics NUTS). This level is particularly relevant for analysing socio-economic and environmental factors, as it aligns with the regions targeted by EU cohesion policies and regional development programs.

## 3.1 Datasets and variables

A detailed description of each dataset and the variables included in the analysis is provided in the following sections. This aims to offer a comprehensive understanding of the data structure, the nature of each variable, and the rationale behind their selection.

### 3.1.1 European Social Survey (ESS)

Firstly a dataset that captured individual characteristics, preferences, behaviors and the most possible aspects of an individual's life had to be identified. The European Social Survey (ESS) is an academically driven cross-national survey that has been conducted across Europe since its establishment in 2001. Every two years, face-to-face interviews are conducted with newly selected, cross-sectional samples. The European Social Survey (ESS) is a large-scale, cross-national survey that collects high-quality data on attitudes, beliefs, and behavior across more than thirty European countries. Its main objective is to monitor social change and stability over time within and between countries. The ESS is known for promoting rigorous methodological standards in comparative social research and for offering freely accessible data to the academic community and policymakers. Operated under the European Research Infrastructure Consortium (ERIC) status since 2013.

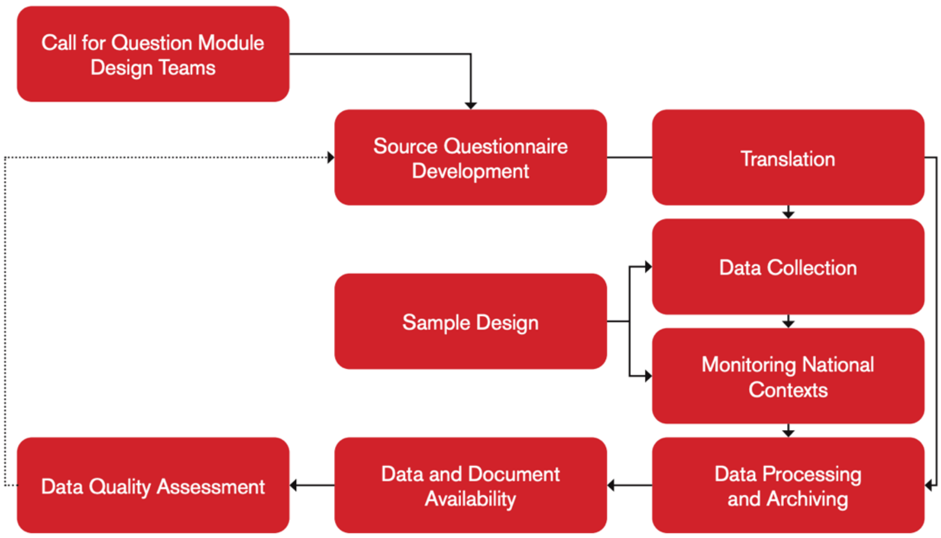


*Figure 1: ESS Methodology Diagram (From ESS official website: "Methodology")*

The methodological framework of the European Social Survey (ESS) is formally outlined in the Survey Specification; a document revised before each survey round to ensure consistency and high standards across all participating countries. The Specification defines the tasks and responsibilities of national coordinators and survey agencies, detailing every phase of the data collection process. Its overarching aim is to guarantee that data are collected in a way that is both rigorous and internationally comparable, so that they accurately reflect both the populations surveyed and the concepts under investigation. The four core components of the Specification include: the preparation and translation of the national questionnaire; the design and implementation of the sampling strategy; the actual fieldwork, including interviewer training and process data collection; and finally, the post-survey data processing and delivery. By enforcing strict methodological guidelines in each country, the ESS ensures that the resulting data are of high scientific quality and suitable for robust comparative analysis.

The ESS source questionnaire is composed of two main parts: a core module and rotating modules**.** The core module contains questions on long-term themes relevant to the social sciences, including detailed socio-demographic and structural background variables. Its purpose is to enable reliable time-series analysis of key attitudes and values across countries and over time. Rotating modules, on the other hand, are designed by international research teams selected through open calls and vary from round to round. These modules address specific, topical themes and may be newly introduced or repeated from previous rounds to allow for longitudinal comparisons. Since Round 7, the previously separate supplementary questionnaire such as the 21-item human values scale has been integrated into the main questionnaire structure, enhancing the consistency and comparability of the data collected. The round 8 was specifically chosen for this analysis because in its rotating modules it contained the module: “Attitudes to climate and energy” which fits perfectly with this study. The round 8 survey was conducted in 2016, which is not the most recent edition, but it is the latest that contained questions on environmental concerns and issues.

To ensure cross-national comparability, the ESS adheres to a rigorous and standardized translation process guided by the principle of functional equivalence. The source questionnaire is originally developed in British English and then translated by each national team into the languages spoken by at least 5% of the country’s population. The ESS adopts the TRAPD methodology (Translation, Review, Adjudication, Pretesting, and Documentation) which ensures both linguistic and conceptual consistency across countries. Each team receives comprehensive Translation Guidelines and a Translation Quality Checklist to support adherence to best practices. Moreover, translated questionnaires undergo additional quality control steps, including translation verification and assessment conducted by the team at Universitat Pompeu Fabra (UPF). All translations must be pre-tested after these checks to confirm their validity and clarity before field implementation. This meticulous process is central to maintaining the scientific reliability of the ESS data across different cultural and linguistic contexts.

The sampling strategy of the ESS is designed to ensure comparability and representativeness across all participating countries. In accordance with the Survey Specification, each national sample must include all individuals aged 15 and over living in private households, regardless of nationality, citizenship, or language. The ESS strictly requires the use of random probability sampling methods at every stage of selection (whether based on individuals, households, or addresses). Quota sampling is explicitly prohibited, as is the substitution of non-respondents. To ensure statistical reliability, countries must aim for a minimum effective sample size of 1,500 respondents, or 800 in countries with populations below 2 million, after adjusting for design effects. These methodological constraints are fundamental to preserving the quality, comparability, and scientific integrity of the ESS data across diverse national contexts.

The ESS has historically relied on face-to-face data collection through Computer-Assisted Personal Interviews (CAPI) across all participating countries. However, starting from May 2022, the ESS General Assembly endorsed a gradual transition toward a self-completion design, prioritizing web-based questionnaires with paper-based alternatives where necessary. Despite this methodological shift, the core objective remains unchanged: to ensure high-quality and internationally comparable data. Each country appoints a National Coordinator and a survey organization responsible for implementing the survey in accordance with the ESS Specification. Key standards include a target response rate of 70%, a non-contact rate below 3%, and a minimum fieldwork period of six weeks. Interviewers receive detailed in-person training and are required to follow a strict contact protocol, including at least four contact attempts with at least one in the evening and one during the weekend. Throughout the survey cycle, the Core Scientific Team (CST) provides training materials, monitors implementation, collects process data, and gives structured feedback based on predefined quality benchmarks. After data collection, each country submits both the dataset and accompanying documentation (including metadata, paradata, and fieldwork materials) to the ESS Archive. This robust quality assurance system reflects the ESS's ongoing commitment to methodological transparency and continuous improvement. ESS round 8 in particular uses a face-to-face methodology of interview.

To enhance analytical power and account for national-level influences, the ESS integrates contextual data into its main datasets. This allows researchers to distinguish between attitudinal differences and effects driven by external events. In early rounds (1–5), contextual data were collected through event tracking, though this proved ambiguous and limited. A more structured method based on media claims was adopted in rounds 6–8, but due to methodological and practical challenges, it was discontinued from round 9 onwards. In 2018, the ESS commissioned an independent study to explore automated tools (such as topic modelling) for capturing media context, but these were not yet considered sufficiently mature for adoption. The ESS continues to explore improved methods for integrating contextual influences in future rounds.

The European Social Survey adopts a comprehensive strategy to assess and ensure data quality throughout all stages of the survey process. This includes evaluating the reliability and validity of individual survey items through multitrait-multimethod (MTMM) experiments and incorporating their results into the Survey Quality Predictor (SQP), a tool that supports the design and translation of high-quality survey questions. The ESS also conducts tests for cross-national measurement equivalence to verify that concepts are interpreted consistently across countries. In addition, the socio-demographic composition of national samples is compared with external benchmarks, such as the EU Labour Force Survey, to assess representativeness. Since Round 6, each wave concludes with a detailed Quality Report produced by the Core Scientific Team, which documents both process and output quality and provides country-specific feedback for future rounds. This structured approach allows the ESS to maintain high methodological standards and ensure the comparability and reliability of its data across time and space.

In the European Social Survey, interviewers play a central role in data collection, particularly given the traditional reliance on face-to-face interviews. Ensuring desirable interviewer behaviour (DIB) is therefore essential to maintaining data quality and cross-national comparability. The ESS investigates how interviewer actions can influence both measurement accuracy and sample representativeness. Research findings are integrated into the survey life cycle across three stages: preparation and prevention, which includes interviewer training and the use of paradata for quality control; monitoring and detection, involving real-time quality checks and systems for tracking interviewer activity across countries; and assessment and evaluation, which focuses on measuring interviewer effects, compliance with contact protocols, and distinguishing between interviewer-related and contextual data issues. These efforts support the ESS's broader goal of minimizing interviewer-induced bias and enhancing overall survey reliability.

Achieving high response rates is a central objective of the ESS, as they are commonly associated with improved data quality and reduced risk of nonresponse bias. The ESS

Specification recommends a minimum target response rate of 70% per country, or an increase over the previous round where that threshold is unrealistic. To support this goal, various measures are implemented: interviewer training, adequate remuneration, advance letters, respondent incentives, flexible scheduling for visits, and continuous fieldwork monitoring. Nevertheless, response rates alone do not fully eliminate bias; what matters equally is the balance of participation across subgroups. If certain demographic groups respond at higher rates than others (such as individuals with higher education) nonresponse bias may still occur. Therefore, the ESS promotes the pursuit of not only high but also balanced response rates. At the end of each round, standard response rates are calculated using detailed contact forms, and nonresponse bias analyses are conducted to identify underrepresented groups. To correct for sampling imbalances, post-stratification weights are applied, ensuring the final dataset is representative of the national population aged 25 and over in terms of age, gender, education, and region.

### 3.1.2 ESS Round 8 and Each Variable Description

The ESS Round 8 is the 8th edition of the ESS questionnaires; it was conducted in 2016 in countries belonging to the EU. Countries that were analysed were: Austria, Belgium, Czechia, Denmark, Estonia, Finland, France, Germany, Hungary, Iceland, Ireland, Israel, Italy, Lithuania, Netherlands, Norway, Poland, Portugal, Russian Federation, Serbia, Slovakia, Slovenia, Spain, Sweden, Switzerland, United Kingdom.

Some countries were not included in the analysis, and they were: Albania, Bulgaria, Croatia, Cyprus, Greece, Kosovo, Latvia, Luxembourg, Montenegro, North Macedonia, Romania, Turkey, Ukraine

The total of all individuals interviewed amounts to 44,388.

List and description of each variable selected from the ESS8.

**Individual Variables:**

- **Region**: NUTS code of the region of origin of each individual (ex. AL: Albania, AL0: Shqipëria, AL01: Veri etc...)
- **Gender**: Sex of the respondent, Male, Female or No answer.
- **Age**: Age of the respondent calculated based on the date of birth.
- **Income Level**: Household's total net income, all sources, the question was: Using this card, please tell me which letter describes your household's total income, after tax and compulsory deductions, from all sources? If you don't know the exact figure, please give an estimate. Use the part of the card that you know best: weekly, monthly or annual

income. Possible answers were coded by choosing from 10 possible deciles or refusal to answer.

- **Education Level**: Highest level of education, ES – ISCED, levels of education are coded as: 0, Not possible to harmonise into ES-ISCED; 1, ES-ISCED I , less than lower secondary; 2, ES-ISCED II, lower secondary; 3, ES-ISCED IIIb, lower tier upper secondary; 4, ES-ISCED IIIa, upper tier upper secondary; 5, ES-ISCED IV, advanced vocational, sub-degree; 6, ES-ISCED V1, lower tertiary education, BA level; 7, ES-ISCED V2, higher tertiary education. These levels were then translated into low, medium and high education to simplify the understanding of the analysis.
- **Father and Mother Education**: These are two distinct variables, coded exactly as the education level variable (low, medium high).
- **With Children:** Children living at home or not. This was coded as dummy variable taking value 1 when living with children and 0 when not.
- **With Job:** This is a dummy variable created from the employment relation of the respondent, possible answers were: employee, self-employed, working for family business, not applicable and refusal. The first three were considered as having a job.
- **Happy:** This is a variable measuring the level of happiness of the respondent going from a scale of 1 to 10.
- **Health:** This variable measures the subjective general health of the individual from a scale of 1 to 5.
- **Attached to Country:** This variable measures the emotional attachment of the respondent to his country from a scale of 1 to 10, the question asked was: How emotionally attached do you feel to your country? Please choose a number from 0 to 10, where 0 means not at all emotionally attached and 10 means very emotionally attached.
- **Crime Victim:** Respondent or household member victim of burglary/assault last 5 years, this is a dummy variable taking value 1 for positive answers and 0 for negative.
- **Born in Country:** This is a dummy variable taking value 1 for natives and 0 for non-natives.
- **Minority:** Dummy variable that takes value 1 for individuals that belong to minorities of ethnic groups and 0 if not.

**Environmental Variables:** These are variables taken from the rotating module of the ESS8: attitudes to climate change. With the selection of these question an environmental individual awareness is delineated and some pro-environmental behaviors also. All variables were coded or transformed in order to be in a positive scale. Increasing values translate into positive attitudes, a higher awareness and behavior.

- **Climate Changing:** You may have heard the idea that the world's climate is changing due to increases in temperature over the past 100 years. What is your personal opinion on this? Do you think the world's climate is changing?
  The answers go from 1: Definitely Changing, to 5: Definitely not changing. This scale must be inverted in order to obtain a positive scale that with 1 represents the worst awareness and with 5 the best.
- **Human Cause Climate Change:** Do you think that climate change is caused by natural processes, human activity, or both?
  The possible answers go from 1: Entirely by natural processes, to 5: Entirely by human processes. Also, there is the possibility to answer: "I don't think climate change is happening" and it is coded with 55. In this instance also the scale must be inverted in order to obtain a positive logic and 55 was recoded as 0.
- **Responsible to Reduce:** To what extent do you feel a personal responsibility to try to reduce climate change?
  This variable is coded as a scale going from 0 to 10, 0 being "not at all responsible" and 10 being "a great deal". There was no need to invert the scale in this case.
- **Worried About Climate Change:** How worried are you about climate change?
  Possible answers go from 1: "not at all worried", to 5: "extremely worried". Here there is no need to invert the order since the scale is positive.
- **How Often Save Energy:** There are some things that can be done to reduce energy use, such as switching off appliances that are not being used, walking for short journeys, or only using the heating or air conditioning when really needed. In your daily life, how often do you do things to reduce your energy use?
  This variable takes values 1 for Never and goes up to 6 for Always. 55 is the code for the answer: "Cannot reduce energy use" that is not taken into consideration. No need to invert the scale here also.
- **Confident Less Energy:** Overall, how confident are you that you could use less energy than you do now?
  This variable can take values from 0: "not at all confident", to 10: "completely confident". The scale remains as is.
- **Helping by Reducing Self use:** How likely do you think it is that limiting your own energy use would help reduce climate change?
  This variable goes from 0: "not at all likely", to 10: "Extremely likely". Here the scale has the right direction also.

- **Buy Efficient Tech:** If you were to buy a large electrical appliance for your home, how likely is it that you would buy one of the most energy efficient ones?
  The scale of answers goes from 0: “not at all likely”, to 10: “extremely likely”. Scale does not need to be inverted.

### 3.1.3 Eurostat Databases and Regional Variables

Eurostat is the statistical office of the European Commission, responsible for providing high-quality European statistics to support policymaking, research, and public debate. It achieves this by producing and disseminating data that are reliable, comparable, and accessible across all EU member states. Eurostat coordinates and harmonises the work of national statistical institutes through the European Statistical System (ESS), ensuring methodological consistency between countries. Its activities span a wide range of domains, including economy, demography, environment, health, and education. In line with its principles of transparency, impartiality, and professional independence, Eurostat makes all data openly available through its official online portal. In the context of this study, accounting for regional differences is crucial to capturing the social, economic, and environmental heterogeneity both within and across countries. The Eurostat database is particularly valuable in this regard, as it systematically collects, organizes, and publishes regional indicators often disaggregated at the NUTS2 level. These include variables such as economic development, labor market conditions, educational attainment, life expectancy, and environmental quality. Incorporating such contextual data allows for a more nuanced interpretation of individual behaviors and attitudes, as it helps isolate the influence of structural conditions from underlying personal dispositions. The integration of Eurostat regional data with individual-level survey responses enhances both the depth and precision of the analysis, revealing patterns that might otherwise remain hidden in national-level aggregates.

- **Eurostat Datasets on Regional Education**
  The dataset titled "Participation rates of selected age groups in education at regional level" (Eurostat code: educ_uoe_enra14) provides statistical information on the proportion of individuals within specific age groups who are enrolled in educational programs, disaggregated by NUTS2 regions across European countries. This dataset is instrumental in analysing regional disparities in educational participation, facilitating the assessment of access to education and the effectiveness of educational policies at the sub-national level. For this analysis we considered only the data from 2016 to have compatibility with the ESS dataset. The age class considered for the proportion of students enrolled is from 15 to 24 years old.

- **Eurostat Dataset on Regional Unemployment**

  The dataset "Unemployment rates by NUTS 2 regions (%)" (Eurostat code: lfst_r_lfu3rt) provides the unemployment rates as percentages for European regions defined at the NUTS 2 level. It presents the proportion of unemployed individuals within the labor force, following the standardized definitions of the International Labour Organization (ILO). The data is disaggregated by region and by year, allowing for direct comparison of labor market conditions across EU regions. This dataset is a valuable tool for analyzing regional labor disparities and assessing the effectiveness of employment policies. It also enables monitoring of economic trends and the impact of structural changes at a sub-national level. Year 2016 only was used for this analysis.

- **Eurostat Dataset on Regional GDP pro Capita**

  The dataset "Gross domestic product (GDP) at current market prices by NUTS 2 regions" (Eurostat code: nama_10r_2gdp) contains annual regional GDP pro capita figures expressed in thousands of euros. The data is disaggregated by NUTS 2 regions, allowing for analysis of regional economic performance across the European Union. GDP pro capita at current market prices reflects the total economic output of a region, without adjustments for inflation, and includes taxes minus subsidies on products. This dataset is essential for comparing the relative size and economic development of regions, assessing territorial imbalances, and informing regional policy and funding decisions within the EU framework.

- **Eurostat Dataset on Regional Life Expectancy**

  The dataset "Life expectancy at birth by sex and NUTS 2 region" (Eurostat code: tgs00101) provides annual data on the average number of years a newborn is expected to live, assuming current mortality rates remain constant throughout their life. This information is disaggregated by sex and by NUTS 2 regions, offering a detailed view of regional disparities in life expectancy across Europe. Such data is crucial for public health analysis, regional development planning, and assessing the effectiveness of health policies at the sub-national level. It enables comparisons between regions and helps identify areas where interventions may be needed to improve health outcomes.

- **Eurostat Dataset on Regional Forest Land Percentage**

  The dataset "Land cover by NUTS 2 regions" (Eurostat code: lan_lcv_fao) provides data on the distribution of land use categories across European regions, following the FAO classification system. It includes information on the percentage of land used for agriculture, forests, urban areas, and other cover types. The data is disaggregated by NUTS 2 regions, enabling spatial analysis of environmental and land-use patterns at a sub-national level. This dataset is useful for assessing regional differences in land use, monitoring changes over time, and supporting policy development in areas such as environmental protection, urban planning, and sustainable agriculture.

### 3.1.4 Final Dataset Description

The final dataset used in this analysis is constructed by combining all selected variables from the ESS Round 8 with additional contextual information at the NUTS2 regional level. Each individual in the ESS sample is matched to their corresponding region, allowing the integration of external data retrieved from the Eurostat database (including life expectancy, GDP per capita, unemployment rate, education level, and forest coverage). Although the individual datasets did not cover exactly the same set of countries, they shared substantial overlap. The final harmonised sample includes the following countries: Austria, Belgium, Czechia, Germany, Estonia, Spain, Finland, France, Hungary, Ireland, Italy, Lithuania, Netherlands, Poland, Portugal, Sweden, and Slovenia. All variables were cleaned and harmonised to ensure they were suitable for direct use in the analysis.

The final sample consists of approximately sixteen thousand individuals. The dataset was restricted to respondents who were born in their country of residence and who were between 25 and 65 years of age, ensuring a more homogeneous and analytically relevant population. This restriction was applied in order to reduce potential endogeneity concerns and to exclude younger individuals whose environmental consciousness may not yet be fully developed. Including such respondents could introduce noise and bias into the analysis, potentially distorting the estimation of the relationships under investigation and undermining the robustness of the results.

## 3.2 Exploratory Data Analysis (EDA)

In this paragraph, all relevant data will be systematically explored and analysed in order to identify potential outliers, assess the distribution of key variables, and uncover underlying patterns within the dataset. This exploratory step is essential to understand the structure of the data, evaluate data quality, and guide the choice of appropriate statistical methods for the subsequent analysis. Descriptive statistics, visualisation techniques, and correlation assessments will be employed to highlight relationships between variables and reveal any irregularities or trends that may influence the interpretation of results. This dataset has been constructed by integrating all relevant external regional variables with the individual-level data from the European Social Survey (ESS). Moreover, the sample has been restricted to individuals who are native to their country of residence, and all rows containing missing values have been removed to ensure analytical consistency and robustness in the modelling phase.

### 3.2.1 Individual Variables

A brief table of descriptive statistics for the individual variables is shown below. Most of these variables (except for age, income and education level) are dummy variables, so their means can be interpreted as the proportion of individuals for whom the condition holds.

| Variable | Count | Mean | Std | Min | 25% | 50% | 75% | Max |
|---|---|---|---|---|---|---|---|---|
| **age** | 11492 | 45.97 | 11.74 | 25.0 | 36.0 | 46.0 | 56.0 | 65.0 |
| **male** | 11492 | 0.480 | 0.500 | 0.0 | 0.0 | 0.0 | 1.0 | 1.0 |
| **with_children** | 11492 | 0.458 | 0.498 | 0.0 | 0.0 | 0.0 | 1.0 | 1.0 |
| **has_job** | 11492 | 0.974 | 0.158 | 0.0 | 1.0 | 1.0 | 1.0 | 1.0 |
| **happy** | 11492 | 7.50 | 1.70 | 0.0 | 7.0 | 8.0 | 9.0 | 10.0 |
| **health** | 11492 | 3.90 | 0.82 | 1.0 | 3.0 | 4.0 | 4.0 | 5.0 |
| **attached_to_country** | 11492 | 7.89 | 2.06 | 0.0 | 7.0 | 8.0 | 10.0 | 10.0 |
| **education_level** | 11492 | 62.13 | 10.35 | 33.4 | 56.2 | 61.7 | 68.5 | 100.0 |
| **edu_low** | 11492 | 0.183 | 0.387 | 0.0 | 0.0 | 0.0 | 0.0 | 1.0 |
| **edu_mid** | 11492 | 0.412 | 0.492 | 0.0 | 0.0 | 0.0 | 1.0 | 1.0 |
| **edu_high** | 11492 | 0.405 | 0.491 | 0.0 | 0.0 | 0.0 | 1.0 | 1.0 |
| **edu_father_low** | 11492 | 0.502 | 0.500 | 0.0 | 0.0 | 1.0 | 1.0 | 1.0 |
| **edu_father_medium** | 11492 | 0.307 | 0.461 | 0.0 | 0.0 | 0.0 | 1.0 | 1.0 |
| **edu_father_high** | 11492 | 0.191 | 0.393 | 0.0 | 0.0 | 0.0 | 0.0 | 1.0 |
| **edu_mother_low** | 11492 | 0.551 | 0.497 | 0.0 | 0.0 | 1.0 | 1.0 | 1.0 |
| **edu_mother_medium** | 11492 | 0.286 | 0.452 | 0.0 | 0.0 | 0.0 | 1.0 | 1.0 |
| **edu_mother_high** | 11492 | 0.163 | 0.370 | 0.0 | 0.0 | 0.0 | 0.0 | 1.0 |
| **victim_crime** | 11492 | 0.178 | 0.382 | 0.0 | 0.0 | 0.0 | 0.0 | 1.0 |
| **minority** | 11492 | 0.026 | 0.159 | 0.0 | 0.0 | 0.0 | 0.0 | 1.0 |
| **income_level** | 11492 | 5.06 | 3.19 | 0.0 | 2.0 | 5.0 | 8.0 | 10.0 |

*Table 1: Individual Variables Description*

The table presents summary statistics for a wide range of individual-level variables included in the dataset, offering an overview of the demographic, socioeconomic, and attitudinal composition of the sample (N = 11,492). Continuous variables are described using measures of central tendency and dispersion, while dummy variables indicate the proportion of individuals within each category. The average age of respondents is approximately 46 years, with values ranging from 25 to 65. The gender distribution is balanced, with 48% of the sample identified as male. Roughly 46% of respondents report having children, and an overwhelming majority (97.4%) are employed, suggesting a relatively stable and economically active population. Attitudinal measures such as happiness and health are reported on bounded scales. The mean happiness score is 7.49 (on a 0–10 scale), with most observations concentrated between 7 and 9, indicating a generally high level of subjective well-being. Self-reported health is measured on a 1–5 scale, with a mean of 3.90 and most values clustered around 4, reflecting generally positive health perceptions. Similarly, the variable attached_to_country, also on a 0–10 scale, has a high mean of 7.89, suggesting that respondents tend to express strong emotional or cultural attachment to their country. The education_level variable, likely coded as a percentage score (0–100), shows a mean of 62.1, and is further complemented by categorical variables indicating whether an individual's educational attainment is low (18.3%), medium (41.2%), or high (40.5%). Education background is also recorded for both parents: for instance, 55.1% of respondents report their mother had a low education level, while 50.2% say the same for their father. The education variables suggest relatively high educational attainment overall, especially for the respondents themselves. Other indicators capture aspects of household and social conditions. Around 17.8% of respondents report being a victim of crime, and 2.6% identify as part of a minority group. Finally, income_level is recorded on a 1–10 scale, with a mean of 5.06, indicating a relatively symmetric distribution across income brackets, and with a wide range suggesting some variability in economic conditions. Overall, the table provides a detailed snapshot of the individuals included in the analysis, highlighting variation in key sociodemographic and subjective indicators that will inform subsequent analytical work.

### 3.2.2 Regional Variables

A brief table with the descriptive statistics of regional variables.

| Variable | Count | Mean | Std | Min | 25% | 50% | 75% | Max |
|---|---|---|---|---|---|---|---|---|
| **unemployment_rate** | 11492 | 8.613209 | 5.213207 | 2.2 | 5.30 | 7.0 | 9.9 | 28.9 |
| **gdp_per_capita** | 11492 | 282.408023 | 133.288974 | 75.0 | 169.0 | 288.0 | 372.0 | 667.0 |
| **education_level** | 11492 | 62.133806 | 10.346137 | 33.4 | 56.2 | 61.7 | 68.5 | 100.0 |
| **forest_rate** | 11492 | 35.357718 | 17.077530 | 1.2 | 22.55 | 35.7 | 49.1 | 72.8 |
| **life_exp** | 11492 | 80.241116 | 7.757861 | 8.8 | 79.3 | 81.7 | 82.6 | 85.2 |

*Table 2: Regional Variables Descriptive Statistics*

- **Unemployment Rate:**

The unemployment_rate variable shows a pronounced right-skewed distribution, with the majority of observations clustered between 4% and 10%, and a long tail of higher values. The boxplot confirms a large number of outliers, indicating regional disparities in labor market conditions. Country-level averages reveal considerable variation: Spain stands out with the highest unemployment rate, followed by Portugal and Italy, while countries like the Netherlands, Czech Republic, and Germany exhibit significantly lower rates. These differences reflect broader structural and economic contrasts across the European regions included in the dataset.

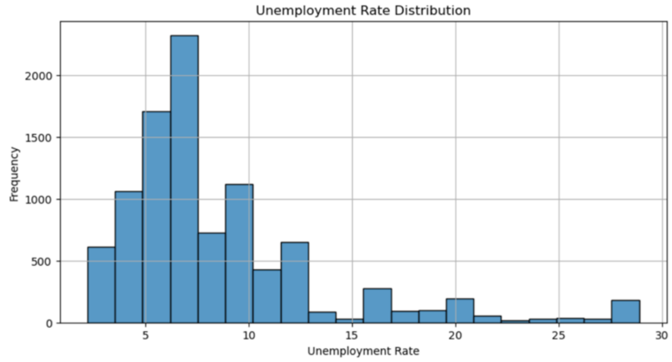


*Figure 2: Unemployment Rate Distribution*

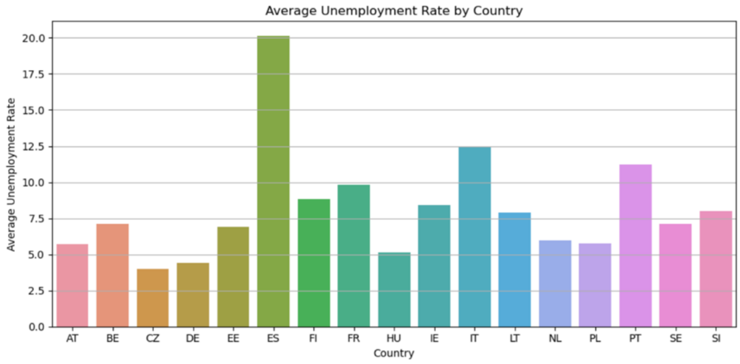


*Figure 3: Unemployment Rate Mean by Country*

- **GDP per Capita:**

The gdp_per_capita variable displays a multimodal distribution, with peaks around €15k, €30k, and €60k, reflecting the economic heterogeneity across regions. The boxplot shows a broad and symmetric spread without statistical outliers, indicating a relatively even distribution of values. When examining the country-level averages, Ireland clearly stands out with the highest GDP per capita, followed by the Netherlands, Sweden, and Austria. On the lower end, countries like Hungary, Portugal, and Latvia report considerably lower averages. These patterns highlight the persistent economic divide between more affluent and less developed areas within the European sample.

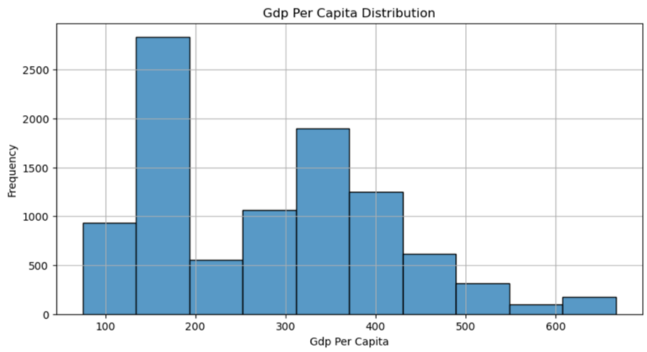


*Figure 4: GDP per capita Distribution*

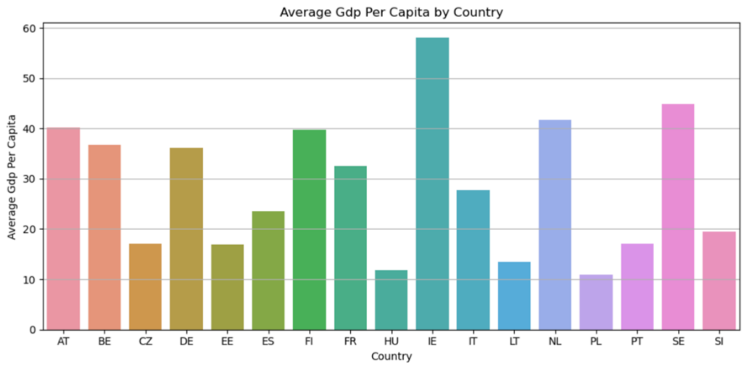


*Figure 5: GDP per capita Mean by Country*

- **Education Level:**

The education_level variable shows a distribution with multiple peaks, indicating heterogeneity in regional educational attainment. The majority of values fall between 55% and 75%, though several outliers are present at both the lower and upper ends of the spectrum. The boxplot reflects this spread and confirms the presence of mild outliers, including a number of cases reporting 100%. At the country level, Ireland and Slovenia report the highest average education levels, while Hungary and France show the lowest. These results highlight meaningful cross-country differences in the proportion of the population with at least upper secondary education.

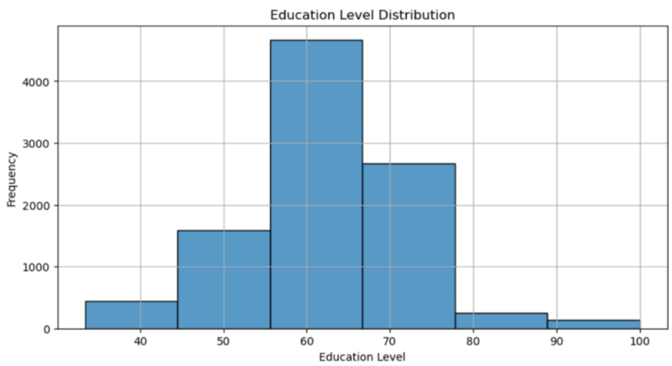


*Figure 6: Education Level Distribution*

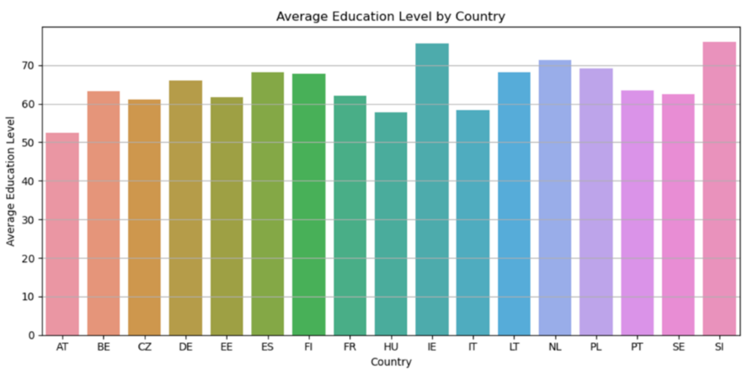


*Figure 7: Education Level Mean by Country*

- **Percentage of Land covered by Forests (Forest rate):**

The forest_rate variable shows a broad and relatively balanced distribution, with several peaks between 10% and 60%, reflecting diverse land cover patterns across regions. The boxplot confirms a symmetric spread without any statistical outliers. Country-level averages highlight significant variation: Finland, Slovenia, and Sweden report the highest average forest coverage, while countries like the Netherlands, Ireland, and Italy show notably lower values. These differences underscore the environmental and geographical heterogeneity among the regions considered.

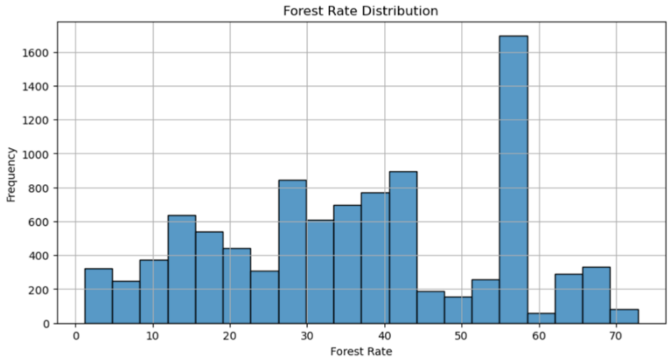


*Figure 8: Forest Rate Distribution*

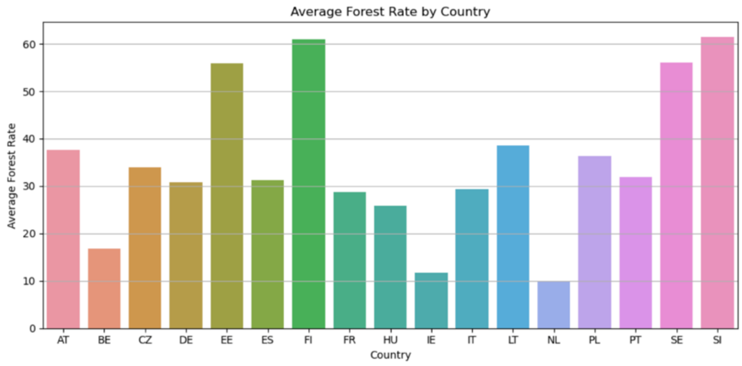


*Figure 9: Forest Rate Mean by Country*

- **Expectancy of Life (life exp):**

The life_exp variable is tightly clustered between 75 and 85 years, indicating relatively uniform life expectancy across regions, with the exception of a few outliers. The histogram and boxplot both reveal a strong central tendency, while the extreme low value around 8.8 suggests a potential data anomaly or error. At the country level, Italy, Spain, and Sweden exhibit the highest average life expectancies, whereas Hungary and Latvia fall on the lower end of the scale. Overall, the data reflect consistent health outcomes in most regions, with some notable exceptions.

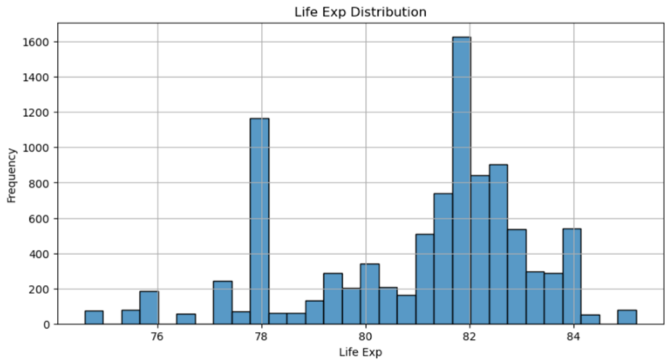


*Figure 10: Life Expectancy Distribution*

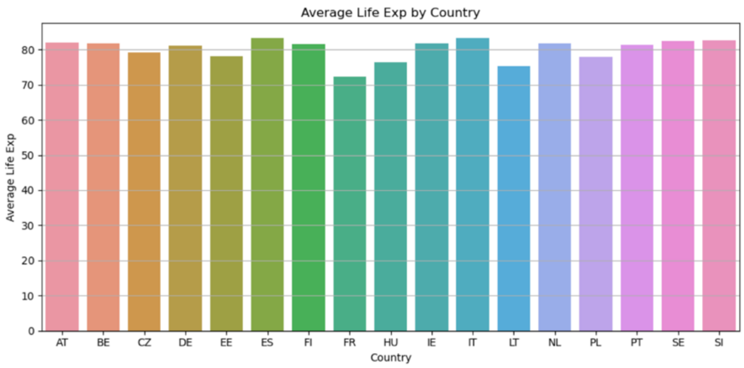


*Figure 11: Life Expectancy Mean by Country*

### 3.2.3 Environmental Variables

A brief table with the descriptive statistics of environmental variables.

| Variable | Count | Mean | Std | Min | 25% | 50% | 75% | Max |
|---|---|---|---|---|---|---|---|---|
| **is_climate_changing** | 11492 | 3.55 | 0.58 | 2.0 | 3.0 | 4.0 | 4.0 | 4.0 |
| **human_cause_clim_chng** | 11492 | 3.51 | 0.77 | 1.0 | 3.0 | 4.0 | 4.0 | 5.0 |
| **responsible_to_reduce** | 11492 | 5.77 | 2.66 | 0.0 | 4.0 | 6.0 | 8.0 | 10.0 |
| **Worried_abt_clim_chng** | 11492 | 3.11 | 0.91 | 1.0 | 3.0 | 3.0 | 4.0 | 5.0 |
| **how_often_save_energy** | 11492 | 4.23 | 1.12 | 1.0 | 3.0 | 4.0 | 5.0 | 6.0 |
| **confident_less_energy** | 11492 | 6.24 | 2.50 | 0.0 | 5.0 | 7.0 | 8.0 | 10.0 |
| **likely_to_reduce_selfuse** | 11492 | 4.42 | 2.62 | 0.0 | 2.0 | 5.0 | 6.0 | 10.0 |
| **buy_efficient_tech** | 11492 | 8.13 | 1.97 | 0.0 | 7.0 | 9.0 | 10.0 | 10.0 |

*Table 3: Descriptive Statistics of Environmental Variables*

- **Climate Change (is climate changing?):**

The variable is_climate_changing captures individual perceptions about the existence of climate change, measured on a discrete ordinal scale. The distribution shows a clear concentration at the highest category, indicating that the majority of respondents firmly believe that climate change is occurring. The boxplot confirms a right-skewed pattern with no statistical outliers. When comparing country-level averages, all countries score above 3, suggesting strong consensus across the sample, with Spain and Slovenia showing the highest average agreement.

This points to widespread acknowledgment of climate change throughout the European countries surveyed.

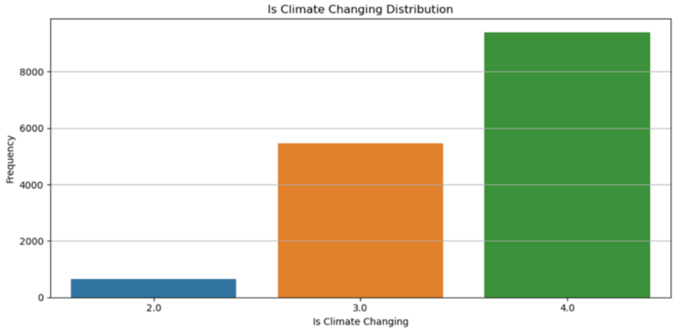


*Figure 12: Is Climate Changing Distribution*

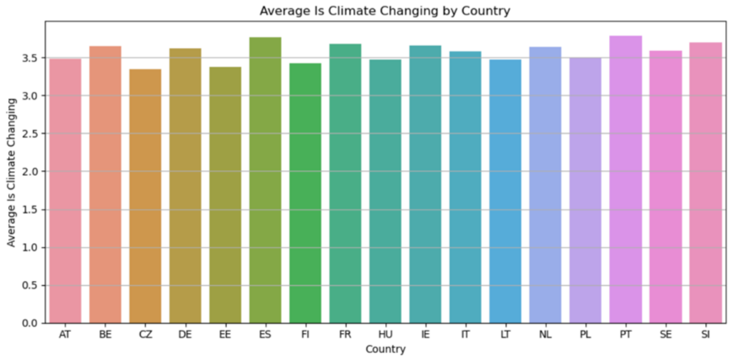


*Figure 13: Is Climate Changing Mean by Country*

- **Who Causes Climate Change (human cause climate change):**

The variable human_cause_clim_chng reflects individual beliefs about whether climate change is caused by human activity, measured on a discrete scale from 1 to 5. The distribution is concentrated around the middle and higher values, with most respondents selecting 3 or 4, indicating moderate to strong agreement. A small number of responses at the extreme low end (value 1) are identified as outliers. The boxplot supports this distribution, showing mild asymmetry but no extreme deviations beyond the IQR bounds. At the country level, Austria and Spain show the highest average agreement with the human causation of climate change, while Czechia and Estonia report the lowest averages, though overall differences across countries remain modest.

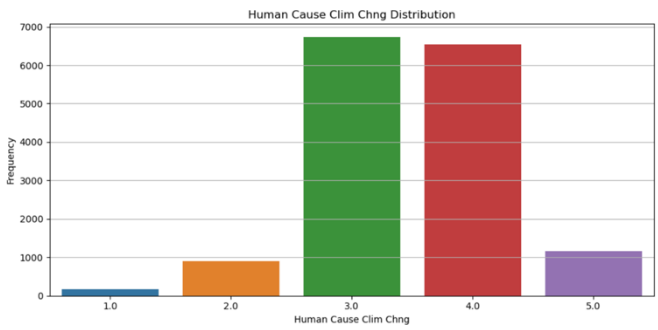


*Figure 14: Human Cause Climate Change Distribution*

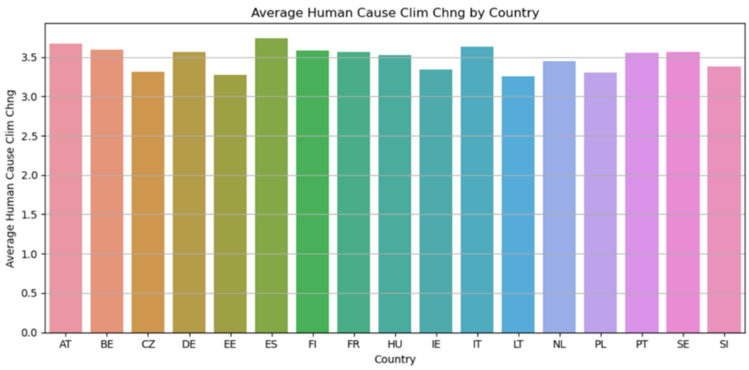


*Figure 15: Human Cause Climate Change Mean by Country*

- **Feeling Responsible to Reduce Climate Change:**

The variable responsible_to_reduce measures the perceived individual responsibility to take action against climate change, on a scale from 0 to 10. The distribution is moderately right skewed, with most responses clustered between 5 and 8, indicating that a large share of individuals feel personally accountable. A smaller peak at the maximum value of 10 suggests strong engagement among some respondents, while the value 0 is treated as an outlier. The boxplot confirms this pattern, showing a concentration in the upper range. Country-level averages reveal that Finland and France score highest in perceived responsibility, whereas Hungary and Estonia report lower averages. These results highlight meaningful cross-country differences in how individuals internalize environmental responsibility.

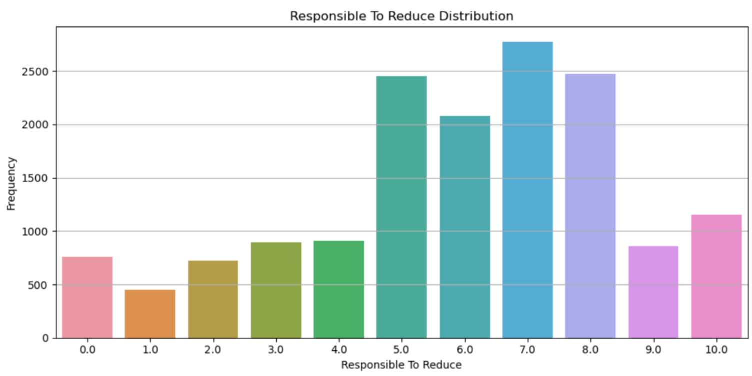


*Figure 16: Responsible to Reduce Distribution*

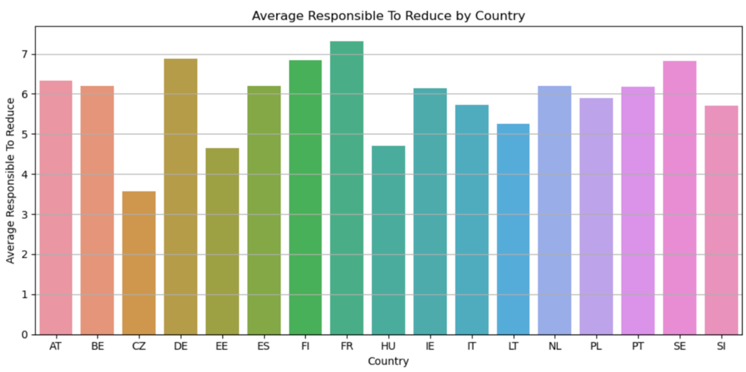


*Figure 17: Responsible to Reduce Mean by Country*

▪ **Worried About Climate Change:**

The variable worried_abt_clim_chng captures individuals' levels of concern about climate change, measured on a 5-point ordinal scale. The distribution shows a concentration around value 3, suggesting moderate concern among most respondents, with fewer selecting the highest or lowest categories. The boxplot confirms this central tendency, though a cluster of low responses (value 1) is flagged as outliers. At the country level, Spain and Portugal exhibit the highest average levels of concern, while Estonia, Czechia, and Ireland report the lowest. Overall, there is a general pattern of moderate to high climate concern across countries, with some regional variation.

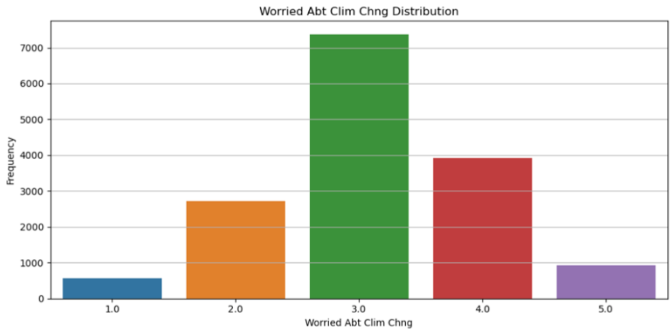


*Figure 18: Worried About Climate Change Distribution*

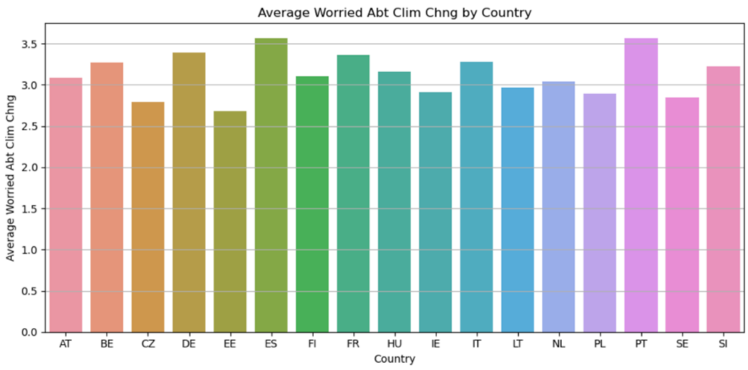


*Figure 19: Worried About Climate Change Mean by Country*

▪ **How Often Do Things to Save Energy:**

The variable how_often_save_energy measures the frequency with which individuals report engaging in energy-saving behaviors, on a 6-point ordinal scale. The distribution is centered around values 3 to 5, suggesting that most respondents engage in such behaviors with moderate to high frequency. The boxplot confirms this concentration and indicates no statistical outliers. At the country level, Spain, Finland, and France show the highest average levels of self-reported energy-saving behavior, while Czechia and Poland are among the lowest. These patterns highlight notable, though not extreme, cross-national differences in the adoption of everyday pro-environmental practices.

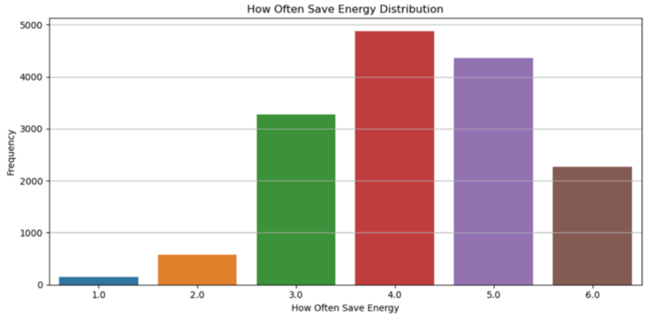


*Figure 20: How Often Save Energy Distribution*

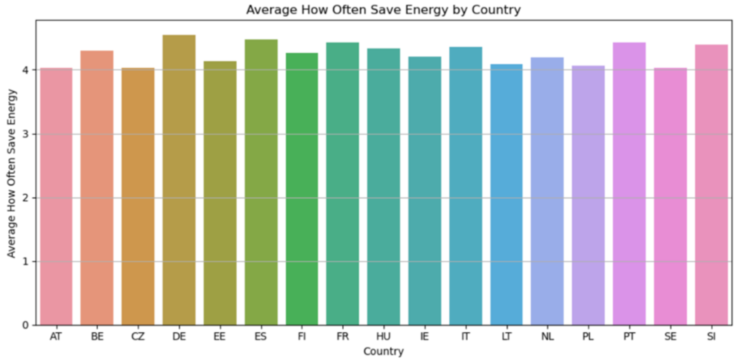


*Figure 21: How Often Save Energy Mean by Country*

- **Confidence in Using Less Energy:**

The variable confident_less_energy reflects individuals' confidence in their ability to reduce personal energy consumption, measured on a scale from 0 to 10. The distribution is skewed toward higher values, indicating generally high self-efficacy among respondents, with a peak around 7 and 8. The value 0 is treated as an outlier, suggesting that very few individuals feel completely unable to make a difference. The boxplot supports this interpretation, showing a dense upper range and mild asymmetry. Country-level averages show that Sweden, France, and Finland score the highest, while Czechia, Estonia, and Portugal display comparatively lower levels of self-reported confidence. These differences point to varying perceptions of personal agency in environmental behavior across Europe.

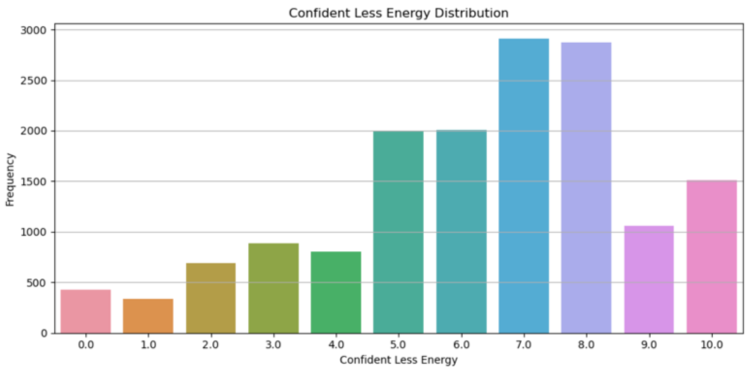


*Figure 22: Confident Less Energy Distribution*

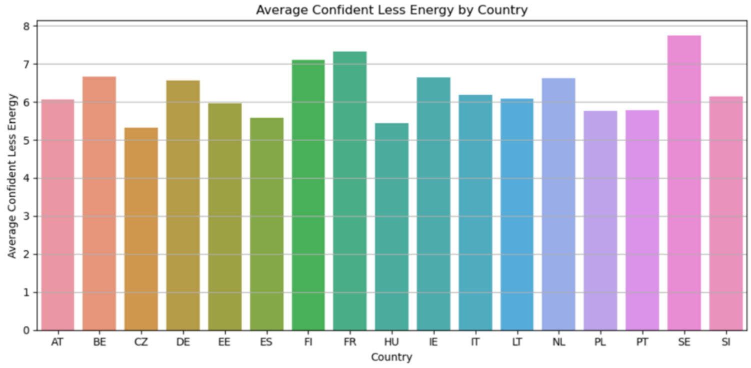


*Figure 23: Confident Less Energy Mean by Country*

- **Likely to Reduce Selfuse of Energy:**

The variable likely_to_reduce_selfuse measures the self-reported likelihood that individuals will reduce their own energy consumption, on a scale from 0 to 10. The distribution is centered around values 4 to 6, with a gradual decline toward both extremes, indicating a general openness to behavior change but with varied intensity. The boxplot confirms this pattern and reveals no outliers. Country-level averages show that Austria, Lithuania, and Italy report the highest willingness to reduce personal energy use, while Belgium, Czechia, and Slovenia score the lowest. These results suggest moderate but uneven readiness across countries to adopt more sustainable individual practices.

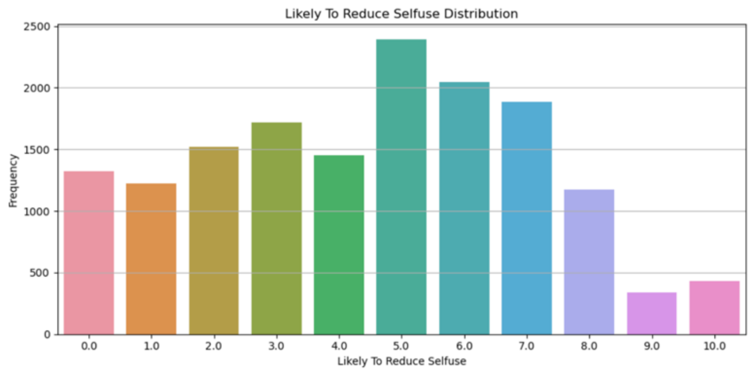


*Figure 24: Likely Reduce Selfuse Distribution*

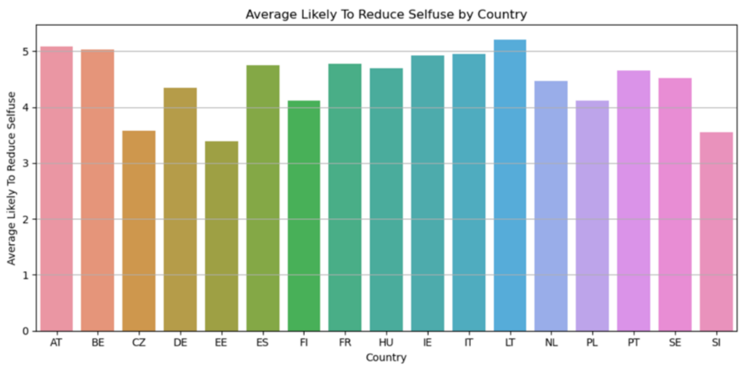


*Figure 25: Likely Reduce Selfuse Mean by Country*

- **Buy Efficient Technology for Home Appliance:**

The variable buy_efficient_tech captures individuals' willingness or likelihood to purchase environmentally efficient technologies, measured on a scale from 0 to 10. The distribution is strongly skewed to the right, with a clear peak at the maximum value of 10, indicating widespread positive attitudes. Lower values, especially 0, are treated as outliers and represent a small minority of respondents. The boxplot confirms this, showing a high median and compressed interquartile range in the upper part of the scale. At the country level, Germany and Portugal show the highest average scores, while Sweden reports the lowest, though all countries maintain relatively high averages, reflecting strong support for sustainable consumption across the sample.

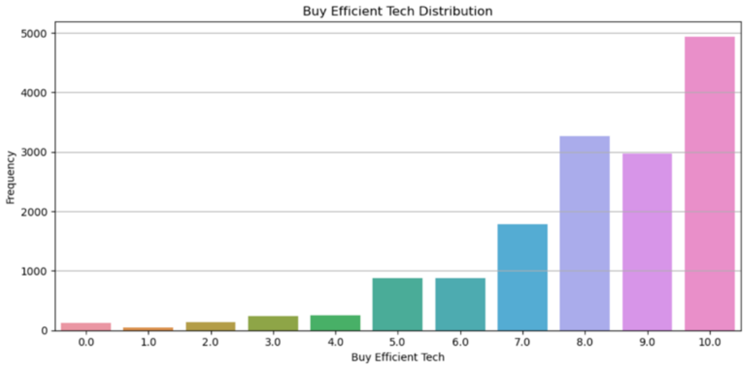


*Figure 26: Buy Efficient Tech Distribution*

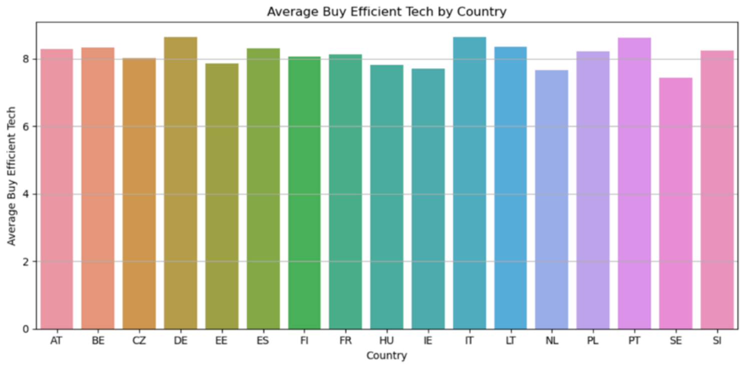


*Figure 27: Buy Efficient Tech Mean by Country*

# 4. Methodology

To begin the analysis, it is essential to clearly define the type of study being conducted. In this case, the objective is to estimate the causal effect of individuals' environmental consciousness on their pro-environmental behavior, using microdata from our dataset. The first step involves specifying how environmental consciousness is conceptualized and measured. This requires selecting appropriate variables and justifying their inclusion in the construction of an index or indicator that captures this latent trait. The same applies to the outcome of interest: pro-environmental behavior must be clearly operationalized through a set of observable actions or attitudes, aggregated into a meaningful metric. Secondly, the empirical strategy must be defined. This includes choosing the appropriate econometric model to estimate the causal relationship, as well as the estimator itself, which must be suited to the data structure and the potential presence of endogeneity.

## 4.1 Estimation of Environmental Consciousness Index

In order to obtain a synthetic and continuous measure of individual environmental consciousness, a dimensionality reduction technique is applied to a selected group of survey items reflecting attitudes, beliefs, and perceptions related to the environment. Specifically, Principal Component Analysis (PCA) is employed to extract the underlying latent structure from a set of observed variables associated with environmental awareness. The process begins by identifying a subset of variables that capture different dimensions of environmental concern. These include, for example, beliefs about the existence and causes of climate change, perceived severity of environmental problems, the extent to which individuals feel personally concerned, and other attitudinal indicators. These variables are collected into a predefined list based on theoretical relevance and their internal coherence. Prior to conducting PCA, the dataset is restricted to observations for which all selected variables are non-missing. This ensures that the principal components are computed from a complete and consistent subset of the sample. The variables are then standardized using z-scores, as PCA is sensitive to the scale of measurement and requires all inputs to be on a comparable metric. Once standardized, PCA is performed on the matrix of environmental awareness variables. The analysis extracts a set of uncorrelated principal components, each representing a linear combination of the original variables. The first principal component is retained and interpreted as a synthetic index of environmental consciousness, as it accounts for the largest proportion of the total variance in the data. This component is assumed to capture the dominant latent dimension underlying the observed responses and is therefore used as a proxy for the individual's overall level of environmental awareness. The resulting score from the first principal component is assigned to each individual and added to the dataset as a new continuous variable. This index is then used as the main explanatory variable in the subsequent empirical analysis.

### 4.1.1 PCA and the application on Environmental Consciousness

Principal Component Analysis (PCA) is a statistical technique widely used for dimensionality reduction in datasets containing multiple correlated variables. The method transforms the original variables into a new set of uncorrelated components, known as principal components, which are ordered according to the amount of variance they capture in the data. By retaining only the first few components, it is possible to summarize the main patterns of variation while minimizing information loss. Each principal component represents a linear combination of the original variables, and the first component is constructed in such a way that it captures the largest possible share of the total variance (Ringnér, 2008). In the context of social science or survey data, PCA can be applied to compress multidimensional attitudinal indicators into a single continuous score, which serves as a synthetic measure of a latent construct. This approach is particularly useful when there is no single variable that can fully represent a concept of interest, such as environmental consciousness. Because the resulting components are uncorrelated, PCA helps mitigate multicollinearity and provides a more parsimonious input for further econometric modelling. As highlighted by Ringnér (2008), PCA is not only a tool for data simplification, but also a method that reveals the dominant structure underlying the observed variables. The variables used to construct the environmental consciousness index are: is climate changing, human cause climate change, responsible to reduce, and Worried about climate change. As shown in Figure 55, the correlation matrix reveals a substantial degree of association among these variables, suggesting that they capture a common underlying dimension of environmental awareness.

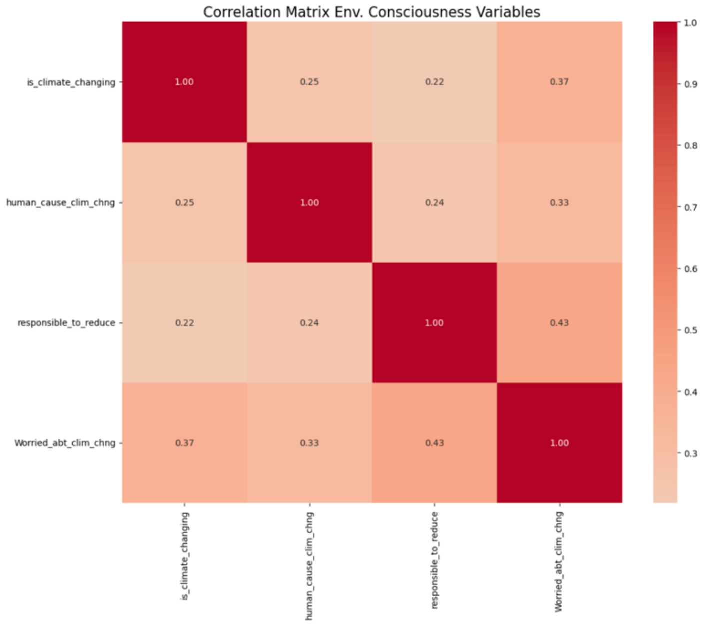


*Figure 28: Correlation Matrix of Environmental Variables*

Figure 29 presents the scree plot from the principal component analysis, illustrating the proportion of variance explained by each component. The first principal component alone accounts for approximately 48% of the total variance, indicating that it captures the dominant structure in the data and is suitable to serve as a synthetic index of environmental consciousness.

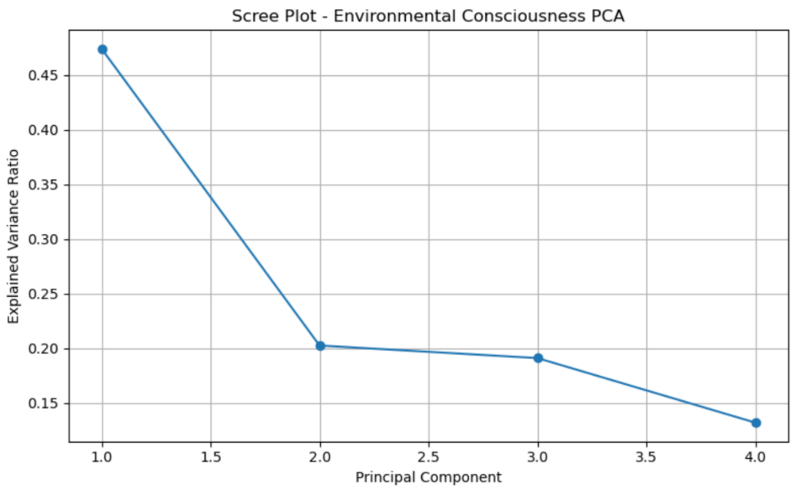


*Figure 29: Principal Components and Variance Explained*

Figure 30 displays the distribution of the environmental consciousness index, derived from the first principal component (PC1) of a set of standardized variables related to environmental attitudes. The distribution appears approximately symmetric and bell-shaped, centered around zero as expected from the standardization procedure. Most observations fall within a range of −3 to +3, indicating moderate variability in levels of environmental consciousness across individuals in the sample. This confirms the suitability of the index as a continuous measure for use in subsequent analysis. The PC1 represents already the environmental index, there is no need for further transformations.

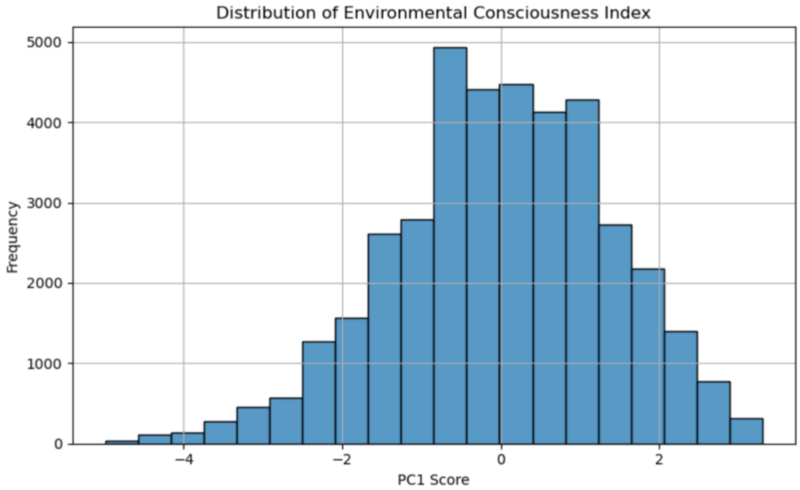


*Figure 30: Distribution of PC1 Score Among Sample*

Table 4 reports the loadings of the environmental variables on the first principal component (PC1), which forms the basis of the environmental consciousness index. The variable "Worried About Climate Change" contributes most strongly to the index, followed by the sense of personal responsibility to reduce climate change, belief in the existence of climate change, and belief in its human origin. The relatively balanced loadings across these variables suggest that the index captures a broad and coherent dimension of environmental awareness, integrating both cognitive beliefs and emotional concern.

| **VARIABLE** | **PC1 Loading** |
|---|---|
| Worried About Climate Change | 0.577 |
| Responsible for Reducing Climate Change | 0.504 |
| Is Climate Changing? | 0.456 |
| Human Cause Climate Change | 0.453 |

*Table 4: Loadings of PC1 for Environ. Con. Index*

Figure 31 shows the average environmental consciousness index by country, based on the first principal component derived from attitudinal variables. The results reveal clear cross-country differences: Spain, France, and Portugal exhibit the highest average levels of environmental consciousness, while countries such as the Czech Republic, Estonia, and Lithuania display the lowest scores. The variation in average index values suggests that attitudes toward environmental issues are not evenly distributed across Europe and may be influenced by national contexts, cultural factors, or policy environments. When looking at the data from a broader geographical perspective, a clear gap emerges between the major cardinal regions of

Europe. Respondents from Southern and Northern Europe exhibit the highest levels of environmental consciousness, while those from Eastern Europe consistently report the lowest scores, highlighting a significant regional divide.

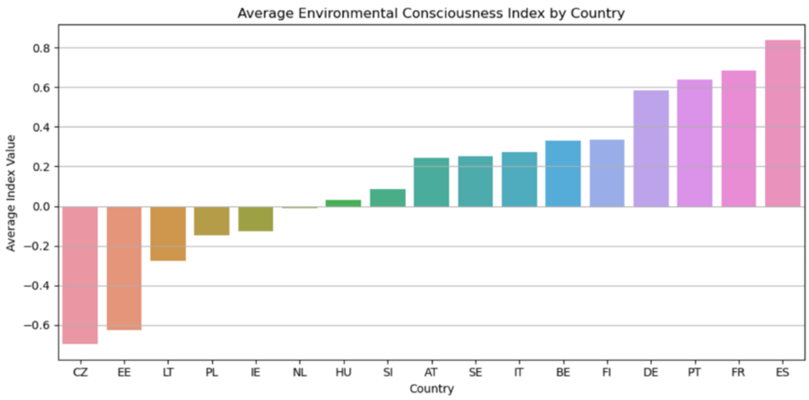


*Figure 31: Environmental Consciousness Mean by Country*

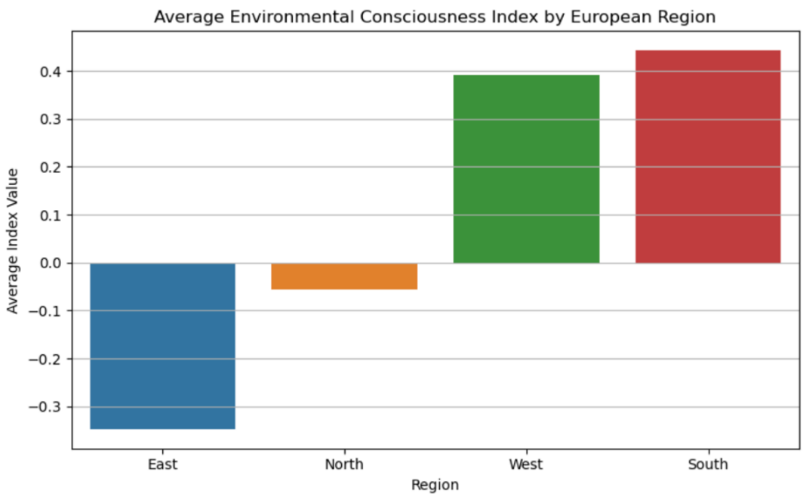


*Figure 32:Environmental Consciousness Mean by EU Zone*

### 4.1.2 Pro-Environmental Behavior

Unlike the environmental consciousness index, no dimensionality reduction was applied to construct a single index for pro-environmental behavior. Instead, to enable a deeper and more detailed analysis, three distinct variables were identified as outcome variables (Y) and used individually to evaluate the impact of environmental consciousness. Those variables are the remaining environmental variables seen before: How Often Do Things to Save Energy, Confidence in Using Less Energy, Likely to Reduce Selfuse of Energy and Buy Efficient Technology for Home Appliance. This approach makes it possible to explore whether environmental consciousness influences different types of behavior in the same way or if its effect varies depending on the nature of the action, whether it involves intention, perceived ability, or actual purchase decisions. The separate use of these outcome variables also allows for a more precise identification of where pro-environmental awareness translates into concrete behavioral change, and where it does not, thereby providing a richer understanding of the awareness action gap. Moreover, an inspection of the correlations among these variables reveals that they are not strongly correlated. As a result, synthesizing them into a single index through PCA could produce an index that captures little meaningful variance and fails to adequately represent the underlying construct.

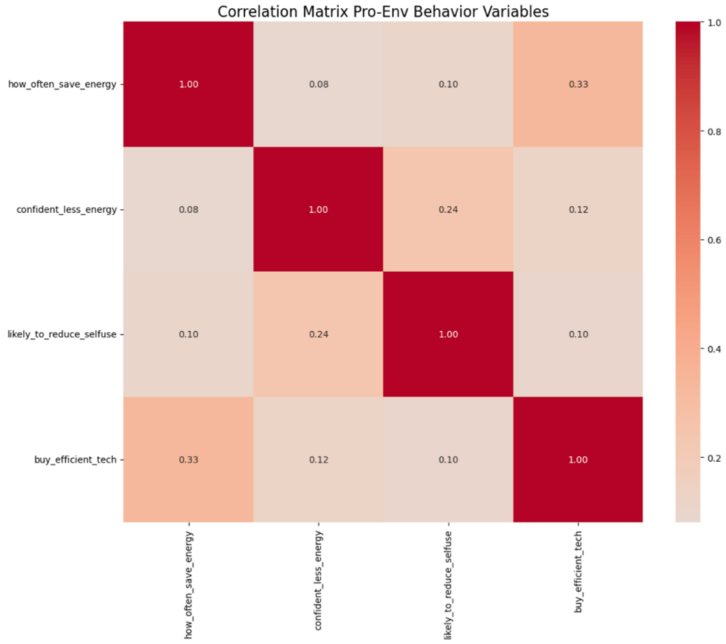


*Figure 33: Correlation Matrix of Pro-Env. Behavior Variables*

## 4.2 The Model

After considering various estimation strategies, the Two-Stage Least Squares (2SLS) method was ultimately selected as the preferred approach. In the presence of potential endogeneity between environmental consciousness and pro-environmental behavior, the Two-Stage Least Squares (2SLS) estimator is adopted to ensure consistency of the estimated causal effect. As highlighted by Maydeu-Olivares et al. (2019), 2SLS provides more accurate and reliable estimates than OLS in cases where the predictor and the error term are correlated, such as when important explanatory variables are omitted or when measurement error is present. While OLS remains more efficient under strict exogeneity, it yields biased estimates under endogeneity. In contrast, 2SLS sacrifices some efficiency but gains robustness, especially in moderate to large samples and when instruments are sufficiently strong. Moreover, 2SLS does not rely on distributional assumptions and offers a closed-form solution, making it computationally stable and particularly advantageous when using observational data.

### 4.2.1 Two Stage Least Square (2SLS)

Two-Stage Least Squares (2SLS) is an instrumental variable (IV) estimation technique used to obtain consistent estimates of causal effects when the explanatory variable of interest is endogenous, that is, when it is correlated with the error term in the structural equation. This correlation may arise due to omitted variables, measurement error, or simultaneity. The 2SLS procedure overcomes this problem by using one or more external instruments that are correlated with the endogenous regressor but uncorrelated with the error term. The method is implemented in two successive stages:

- First Stage:

The endogenous regressor X is regressed on the instrument(s) Z and any included exogenous control variables:

$$X_i = \pi_0 + \pi_1 Z_i + \pi_2 W_i + v_i$$

*Equation 1: First Stage of 2SLS*

where W represents the exogenous covariates. This stage isolates the variation in X that is explained by the instruments. The fitted values X^ from this regression are, by construction, uncorrelated with the structural error term.

- Second Stage:

The dependent variable Y is then regressed on the predicted values X^ from the first stage and the control variables W:

$$Y_i = \beta_0 + \beta_1 \hat{X}_i + \beta_2 W_i + \varepsilon_i$$

*Equation 2: Second Stage of 2SLS*

The coefficient β1 represents the causal effect of X on Y, purged of endogeneity.
This procedure guarantees consistency under two main conditions:

1. Instrument relevance: the instruments Z must be significantly correlated with the endogenous regressor X (typically checked via the first-stage F-statistic).

2. Instrument exogeneity: the instruments must be uncorrelated with the structural error term ε.

As noted by Maydeu-Olivares et al. (2019), 2SLS offers several practical advantages. It does not require distributional assumptions such as normality, provides a closed-form solution, and is more stable than maximum likelihood approaches in small samples. While less efficient than

OLS under strict exogeneity, 2SLS remains consistent even when endogeneity is present, which makes it a robust choice for estimating causal effects in observational data.

In this analysis, the environmental consciousness variable may be influenced by external factors that are not explicitly included in the model, such as unobserved individual traits, social norms, or contextual dynamics. As a result, the variable could be endogenous, meaning it might be correlated with the error term of the behavioral equation. This would violate the classical assumptions of exogeneity and lead to biased and inconsistent estimates if standard OLS methods were applied. The key requirement is that the instrument must be strongly correlated with the endogenous regressor, while remaining orthogonal to the structural error term. This ensures that the instrument influences the outcome only through its effect on environmental consciousness. While the methodological advantages of IV estimation are clear, the main challenge lies in identifying a variable that fulfils both the relevance and exogeneity conditions. The next section discusses the proposed instrument, its theoretical justification, and the empirical strategies employed to test its validity.

# 5. The Instrument

The reliability of a Two-Stage Least Squares (2SLS) estimation hinges critically on the validity of the instrumental variable employed. As outlined by Bastardoz et al. (2023), the choice of instrument must satisfy three essential conditions. First, the instrument must demonstrate strong relevance, it must be significantly correlated with the endogenous regressor. This is typically assessed through the first-stage F-statistic, with values above 10 considered indicative of sufficient instrument strength. Second, the instrument must meet the “as-if randomization” condition, meaning it should be uncorrelated with any unobserved confounders that affect the outcome variable. Although this assumption is not directly testable, it requires a theoretically grounded justification and an understanding of the context in which the instrument varies. Third, the exclusion restriction must hold: the instrument should influence the dependent variable only through its effect on the endogenous regressor, and not via any other causal pathway. Failure to satisfy any of these criteria can lead to biased and inconsistent estimates, undermining the inferential credibility of the model. Therefore, careful theoretical reasoning, supported by institutional knowledge and empirical diagnostics, is required when selecting a candidate instrument. The following section introduces the proposed instrument used in this study, details its theoretical foundation, and describes the empirical strategy employed to assess its validity.

In this study, the radioactive fallout resulting from the Chernobyl nuclear disaster has been identified as a suitable instrument for environmental consciousness. Specifically, the analysis exploits regional variation in long-term gamma radiation exposure due to the dispersion of the radioactive cloud that spread across Europe in the days following the explosion at the Chernobyl nuclear power plant in April 1986. This event created quasi-random differences in contamination levels across regions, largely depending on meteorological factors such as wind direction and rainfall, rather than social, economic, or political characteristics of the areas affected. This spatial variation in exposure fulfills the three fundamental conditions for a valid instrument. First, relevance: the historical presence of environmental contamination (especially one as symbolically powerful as nuclear radiation) can plausibly influence individuals’ environmental consciousness. People living in areas affected by fallout may have developed greater environmental awareness as a result of local media attention, public health discourse, or intergenerational transmission of concern, thereby satisfying the relevance condition. Second, the as-if random assignment condition is supported by the nature of the Chernobyl plume's trajectory, which was not correlated with local preferences, behaviors, or environmental attitudes. Finally, the exclusion restriction is justified by the fact that long-term background radiation levels are unlikely to affect current pro-environmental behavior directly, except through their influence on environmental consciousness. Regions did not experience immediate health or economic impacts equivalent to a conventional disaster; rather, the fallout had a silent, symbolic presence, making it ideal for isolating changes in environmental perception rather than direct behavior.

Moreover, the use of historical radiation as an instrument is aligned with existing research using environmental shocks as quasi-natural experiments to study attitudinal change. Its plausibly exogenous variation, coupled with its potential long-term salience in affected communities, makes the Chernobyl fallout a theoretically and empirically sound instrument for identifying the causal effect of environmental consciousness on pro-environmental behavior.

## 5.1 Building the Instrument

In order to estimate the long-term impact of radioactive exposure across European regions, this study relies on data from the Atlas of Caesium Deposition on Europe after the Chernobyl Accident, one of the most authoritative and comprehensive sources available on the topic. The atlas, produced by the European Commission in collaboration with the French Institute for Radiological Protection and Nuclear Safety (IRSN) and other scientific institutions, provides standardized radiation data compiled from more than thirty countries. Importantly, it includes not one but two separate maps: one showing caesium-137 deposition caused by the Chernobyl accident in 1986, and a second showing pre-existing radiation levels resulting from global nuclear weapons testing during the 1950s and 60s. These two maps, though often used interchangeably in visual communication, reflect distinct sources and timelines of radioactive contamination. The first map represents an acute and localized event (Chernobyl) while the second captures background radiation accumulated over decades of atmospheric nuclear tests. Recognizing this distinction was essential in the construction of the radiation instruments used in this analysis. To operationalize these data, two separate instruments were developed. The first, based solely on the Chernobyl fallout map, was used to construct a simple yet robust indicator of high exposure. However, due to the relatively low spatial resolution of the map and the limited variation across many NUTS-2 regions, especially outside the most affected areas, the raw radiation values were insufficiently informative for continuous analysis. For this reason, the values were transformed into a binary variable: regions falling above the 75th percentile of contamination were coded as 1, indicating high radiation exposure, while all others were assigned 0. This dummy variable (referred to as high_radiation) captures the most severely affected regions in a straightforward and interpretable way and was primarily used in robustness checks and threshold-based regressions. The second instrument was designed to provide a more detailed and continuous measure of exposure, by integrating information from both maps and leaving the level of radiations as a number for each region. To do so, the original images were first georeferenced and converted into raster format. Then, using official Eurostat shapefiles for all NUTS-2 regions, the two layers were aligned to ensure accurate spatial correspondence. For each region, the centroid was identified, and the corresponding RGB pixel value from the composite raster image was extracted. This composite was built by combining color-coded information from both the Chernobyl-specific fallout map and the background radiation map, thereby producing a total radiation surface that reflects both acute and chronic exposure. RGB values were then matched to numeric radiation levels using a custom mapping based on the original legends. In ambiguous cases (often caused by color overlaps or resolution artifacts) manual corrections were applied. The result is a dataset that contains two radiation-related variables: a binary indicator for identifying the most contaminated regions, and a continuous measure that allows for more sensitive analysis of geographic variation. Using both instruments provides a dual advantage: the dummy ensures robustness and interpretability, while the continuous variable offers granularity and statistical power. This layered approach reflects both the complexity of the original data and the analytical needs of causal identification.

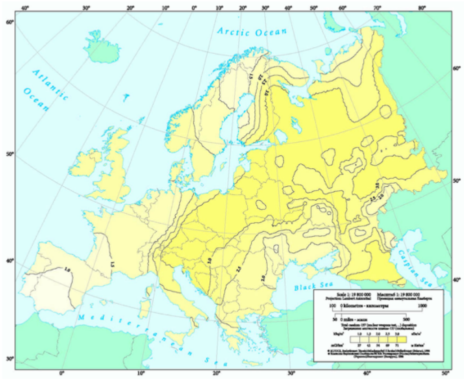

*Figure 34: Radiation Fallout in May 1986 After nuclear Testing*

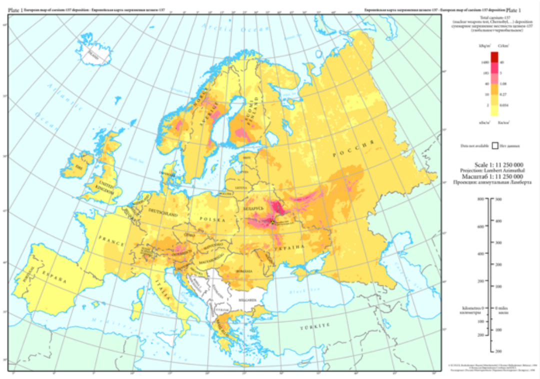

*Figure 35: Radiation Fallout in May1986 After Chernobyl Disaster*

*Figure 36: Figure 34 Rasterized*

*Figure 37: Overlay of Nuts2 Borders and Fig. 36*

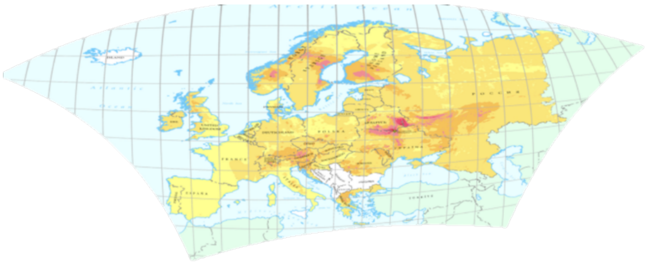

*Figure 38: Figure 35 Rasterized*

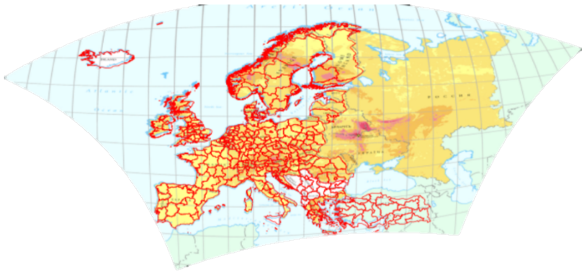

*Figure 39: Overlay of Nuts 2 Borders and Fig. 38*

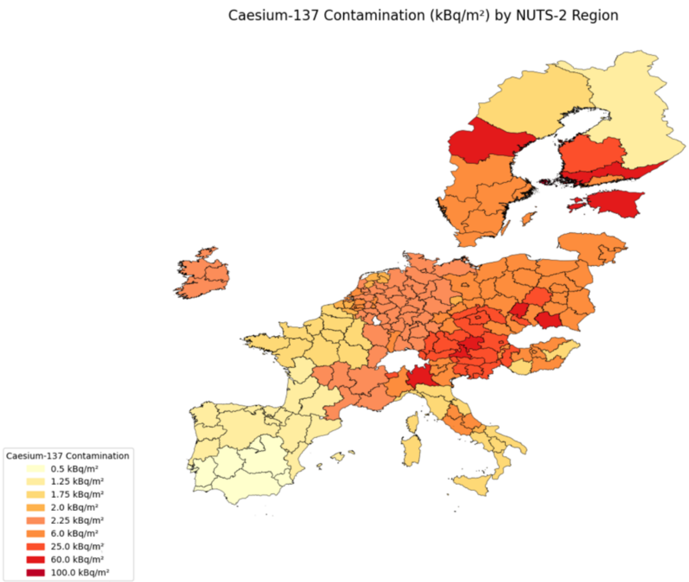


*Figure 40: Radiation Level per NUTS2, After Chernobyl Data*

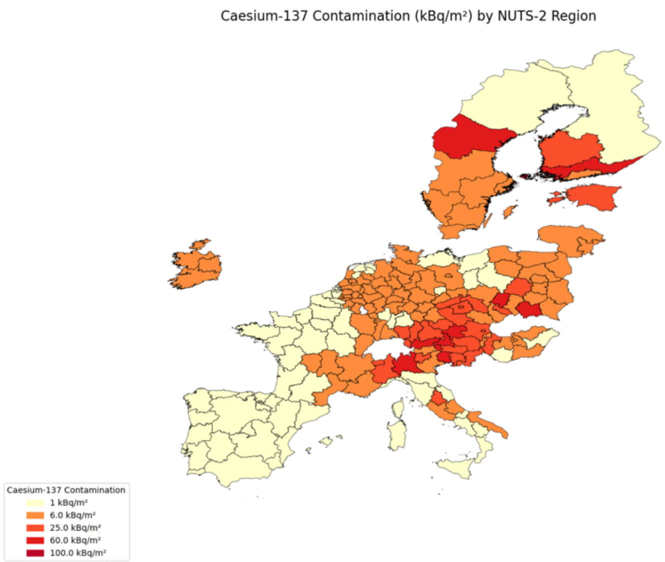


*Figure 41: Radiation Level per NUTS2, Combined Data*

## 5.2 Potential Violations of the Exclusion Restriction

While the instrument based on radioactive fallout from the Chernobyl disaster is grounded in strong theoretical exogeneity, it is important to acknowledge and discuss potential violations of the exclusion restriction. Specifically, the concern lies in the possibility that the level of radiation in a region may influence pro-environmental behavior through channels other than environmental consciousness, thereby violating the core identifying assumption of instrumental variable estimation. Two plausible pathways merit particular attention. First, the long-term socioeconomic consequences of radioactive exposure may affect behavioral outcomes independently of environmental awareness. Regions with higher contamination levels may have experienced selective out-migration, reduced investment, lower employment opportunities, or broader institutional decline. These structural conditions could shape individual behavior by reducing the capacity, motivation, or perceived efficacy of environmental engagement, regardless of personal awareness. In such cases, the instrument would be indirectly correlated with the outcome variable via unobserved regional or community-level characteristics. Second, radiation exposure may have lasting effects on health, either through actual medical consequences or perceived health risks. Individuals with chronic health concerns or those living in regions with heightened health anxiety may adopt energy-saving behaviors as a form of self-protection or resource conservation, without such actions necessarily reflecting a conscious environmental concern. If this is the case, the observed behavioral change may stem from health-related motivations rather than environmental awareness, again undermining the exclusivity of the instrument's pathway. To address these potential concerns, the empirical strategy includes a comprehensive set of controls for socioeconomic status, health, institutional trust, and regional characteristics. Additionally, robustness and stability checks (such as stepwise regressions) are employed to assess the stability of the estimated coefficients and provide further credibility to the exclusion restriction assumption, is all analysed and results are reported in section 6.3: Validation of the Instruments.

## 5.3 The Role of Controls

To ensure the validity of the instrumental variable strategy adopted in this study, particular attention is paid to the selection and inclusion of control variables. While the exclusion restriction assumes that the instrument, regional radioactive fallout from the Chernobyl disaster, affects pro-environmental behavior exclusively through environmental consciousness, this condition could be violated if the instrument is correlated with other regional or individual characteristics that independently influence behavior. To address this concern, a rich set of controls is incorporated into all empirical specifications, with the goal of partialling out potentially confounding variation. The control variables span several dimensions. Socio-demographic traits such as age, gender (male), income level, employment status (has_job, unemployment_rate), and minority status are included to capture heterogeneity in both awareness and behavioral outcomes. Health-related and attitudinal measures such as health status, happiness, and attachment to country are introduced to account for psychological and motivational differences that could affect both environmental perception and behavior. Educational background is controlled for through both individual and parental educational attainment, using categorical indicators like education_level, edu_low, edu_high, as well as edu_father_low/high and edu_mother_low/high, which reflect intergenerational educational effects. In addition, several regional-level variables, such as GDP per capita, life expectancy, and forest cover (forest_rate), are included to absorb local economic development, quality of life, and environmental exposure, all of which may correlate with both the instrument and behavioral outcomes. Indicators of crime exposure (victim_crime) and family context (with_children) further enrich the specification. Finally, a set of geographical dummies (is_north, is_south, is_west) controls for broad regional fixed effects, capturing structural and cultural differences across macro-areas of Europe. Overall, the inclusion of this comprehensive set of covariates strengthens the credibility of the exclusion restriction by reducing the risk that the instrument is indirectly capturing omitted determinants of pro-environmental behavior. Although the coefficient estimates of these controls are not reported for brevity, their role in securing identification remains central to the empirical design.

# 6. Results

This section reports the main findings of the analysis. The causal effect of environmental consciousness on a range of pro-environmental behaviors is estimated using a two-stage least squares (2SLS) approach, with regional radiation exposure employed as an instrumental variable. This allows for the identification of whether higher levels of environmental awareness are associated with more consistent pro-environmental actions at the individual level. For comparison, estimates from a standard ordinary least squares (OLS) model are also presented, in order to evaluate the presence and extent of any significant differences between the two approaches. Regressions with all controls are shown in the Appendix.

## 6.1 Results with High Radiation Instrument

The results from the analysis using the high-radiation instrument are presented first. All outcomes are summarized in a table consisting of four columns: Second Stage, First Stage, Reduced Form, and OLS, allowing for a clear and direct comparison across estimation strategies. The main dependent variable examined is the frequency with which individuals report engaging in actions to save energy (how_often_save_energy), which serves as the central behavioral indicator in this analysis. The model is then explored in greater depth by examining specific subgroups within the population to assess potential heterogeneity in the effects. In the following sections, the analysis is extended to include the other two pro-environmental behavior variables, allowing for a more comprehensive evaluation of the relationship between environmental consciousness and individual action. Building on this structure, Table 5 presents the detailed estimation results for the first behavioral outcome, how_often_save_energy, using high-radiation exposure as an instrumental variable for environmental consciousness. The table includes estimates from the second-stage 2SLS regression, the first-stage regression, the reduced-form equation, and the baseline OLS model.

In the first stage, the instrument (high_radiation) is strongly and negatively associated with the environmental consciousness index (−0.370, $p < 0.01$), indicating that individuals living in highly contaminated areas tend to report lower levels of environmental awareness. This result confirms that the instrument satisfies the relevance condition required for valid IV estimation.

The second-stage 2SLS estimate shows that environmental consciousness has a significant and positive effect on pro-environmental behavior (0.272, $p < 0.01$), and notably, the magnitude of this effect exceeds that of the OLS estimate (0.183, $p < 0.01$), suggesting that the OLS model may underestimate the true causal impact due to endogeneity bias. Among the control variables, several covariates are significantly associated with the outcome. Happiness (0.0164, $p < 0.05$),

health (0.0436, $p < 0.01$), and attachment to one's country (0.0181, $p < 0.01$) all positively and significantly predict the likelihood of engaging in energy-saving actions. Age also has a robust positive effect (0.0123, $p < 0.01$), suggesting that older individuals are more likely to adopt such behaviors. Conversely, being male is associated with a significantly lower probability of engaging in energy-saving practices (−0.0714, $p < 0.01$), holding other factors constant. This gender difference is consistent across specifications and indicates a structural behavioral gap.
Regarding socioeconomic status, income level shows a negative and highly significant association with pro-environmental behavior (−0.0311, $p < 0.01$), possibly reflecting a tendency for higher-income individuals to rely more on energy-intensive lifestyles. Similarly, individuals with missing income data also display significantly lower levels of behavioral engagement (−0.197, $p < 0.01$). Educational background exhibits mixed effects: those with low education (−0.0757, $p < 0.05$) are significantly less likely to act pro-environmentally, while individuals whose mothers had a low level of education exhibit higher engagement (0.0613, $p < 0.05$), an effect that may reflect intergenerational or cultural dynamics. Regionally, residents in northern Europe are significantly more likely to engage in energy-saving behavior (0.119, $p < 0.01$), reinforcing known geographic patterns in environmental concern across the continent.
Overall, the consistency of the coefficients across models, the strength of the instrument, and the magnitude of the second-stage effect all point to a clear conclusion: environmental consciousness exerts a meaningful and statistically robust influence on individual-level pro-environmental behavior. Notably, while the OLS estimate is also positive and highly significant, its smaller magnitude compared to the 2SLS result suggests that OLS may be attenuated by endogeneity bias (likely due to omitted variables or reverse causality) thereby reinforcing the necessity of using an instrumental variable approach to uncover the true causal relationship.

| | (1)<br>2SLS (DV: Save Energy) | (2)<br>1st Stage (DV: Env. Consciousness) | (3)<br>Reduced Form (DV: Save Energy) | (4)<br>OLS (DV: Save Energy) |
|---|---|---|---|---|
| env_con_index | $0.272^{***}$ | | | $0.184^{***}$ |
| | (0.0673) | | | (0.00824) |
| high_radiation | | $-0.370^{***}$ | $-0.100^{***}$ | |
| | | (0.0305) | (0.0254) | |
| Constant | $3.851^{***}$ | $-1.237^{***}$ | $3.516^{***}$ | $3.706^{***}$ |
| | (0.292) | (0.304) | (0.182) | (0.177) |
| R-squared | 0.0768 | 0.145 | 0.0450 | 0.0859 |
| Observations | 11492 | 11492 | 11492 | 11492 |

Standard errors in parentheses
$^{*}$ $p < 0.10$, $^{**}$ $p < 0.05$, $^{***}$ $p < 0.01$

*Table 5: Comparison Between all Models of Full Regression for High Radiation Instrument*

### 6.1.1 Subgroup Analysis for High Radiation Instrument

Next a subgroup analysis to see if there are any differences between genders in environmental consciousness and behavioral relations, the two genders are split and a full analysis is done on each one of them. The results of the gender-based subgroup analysis reveal meaningful differences in the behavioral response to environmental consciousness. Among men (Table 6), the second-stage 2SLS estimate for env_con_index is 0.349 ($p < 0.01$), indicating a strong and highly significant causal effect on energy-saving behavior. For women (Table 7), the corresponding coefficient is 0.201 ($p < 0.05$), still statistically significant but notably lower in magnitude. These findings suggest that environmental awareness, once internalized, translates into behavioral engagement more strongly among men than women in this sample. However, this does not imply that men are systematically more conscious or engaged. In fact, in the full-sample model, the dummy variable male is negatively and significantly associated with both env_con_index and how_often_save_energy, indicating that, on average, men tend to report lower levels of both environmental awareness and action when controlling for observables. The apparent contrast may reflect gender-specific patterns in responsiveness: women may exhibit higher baseline awareness and more consistent behavioral alignment, while men, though less aware on average, may show a steeper behavioral adjustment once they reach a comparable level of consciousness. The subgroup regressions also point to differential influences of key covariates. For instance, health is a significant positive predictor of behavior only among men (coef = 0.0864, $p < 0.01$), while happiness is significant only among women (coef = 0.0275, $p < 0.01$), highlighting distinct motivational structures across genders. Educational background also plays a stronger role among men: both edu_low and edu_high are significant and substantial, whereas they are not for women. Taken together, these results underscore the importance of disaggregated analysis: while environmental consciousness positively influences pro-environmental behavior in both groups, the magnitude, conditioning factors, and correlates of this effect differ by gender. This highlights the value of tailoring environmental interventions to account for such heterogeneity in responsiveness.

| | (1)<br>2SLS (DV: Save Energy) | (2)<br>1st Stage (DV: Env. Consciousness) | (3)<br>Reduced Form (DV: Save Energy) | (4)<br>OLS (DV: Save Energy) |
|---|---|---|---|---|
| env_con_index | 0.349*** | | | 0.176*** |
| | (0.104) | | | (0.0117) |
| high_radiation | | −0.354*** | −0.123*** | |
| | | (0.0454) | (0.0369) | |
| Constant | 3.584*** | −1.125*** | 3.191*** | 3.356*** |
| | (0.305) | (0.315) | (0.286) | (0.275) |
| R-squared | 0.0440 | 0.154 | 0.0445 | 0.0846 |
| Observations | 5531 | 5531 | 5531 | 5531 |

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

*Table 6: Regression for Men Subset for High Radiation Instrument*

| | (1) 2SLS (DV: Save Energy) | (2) 1st Stage (DV: Env. Consciousness) | (3) Reduced Form (DV: Save Energy) | (4) OLS (DV: Save Energy) |
|---|---|---|---|---|
| env_con_index | 0.201** | | | 0.194*** |
| | (0.0882) | | | (0.0117) |
| high_radiation | | −0.386*** | −0.0775** | |
| | | (0.0408) | (0.0351) | |
| Constant | 3.909*** | −1.327*** | 3.643*** | 3.899*** |
| | (0.268) | (0.268) | (0.243) | (0.235) |
| R-squared | 0.0860 | 0.133 | 0.0395 | 0.0861 |
| Observations | 6001 | 6001 | 6001 | 6001 |

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

*Table 7: Regression for Women Subset for High Radiation Instrument*

An additional analysis was conducted across different age subgroups. Specifically, the sample was divided into three distinct age brackets (25–34, 35–49, and 50–65), and the corresponding results are summarized in Table 8. For presentation purposes, only the second-stage 2SLS estimates are reported and compared across groups. The effect of environmental consciousness (env_con_index) remains positive and statistically significant in all three subgroups, but the magnitude varies. It is strongest among individuals aged 35–49 (0.310, $p < 0.01$), followed by the 25–34 group (0.267, $p < 0.05$), and lowest for those aged 50–65 (0.224, $p < 0.10$). These differences suggest that individuals in mid-adulthood may be more behaviorally responsive to environmental awareness, possibly due to greater autonomy in consumption decisions or heightened environmental concern during their formative years. Across the covariates, several patterns emerge. The coefficient for attached_to_country increases with age and is most influential in the 50–65 bracket (0.0343, $p < 0.01$), indicating that place attachment becomes a stronger behavioral motivator later in life. Income level is negatively associated with behavior in all groups, with the largest effect in the 35–49 group (−0.0449, $p < 0.01$). In terms of regional variables, living in the North or South of Europe significantly predicts greater behavioral engagement only among older individuals, while is_west shows a negative association in the youngest group (−0.242, $p < 0.05$). Educational attainment also varies: edu_high is positively associated with behavior in both the youngest and oldest brackets, while edu_low is significantly negative only for the middle group. Together, these results suggest that while environmental consciousness is a significant driver of pro-environmental behavior across all age groups, the pathways and intensity of this effect differ notably by age. These findings underscore the importance of incorporating life-cycle dynamics into policy design and highlight the potential for age-targeted communication strategies to enhance behavioral effectiveness.

| | (1) Age 25–34 | (2) Age 35–49 | (3) Age 50–65 |
|---|---|---|---|
| env_con_index | 0.267** | 0.310*** | 0.224* |
| | (0.111) | (0.104) | (0.131) |
| Constant | 3.395*** | 4.646*** | 4.644*** |
| | (0.352) | (0.326) | (0.387) |
| R-squared | 0.0916 | 0.0754 | 0.0590 |
| Observations | 2484 | 4202 | 4846 |

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

*Table 8: Regression for Agegroups for High Radiation Instrument*

To further explore heterogeneity in behavioral responsiveness, additional subgroup analyses were conducted by educational attainment and family structure, with results summarized in Table 9. The effect of environmental consciousness (env_con_index) remains positive and statistically significant in all groups except for the low education subgroup. Among individuals with high education, the coefficient is 0.168 ($p < 0.05$), while for respondents with children it is 0.393 ($p < 0.01$), and 0.206 ($p < 0.05$) for those without children. These findings suggest that environmental consciousness translates more effectively into behavior among more educated individuals and those with children. The lack of significance among the low-education group, despite the large coefficient, may be due to greater noise or lower behavioral consistency within that group. In terms of covariates, there are notable differences across subgroups. Happiness is positively and significantly associated with behavior only in the high-education and no-children groups, while health is significant across high-education and with-children individuals. Age has a consistently strong and positive effect in all subgroups except the low-education group, where it is insignificant. Income level is a negative predictor across the board, particularly strong and highly significant for the high-education and family groups. The role of parental background in education is particularly strong among individuals without children, where both edu_mother_low and edu_mother_high show significant positive associations with behavior (0.154 and 0.139, respectively, both at $p < 0.01$), suggesting possible long-term cultural transmission of pro-environmental values.

Overall, the analysis reinforces the idea that while environmental consciousness is generally a robust predictor of pro-environmental behavior, its effectiveness depends on socioeconomic and family context. Higher education and parenthood appear to amplify this effect, likely through greater information processing, engagement with policy narratives, or social norms embedded in family life. These findings underline the importance of tailoring environmental outreach strategies to demographic and educational profiles.

| | (1) Low Educ. | (2) High Educ. | (3) With Children | (4) Without Children |
|---|---|---|---|---|
| env_con_index | 1.786 | 0.168** | 0.393*** | 0.206** |
| | (1.902) | (0.0844) | (0.119) | (0.0848) |
| Constant | 8.471* | 2.993*** | 4.029*** | 3.755*** |
| | (5.102) | (0.309) | (0.326) | (0.261) |
| R-squared | 0.0950 | 0.0227 | 0.0949 | 0.0949 |
| Observations | 2127 | 4663 | 5278 | 6254 |

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

*Table 9: Regression for Education Groups and Individuals with Children for High Radiation Instrument*

### 6.1.2 Analysis of Additional Behavioral Indicators for High Radiation Instrument

After presenting the main results on the behavioral outcome how_often_save_energy, the analysis proceeds by examining additional indicators of pro-environmental behavior to assess the consistency and robustness of the estimated relationship. Specifically, three secondary outcome variables are considered: confident_less_energy, which captures the respondent's confidence in their ability to reduce energy consumption; likely_to_reduce_selfuse, which measures the stated likelihood of cutting down on personal energy use; and buy_efficient_tech, which reflects the reported intention to purchase energy-efficient household appliances. Each of these variables targets a different dimension of behavioral engagement, perceived control, willingness to act, and future-oriented commitment, thus providing a broader perspective on how environmental consciousness influences individual-level action. The same 2SLS estimation strategy is applied to ensure comparability across models.

Table 10 reports the results for the secondary outcome variable confident_less_energy, which captures individuals' perceived ability to reduce energy consumption. The second-stage 2SLS estimate for env_con_index is highly significant and remarkably large (1.667, $p < 0.01$), far exceeding the OLS estimate (0.296, $p < 0.01$). This large discrepancy suggests a substantial attenuation bias in the OLS model, likely driven by endogeneity of the awareness variable. These findings indicate that individuals with stronger environmental consciousness feel considerably more confident in their capacity to reduce energy usage. Among the covariates, health (0.211, $p < 0.01$), income level (0.0736, $p < 0.01$), and missing_income (0.523, $p < 0.01$) emerge as strong positive predictors, while age, victim_crime, and edu_low show significant negative associations. Regional effects remain consistent with previous models, with individuals in northern and western Europe displaying stronger behavioral indicators. Table 11 presents the estimates for buy_efficient_tech, a variable that reflects respondents' reported willingness to invest in energy-efficient appliances. The second-stage IV estimate for env_con_index is negative and not statistically significant (−0.111), contrasting with the strong and positive OLS coefficient (0.265, $p < 0.01$). This divergence may indicate that environmental awareness alone does not directly drive purchasing intentions once endogeneity is accounted for, or it may reflect limited instrument strength in this specific behavioral channel. Nevertheless, the reduced-form and first-stage regressions remain significant and directionally aligned. Several covariates such as happy, age, attached_to_country, with_children, victim_crime, edu_low, edu_high, and region dummies show strong significance, suggesting that attitudinal and structural factors play a larger role than pure awareness in shaping purchase intentions. In Table 12, the outcome variable is likely_to_reduce_selfuse, which captures respondents' declared willingness to cut down on their own energy consumption. The second-stage 2SLS estimate for env_con_index is positive and statistically significant (0.465, $p < 0.01$), confirming that environmental consciousness increases individuals' self-reported willingness to take direct action. Notably, the OLS estimate is even larger (0.575, $p < 0.01$), though the gap between the two suggests that endogeneity is present but less pronounced than in Table 10. The first stage and reduced-form results are also strong and consistent. Among the controls, happy, age, gdp_per_capita, and missing_income are robustly significant.

Taken together, the results provide strong and consistent evidence that environmental consciousness exerts a significant and robust influence on a range of pro-environmental behaviors. The primary outcome, self-reported frequency of energy-saving actions, is positively and causally driven by environmental awareness, as shown by the 2SLS estimates and reinforced by multiple subgroup analyses. Notably, the effect is stronger among men and middle-aged individuals, as well as among those with higher education or children, pointing to important sociodemographic heterogeneity in behavioral responsiveness.To address the potential endogeneity of environmental consciousness, the analysis employs an instrumental variable approach using regional variation in radioactive fallout from the Chernobyl disaster as a source of exogenous exposure. The high_radiation instrument, satisfies both the relevance and exogeneity conditions, providing a credible source of variation to isolate the causal effect. The strength and consistency of the first-stage results further support the validity of this strategy. The secondary behavioral outcomes, confidence in one's ability to save energy, willingness to reduce personal energy use, and intention to buy efficient technology, largely confirm the main findings. While the effect on stated purchasing intentions appears less robust, possibly due to economic constraints or delayed behavioral adjustment, the broader pattern remains clear: individuals with stronger environmental consciousness are more engaged and more willing to take action across multiple behavioral domains.

| | (1) 2SLS (DV: Confidence) | (2) 1st Stage (DV: Env. Consciousness) | (3) Reduced Form (DV: Confidence) | (4) OLS (DV: Confidence) |
|---|---|---|---|---|
| env_con_index | 0.465*** | | | 0.575*** |
| | (0.155) | | | (0.0186) |
| high_radiation | | −0.368*** | −0.171*** | |
| | | (0.0306) | (0.0599) | |
| Constant | 3.334*** | −1.281*** | 2.738*** | 3.495*** |
| | (0.440) | (0.202) | (0.391) | (0.376) |
| R-squared | 0.119 | 0.141 | 0.0425 | 0.122 |
| Observations | 11492 | 11492 | 11492 | 11492 |

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

*Table 10: Full Regression on Confidence to Reduce Selfuse for High Radiation Instrument*

| | (1) 2SLS (DV: Willingness) | (2) 1st Stage (DV: Env. Consciousness) | (3) Reduced Form (DV: Willingness) | (4) OLS (DV: Willingness) |
|---|---|---|---|---|
| env_con_index | −0.111 | | | 0.265*** |
| | (0.124) | | | (0.0142) |
| high_radiation | | −0.368*** | 0.0407 | |
| | | (0.0306) | (0.0448) | |
| Constant | 5.233*** | −1.281*** | 5.375*** | 5.785*** |
| | (0.355) | (0.202) | (0.299) | (0.294) |
| R-squared | 0.0433 | 0.141 | 0.0739 | 0.104 |
| Observations | 11492 | 11492 | 11492 | 11492 |

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

*Table 11: Full Regression on Willingness to Buy Efficient Tech for High Radiation Instrument*

| | (1) 2SLS (DV: Selfuse) | (2) 1st Stage (DV: Env. Consciousness) | (3) Reduced Form (DV: Selfuse) | (4) OLS (DV: Selfuse) |
|---|---|---|---|---|
| env_con_index | 1.667*** | | | 0.296*** |
| | (0.187) | | | (0.0186) |
| high_radiation | | −0.368*** | −0.613*** | |
| | | (0.0306) | (0.0542) | |
| Constant | 5.354*** | −1.281*** | 3.219*** | 3.342*** |
| | (0.531) | (0.202) | (0.363) | (0.358) |
| R-squared | 0.141 | 0.104 | 0.118 | 0.104 |
| Observations | 11492 | 11492 | 11492 | 11492 |

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

*Table 12: Full Regression on Willingness to Reduce Selfuse of Energy for High Radiation Instrument*

## 6.2 Results with Mixed Radiation Instrument

This section presents all results obtained using the continuous radiation instrument. As previously described, this variable captures the cumulative exposure to radioactive fallout before (nuclear weapons testing) and immediately following the Chernobyl disaster. This version retains the full variation of the radiation index, particularly at the lower and intermediate levels of exposure. The instrument displays sufficient dispersion across regions, allowing it to be used in its continuous form without a transformation into a radiation dummy. This approach enables a more granular analysis of how different intensities of environmental shock relate to environmental consciousness and behavioral responses. The full model using the continuous radiation instrument (Table 13) provides additional support for the causal role of environmental consciousness in shaping pro-environmental behavior. The second-stage 2SLS estimate for the environmental consciousness index is positive and highly significant (0.284, $p < 0.01$), closely aligned with previous results from the high-radiation binary specification. This consistency reinforces the robustness of the causal relationship. The use of the continuous measure of radiation exposure allows for greater precision, capturing finer gradients in exogenous environmental shock, and is supported by a strong and significant first-stage relationship (coefficient on radiation = −0.00813, $p < 0.01$), satisfying the instrument relevance condition. The OLS estimate of the effect (0.183, $p < 0.01$) remains substantially smaller than the IV estimate, again suggesting the presence of downward bias due to endogeneity, likely driven by unobserved confounders such as environmental values or omitted social factors. The reduced-form and first-stage models are statistically robust and consistent in sign and magnitude with theoretical expectations. Several covariates behave as in prior specifications. Happiness, health, and attachment to country are all positively and significantly associated with energy-saving behavior. Income level remains negatively correlated with behavior, possibly reflecting consumption-driven lifestyles. Educational attainment also continues to matter low education is significantly negative while high education is positive, both at $p < 0.01$, further reinforcing the importance of socio-cognitive factors. Interestingly, the regional variable for northern Europe is significant in the second stage (0.122, $p < 0.05$), while the indicators for southern and western Europe are only significant in the first stage, suggesting that regional exposure may shape awareness but not necessarily behavior directly when controls are included. Overall, the full model with the continuous radiation instrument confirms the key insights from previous analyses: environmental consciousness exerts a substantial and statistically robust causal effect on individual pro-environmental behavior. The instrument performs well in terms of identification strength and adds further credibility to the empirical strategy.

| | (1)<br>2SLS (DV: Save Energy) | (2)<br>1st Stage (DV: Env. Consciousness) | (3)<br>Reduced Form (DV: Save Energy) | (4)<br>OLS (DV: Save Energy) |
|---|---|---|---|---|
| env_con_index | 0.284*** | | | 0.183*** |
| | (0.0742) | | | (0.00825) |
| radiation | | −0.00813*** | −0.00231*** | |
| | | (0.000741) | (0.000619) | |
| Constant | 3.841*** | −1.160*** | 3.512*** | 3.694*** |
| | (0.208) | (0.205) | (0.185) | (0.177) |
| R-squared | 0.0737 | 0.143 | 0.0441 | 0.0869 |
| Observations | 11532 | 11532 | 11532 | 11532 |

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

*Table 13: Full Model Comparison for Mixed Radiation Instrument*

### 6.2.1 Subgroup Analysis for Mixed Radiation Instrument

The gender-disaggregated analysis using the continuous radiation instrument reveals both consistent and nuanced patterns in the estimated causal effect of environmental consciousness. For men (Table 14), the second-stage coefficient for the environmental consciousness index is 0.269 and statistically significant at the 5% level, while for women (Table 15), the coefficient is slightly higher at 0.286 and significant at the 1% level. This suggests that, although men and women may differ in baseline levels of awareness or engagement, the behavioral responsiveness to increased environmental consciousness is comparably strong across genders. Importantly, both estimates are in line with the full-sample result (0.284), reinforcing the robustness of the core relationship across subsamples. The first-stage regressions in both groups confirm the strength of the instrument, with the radiation variable being highly significant and negatively associated with the environmental consciousness index (−0.00825 for men and −0.00811 for women, both $p < 0.01$), satisfying the relevance condition. The OLS estimates for both groups (0.176 for men, 0.194 for women) remain lower than the IV estimates, suggesting that endogeneity affects both subsamples and that the 2SLS approach corrects for this bias effectively. While the magnitude of the causal effect is slightly higher among women, the broader structure of the models remains consistent, with variables such as age, education, and attachment to country contributing similarly in both cases. This strengthens the conclusion that environmental consciousness is a key driver of energy-saving behavior for both men and women, with IV estimates providing a more accurate measure of this effect. These subgroup results reinforce the general finding that awareness is a central and causally valid predictor of individual pro-environmental action, across demographic lines.

| | (1)<br>2SLS (DV: Save Energy) | (2)<br>1st Stage (DV: Env. Consciousness) | (3)<br>Reduced Form (DV: Save Energy) | (4)<br>OLS (DV: Save Energy) |
|---|---|---|---|---|
| env_con_index | $0.269^{**}$<br>(0.108) | | | $0.176^{***}$<br>(0.0117) |
| radiation | | $-0.00825^{***}$<br>(0.00111) | $-0.00222^{**}$<br>(0.000915) | |
| Constant | $3.479^{***}$<br>(0.308) | $-0.990^{***}$<br>(0.316) | $3.212^{***}$<br>(0.289) | $3.356^{***}$<br>(0.275) |
| R-squared | 0.0727 | 0.153 | 0.0437 | 0.0846 |
| Observations | 5531 | 5531 | 5531 | 5531 |

Standard errors in parentheses
$^{*}$ $p < 0.10$, $^{**}$ $p < 0.05$, $^{***}$ $p < 0.01$

*Table 14: Males Regression for Mixed Radiation Instrument*

| | (1)<br>2SLS (DV: Save Energy) | (2)<br>1st Stage (DV: Env. Consciousness) | (3)<br>Reduced Form (DV: Save Energy) | (4)<br>OLS (DV: Save Energy) |
|---|---|---|---|---|
| env_con_index | 0.286*** | | | 0.194*** |
| | (0.101) | | | (0.0117) |
| radiation | | −0.00811*** | −0.00232*** | |
| | | (0.000989) | (0.000840) | |
| Constant | 4.038*** | −1.227*** | 3.687*** | 3.899*** |
| | (0.280) | (0.269) | (0.244) | (0.235) |
| R-squared | 0.0754 | 0.130 | 0.0399 | 0.0861 |
| Observations | 6001 | 6001 | 6001 | 6001 |

Standard errors in parentheses
$^{*}$ $p < 0.10$, $^{**}$ $p < 0.05$, $^{***}$ $p < 0.01$

*Table 15: Females Regression for Mixed Radiation Instrument*

The age-based analysis using the continuous radiation instrument (Table 16) provides a refined understanding of how the causal impact of environmental consciousness varies across different stages of adulthood. The effect is strongest and statistically significant among individuals aged 35–49 (coefficient = 0.350, p < 0.01), confirming this group as the most behaviorally responsive segment. The effect remains positive but becomes weaker and statistically non-significant in the 25–34 (0.204) and 50–65 (0.235) groups, suggesting a nonlinear relationship between age and environmental responsiveness. In terms of covariates, attachment to country increases in magnitude with age, peaking in the 50–65 group, while income level is consistently negative across all cohorts, most strongly in midlife. Regional patterns are also age-sensitive: living in Northern or Southern Europe significantly predicts higher behavior only in the oldest group, while a negative association with Western Europe is found exclusively among the youngest adults. Educational variables exhibit contrasting effects: high education is positively significant for both younger and older individuals, whereas low education is particularly detrimental in the 35–49 group. Overall, these results highlight that while environmental consciousness is a relevant predictor across the board, the mechanisms through which it operates are clearly age-dependent, reflecting shifting priorities, capacities, and social roles.

Complementary subgroup analysis across educational level and parental status (Table 17) further refines the understanding of heterogeneity in behavioral response. Among individuals with children, the effect of environmental consciousness is strong and significant (coefficient = 0.498, p < 0.01), while for those without children, the effect is weaker but still significant (0.156, p < 0.10). This suggests that having dependents may amplify the motivation to act on environmental concerns. In terms of education, the estimate is large but imprecise for low-educated individuals (1.742, not significant), whereas it is much smaller but precisely estimated for the high-educated group (0.084), though not statistically significant. These contrasting patterns point to the dual role of awareness and capability: while low-educated individuals may show high responsiveness, this effect is heterogeneous and less consistent; among high-educated individuals, behavioral action may be constrained more by saturation or structural factors than by awareness itself. Together, these results emphasize that the relationship between environmental consciousness and behavior is not uniform, and policy interventions should consider sociodemographic profiles to increase effectiveness.

| | (1) Age 25–34 | (2) Age 35–49 | (3) Age 50–65 |
|---|---|---|---|
| env_con_index | 0.204 | 0.350*** | 0.235 |
| | (0.140) | (0.102) | (0.157) |
| Constant | 3.367*** | 4.709*** | 4.667*** |
| | (0.358) | (0.326) | (0.432) |
| R-squared | 0.0968 | 0.0617 | 0.0571 |
| Observations | 2484 | 4202 | 4846 |

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

*Table 16: Agegroup Regression for Mixed Radiation Instrument*

| | (1) Low Educ. | (2) High Educ. | (3) With Children | (4) Without Children |
|---|---|---|---|---|
| env_con_index | 1.742 | 0.0839 | 0.498*** | 0.156* |
| | (1.787) | (0.0924) | (0.140) | (0.0894) |
| Constant | 8.355* | 2.888*** | 4.177*** | 3.686*** |
| | (4.771) | (0.319) | (0.349) | (0.266) |
| R-squared | 0.0754 | 0.0795 | 0.0939 | 0.0939 |
| Observations | 2127 | 4663 | 5278 | 6254 |

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

*Table 17: Regression for Education Groups and Individuals with Children for Mixed Radiation Instrument*

### 6.2.2 Analysis of Additional Behavioral Indicators for High Radiation Instrument

After establishing the main results using the continuous radiation instrument on the primary outcome how_often_save_energy, the analysis turns to the three additional behavioral indicators to test the robustness and consistency of the estimated causal effect. These outcomes include confident_less_energy, which measures respondents' self-perceived ability to reduce energy consumption; likely_to_reduce_selfuse, capturing the stated intention to reduce one's own energy use; and buy_efficient_tech, reflecting the willingness to purchase energy-efficient household appliances. These variables tap into different psychological and behavioral mechanisms, self-efficacy, intention, and economic commitment and together provide a comprehensive picture of how environmental consciousness operates across multiple dimensions of behavior. The same 2SLS estimation strategy with the continuous radiation instrument is applied to ensure methodological consistency.

Table 18 reports the results for confident_less_energy. The second stage estimate for env_con_index is large and highly significant (1.751, $p < 0.01$), and once again far exceeds the corresponding OLS coefficient (0.296, $p < 0.01$). This pattern, consistent with attenuation bias in the OLS model, highlights the importance of correcting for endogeneity in capturing the true behavioral effect of environmental consciousness. Respondents who are more aware of environmental issues are significantly more confident in their ability to take energy-saving action. Among the controls, strong positive associations emerge for health, income, and missing income status, while negative effects are observed for age, exposure to crime, and low education.

In Table 19, the outcome buy_efficient_tech presents a markedly different pattern. The second-stage coefficient for env_con_index is negative and statistically insignificant (−0.114), despite a positive and highly significant OLS estimate (0.265, $p < 0.01$). This divergence suggests that, when accounting for endogeneity, environmental awareness may not be sufficient on its own to drive intentions related to more resource-intensive behavior such as purchasing appliances. It may reflect the role of economic constraints, long-term planning, or lack of structural opportunities to act. Nonetheless, the instrument remains valid, as shown by a strong first-stage relationship, and many covariates, such as age, attachment to country, parenthood, education, and region retain predictive power, underscoring that these factors are likely more influential in shaping such consumer decisions.

Table 20 focuses on likely_to_reduce_selfuse, a variable that captures self-reported willingness to cut down personal energy use. The second-stage estimate (0.541, $p < 0.01$) is again large and statistically robust, confirming that environmental consciousness leads to stronger behavioral intention, even after correcting for endogeneity. Interestingly, the OLS coefficient (0.575, $p < 0.01$) is close in magnitude, suggesting that endogeneity plays a less distorting role here compared to the other outcomes. The first-stage and reduced-form regressions remain statistically strong and directionally coherent. Among covariates, happiness, income level, children, education, and regional dummies all show significant associations, reinforcing the idea that both personal and contextual factors mediate how environmental awareness translates into future-oriented behavior. Taken together, the results across all three secondary outcomes reinforce the core message of the analysis. Environmental consciousness exerts a significant and positive causal influence on behavioral self-efficacy and intention, while its effect on purchasing intentions appears more attenuated possibly due to resource limitations or unobserved structural barriers. By leveraging the continuous variation in radiation fallout from Chernobyl as an exogenous source of awareness, the analysis confirms that even subtle environmental shocks can shape long-lasting patterns of behavior through increased consciousness.

| | (1) 2SLS (DV: Confidence) | (2) 1st Stage (DV: Env. Consciousness) | (3) Reduced Form (DV: Confidence) | (4) OLS (DV: Confidence) |
|---|---|---|---|---|
| env_con_index | 1.751*** | | | 0.296*** |
| | (0.212) | | | (0.0186) |
| radiation | | −0.00806*** | −0.0141*** | |
| | | (0.000744) | (0.00132) | |
| Constant | 5.476*** | −1.168*** | 3.341*** | 3.342*** |
| | (0.557) | (0.204) | (0.365) | (0.358) |
| R-squared | 0.139 | 0.139 | 0.103 | 0.118 |
| Observations | 11492 | 11492 | 11492 | 11492 |

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

*Table 18: Full Regression on Confidence to Reduce Selfuse for Mixed Radiation Instrument*

| | (1) 2SLS (DV: Willingness) | (2) 1st Stage (DV: Env. Consciousness) | (3) Reduced Form (DV: Willingness) | (4) OLS (DV: Willingness) |
|---|---|---|---|---|
| env_con_index | −0.114 | | | 0.265*** |
| | (0.141) | | | (0.0142) |
| radiation | | −0.00806*** | 0.000917 | |
| | | (0.000744) | (0.00111) | |
| Constant | 5.229*** | −1.168*** | 5.362*** | 5.785*** |
| | (0.368) | (0.204) | (0.302) | (0.294) |
| R-squared | 0.0422 | 0.139 | 0.0738 | 0.104 |
| Observations | 11492 | 11492 | 11492 | 11492 |

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

*Table 19: Full Regression on Willingness to Buy Efficient Tech for Mixed Radiation Instrument*

| | (1) 2SLS (DV: Selfuse) | (2) 1st Stage (DV: Env. Consciousness) | (3) Reduced Form (DV: Selfuse) | (4) OLS (DV: Selfuse) |
|---|---|---|---|---|
| env_con_index | 0.541*** | | | 0.575*** |
| | (0.172) | | | (0.0186) |
| radiation | | −0.00806*** | −0.00436*** | |
| | | (0.000744) | (0.00143) | |
| Constant | 3.445*** | −1.168*** | 2.813*** | 3.495*** |
| | (0.452) | (0.204) | (0.393) | (0.376) |
| R-squared | 0.122 | 0.139 | 0.0425 | 0.122 |
| Observations | 11492 | 11492 | 11492 | 11492 |

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

*Table 20: Full Regression on Willingness to Reduce Selfuse of Energy for Mixed Radiation Instrument*

## 6.3 Instrument's Negative Coefficient Analysis and Interpretation

While the empirical analysis demonstrates that the instrumental variable based on Chernobyl-related radioactive fallout meets the relevance condition, its consistently negative coefficient across first and second stage regressions may appear counterintuitive at first. One would reasonably expect that exposure to a major environmental catastrophe might increase environmental consciousness. However, several strands of literature offer compelling explanations for why the opposite effect may emerge. First, the psychological literature on natural disasters and fatalism suggefsts that individuals who experience severe and uncontrollable environmental shocks may develop learned helplessness or fatalistic reasoning. As shown by McClure (2017), direct exposure to large-scale hazards like Chernobyl can lead to the belief that environmental outcomes are beyond individual control. In this framework, the perceived effectiveness of one's actions declines, weakening the motivation to engage in pro-environmental behavior. Individuals internalize the idea that environmental degradation is inevitable, which suppresses consciousness and personal responsibility. Second, the desensitization mechanism plays a crucial role. Alhadeff (2015) explains that chronic exposure to degraded environments, whether physical, visual, or symbolic, can erode people's sensitivity to environmental decline. Over time, living in polluted or compromised areas becomes "normal," lowering baseline expectations and decreasing the urgency to act. Applied to the Chernobyl context, individuals in high-radiation regions may have developed a diminished environmental standard, reducing their likelihood to score high on environmental awareness items. A third explanatory lens comes from the Broken Windows Theory. O'Brien et al. (2019) provide meta-analytic evidence that residents of socially or environmentally deteriorated areas often adjust their behavior to the visible norms of their surroundings. When disorder becomes ubiquitous, individuals are less likely to resist it, instead adapting by mirroring low-engagement behaviors. This social adaptation dynamic may also explain why individuals in fallout-affected areas report lower environmental concern, as they align with the prevailing norms of disengagement. Importantly, this interpretation is consistent with the behavior of the first instrument used in the analysis, regional pollution exposure, which also displays a negative relationship with environmental awareness. This coherence reinforces the hypothesis that exposure to environmental degradation can, paradoxically, depress environmental consciousness rather than activate it. Whether through psychological detachment, social adaptation, or fatalistic resignation, individuals in more polluted or environmentally traumatized contexts may be less inclined to see environmental improvement as achievable or personally relevant. This theoretical interpretation does not invalidate the instrument but rather enriches the understanding of its directionality. The relevance of the instrument remains strong, but these findings invite caution when interpreting the behavioral mechanisms that connect environmental context and consciousness.

## 6.4 Validation of the Instruments

To further assess the robustness of the instrumental variable strategy and the stability of the estimated causal effect of environmental consciousness, a stepwise regression procedure was implemented. This approach, inspired by the framework proposed by Oster (Unobservable Selection and Coefficient Stability: Theory and Evidence, 2019), offers a complementary robustness check to the standard examination of partial F-statistics typically reported in instrumental variable analyses. The method involves estimating a series of second-stage 2SLS regressions in which control variables are added incrementally across specifications. The purpose is to observe how the coefficient of interest (environmental consciousness) evolves as additional sets of covariates, sociodemographic, economic, and regional are included in the model. For each specification, both the estimated coefficient and the corresponding $R^2$ are recorded. According to Oster (2019), if the coefficient remains stable across nested models and the explained variance increases with the addition of controls, this pattern provides support for the argument that selection on unobservable would have to be disproportionately large relative to selection on observables in order to invalidate the causal interpretation. This reasoning extends the logic of Altonji, Elder, and Taber (Selection on Observed and Unobserved Variables: Assessing the Effectiveness of Catholic Schools, 2005), formalizing a method to assess the likelihood that omitted variable bias drives the estimated effect. In this context, stability of the coefficient across specifications is interpreted as evidence of robustness, suggesting that the relationship between environmental consciousness and pro-environmental behavior is not unduly sensitive to model specification or omitted variable concerns. The stepwise analysis therefore complements the 2SLS strategy by providing additional reassurance regarding the credibility of the instrument and the validity of the causal conclusions. The stepwise regressions were conducted to evaluate the stability of the estimated coefficients across different model specifications. As a baseline, the stepwise procedure was first applied to the OLS model. Subsequently, the same approach was used for both the reduced form and the first-stage regressions. Variables were added in sequential blocks corresponding to the categories introduced during the exploratory data analysis. Specifically, the first step included geographical indicators (e.g., is_north, is_south), the second added regional contextual variables (e.g., gdp_per_capita, forest_rate), the third step incorporated predetermined individual characteristics (e.g., age, gender), and the final step included additional individual-level controls (e.g., with_children, health, education). This structure allows for a clear assessment of whether the coefficient of interest remains stable as more covariates are introduced.

| **Step** | **Coefficient Env_Con_Index** ($\beta$) | $\mathbf{R^2}$ |
|---|---|---|
| 1 | 0.1872 | 0.058 |
| 2 | 0.1887 | 0.063 |
| 3 | 0.1858 | 0.081 |
| 4 | 0.1821 | 0.085 |

*Table 21: Stepwise OLS Coefficients – Stability of Estimates*

| Step | Stage | Coefficient ($\beta$) | $R^2$ |
|---|---|---|---|
| 1 | First Stage | −0.4083 | 0.101 |
| | Reduced Form | −0.1368 | 0.012 |
| 2 | First Stage | −0.3842 | 0.112 |
| | Reduced Form | −0.1120 | 0.016 |
| 3 | First Stage | −0.3717 | 0.137 |
| | Reduced Form | −0.1012 | 0.037 |
| 4 | First Stage | −0.3688 | 0.145 |
| | Reduced Form | −0.1049 | 0.043 |

*Table 22: Stepwise Coefficients – First Stage and Reduced Form from High Radiation Instrument*

| Step | Stage | Coefficient ($\beta$) | $R^2$ |
|---|---|---|---|
| 1 | First Stage | −0.0103 | 0.102 |
| | Reduced Form | −0.0029 | 0.011 |
| 2 | First Stage | −0.0085 | 0.110 |
| | Reduced Form | −0.0027 | 0.016 |
| 3 | First Stage | −0.0082 | 0.135 |
| | Reduced Form | −0.0023 | 0.037 |
| 4 | First Stage | −0.0081 | 0.143 |
| | Reduced Form | −0.0024 | 0.043 |

*Table 23: Stepwise Coefficients – First Stage and Reduced Form for Mixed Instrument*

The stepwise regression results presented in Tables 21 to 23 offer a visual and empirical validation of the stability and robustness of the estimated coefficients across model specifications. In line with the theoretical framework of Oster (2019), the coefficient for environmental consciousness remains remarkably stable in the OLS stepwise estimates, varying only slightly from 0.1872 in the baseline to 0.1821 in the fully saturated model. This suggests that the inclusion of additional controls does not substantially alter the estimated relationship, alleviating concerns about omitted variable bias. A similar pattern is observed in the instrumental variable setting for both the high radiation and mixed radiation instruments. Across steps, the first-stage coefficients remain consistently strong, indicating sustained instrument relevance even as additional covariates are introduced. Meanwhile, the reduced form coefficients, although smaller in magnitude, exhibit a clear convergence and stability, particularly from step 2 onward. This pattern reinforces the notion that the causal effect is not driven by unstable relationships or spurious variation but rather reflects a robust link between the exogenous variation in environmental consciousness and pro-environmental behavior.

# 7. Conclusions and Final Considerations

This thesis set out to investigate the causal impact of environmental consciousness on pro-environmental behavior using large-scale microdata from the European Social Survey (ESS Round 8). Recognizing the potential endogeneity of environmental awareness, an instrumental variable approach was employed, exploiting exogenous variation in regional exposure to radioactive fallout from the Chernobyl disaster. The two-stage least squares (2SLS) estimation revealed a robust and statistically significant positive effect of environmental consciousness on various pro-environmental outcomes, particularly on individuals' self-reported frequency of energy-saving actions. The strength of this causal relationship remained consistent across multiple model specifications and robustness checks, including a stepwise stability analysis. Additionally, subgroup regressions uncovered meaningful heterogeneity: the effect was notably stronger among middle-aged individuals and men, suggesting differentiated behavioral responsiveness across demographic groups. When extending the analysis to alternative outcome variables, such as willingness to reduce self-consumption, confidence in energy saving, and intention to buy efficient technologies, the results largely confirmed the central role of environmental awareness, albeit with some variation in magnitude and significance. Overall, the empirical evidence points to environmental consciousness as a key driver of behavioral change and supports the relevance of awareness-based interventions in shaping sustainable individual practices. By combining methodological rigor with novel data sources, this study contributes to the existing literature in several ways. First, it provides one of the few cross-country causal estimates of the awareness–action link using a multidimensional measure of environmental consciousness constructed via principal component analysis. Second, it introduces an innovative instrumental variable regional variation in Chernobyl-related radiation exposure, to address endogeneity, offering a credible identification strategy rooted in historical and geographic determinants. Third, the analysis extends beyond a single behavioral outcome by examining multiple facets of pro-environmental engagement, capturing both intentions and actions. Finally, the integration of extensive robustness checks, including subgroup analyses and stepwise regression tests strengthens the credibility of the findings and offers useful insights for future research and policy design.

Despite the strengths of this study, several limitations must be acknowledged. First, while the radiation-based instrument offers a credible source of exogenous variation, it may still be subject to exclusion restriction concerns if long-term radiation exposure affects behavioral traits through channels other than environmental awareness, such as psychological stress or institutional trust. Although robustness checks partially mitigate these concerns, future work should explore alternative instruments or quasi-experimental designs. Second, the use of self-reported behavioral outcomes may introduce social desirability bias, potentially inflating the association between environmental awareness and pro-environmental actions. Moreover, cross-sectional data limit the possibility of examining dynamic or long-term behavioral adjustments. Another limitation lies in the geographical coverage of the analysis: although the study draws on a large dataset of European regions, it does not include all EU countries, potentially limiting the external validity and comparability of the findings across diverse institutional settings. Future research could address this gap by incorporating a broader and more representative set of countries. Additionally, longitudinal or experimental data could help track behavioral change over time and better isolate causal pathways. Finally, contextual factors such as media influence, climate shocks, and national environmental regulations remain largely unexplored in this framework, but they could substantially enrich future identification strategies and policy implications.

The findings of this thesis carry important implications for policy design and future academic inquiry. By demonstrating a robust causal link between environmental consciousness and various forms of pro-environmental behavior, the study reinforces the importance of investing in awareness-building initiatives. However, the presence of heterogeneity across age, gender, and regional subgroups suggests that one-size-fits-all strategies may be suboptimal. Policymakers should consider tailoring interventions to demographic and cultural contexts leveraging, for example, place attachment among older adults or targeting mid-life individuals who appear most responsive to awareness shifts. In parallel, educational systems and public information campaigns should be designed not only to inform, but also to empower action through credibility, accessibility, and reinforcement of social norms. From a methodological standpoint, the thesis contributes to the growing literature on causal inference in environmental behavior, showing how instrumental variable techniques can overcome key identification challenges. Further research should continue to refine the measurement of environmental consciousness and explore the interplay of structural, psychological, and institutional mediators in shaping behavior. Ultimately, fostering a more sustainable society requires a deeper understanding not only of what people know and believe, but of how that knowledge is transformed into consistent, meaningful action.

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# Appendix

| | (1) Second Stage | (2) First Stage | (3) Reduced Form | (4) OLS |
|---|---|---|---|---|
| env_con_index | 0.272*** | | | 0.183*** |
| | (0.0673) | | | (0.00825) |
| happy | 0.0164** | 0.0399*** | 0.0273*** | 0.0201*** |
| | (0.00768) | (0.00836) | (0.00736) | (0.00718) |
| health | 0.0436*** | −0.0632*** | 0.0264* | 0.0376*** |
| | (0.0152) | (0.0171) | (0.0150) | (0.0146) |
| attached_to_country | 0.0181*** | 0.0351*** | 0.0276*** | 0.0208*** |
| | (0.00586) | (0.00653) | (0.00565) | (0.00549) |
| age | 0.0123*** | −0.00221* | 0.0117*** | 0.0120*** |
| | (0.00101) | (0.00117) | (0.00101) | (0.000987) |
| income_level | −0.0311*** | 0.00785 | −0.0290*** | −0.0302*** |
| | (0.00489) | (0.00580) | (0.00493) | (0.00481) |
| has_job | −0.0125 | 0.0782 | 0.00876 | −0.00536 |
| | (0.0706) | (0.0753) | (0.0734) | (0.0708) |
| male | −0.0714*** | −0.171*** | −0.118*** | −0.0863*** |
| | (0.0234) | (0.0245) | (0.0210) | (0.0205) |
| unemployment_rate | 0.000379 | 0.0295*** | 0.00839*** | 0.00375 |
| | (0.00394) | (0.00339) | (0.00310) | (0.00302) |
| education_level | 0.000475 | −0.00155 | 0.0000525 | 0.000448 |
| | (0.00111) | (0.00133) | (0.00114) | (0.00110) |
| life_exp | −0.00215 | 0.00166 | −0.00170 | −0.00204 |
| | (0.00146) | (0.00163) | (0.00152) | (0.00147) |
| gdp_per_capita | −0.000736*** | 0.00103*** | −0.000457*** | −0.000631*** |
| | (0.000141) | (0.000137) | (0.000117) | (0.000114) |
| forest_rate | −0.00385*** | 0.00759*** | −0.00179* | −0.00344*** |
| | (0.000987) | (0.00113) | (0.000984) | (0.000941) |
| missing_income | −0.197*** | 0.0273 | −0.190*** | −0.197*** |
| | (0.0421) | (0.0497) | (0.0431) | (0.0420) |
| with_children | 0.0487** | 0.0555** | 0.0637*** | 0.0548*** |
| | (0.0218) | (0.0254) | (0.0216) | (0.0211) |
| victim_crime | 0.0571** | 0.168*** | 0.103*** | 0.0733*** |
| | (0.0291) | (0.0317) | (0.0271) | (0.0263) |
| edu_low | −0.0757** | −0.198*** | −0.130*** | −0.0916*** |
| | (0.0349) | (0.0366) | (0.0334) | (0.0328) |
| edu_high | 0.0520* | 0.212*** | 0.110*** | 0.0737*** |
| | (0.0287) | (0.0293) | (0.0244) | (0.0237) |
| edu_father_low | −0.0161 | 0.00609 | −0.0144 | −0.0115 |
| | (0.0289) | (0.0349) | (0.0296) | (0.0287) |
| edu_father_high | −0.0233 | 0.0446 | −0.0111 | −0.0174 |
| | (0.0323) | (0.0398) | (0.0327) | (0.0318) |
| edu_mother_low | 0.0613** | −0.0157 | 0.0570* | 0.0631** |
| | (0.0294) | (0.0360) | (0.0303) | (0.0294) |
| edu_mother_high | 0.0548 | 0.147*** | 0.0947*** | 0.0685** |
| | (0.0357) | (0.0419) | (0.0345) | (0.0337) |
| minority | 0.0631 | −0.0881 | 0.0392 | 0.0523 |
| | (0.0692) | (0.0797) | (0.0721) | (0.0691) |
| is_north | 0.119** | −0.193*** | 0.0669 | 0.0981* |
| | (0.0537) | (0.0615) | (0.0520) | (0.0511) |
| is_south | 0.0298 | 0.561*** | 0.182*** | 0.0776 |
| | (0.0610) | (0.0554) | (0.0494) | (0.0488) |
| is_west | −0.0263 | 0.519*** | 0.115*** | 0.0161 |
| | (0.0531) | (0.0506) | (0.0433) | (0.0424) |
| high_radiation | | −0.370*** | −0.101*** | |
| | | (0.0304) | (0.0254) | |
| Constant | 3.823*** | −1.273*** | 3.477*** | 3.694*** |
| | (0.202) | (0.204) | (0.184) | (0.177) |
| R-squared | 0.0767 | 0.145 | 0.0443 | 0.0869 |
| Observations | 11532 | 11532 | 11532 | 11532 |

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

*Table 24: Comparison Between all Models of Full Regression for High Radiation Instrument*

| | (1)<br>Second Stage | (2)<br>First Stage | (3)<br>Reduced Form | (4)<br>OLS |
|---|---|---|---|---|
| env_con_index | 0.349*** | | | 0.176*** |
| | (0.104) | | | (0.0117) |
| happy | 0.00383 | 0.0500*** | 0.0213** | 0.0126 |
| | (0.0117) | (0.0121) | (0.0105) | (0.0103) |
| health | 0.0864*** | −0.0669*** | 0.0631*** | 0.0745*** |
| | (0.0238) | (0.0259) | (0.0232) | (0.0225) |
| attached_to_country | 0.0181** | 0.0258*** | 0.0271*** | 0.0219*** |
| | (0.00804) | (0.00948) | (0.00781) | (0.00758) |
| age | 0.0128*** | −0.00133 | 0.0124*** | 0.0125*** |
| | (0.00147) | (0.00173) | (0.00147) | (0.00144) |
| income_level | −0.0357*** | 0.0183** | −0.0293*** | −0.0321*** |
| | (0.00773) | (0.00907) | (0.00746) | (0.00728) |
| has_job | −0.0347 | 0.0250 | −0.0260 | −0.0320 |
| | (0.128) | (0.138) | (0.138) | (0.131) |
| unemployment_rate | −0.00337 | 0.0286*** | 0.00661 | 0.00302 |
| | (0.00584) | (0.00501) | (0.00450) | (0.00438) |
| education_level | 0.00202 | −0.00165 | 0.00145 | 0.00196 |
| | (0.00166) | (0.00198) | (0.00169) | (0.00164) |
| life_exp | −0.00104 | −0.00300 | −0.00208 | −0.00161 |
| | (0.00222) | (0.00262) | (0.00233) | (0.00222) |
| gdp_per_capita | −0.000941*** | 0.000884*** | −0.000633*** | −0.000758*** |
| | (0.000204) | (0.000208) | (0.000171) | (0.000167) |
| forest_rate | −0.00301** | 0.00728*** | −0.000467 | −0.00224 |
| | (0.00149) | (0.00173) | (0.00146) | (0.00140) |
| missing_income | −0.222*** | 0.0852 | −0.192*** | −0.211*** |
| | (0.0646) | (0.0758) | (0.0655) | (0.0636) |
| with_children | 0.0599* | 0.0672* | 0.0834*** | 0.0743** |
| | (0.0334) | (0.0385) | (0.0322) | (0.0315) |
| victim_crime | 0.0194 | 0.192*** | 0.0863** | 0.0546 |
| | (0.0442) | (0.0494) | (0.0396) | (0.0383) |
| edu_low | −0.123** | −0.154*** | −0.177*** | −0.146*** |
| | (0.0494) | (0.0528) | (0.0479) | (0.0470) |
| edu_high | 0.0816** | 0.182*** | 0.145*** | 0.119*** |
| | (0.0414) | (0.0442) | (0.0357) | (0.0348) |
| edu_father_low | −0.00356 | 0.0387 | 0.00994 | 0.0117 |
| | (0.0430) | (0.0525) | (0.0432) | (0.0417) |
| edu_father_high | −0.0385 | 0.0515 | −0.0206 | −0.0250 |
| | (0.0482) | (0.0596) | (0.0480) | (0.0468) |
| edu_mother_low | 0.0561 | −0.0416 | 0.0416 | 0.0539 |
| | (0.0434) | (0.0544) | (0.0445) | (0.0429) |
| edu_mother_high | 0.0618 | 0.0965 | 0.0954* | 0.0801* |
| | (0.0511) | (0.0626) | (0.0499) | (0.0487) |
| minority | 0.00738 | −0.0781 | −0.0198 | −0.0132 |
| | (0.106) | (0.113) | (0.108) | (0.105) |
| is_north | 0.179** | −0.200** | 0.109 | 0.136* |
| | (0.0810) | (0.0924) | (0.0761) | (0.0750) |
| is_south | −0.0235 | 0.719*** | 0.227*** | 0.0969 |
| | (0.103) | (0.0819) | (0.0722) | (0.0714) |
| is_west | −0.0511 | 0.642*** | 0.173*** | 0.0534 |
| | (0.0893) | (0.0757) | (0.0635) | (0.0627) |
| high_radiation | | −0.354*** | −0.123*** | |
| | | (0.0454) | (0.0369) | |
| Constant | 3.584*** | −1.125*** | 3.191*** | 3.356*** |
| | (0.305) | (0.315) | (0.286) | (0.275) |
| R-squared | 0.0440 | 0.154 | 0.0445 | 0.0846 |
| Observations | 5531 | 5531 | 5531 | 5531 |

Standard errors in parentheses
$^{*}$ $p < 0.10$, $^{**}$ $p < 0.05$, $^{***}$ $p < 0.01$

*Table 25: Regression for Men Subset for High Radiation Instrument*

| | (1) Second Stage | (2) First Stage | (3) Reduced Form | (4) OLS |
|---|---|---|---|---|
| env_con_index | 0.201** | | | 0.194*** |
| | (0.0882) | | | (0.0117) |
| happy | 0.0275*** | 0.0282** | 0.0332*** | 0.0277*** |
| | (0.0103) | (0.0115) | (0.0104) | (0.0100) |
| health | 0.00740 | −0.0623*** | −0.00509 | 0.00696 |
| | (0.0197) | (0.0227) | (0.0196) | (0.0189) |
| attached_to_country | 0.0202** | 0.0431*** | 0.0288*** | 0.0204** |
| | (0.00858) | (0.00898) | (0.00821) | (0.00796) |
| age | 0.0114*** | −0.00334** | 0.0108*** | 0.0114*** |
| | (0.00141) | (0.00160) | (0.00141) | (0.00138) |
| income_level | −0.0294*** | −0.000507 | −0.0295*** | −0.0294*** |
| | (0.00643) | (0.00748) | (0.00659) | (0.00643) |
| has_job | 0.0446 | 0.0478 | 0.0542 | 0.0449 |
| | (0.0850) | (0.0911) | (0.0876) | (0.0850) |
| unemployment_rate | 0.00424 | 0.0300*** | 0.0103** | 0.00449 |
| | (0.00535) | (0.00458) | (0.00428) | (0.00418) |
| education_level | −0.00106 | −0.00143 | −0.00135 | −0.00106 |
| | (0.00149) | (0.00178) | (0.00155) | (0.00149) |
| life_exp | −0.00234 | 0.00426** | −0.00149 | −0.00232 |
| | (0.00194) | (0.00205) | (0.00198) | (0.00192) |
| gdp_per_capita | −0.000552*** | 0.00119*** | −0.000314* | −0.000543*** |
| | (0.000198) | (0.000178) | (0.000161) | (0.000156) |
| forest_rate | −0.00479*** | 0.00821*** | −0.00315** | −0.00476*** |
| | (0.00132) | (0.00149) | (0.00133) | (0.00127) |
| missing_income | −0.189*** | −0.0195 | −0.193*** | −0.189*** |
| | (0.0558) | (0.0660) | (0.0573) | (0.0559) |
| with_children | 0.0369 | 0.0400 | 0.0449 | 0.0372 |
| | (0.0291) | (0.0338) | (0.0295) | (0.0287) |
| victim_crime | 0.0861** | 0.151*** | 0.116*** | 0.0872** |
| | (0.0392) | (0.0403) | (0.0370) | (0.0360) |
| edu_low | −0.0329 | −0.246*** | −0.0823* | −0.0343 |
| | (0.0498) | (0.0507) | (0.0466) | (0.0459) |
| edu_high | 0.0412 | 0.221*** | 0.0854** | 0.0428 |
| | (0.0393) | (0.0392) | (0.0335) | (0.0326) |
| edu_father_low | −0.0308 | −0.0181 | −0.0344 | −0.0306 |
| | (0.0394) | (0.0463) | (0.0404) | (0.0394) |
| edu_father_high | −0.0172 | 0.0474 | −0.00772 | −0.0168 |
| | (0.0440) | (0.0532) | (0.0447) | (0.0436) |
| edu_mother_low | 0.0694* | 0.00557 | 0.0705* | 0.0697* |
| | (0.0404) | (0.0475) | (0.0414) | (0.0402) |
| edu_mother_high | 0.0588 | 0.185*** | 0.0959** | 0.0600 |
| | (0.0501) | (0.0563) | (0.0479) | (0.0468) |
| minority | 0.130 | −0.117 | 0.106 | 0.129 |
| | (0.0893) | (0.113) | (0.0948) | (0.0888) |
| is_north | 0.0732 | −0.188** | 0.0354 | 0.0717 |
| | (0.0725) | (0.0820) | (0.0714) | (0.0699) |
| is_south | 0.0575 | 0.420*** | 0.142** | 0.0601 |
| | (0.0753) | (0.0747) | (0.0677) | (0.0667) |
| is_west | −0.0212 | 0.413*** | 0.0617 | −0.0188 |
| | (0.0655) | (0.0674) | (0.0593) | (0.0577) |
| high_radiation | | −0.386*** | −0.0775** | |
| | | (0.0408) | (0.0351) | |
| Constant | 3.909*** | −1.327*** | 3.643*** | 3.899*** |
| | (0.268) | (0.268) | (0.243) | (0.235) |
| R-squared | 0.0860 | 0.133 | 0.0395 | 0.0861 |
| Observations | 6001 | 6001 | 6001 | 6001 |

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

*Table 26: Regression for Women Subset for High Radiation Instrument*

| | (1) Age 25–34 | (2) Age 35–49 | (3) Age 50–65 |
|---|---|---|---|
| env_con_index | 0.267** | 0.310*** | 0.224* |
| | (0.111) | (0.104) | (0.131) |
| happy | 0.0247 | 0.0113 | 0.0145 |
| | (0.0168) | (0.0129) | (0.0119) |
| health | 0.0437 | 0.0549** | 0.0246 |
| | (0.0332) | (0.0268) | (0.0223) |
| attached_to_country | 0.00287 | 0.0177* | 0.0343*** |
| | (0.0114) | (0.00911) | (0.0105) |
| income_level | −0.0231** | −0.0449*** | −0.0182** |
| | (0.0101) | (0.00840) | (0.00813) |
| has_job | 0.0396 | −0.0906 | −0.0124 |
| | (0.132) | (0.146) | (0.110) |
| male | −0.0186 | −0.0564 | −0.102** |
| | (0.0510) | (0.0364) | (0.0399) |
| unemployment_rate | 0.00392 | 0.0109** | −0.0109 |
| | (0.00777) | (0.00547) | (0.00808) |
| education_level | 0.000920 | −0.0000757 | 0.0000360 |
| | (0.00231) | (0.00184) | (0.00182) |
| life_exp | 0.00577* | −0.00344 | −0.00483** |
| | (0.00300) | (0.00219) | (0.00238) |
| gdp_per_capita | −0.000296 | −0.000791*** | −0.000883*** |
| | (0.000249) | (0.000229) | (0.000265) |
| forest_rate | −0.00464** | −0.00338** | −0.00400** |
| | (0.00208) | (0.00160) | (0.00162) |
| missing_income | −0.0976 | −0.341*** | −0.111* |
| | (0.0939) | (0.0721) | (0.0642) |
| with_children | 0.107** | 0.0374 | 0.0137 |
| | (0.0496) | (0.0410) | (0.0347) |
| victim_crime | −0.00206 | 0.103** | 0.0413 |
| | (0.0582) | (0.0478) | (0.0475) |
| edu_low | −0.0392 | −0.153** | −0.0278 |
| | (0.0907) | (0.0627) | (0.0502) |
| edu_high | 0.114* | −0.0312 | 0.0968** |
| | (0.0624) | (0.0504) | (0.0415) |
| edu_father_low | 0.0464 | −0.0249 | −0.0291 |
| | (0.0651) | (0.0480) | (0.0459) |
| edu_father_high | −0.0495 | −0.0146 | −0.00266 |
| | (0.0585) | (0.0529) | (0.0572) |
| edu_mother_low | −0.0146 | 0.0220 | 0.155*** |
| | (0.0681) | (0.0468) | (0.0472) |
| edu_mother_high | 0.0809 | 0.0240 | 0.0479 |
| | (0.0620) | (0.0553) | (0.0698) |
| minority | 0.0201 | 0.143 | 0.0274 |
| | (0.121) | (0.120) | (0.120) |
| is_north | 0.0427 | 0.0835 | 0.176* |
| | (0.103) | (0.0904) | (0.0951) |
| is_south | −0.0993 | −0.0450 | 0.177* |
| | (0.126) | (0.101) | (0.0962) |
| is_west | −0.242** | −0.0323 | 0.100 |
| | (0.104) | (0.0819) | (0.0918) |
| Constant | 3.395*** | 4.646*** | 4.644*** |
| | (0.352) | (0.326) | (0.387) |
| R-squared | 0.0916 | 0.0754 | 0.0590 |
| Observations | 2484 | 4202 | 4846 |

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

*Table 27: Regression for Agegroups for High Radiation Instrument*

| | (1)<br>Low Educ. | (2)<br>High Educ. | (3)<br>With Children | (4)<br>Without Children |
|---|---|---|---|---|
| env_con_index | 1.786 | 0.168** | 0.393*** | 0.206** |
| | (1.902) | (0.0844) | (0.119) | (0.0848) |
| happy | −0.0269 | 0.0225* | 0.00940 | 0.0202** |
| | (0.0365) | (0.0118) | (0.0127) | (0.00982) |
| health | 0.0729 | 0.0731*** | 0.0656*** | 0.0279 |
| | (0.0721) | (0.0225) | (0.0235) | (0.0203) |
| attached_to_country | −0.0427 | 0.0158* | 0.0171* | 0.0193** |
| | (0.0670) | (0.00855) | (0.00882) | (0.00797) |
| age | 0.00389 | 0.0125*** | 0.0133*** | 0.0113*** |
| | (0.0114) | (0.00160) | (0.00191) | (0.00123) |
| income_level | −0.0609 | −0.0312*** | −0.0323*** | −0.0292*** |
| | (0.0697) | (0.00704) | (0.00776) | (0.00639) |
| has_job | −0.112 | 0.127 | −0.0866 | 0.0270 |
| | (0.285) | (0.173) | (0.112) | (0.0934) |
| male | −0.158 | −0.0275 | −0.0400 | −0.0953*** |
| | (0.129) | (0.0352) | (0.0353) | (0.0324) |
| unemployment_rate | −0.0671 | 0.0140*** | −0.00402 | 0.00273 |
| | (0.0703) | (0.00536) | (0.00588) | (0.00560) |
| education_level | −0.00658 | 0.000946 | −0.000833 | 0.00134 |
| | (0.00867) | (0.00179) | (0.00172) | (0.00148) |
| life_exp | −0.0162 | 0.000638 | −0.00143 | −0.00276 |
| | (0.0157) | (0.00177) | (0.00223) | (0.00196) |
| gdp_per_capita | −0.00163 | −0.000348 | −0.00104*** | −0.000566*** |
| | (0.00109) | (0.000213) | (0.000247) | (0.000178) |
| forest_rate | −0.0148 | 0.00156 | −0.00436*** | −0.00382*** |
| | (0.0103) | (0.00153) | (0.00152) | (0.00135) |
| missing_income | −0.0720 | −0.195*** | −0.212*** | −0.181*** |
| | (0.211) | (0.0686) | (0.0694) | (0.0537) |
| with_children | −0.0583 | 0.0229 | | |
| | (0.216) | (0.0311) | | |
| victim_crime | −0.245 | 0.0557 | 0.0503 | 0.0587 |
| | (0.444) | (0.0387) | (0.0432) | (0.0407) |
| edu_father_low | −0.116 | 0.0321 | 0.0343 | −0.0489 |
| | (0.202) | (0.0430) | (0.0435) | (0.0394) |
| edu_father_high | −0.0943 | −0.0765* | 0.0300 | −0.0675 |
| | (0.440) | (0.0411) | (0.0492) | (0.0437) |
| edu_mother_low | 0.0565 | 0.0224 | −0.0622 | 0.154*** |
| | (0.303) | (0.0429) | (0.0446) | (0.0401) |
| edu_mother_high | −0.328 | 0.111** | −0.0438 | 0.139*** |
| | (0.534) | (0.0447) | (0.0533) | (0.0497) |
| minority | 0.265 | 0.0754 | 0.200* | −0.00994 |
| | (0.347) | (0.105) | (0.113) | (0.0916) |
| is_north | 1.114* | −0.136* | 0.192** | 0.0938 |
| | (0.605) | (0.0780) | (0.0947) | (0.0697) |
| is_south | −0.436 | −0.0114 | 0.0713 | 0.00430 |
| | (1.055) | (0.0923) | (0.0889) | (0.0855) |
| is_west | −0.615 | 0.0302 | 0.0352 | −0.0541 |
| | (1.185) | (0.0746) | (0.0718) | (0.0779) |
| edu_low | | | −0.0486 | −0.105** |
| | | | (0.0536) | (0.0467) |
| edu_high | | | −0.00838 | 0.0881** |
| | | | (0.0483) | (0.0369) |
| Constant | 8.471* | 2.993*** | 4.029*** | 3.755*** |
| | (5.102) | (0.309) | (0.326) | (0.261) |
| R-squared | | 0.0950 | 0.0227 | 0.0949 |
| Observations | 2127 | 4663 | 5278 | 6254 |

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

*Table 28: Regression for Education Groups and Individuals with Children for High Radiation Instrument*

| | (1) Second Stage | (2) First Stage | (3) Reduced Form | (4) OLS |
|---|---|---|---|---|
| env_con_index | 0.465*** | | | 0.575*** |
| | (0.155) | | | (0.0186) |
| happy | 0.0703*** | 0.0413*** | 0.0895*** | 0.0657*** |
| | (0.0171) | (0.00837) | (0.0164) | (0.0158) |
| health | 0.0505 | −0.0671*** | 0.0193 | 0.0584* |
| | (0.0348) | (0.0171) | (0.0345) | (0.0330) |
| attached_to_country | 0.0352*** | 0.0362*** | 0.0520*** | 0.0317*** |
| | (0.0133) | (0.00655) | (0.0127) | (0.0122) |
| age | 0.00591*** | −0.00204* | 0.00496** | 0.00617*** |
| | (0.00228) | (0.00118) | (0.00233) | (0.00224) |
| income_level | 0.00447 | 0.00311 | 0.00592 | 0.00384 |
| | (0.0112) | (0.00578) | (0.0116) | (0.0111) |
| has_job | −0.0870 | 0.0422 | −0.0674 | −0.0919 |
| | (0.151) | (0.0758) | (0.154) | (0.151) |
| unemployment_rate | −0.000522 | 0.0282*** | 0.0126* | −0.00455 |
| | (0.00882) | (0.00339) | (0.00706) | (0.00670) |
| education_level | −0.0101*** | −0.00133 | −0.0108*** | −0.0101*** |
| | (0.00246) | (0.00133) | (0.00258) | (0.00245) |
| life_exp | 0.000334 | 0.00101 | 0.000804 | 0.000272 |
| | (0.00286) | (0.00158) | (0.00298) | (0.00286) |
| gdp_per_capita | 0.000716** | 0.00103*** | 0.00120*** | 0.000585** |
| | (0.000325) | (0.000138) | (0.000282) | (0.000268) |
| forest_rate | 0.000628 | 0.00780*** | 0.00426* | 0.0000964 |
| | (0.00231) | (0.00114) | (0.00231) | (0.00217) |
| missing_income | 0.196** | −0.000869 | 0.195** | 0.198** |
| | (0.0940) | (0.0498) | (0.0985) | (0.0938) |
| with_children | 0.0676 | 0.0713*** | 0.101** | 0.0583 |
| | (0.0500) | (0.0252) | (0.0506) | (0.0484) |
| victim_crime | −0.0250 | 0.166*** | 0.0520 | −0.0448 |
| | (0.0683) | (0.0318) | (0.0648) | (0.0624) |
| edu_low | 0.0779 | −0.198*** | −0.0142 | 0.0976 |
| | (0.0751) | (0.0368) | (0.0727) | (0.0699) |
| edu_high | 0.00257 | 0.236*** | 0.112* | −0.0270 |
| | (0.0686) | (0.0292) | (0.0578) | (0.0551) |
| edu_father_low | 0.0174 | 0.00894 | 0.0216 | 0.0114 |
| | (0.0658) | (0.0350) | (0.0686) | (0.0652) |
| edu_father_high | 0.110 | 0.0416 | 0.129 | 0.103 |
| | (0.0756) | (0.0401) | (0.0791) | (0.0746) |
| edu_mother_low | 0.0789 | −0.0171 | 0.0710 | 0.0769 |
| | (0.0672) | (0.0361) | (0.0707) | (0.0670) |
| edu_mother_high | −0.185** | 0.148*** | −0.117 | −0.203** |
| | (0.0832) | (0.0422) | (0.0840) | (0.0795) |
| minority | −0.0549 | −0.0950 | −0.0991 | −0.0408 |
| | (0.150) | (0.0802) | (0.156) | (0.148) |
| is_north | −0.280** | −0.203*** | −0.375*** | −0.253** |
| | (0.120) | (0.0618) | (0.121) | (0.114) |
| is_south | 0.254* | 0.572*** | 0.520*** | 0.194* |
| | (0.140) | (0.0555) | (0.114) | (0.110) |
| is_west | 0.334*** | 0.524*** | 0.578*** | 0.281*** |
| | (0.125) | (0.0509) | (0.102) | (0.0976) |
| high_radiation | | −0.368*** | −0.171*** | |
| | | (0.0306) | (0.0599) | |
| Constant | 3.334*** | −1.281*** | 2.738*** | 3.495*** |
| | (0.440) | (0.202) | (0.391) | (0.376) |
| R-squared | 0.119 | 0.141 | 0.0425 | 0.122 |
| Observations | 11492 | 11492 | 11492 | 11492 |

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

*Table 29: Full Regression on Confidence to Reduce Selfuse for High Radiation Instrument*

| | (1) Second Stage | (2) First Stage | (3) Reduced Form | (4) OLS |
|---|---|---|---|---|
| env_con_index | $-0.111$ | | | $0.265^{***}$ |
| | (0.124) | | | (0.0142) |
| happy | $0.136^{***}$ | $0.0413^{***}$ | $0.131^{***}$ | $0.120^{***}$ |
| | (0.0145) | (0.00837) | (0.0133) | (0.0130) |
| health | 0.0107 | $-0.0671^{***}$ | 0.0181 | 0.0375 |
| | (0.0276) | (0.0171) | (0.0260) | (0.0255) |
| attached_to_country | $0.123^{***}$ | $0.0362^{***}$ | $0.119^{***}$ | $0.111^{***}$ |
| | (0.0112) | (0.00655) | (0.0104) | (0.0102) |
| age | $0.0156^{***}$ | $-0.00204^{*}$ | $0.0158^{***}$ | $0.0165^{***}$ |
| | (0.00179) | (0.00118) | (0.00175) | (0.00173) |
| income_level | 0.00846 | 0.00311 | 0.00812 | 0.00631 |
| | (0.00875) | (0.00578) | (0.00860) | (0.00847) |
| has_job | $-0.209^{*}$ | 0.0422 | $-0.214^{**}$ | $-0.226^{**}$ |
| | (0.109) | (0.0758) | (0.107) | (0.106) |
| unemployment_rate | $-0.0131^{*}$ | $0.0282^{***}$ | $-0.0162^{***}$ | $-0.0269^{***}$ |
| | (0.00676) | (0.00339) | (0.00506) | (0.00494) |
| education_level | 0.00315 | $-0.00133$ | $0.00329^{*}$ | $0.00318^{*}$ |
| | (0.00192) | (0.00133) | (0.00189) | (0.00185) |
| life_exp | 0.000204 | 0.00101 | 0.0000923 | $-0.00000756$ |
| | (0.00238) | (0.00158) | (0.00233) | (0.00227) |
| gdp_per_capita | $-0.000885^{***}$ | $0.00103^{***}$ | $-0.001000^{***}$ | $-0.00133^{***}$ |
| | (0.000250) | (0.000138) | (0.000208) | (0.000205) |
| forest_rate | $0.00337^{*}$ | $0.00780^{***}$ | 0.00251 | 0.00155 |
| | (0.00176) | (0.00114) | (0.00166) | (0.00160) |
| missing_income | 0.122 | $-0.000869$ | $0.122^{*}$ | $0.131^{*}$ |
| | (0.0750) | (0.0498) | (0.0739) | (0.0727) |
| with_children | $0.182^{***}$ | $0.0713^{***}$ | $0.174^{***}$ | $0.150^{***}$ |
| | (0.0390) | (0.0252) | (0.0370) | (0.0364) |
| victim_crime | $0.206^{***}$ | $0.166^{***}$ | $0.187^{***}$ | $0.138^{***}$ |
| | (0.0537) | (0.0318) | (0.0475) | (0.0466) |
| edu_low | $-0.370^{***}$ | $-0.198^{***}$ | $-0.348^{***}$ | $-0.303^{***}$ |
| | (0.0610) | (0.0368) | (0.0569) | (0.0561) |
| edu_high | $0.220^{***}$ | $0.236^{***}$ | $0.193^{***}$ | $0.118^{***}$ |
| | (0.0551) | (0.0292) | (0.0425) | (0.0418) |
| edu_father_low | $-0.0687$ | 0.00894 | $-0.0697$ | $-0.0893^{*}$ |
| | (0.0519) | (0.0350) | (0.0509) | (0.0496) |
| edu_father_high | $-0.0146$ | 0.0416 | $-0.0193$ | $-0.0385$ |
| | (0.0586) | (0.0401) | (0.0571) | (0.0560) |
| edu_mother_low | 0.0464 | $-0.0171$ | 0.0483 | 0.0394 |
| | (0.0526) | (0.0361) | (0.0519) | (0.0506) |
| edu_mother_high | 0.0637 | $0.148^{***}$ | 0.0474 | 0.00531 |
| | (0.0660) | (0.0422) | (0.0622) | (0.0611) |
| minority | $-0.181$ | $-0.0950$ | $-0.170$ | $-0.132$ |
| | (0.136) | (0.0802) | (0.134) | (0.132) |
| is_north | $-0.346^{***}$ | $-0.203^{***}$ | $-0.324^{***}$ | $-0.253^{***}$ |
| | (0.0958) | (0.0618) | (0.0899) | (0.0890) |
| is_south | $0.760^{***}$ | $0.572^{***}$ | $0.697^{***}$ | $0.553^{***}$ |
| | (0.107) | (0.0555) | (0.0802) | (0.0795) |
| is_west | $0.313^{***}$ | $0.524^{***}$ | $0.255^{***}$ | $0.131^{*}$ |
| | (0.0990) | (0.0509) | (0.0756) | (0.0746) |
| high_radiation | | $-0.368^{***}$ | 0.0407 | |
| | | (0.0306) | (0.0448) | |
| Constant | $5.233^{***}$ | $-1.281^{***}$ | $5.375^{***}$ | $5.785^{***}$ |
| | (0.355) | (0.202) | (0.299) | (0.294) |
| R-squared | 0.0433 | 0.141 | 0.0739 | 0.104 |
| Observations | 11492 | 11492 | 11492 | 11492 |

Standard errors in parentheses
$^{*}$ $p < 0.10$, $^{**}$ $p < 0.05$, $^{***}$ $p < 0.01$

*Table 30: Full Regression on Willingness to Buy Efficient Tech for High Radiation Instrument*

| | (1) Second Stage | (2) First Stage | (3) Reduced Form | (4) OLS |
|---|---|---|---|---|
| env_con_index | 1.667*** | | | 0.296*** |
| | (0.187) | | | (0.0186) |
| happy | 0.00297 | 0.0413*** | 0.0718*** | 0.0608*** |
| | (0.0212) | (0.00837) | (0.0163) | (0.0162) |
| health | 0.211*** | −0.0671*** | 0.0991*** | 0.113*** |
| | (0.0419) | (0.0171) | (0.0326) | (0.0323) |
| attached_to_country | 0.00562 | 0.0362*** | 0.0660*** | 0.0498*** |
| | (0.0160) | (0.00655) | (0.0123) | (0.0122) |
| age | −0.00168 | −0.00204* | −0.00508** | −0.00490** |
| | (0.00272) | (0.00118) | (0.00216) | (0.00215) |
| income_level | 0.0736*** | 0.00311 | 0.0788*** | 0.0815*** |
| | (0.0134) | (0.00578) | (0.0109) | (0.0108) |
| has_job | −0.0287 | 0.0422 | 0.0416 | 0.0330 |
| | (0.174) | (0.0758) | (0.142) | (0.141) |
| unemployment_rate | −0.0318*** | 0.0282*** | 0.0152** | 0.0185*** |
| | (0.0108) | (0.00339) | (0.00669) | (0.00658) |
| education_level | −0.000104 | −0.00133 | −0.00232 | −0.000238 |
| | (0.00302) | (0.00133) | (0.00238) | (0.00236) |
| life_exp | 0.00405 | 0.00101 | 0.00573** | 0.00482* |
| | (0.00321) | (0.00158) | (0.00258) | (0.00251) |
| gdp_per_capita | −0.000506 | 0.00103*** | 0.00122*** | 0.00113*** |
| | (0.000388) | (0.000138) | (0.000259) | (0.000257) |
| forest_rate | −0.00841*** | 0.00780*** | 0.00460** | −0.00177 |
| | (0.00275) | (0.00114) | (0.00212) | (0.00207) |
| missing_income | 0.523*** | −0.000869 | 0.522*** | 0.492*** |
| | (0.114) | (0.0498) | (0.0939) | (0.0926) |
| with_children | 0.0115 | 0.0713*** | 0.130*** | 0.128*** |
| | (0.0594) | (0.0252) | (0.0462) | (0.0458) |
| victim_crime | −0.0519 | 0.166*** | 0.224*** | 0.196*** |
| | (0.0810) | (0.0318) | (0.0587) | (0.0583) |
| edu_low | 0.0611 | −0.198*** | −0.269*** | −0.185*** |
| | (0.0936) | (0.0368) | (0.0718) | (0.0715) |
| edu_high | −0.187** | 0.236*** | 0.206*** | 0.182*** |
| | (0.0837) | (0.0292) | (0.0532) | (0.0528) |
| edu_father_low | 0.0772 | 0.00894 | 0.0921 | 0.152** |
| | (0.0795) | (0.0350) | (0.0635) | (0.0629) |
| edu_father_high | 0.0497 | 0.0416 | 0.119* | 0.137* |
| | (0.0914) | (0.0401) | (0.0715) | (0.0710) |
| edu_mother_low | −0.0758 | −0.0171 | −0.104 | −0.0502 |
| | (0.0811) | (0.0361) | (0.0646) | (0.0641) |
| edu_mother_high | −0.161 | 0.148*** | 0.0857 | 0.0523 |
| | (0.0980) | (0.0422) | (0.0748) | (0.0741) |
| minority | −0.376** | −0.0950 | −0.534*** | −0.552*** |
| | (0.187) | (0.0802) | (0.150) | (0.149) |
| is_north | 1.147*** | −0.203*** | 0.809*** | 0.807*** |
| | (0.149) | (0.0618) | (0.117) | (0.116) |
| is_south | −0.963*** | 0.572*** | −0.0101 | −0.207* |
| | (0.165) | (0.0555) | (0.110) | (0.109) |
| is_west | −0.139 | 0.524*** | 0.734*** | 0.525*** |
| | (0.147) | (0.0509) | (0.0936) | (0.0933) |
| high_radiation | | −0.368*** | −0.613*** | |
| | | (0.0306) | (0.0542) | |
| Constant | 5.354*** | −1.281*** | 3.219*** | 3.342*** |
| | (0.531) | (0.202) | (0.363) | (0.358) |
| R-squared | | 0.141 | 0.104 | 0.118 |
| Observations | 11492 | 11492 | 11492 | 11492 |

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

*Table 31: Full Regression on Willingnes to Reduce Selfuse of Energy for High Radiation Instrument*

| | (1)<br>Second Stage | (2)<br>First Stage | (3)<br>Reduced Form | (4)<br>OLS |
|---|---|---|---|---|
| env_con_index | 0.284*** | | | 0.183*** |
| | (0.0742) | | | (0.00825) |
| happy | 0.0160** | 0.0397*** | 0.0272*** | 0.0201*** |
| | (0.00783) | (0.00835) | (0.00736) | (0.00718) |
| health | 0.0444*** | −0.0668*** | 0.0255* | 0.0376*** |
| | (0.0154) | (0.0171) | (0.0150) | (0.0146) |
| attached_to_country | 0.0177*** | 0.0343*** | 0.0274*** | 0.0208*** |
| | (0.00595) | (0.00653) | (0.00565) | (0.00549) |
| age | 0.0123*** | −0.00254** | 0.0116*** | 0.0120*** |
| | (0.00101) | (0.00118) | (0.00101) | (0.000987) |
| income_level | −0.0312*** | 0.00825 | −0.0289*** | −0.0302*** |
| | (0.00491) | (0.00581) | (0.00493) | (0.00481) |
| has_job | −0.0134 | 0.0729 | 0.00724 | −0.00536 |
| | (0.0707) | (0.0753) | (0.0735) | (0.0708) |
| male | −0.0694*** | −0.171*** | −0.118*** | −0.0863*** |
| | (0.0240) | (0.0245) | (0.0210) | (0.0205) |
| unemployment_rate | −0.0000785 | 0.0275*** | 0.00772** | 0.00375 |
| | (0.00415) | (0.00344) | (0.00316) | (0.00302) |
| education_level | 0.000478 | −0.000695 | 0.000281 | 0.000448 |
| | (0.00111) | (0.00133) | (0.00114) | (0.00110) |
| life_exp | −0.00217 | 0.000558 | −0.00201 | −0.00204 |
| | (0.00146) | (0.00163) | (0.00152) | (0.00147) |
| gdp_per_capita | −0.000750*** | 0.000793*** | −0.000525*** | −0.000631*** |
| | (0.000146) | (0.000141) | (0.000121) | (0.000114) |
| forest_rate | −0.00391*** | 0.00580*** | −0.00226** | −0.00344*** |
| | (0.00100) | (0.00111) | (0.000963) | (0.000941) |
| missing_income | −0.197*** | 0.0219 | −0.191*** | −0.197*** |
| | (0.0421) | (0.0497) | (0.0431) | (0.0420) |
| with_children | 0.0478** | 0.0651** | 0.0663*** | 0.0548*** |
| | (0.0219) | (0.0254) | (0.0216) | (0.0211) |
| victim_crime | 0.0549* | 0.167*** | 0.102*** | 0.0733*** |
| | (0.0297) | (0.0317) | (0.0271) | (0.0263) |
| edu_low | −0.0735** | −0.189*** | −0.127*** | −0.0916*** |
| | (0.0356) | (0.0366) | (0.0333) | (0.0328) |
| edu_high | 0.0490* | 0.223*** | 0.112*** | 0.0737*** |
| | (0.0297) | (0.0294) | (0.0243) | (0.0237) |
| edu_father_low | −0.0167 | 0.0203 | −0.0109 | −0.0115 |
| | (0.0290) | (0.0349) | (0.0295) | (0.0287) |
| edu_father_high | −0.0240 | 0.0539 | −0.00874 | −0.0174 |
| | (0.0324) | (0.0399) | (0.0326) | (0.0318) |
| edu_mother_low | 0.0610** | −0.00782 | 0.0588* | 0.0631** |
| | (0.0295) | (0.0360) | (0.0303) | (0.0294) |
| edu_mother_high | 0.0529 | 0.147*** | 0.0946*** | 0.0685** |
| | (0.0360) | (0.0420) | (0.0345) | (0.0337) |
| minority | 0.0646 | −0.0742 | 0.0435 | 0.0523 |
| | (0.0692) | (0.0796) | (0.0721) | (0.0691) |
| is_north | 0.122** | −0.00534 | 0.121** | 0.0981* |
| | (0.0542) | (0.0646) | (0.0548) | (0.0511) |
| is_south | 0.0233 | 0.639*** | 0.205*** | 0.0776 |
| | (0.0633) | (0.0561) | (0.0499) | (0.0488) |
| is_west | −0.0321 | 0.596*** | 0.137*** | 0.0161 |
| | (0.0555) | (0.0515) | (0.0441) | (0.0424) |
| radiation | | −0.00813*** | −0.00231*** | |
| | | (0.000741) | (0.000619) | |
| Constant | 3.841*** | −1.160*** | 3.512*** | 3.694*** |
| | (0.208) | (0.205) | (0.185) | (0.177) |
| R-squared | 0.0737 | 0.143 | 0.0441 | 0.0869 |
| Observations | 11532 | 11532 | 11532 | 11532 |

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

*Table 32: Full Model Comparison for Mixed Radiation Instrument*

| | (1)<br>Second Stage | (2)<br>First Stage | (3)<br>Reduced Form | (4)<br>OLS |
|---|---|---|---|---|
| env_con_index | 0.269** | | | 0.176*** |
| | (0.108) | | | (0.0117) |
| happy | 0.00787 | 0.0498*** | 0.0213** | 0.0126 |
| | (0.0118) | (0.0121) | (0.0105) | (0.0103) |
| health | 0.0809*** | −0.0714*** | 0.0617*** | 0.0745*** |
| | (0.0237) | (0.0259) | (0.0232) | (0.0225) |
| attached_to_country | 0.0199** | 0.0257*** | 0.0268*** | 0.0219*** |
| | (0.00800) | (0.00947) | (0.00780) | (0.00758) |
| age | 0.0127*** | −0.00174 | 0.0122*** | 0.0125*** |
| | (0.00145) | (0.00173) | (0.00147) | (0.00144) |
| income_level | −0.0340*** | 0.0187** | −0.0290*** | −0.0321*** |
| | (0.00763) | (0.00908) | (0.00746) | (0.00728) |
| has_job | −0.0334 | 0.0122 | −0.0302 | −0.0320 |
| | (0.129) | (0.138) | (0.138) | (0.131) |
| unemployment_rate | −0.000440 | 0.0261*** | 0.00658 | 0.00302 |
| | (0.00595) | (0.00510) | (0.00460) | (0.00438) |
| education_level | 0.00199 | −0.000835 | 0.00177 | 0.00196 |
| | (0.00164) | (0.00198) | (0.00168) | (0.00164) |
| life_exp | −0.00130 | −0.00410 | −0.00240 | −0.00161 |
| | (0.00222) | (0.00262) | (0.00233) | (0.00222) |
| gdp_per_capita | −0.000857*** | 0.000641*** | −0.000685*** | −0.000758*** |
| | (0.000204) | (0.000213) | (0.000177) | (0.000167) |
| forest_rate | −0.00265* | 0.00561*** | −0.00114 | −0.00224 |
| | (0.00149) | (0.00169) | (0.00143) | (0.00140) |
| missing_income | −0.217*** | 0.0849 | −0.194*** | −0.211*** |
| | (0.0640) | (0.0758) | (0.0656) | (0.0636) |
| with_children | 0.0665** | 0.0788** | 0.0877*** | 0.0743** |
| | (0.0329) | (0.0385) | (0.0321) | (0.0315) |
| victim_crime | 0.0355 | 0.189*** | 0.0863** | 0.0546 |
| | (0.0443) | (0.0494) | (0.0396) | (0.0383) |
| edu_low | −0.134*** | −0.144*** | −0.172*** | −0.146*** |
| | (0.0492) | (0.0528) | (0.0479) | (0.0470) |
| edu_high | 0.0985** | 0.192*** | 0.150*** | 0.119*** |
| | (0.0413) | (0.0441) | (0.0357) | (0.0348) |
| edu_father_low | 0.00345 | 0.0521 | 0.0175 | 0.0117 |
| | (0.0425) | (0.0526) | (0.0431) | (0.0417) |
| edu_father_high | −0.0323 | 0.0588 | −0.0165 | −0.0250 |
| | (0.0476) | (0.0596) | (0.0480) | (0.0468) |
| edu_mother_low | 0.0551 | −0.0407 | 0.0441 | 0.0539 |
| | (0.0429) | (0.0546) | (0.0445) | (0.0429) |
| edu_mother_high | 0.0702 | 0.0972 | 0.0964* | 0.0801* |
| | (0.0504) | (0.0625) | (0.0500) | (0.0487) |
| minority | −0.00205 | −0.0615 | −0.0186 | −0.0132 |
| | (0.105) | (0.112) | (0.108) | (0.105) |
| is_north | 0.159** | −0.00827 | 0.157* | 0.136* |
| | (0.0800) | (0.0968) | (0.0803) | (0.0750) |
| is_south | 0.0317 | 0.801*** | 0.247*** | 0.0969 |
| | (0.104) | (0.0829) | (0.0732) | (0.0714) |
| is_west | −0.00311 | 0.726*** | 0.192*** | 0.0534 |
| | (0.0909) | (0.0772) | (0.0646) | (0.0627) |
| radiation | | −0.00825*** | −0.00222** | |
| | | (0.00111) | (0.000915) | |
| Constant | 3.479*** | −0.990*** | 3.212*** | 3.356*** |
| | (0.308) | (0.316) | (0.289) | (0.275) |
| R-squared | 0.0727 | 0.153 | 0.0437 | 0.0846 |
| Observations | 5531 | 5531 | 5531 | 5531 |

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

*Table 33: Males Regression for Mixed Radiation Instrument*

| | (1) Second Stage | (2) First Stage | (3) Reduced Form | (4) OLS |
|---|---|---|---|---|
| env_con_index | 0.286*** | | | 0.194*** |
| | (0.101) | | | (0.0117) |
| happy | 0.0250** | 0.0282** | 0.0331*** | 0.0277*** |
| | (0.0104) | (0.0115) | (0.0104) | (0.0100) |
| health | 0.0133 | −0.0653*** | −0.00539 | 0.00696 |
| | (0.0200) | (0.0227) | (0.0196) | (0.0189) |
| attached_to_country | 0.0168* | 0.0416*** | 0.0287*** | 0.0204** |
| | (0.00877) | (0.00899) | (0.00820) | (0.00796) |
| age | 0.0118*** | −0.00362** | 0.0107*** | 0.0114*** |
| | (0.00143) | (0.00160) | (0.00141) | (0.00138) |
| income_level | −0.0296*** | −0.0000648 | −0.0296*** | −0.0294*** |
| | (0.00647) | (0.00751) | (0.00659) | (0.00643) |
| has_job | 0.0398 | 0.0463 | 0.0530 | 0.0449 |
| | (0.0851) | (0.0909) | (0.0875) | (0.0850) |
| unemployment_rate | 0.000911 | 0.0285*** | 0.00905** | 0.00449 |
| | (0.00573) | (0.00464) | (0.00435) | (0.00418) |
| education_level | −0.00104 | −0.000535 | −0.00120 | −0.00106 |
| | (0.00150) | (0.00180) | (0.00154) | (0.00149) |
| life_exp | −0.00266 | 0.00313 | −0.00176 | −0.00232 |
| | (0.00195) | (0.00205) | (0.00198) | (0.00192) |
| gdp_per_capita | −0.000666*** | 0.000957*** | −0.000393** | −0.000543*** |
| | (0.000210) | (0.000184) | (0.000166) | (0.000156) |
| forest_rate | −0.00523*** | 0.00630*** | −0.00342*** | −0.00476*** |
| | (0.00135) | (0.00146) | (0.00130) | (0.00127) |
| missing_income | −0.186*** | −0.0291 | −0.194*** | −0.189*** |
| | (0.0562) | (0.0660) | (0.0573) | (0.0559) |
| with_children | 0.0323 | 0.0482 | 0.0461 | 0.0372 |
| | (0.0293) | (0.0338) | (0.0295) | (0.0287) |
| victim_crime | 0.0715* | 0.152*** | 0.115*** | 0.0872** |
| | (0.0402) | (0.0404) | (0.0370) | (0.0360) |
| edu_low | −0.0132 | −0.238*** | −0.0813* | −0.0343 |
| | (0.0516) | (0.0508) | (0.0465) | (0.0459) |
| edu_high | 0.0193 | 0.232*** | 0.0857** | 0.0428 |
| | (0.0413) | (0.0393) | (0.0335) | (0.0326) |
| edu_father_low | −0.0328 | −0.00364 | −0.0338 | −0.0306 |
| | (0.0396) | (0.0463) | (0.0403) | (0.0394) |
| edu_father_high | −0.0226 | 0.0577 | −0.00611 | −0.0168 |
| | (0.0444) | (0.0536) | (0.0446) | (0.0436) |
| edu_mother_low | 0.0652 | 0.0202 | 0.0710* | 0.0697* |
| | (0.0407) | (0.0475) | (0.0412) | (0.0402) |
| edu_mother_high | 0.0424 | 0.185*** | 0.0952** | 0.0600 |
| | (0.0510) | (0.0566) | (0.0479) | (0.0468) |
| minority | 0.142 | −0.104 | 0.112 | 0.129 |
| | (0.0886) | (0.113) | (0.0949) | (0.0888) |
| is_north | 0.0932 | −0.00349 | 0.0922 | 0.0717 |
| | (0.0736) | (0.0867) | (0.0752) | (0.0699) |
| is_south | 0.0231 | 0.496*** | 0.165** | 0.0601 |
| | (0.0782) | (0.0759) | (0.0684) | (0.0667) |
| is_west | −0.0531 | 0.486*** | 0.0858 | −0.0188 |
| | (0.0684) | (0.0687) | (0.0603) | (0.0577) |
| radiation | | −0.00811*** | −0.00232*** | |
| | | (0.000989) | (0.000840) | |
| Constant | 4.038*** | −1.227*** | 3.687*** | 3.899*** |
| | (0.280) | (0.269) | (0.244) | (0.235) |
| R-squared | 0.0754 | 0.130 | 0.0399 | 0.0861 |
| Observations | 6001 | 6001 | 6001 | 6001 |

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

*Table 34: Females Regression for Mixed Radiation Instrument*

| | (1) Age 25–34 | (2) Age 35–49 | (3) Age 50–65 |
|---|---|---|---|
| env_con_index | 0.204 | 0.350*** | 0.235 |
| | (0.140) | (0.102) | (0.157) |
| happy | 0.0267 | 0.00926 | 0.0141 |
| | (0.0170) | (0.0129) | (0.0124) |
| health | 0.0380 | 0.0592** | 0.0249 |
| | (0.0339) | (0.0266) | (0.0225) |
| attached_to_country | 0.00492 | 0.0169* | 0.0338*** |
| | (0.0118) | (0.00914) | (0.0111) |
| income_level | −0.0237** | −0.0451*** | −0.0184** |
| | (0.0100) | (0.00844) | (0.00837) |
| has_job | 0.0207 | −0.0983 | −0.0153 |
| | (0.135) | (0.147) | (0.113) |
| male | −0.0329 | −0.0516 | −0.100** |
| | (0.0544) | (0.0363) | (0.0430) |
| unemployment_rate | 0.00627 | 0.00984* | −0.0115 |
| | (0.00846) | (0.00545) | (0.00924) |
| education_level | 0.00107 | −0.000131 | 0.0000748 |
| | (0.00231) | (0.00185) | (0.00185) |
| life_exp | 0.00545* | −0.00351 | −0.00487** |
| | (0.00307) | (0.00220) | (0.00241) |
| gdp_per_capita | −0.000246 | −0.000839*** | −0.000899*** |
| | (0.000258) | (0.000229) | (0.000294) |
| forest_rate | −0.00452** | −0.00355** | −0.00407** |
| | (0.00210) | (0.00162) | (0.00171) |
| missing_income | −0.110 | −0.343*** | −0.112* |
| | (0.0943) | (0.0723) | (0.0644) |
| with_children | 0.110** | 0.0324 | 0.0137 |
| | (0.0493) | (0.0411) | (0.0348) |
| victim_crime | 0.00977 | 0.0952** | 0.0396 |
| | (0.0605) | (0.0483) | (0.0491) |
| edu_low | −0.0594 | −0.148** | −0.0258 |
| | (0.0952) | (0.0630) | (0.0530) |
| edu_high | 0.136** | −0.0439 | 0.0955** |
| | (0.0680) | (0.0504) | (0.0428) |
| edu_father_low | 0.0417 | −0.0274 | −0.0301 |
| | (0.0653) | (0.0482) | (0.0466) |
| edu_father_high | −0.0440 | −0.0181 | −0.00267 |
| | (0.0587) | (0.0533) | (0.0573) |
| edu_mother_low | −0.00651 | 0.0230 | 0.155*** |
| | (0.0687) | (0.0471) | (0.0473) |
| edu_mother_high | 0.0932 | 0.0212 | 0.0462 |
| | (0.0640) | (0.0557) | (0.0709) |
| minority | −0.00178 | 0.147 | 0.0271 |
| | (0.124) | (0.120) | (0.120) |
| is_north | 0.0385 | 0.0917 | 0.180* |
| | (0.103) | (0.0907) | (0.101) |
| is_south | −0.0588 | −0.0686 | 0.173* |
| | (0.135) | (0.102) | (0.102) |
| is_west | −0.209* | −0.0484 | 0.0951 |
| | (0.114) | (0.0826) | (0.100) |
| Constant | 3.367*** | 4.709*** | 4.667*** |
| | (0.358) | (0.326) | (0.432) |
| R-squared | 0.0968 | 0.0617 | 0.0571 |
| Observations | 2484 | 4202 | 4846 |

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

*Table 35: Agegroup Regression for Mixed Radiation Instrument*

| | (1) Low Educ. | (2) High Educ. | (3) With Children | (4) Without Children |
|---|---|---|---|---|
| env_con_index | 1.742 | 0.0839 | 0.498*** | 0.156* |
| | (1.787) | (0.0924) | (0.140) | (0.0894) |
| happy | −0.0265 | 0.0248** | 0.00485 | 0.0221** |
| | (0.0350) | (0.0120) | (0.0134) | (0.00994) |
| health | 0.0724 | 0.0692*** | 0.0721*** | 0.0243 |
| | (0.0701) | (0.0227) | (0.0246) | (0.0206) |
| attached_to_country | −0.0413 | 0.0188** | 0.0143 | 0.0210*** |
| | (0.0629) | (0.00874) | (0.00923) | (0.00808) |
| age | 0.00412 | 0.0118*** | 0.0137*** | 0.0112*** |
| | (0.0107) | (0.00164) | (0.00199) | (0.00123) |
| income_level | −0.0593 | −0.0304*** | −0.0331*** | −0.0286*** |
| | (0.0668) | (0.00711) | (0.00804) | (0.00640) |
| has_job | −0.108 | 0.137 | −0.106 | 0.0265 |
| | (0.275) | (0.174) | (0.115) | (0.0940) |
| male | −0.160 | −0.0458 | −0.0261 | −0.105*** |
| | (0.127) | (0.0365) | (0.0376) | (0.0329) |
| unemployment_rate | −0.0655 | 0.0168*** | −0.00746 | 0.00490 |
| | (0.0660) | (0.00554) | (0.00648) | (0.00578) |
| education_level | −0.00643 | 0.000758 | −0.000776 | 0.00132 |
| | (0.00812) | (0.00181) | (0.00178) | (0.00149) |
| life_exp | −0.0159 | 0.000898 | −0.00165 | −0.00272 |
| | (0.0150) | (0.00180) | (0.00230) | (0.00197) |
| gdp_per_capita | −0.00162 | −0.000195 | −0.00119*** | −0.000517*** |
| | (0.00104) | (0.000223) | (0.000272) | (0.000181) |
| forest_rate | −0.0146 | 0.00208 | −0.00500*** | −0.00367*** |
| | (0.00978) | (0.00157) | (0.00163) | (0.00135) |
| missing_income | −0.0741 | −0.190*** | −0.211*** | −0.181*** |
| | (0.202) | (0.0695) | (0.0719) | (0.0538) |
| with_children | −0.0542 | 0.0277 | | |
| | (0.203) | (0.0313) | | |
| victim_crime | −0.235 | 0.0703* | 0.0341 | 0.0694* |
| | (0.418) | (0.0396) | (0.0460) | (0.0413) |
| edu_father_low | −0.116 | 0.0381 | 0.0341 | −0.0448 |
| | (0.197) | (0.0434) | (0.0451) | (0.0395) |
| edu_father_high | −0.0880 | −0.0746* | 0.0247 | −0.0639 |
| | (0.426) | (0.0415) | (0.0514) | (0.0438) |
| edu_mother_low | 0.0607 | 0.0232 | −0.0679 | 0.154*** |
| | (0.292) | (0.0432) | (0.0464) | (0.0402) |
| edu_mother_high | −0.321 | 0.126*** | −0.0557 | 0.149*** |
| | (0.511) | (0.0454) | (0.0560) | (0.0498) |
| minority | 0.265 | 0.0593 | 0.234** | −0.00769 |
| | (0.340) | (0.107) | (0.118) | (0.0926) |
| is_north | 1.101* | −0.157** | 0.239** | 0.0894 |
| | (0.574) | (0.0787) | (0.102) | (0.0697) |
| is_south | −0.412 | 0.0400 | 0.0295 | 0.0362 |
| | (0.995) | (0.0956) | (0.0959) | (0.0869) |
| is_west | −0.588 | 0.0689 | 0.00802 | −0.0227 |
| | (1.119) | (0.0778) | (0.0768) | (0.0801) |
| edu_low | | | −0.0343 | −0.115** |
| | | | (0.0563) | (0.0474) |
| edu_high | | | −0.0368 | 0.0994*** |
| | | | (0.0532) | (0.0374) |
| Constant | 8.355* | 2.888*** | 4.177*** | 3.686*** |
| | (4.771) | (0.319) | (0.349) | (0.266) |
| R-squared | | 0.0795 | | 0.0939 |
| Observations | 2127 | 4663 | 5278 | 6254 |

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

*Table 36: Regression for Education Groups and Individuals with Children for Mixed Radiation Instrument*

| | (1) Second Stage | (2) First Stage | (3) Reduced Form | (4) OLS |
|---|---|---|---|---|
| env_con_index | 1.751*** | | | 0.296*** |
| | (0.212) | | | (0.0186) |
| happy | −0.000542 | 0.0411*** | 0.0714*** | 0.0608*** |
| | (0.0220) | (0.00836) | (0.0163) | (0.0162) |
| health | 0.217*** | −0.0707*** | 0.0931*** | 0.113*** |
| | (0.0433) | (0.0171) | (0.0326) | (0.0323) |
| attached_to_country | 0.00294 | 0.0354*** | 0.0649*** | 0.0498*** |
| | (0.0166) | (0.00655) | (0.0123) | (0.0122) |
| age | −0.00148 | −0.00237** | −0.00564*** | −0.00490** |
| | (0.00280) | (0.00118) | (0.00216) | (0.00215) |
| income_level | 0.0732*** | 0.00351 | 0.0793*** | 0.0815*** |
| | (0.0137) | (0.00580) | (0.0109) | (0.0108) |
| has_job | −0.0325 | 0.0368 | 0.0320 | 0.0330 |
| | (0.178) | (0.0758) | (0.142) | (0.141) |
| unemployment_rate | −0.0349*** | 0.0262*** | 0.0110 | 0.0185*** |
| | (0.0114) | (0.00344) | (0.00681) | (0.00658) |
| education_level | −0.0000963 | −0.000490 | −0.000954 | −0.000238 |
| | (0.00309) | (0.00134) | (0.00237) | (0.00236) |
| life_exp | 0.00400 | −0.0000871 | 0.00385 | 0.00482* |
| | (0.00329) | (0.00158) | (0.00258) | (0.00251) |
| gdp_per_capita | −0.000605 | 0.000803*** | 0.000800*** | 0.00113*** |
| | (0.000410) | (0.000142) | (0.000264) | (0.000257) |
| forest_rate | −0.00881*** | 0.00602*** | 0.00173 | −0.00177 |
| | (0.00285) | (0.00111) | (0.00208) | (0.00207) |
| missing_income | 0.525*** | −0.00612 | 0.514*** | 0.492*** |
| | (0.117) | (0.0499) | (0.0937) | (0.0926) |
| with_children | 0.00442 | 0.0809*** | 0.146*** | 0.128*** |
| | (0.0611) | (0.0252) | (0.0462) | (0.0458) |
| victim_crime | −0.0670 | 0.164*** | 0.221*** | 0.196*** |
| | (0.0841) | (0.0318) | (0.0587) | (0.0583) |
| edu_low | 0.0760 | −0.189*** | −0.255*** | −0.185*** |
| | (0.0970) | (0.0368) | (0.0719) | (0.0715) |
| edu_high | −0.209** | 0.246*** | 0.222*** | 0.182*** |
| | (0.0889) | (0.0292) | (0.0532) | (0.0528) |
| edu_father_low | 0.0726 | 0.0231 | 0.113* | 0.152** |
| | (0.0815) | (0.0351) | (0.0634) | (0.0629) |
| edu_father_high | 0.0445 | 0.0509 | 0.134* | 0.137* |
| | (0.0937) | (0.0402) | (0.0716) | (0.0710) |
| edu_mother_low | −0.0773 | −0.00928 | −0.0936 | −0.0502 |
| | (0.0831) | (0.0362) | (0.0646) | (0.0641) |
| edu_mother_high | −0.174* | 0.148*** | 0.0854 | 0.0523 |
| | (0.101) | (0.0423) | (0.0749) | (0.0741) |
| minority | −0.365* | −0.0815 | −0.508*** | −0.552*** |
| | (0.192) | (0.0800) | (0.149) | (0.149) |
| is_north | 1.168*** | −0.0171 | 1.138*** | 0.807*** |
| | (0.153) | (0.0650) | (0.121) | (0.116) |
| is_south | −1.009*** | 0.649*** | 0.127 | −0.207* |
| | (0.176) | (0.0563) | (0.111) | (0.109) |
| is_west | −0.179 | 0.600*** | 0.871*** | 0.525*** |
| | (0.157) | (0.0518) | (0.0948) | (0.0933) |
| radiation | | −0.00806*** | −0.0141*** | |
| | | (0.000744) | (0.00132) | |
| Constant | 5.476*** | −1.168*** | 3.431*** | 3.342*** |
| | (0.557) | (0.204) | (0.365) | (0.358) |
| R-squared | | 0.139 | 0.103 | 0.118 |
| Observations | 11492 | 11492 | 11492 | 11492 |

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

*Table 37: Full Regression on Confidence to Reduce Selfuse for Mixed Radiation Instrument*

| | (1) Second Stage | (2) First Stage | (3) Reduced Form | (4) OLS |
|---|---|---|---|---|
| env_con_index | −0.114 | | | 0.265*** |
| | (0.141) | | | (0.0142) |
| happy | 0.136*** | 0.0411*** | 0.131*** | 0.120*** |
| | (0.0146) | (0.00836) | (0.0133) | (0.0130) |
| health | 0.0105 | −0.0707*** | 0.0186 | 0.0375 |
| | (0.0280) | (0.0171) | (0.0260) | (0.0255) |
| attached_to_country | 0.123*** | 0.0354*** | 0.119*** | 0.111*** |
| | (0.0116) | (0.00655) | (0.0104) | (0.0102) |
| age | 0.0156*** | −0.00237** | 0.0158*** | 0.0165*** |
| | (0.00180) | (0.00118) | (0.00175) | (0.00173) |
| income_level | 0.00848 | 0.00351 | 0.00808 | 0.00631 |
| | (0.00877) | (0.00580) | (0.00860) | (0.00847) |
| has_job | −0.209* | 0.0368 | −0.213** | −0.226** |
| | (0.109) | (0.0758) | (0.107) | (0.106) |
| unemployment_rate | −0.0130* | 0.0262*** | −0.0160*** | −0.0269*** |
| | (0.00715) | (0.00344) | (0.00515) | (0.00494) |
| education_level | 0.00315 | −0.000490 | 0.00320* | 0.00318* |
| | (0.00192) | (0.00134) | (0.00188) | (0.00185) |
| life_exp | 0.000206 | −0.0000871 | 0.000216 | −0.00000756 |
| | (0.00238) | (0.00158) | (0.00233) | (0.00227) |
| gdp_per_capita | −0.000881*** | 0.000803*** | −0.000973*** | −0.00133*** |
| | (0.000259) | (0.000142) | (0.000211) | (0.000205) |
| forest_rate | 0.00339* | 0.00602*** | 0.00270* | 0.00155 |
| | (0.00178) | (0.00111) | (0.00163) | (0.00160) |
| missing_income | 0.122 | −0.00612 | 0.123* | 0.131* |
| | (0.0751) | (0.0499) | (0.0739) | (0.0727) |
| with_children | 0.182*** | 0.0809*** | 0.173*** | 0.150*** |
| | (0.0396) | (0.0252) | (0.0370) | (0.0364) |
| victim_crime | 0.206*** | 0.164*** | 0.188*** | 0.138*** |
| | (0.0551) | (0.0318) | (0.0475) | (0.0466) |
| edu_low | −0.371*** | −0.189*** | −0.349*** | −0.303*** |
| | (0.0617) | (0.0368) | (0.0569) | (0.0561) |
| edu_high | 0.220*** | 0.246*** | 0.192*** | 0.118*** |
| | (0.0579) | (0.0292) | (0.0423) | (0.0418) |
| edu_father_low | −0.0685 | 0.0231 | −0.0711 | −0.0893* |
| | (0.0519) | (0.0351) | (0.0507) | (0.0496) |
| edu_father_high | −0.0144 | 0.0509 | −0.0202 | −0.0385 |
| | (0.0588) | (0.0402) | (0.0571) | (0.0560) |
| edu_mother_low | 0.0465 | −0.00928 | 0.0475 | 0.0394 |
| | (0.0527) | (0.0362) | (0.0518) | (0.0506) |
| edu_mother_high | 0.0642 | 0.148*** | 0.0474 | 0.00531 |
| | (0.0665) | (0.0423) | (0.0622) | (0.0611) |
| minority | −0.181 | −0.0815 | −0.172 | −0.132 |
| | (0.137) | (0.0800) | (0.134) | (0.132) |
| is_north | −0.347*** | −0.0171 | −0.345*** | −0.253*** |
| | (0.0967) | (0.0650) | (0.0945) | (0.0890) |
| is_south | 0.762*** | 0.649*** | 0.688*** | 0.553*** |
| | (0.115) | (0.0563) | (0.0807) | (0.0795) |
| is_west | 0.315*** | 0.600*** | 0.247*** | 0.131* |
| | (0.105) | (0.0518) | (0.0764) | (0.0746) |
| radiation | | −0.00806*** | 0.000917 | |
| | | (0.000744) | (0.00111) | |
| Constant | 5.229*** | −1.168*** | 5.362*** | 5.785*** |
| | (0.368) | (0.204) | (0.302) | (0.294) |
| R-squared | 0.0422 | 0.139 | 0.0738 | 0.104 |
| Observations | 11492 | 11492 | 11492 | 11492 |

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

*Table 38: Full Regression on Willingness to Buy Efficient Tech for Mixed Radiation Instrument*

| | (1) Second Stage | (2) First Stage | (3) Reduced Form | (4) OLS |
|---|---|---|---|---|
| env_con_index | 0.541*** | | | 0.575*** |
| | (0.172) | | | (0.0186) |
| happy | 0.0671*** | 0.0411*** | 0.0893*** | 0.0657*** |
| | (0.0175) | (0.00836) | (0.0164) | (0.0158) |
| health | 0.0560 | −0.0707*** | 0.0177 | 0.0584* |
| | (0.0351) | (0.0171) | (0.0345) | (0.0330) |
| attached_to_country | 0.0327** | 0.0354*** | 0.0519*** | 0.0317*** |
| | (0.0135) | (0.00655) | (0.0127) | (0.0122) |
| age | 0.00609*** | −0.00237** | 0.00481** | 0.00617*** |
| | (0.00229) | (0.00118) | (0.00232) | (0.00224) |
| income_level | 0.00404 | 0.00351 | 0.00593 | 0.00384 |
| | (0.0111) | (0.00580) | (0.0116) | (0.0111) |
| has_job | −0.0904 | 0.0368 | −0.0705 | −0.0919 |
| | (0.151) | (0.0758) | (0.154) | (0.151) |
| unemployment_rate | −0.00332 | 0.0262*** | 0.0109 | −0.00455 |
| | (0.00920) | (0.00344) | (0.00717) | (0.00670) |
| education_level | −0.0101*** | −0.000490 | −0.0104*** | −0.0101*** |
| | (0.00245) | (0.00134) | (0.00258) | (0.00245) |
| life_exp | 0.000291 | −0.0000871 | 0.000243 | 0.000272 |
| | (0.00286) | (0.00158) | (0.00298) | (0.00286) |
| gdp_per_capita | 0.000625* | 0.000803*** | 0.00106*** | 0.000585** |
| | (0.000337) | (0.000142) | (0.000288) | (0.000268) |
| forest_rate | 0.000259 | 0.00602*** | 0.00352 | 0.0000964 |
| | (0.00232) | (0.00111) | (0.00227) | (0.00217) |
| missing_income | 0.197** | −0.00612 | 0.194** | 0.198** |
| | (0.0938) | (0.0499) | (0.0985) | (0.0938) |
| with_children | 0.0611 | 0.0809*** | 0.105** | 0.0583 |
| | (0.0504) | (0.0252) | (0.0505) | (0.0484) |
| victim_crime | −0.0387 | 0.164*** | 0.0503 | −0.0448 |
| | (0.0696) | (0.0318) | (0.0648) | (0.0624) |
| edu_low | 0.0915 | −0.189*** | −0.0107 | 0.0976 |
| | (0.0763) | (0.0368) | (0.0726) | (0.0699) |
| edu_high | −0.0180 | 0.246*** | 0.115** | −0.0270 |
| | (0.0709) | (0.0292) | (0.0577) | (0.0551) |
| edu_father_low | 0.0132 | 0.0231 | 0.0257 | 0.0114 |
| | (0.0658) | (0.0351) | (0.0685) | (0.0652) |
| edu_father_high | 0.105 | 0.0509 | 0.133* | 0.103 |
| | (0.0755) | (0.0402) | (0.0791) | (0.0746) |
| edu_mother_low | 0.0775 | −0.00928 | 0.0725 | 0.0769 |
| | (0.0671) | (0.0362) | (0.0705) | (0.0670) |
| edu_mother_high | −0.197** | 0.148*** | −0.117 | −0.203** |
| | (0.0836) | (0.0423) | (0.0840) | (0.0795) |
| minority | −0.0451 | −0.0815 | −0.0892 | −0.0408 |
| | (0.150) | (0.0800) | (0.155) | (0.148) |
| is_north | −0.261** | −0.0171 | −0.271** | −0.253** |
| | (0.121) | (0.0650) | (0.126) | (0.114) |
| is_south | 0.212 | 0.649*** | 0.564*** | 0.194* |
| | (0.145) | (0.0563) | (0.115) | (0.110) |
| is_west | 0.297** | 0.600*** | 0.622*** | 0.281*** |
| | (0.130) | (0.0518) | (0.103) | (0.0976) |
| radiation | | −0.00806*** | −0.00436*** | |
| | | (0.000744) | (0.00143) | |
| Constant | 3.445*** | −1.168*** | 2.813*** | 3.495*** |
| | (0.452) | (0.204) | (0.393) | (0.376) |
| R-squared | 0.122 | 0.139 | 0.0425 | 0.122 |
| Observations | 11492 | 11492 | 11492 | 11492 |

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

*Table 39: Full Regression on Willingness to Reduce Selfuse of Energy for Mixed Radiation Instrument*