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Talking in the Present, Caring for the Future: Language and Environment[*]

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ABSTRACT:

This paper identifies a new source that explains environmental behaviour: the presence of future tense marking in language. We predict that languages that grammatically mark the future affect speakers' intertemporal preferences and thereby reduce their willingness to address climate change. We first document that countries with a language that requires future tense marking adopt less stringent climate change policies. We then show that individuals within countries behave consistently: speakers of languages with future tense marking are less likely to adopt environmentally responsible behaviours. The results suggest that there may be deep and surprising obstacles for attempts to address climate change.

JEL classification: D83; Q54; Q58; Z13.

Keywords: language; linguistic relativity, intertemporal preference, climate change, environmental policy.

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Talking in the Present, Caring for the Future: Language and Environment

ABSTRACT: This paper identifies a new source that explains environmental behaviour: the presence of future tense marking in language. We predict that languages that grammatically mark the future affect speakers' intertemporal preferences and thereby reduce their willingness to address climate change. We first document that countries with a language that requires future tense marking adopt less stringent climate change policies. We then show that individuals within countries behave consistently: speakers of languages with future tense marking are less likely to adopt environmentally responsible behaviours. The results suggest that there may be deep and surprising obstacles for attempts to address climate change.

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1. Introduction

Climate change is a serious threat with potentially catastrophic risks for humankind and global ecosystems (IPCC, 2014). It demands an urgent international response that needs to be enforced domestically (Stern, 2008). Yet there are profound differences in the policies and measures adopted to address climate change around the world, even amongst seemingly similar economies. This paper provides a novel explanation for differences in climate change policies across countries: future tense marking in language.

That language may have an effect on economic outcomes has been documented in a nascent, but rapidly growing economics literature on the link between linguistic structures and economic outcomes (see Mavisakalyan and Weber, 2016 for a review). Much of this literature builds on the so-called *Linguistic Relativity Hypothesis* to propose that the structure of our language affects our thinking and behaviour. Speakers of languages without future tense marking speak about the future in the present tense, i.e. as if it were present. In contrast, languages with future tense marking require their speakers to speak in a distinct way about future events. This affects speakers' intertemporal preferences and induces less future-oriented behaviour (Chen, 2013).[1] Consistent with this hypothesis, recent studies have shown that speakers of languages with future tense marking save less and invest less in their health (Chen, 2013; Guin, 2015). At the corporate level, the existing evidence suggests that firms in locations where languages with future tense marking are prevalent have lower precautionary cash holdings (Chen et al., 2015) and invest less in research and development (Su et al., 2016). That time preference is a mechanism potentially mediating these effects of future tense has been shown through experimentally elicited time preference data by Sutter et al. (2015). Our study contributes to this literature by extending the effects of future tense marking to a new and highly significant area of future oriented-behaviour: addressing climate change.

Existing studies on policies concerning climate change and other environmental problems focus mainly on countries' economic (Damania et al., 2003; Damania and Fredriksson,

[1] The literature has additionally considered the effects of two other linguistic features. Linguistic *gender* systems have been linked with gender inequalities in various contexts including the labour market (Mavisakalyan, 2015; Gay et al., 2017), corporate and political leadership (Santacreu-Vasut et al., 2014; Hicks et al., 2016), household division of labour (Hicks et al., 2015), education (Davis and Reynolds, 2016) and health (Bhalotra et al., 2015). Grammatical rules governing *personal pronouns* (pronoun drop and politeness distinctions) have been linked to various cultural traits across countries, including individualism vs collectivism, social distance, etc. (Kashima and Kashima, 1998; Davis and Abdurazokzoda, 2016). Furthermore, studies have exploited these grammatical features to study the causal relationship between culture and various socio-economic outcomes (Licht et al., 2007; Tabellini, 2008; Davis and Williamson, 2016).

2003), institutional (Congleton, 1992; Fredriksson and Neumayer, 2013), historical (Fredriksson and Wollscheid, 2015; Ang and Fredriksson, 2017) and demographic (Tonn et al., 2001; Kahn, 2002) traits. The literature has also studied several determinants of individual action, highlighting the role of both economic factors and norms (Inglehart, 1995; Gelissen, 2007; Franzen and Meyer, 2010; Bechtel et al., 2016). To the best of our knowledge, our study is the first to combine the analysis of the determinants of environmental policies and actions with the study of linguistic relativity in economics, and to identify future time reference in language as a significant source of variation in environmental policies across countries.

We use a large sample of countries to demonstrate that places similar in their economic, demographic and institutional characteristics, yet different in their linguistic structures have different climate change policy outcomes. Policies are less stringent in places where the majority language grammatically marks the future. Econometrically, we are confronted with the issue of omitted variables: both language structures and climate change policies may be the product of deeper, unobserved factors. A conventional approach to deal with this possibility is to use an instrumental variable; however we do not have a credible instrumental variable in our application. Instead, we take two strategies to mitigate the effect of unobserved factors. We first demonstrate that the results are robust to controlling for the geographic and historical relatedness of languages. Second, acknowledging the fact that unobserved heterogeneity can never be fully controlled for, we use a partial identification approach proposed by Oster (2016) to assess the relative size of the unobservables needed to eliminate the entire effect of language structures. The results of this exercise suggest that the estimated language effects are not entirely driven by unobservables. Furthermore, we complement the cross-country analysis with an individual-level analysis of environmental actions based on the World Values Surveys. The results of this analysis are consistent with those obtained in cross-country comparisons: individual speakers of languages with future tense marking are less likely to adopt environmentally responsible behaviours compared to observationally identical individuals speaking languages that do not grammatically separate present and future.

We first provide some background on the linguistic relativity thesis and propose a mechanism which mediates the effect of language on climate change action (section 2). In section 3 we describe the data used in the study, followed by a discussion on empirical approach in section 4. Section 5 presents the results, including various robustness checks. We conclude with a discussion on implications of our findings in section 6.

2. BACKGROUND

In a nutshell, the *Linguistic Relativity Hypothesis* (LRH) states that the language we speak has a systematic influence on our cognition — the way we talk influences the way we think.[2] Different languages represent the world in different ways, by emphasising different aspects of reality. As a result, speakers of a certain language may be more sensitive to various features of the world. For example, Russian has different basic color terms than English: it has one basic term for light blue and another one for dark blue, but none corresponding to the generic "blue". It thus forces its speakers to distinguish light from dark blue. Experiments show that Russian speakers are better at perceptually discriminating different shades of blue as a consequence (Winawer et al., 2007).

For decades, linguists and cognitive scientists have regarded the LRH as misguided. However, starting in the early 1990s, the theory has received a revival, and there is now a substantial and ever-growing body of literature that testifies to its validity (e.g. Levinson, 1996; Boroditsky et al., 2003; Slobin, 2003; Kay and Regier, 2006; Levinson and Wilkins, 2006). The LRH is of interest to economists for a simple reason: linguistic structures shape our thinking and our thinking determines how we behave; linguistic structures therefore have an influence on our behaviour.

A linguistic feature that seems to affect economic outcomes is grammatical *tense*, i.e. how language encodes reference to time (Chen, 2013). In particular, the way a language organises reference to the *future* seems to have consequences for a number of future-directed actions, such as saving, exercising, abstaining from smoking, condom use, retirement savings, and long-run health (Chen, 2013). In some languages, e.g. French and English, speakers are required to use a dedicated form when talking about future events. In other languages, e.g. German and Finnish, speakers can talk about the future in the same grammatical form in which they talk about the present.[3]

[2] For an overview on the LRH see Gumperz and Levinson (1996); Lucy (1997); Casasanto (2015). There are different interpretations of the LRH (Scholz et al., 2016). A *strong* interpretation assumes a *strong* effect of language on thought: language *determines* thought; i.e. no thought (of a certain type) without corresponding linguistic structures. A *moderate* interpretation assumes only a *moderate* effect of language on thought: language *influences* thought in systematic and non-trivial ways. The existing evidence on the LRH supports moderate readings of the LRH better than strong ones. Here, we are only assuming a moderate interpretation of the LRH.

[3] It is true that German, like English, also has the *potential* to explicitly mark reference to the future, e.g. with the auxiliary "werden". It is therefore important to stress that the difference between the two groups of languages concerns whether future time reference "is overtly and *obligatorily* marked" (Dahl, 2000, p. 310, our emphasis).

English: *Tomorrow they will*$_{auxiliary}$ *drive to Paris*.

French: *Demain ils conduiront à Paris* — (Tomorrow they drive$_{future}$ to Paris).

German: *Morgen fahren sie nach Paris* — (Tomorrow they drive$_{present}$ to Paris).

We follow the terminology and classification of Chen (2013) in referring to languages which require a dedicated marking of the future as *strong-FTR* languages (e.g. English, French) and to languages that do not require to grammatically mark future time reference as *weak-FTR* languages (e.g. German, Finnish).[4] The grammatical difference between strong- and weak-FTR seems to influence agents' perception of temporal distance and their inter-temporal preferences, which in turn affects their decision making. Our study suggests that this influence also includes behavior related to climate change.

We propose that the mechanism which underlies the effect of future tense is the joint work of two factors: *temporal displacement* and *temporal discounting*.[5] The idea behind *temporal displacement* is that using a dedicated future tense form subjectively projects future events further away from the speaker's "now"—they appear temporally more distant to the agent. Speaking about the future in a separate form represents the future as discontinuous with the present. Conversely, speaking about the future in the present tense form depicts the future as continuous with the present and subjectively locates future outcomes closer to the agent's current temporal perspective. The effect of temporal displacement combines with that of *temporal discounting*. Humans (and other organisms) have a well-established tendency to discount future costs and rewards (Ramsey, 1928; Solnick et al., 1980; Kirby and Herrnstein, 1995; Frederick et al., 2002). The further in the future an outcome seems, the more we discount its potential costs or benefits. In tandem, temporal displacement and temporal discounting affect agents' inter-temporal preference structure such that future options appear less rewarding and less costly to speakers of a strong-FTR languages, compared to speakers of weak-FTR languages, since they appear temporally more distant, and are thus more strongly affected by temporal discounting.

[4] Chen's (2013) classification is based on that of the European Science Foundation's Typology of Languages in Europe (EUROTYP) project (Dahl, 2000), which undertook a very comprehensive study of the tense and aspect system of the major European languages.

[5] The proposed mechanism is very similar to one postulated in (Chen, 2013, p. 695). There, Chen considers an alternative mechanism, based on differences in the precision of future directed beliefs which are the result of differences in the *partitioning* of future events. While we agree that, in principle, language may affect how finely an agent's space of options gets partitioned (Mavisakalyan and Weber, 2016), we find this second mechanism slightly less convincing and more speculative in the case of FTR. For one thing, as can be seen by the above examples, both weak- and strong-FTR languages are able to communicate the same temporal information with equal ease. In the face of this semantic equivalence, it is unclear why we would expect weak- and strong-FTR languages to engender different temporal partitionings to begin with.

To illustrate, imagine two agents A_{weak} and B_{strong}. A_{weak} is a speaker of a weak-FTR language, presenting the future as if it were present. B_{strong} is a speaker of a strong FTR language, projecting the future away form the present. (Otherwise, A_{strong} and B_{weak} are as similar as possible.) Assume that A_{weak} is indifferent between a present reward x_1 and an intrinsically more rewarding future option x_2: $(x_1, t_{now}) = (x_2, t_{later})$. When B_{strong} is presented with the same choice, s/he may well prefer the less rewarding present option, since, assuming that temporal displacement is operative, the later option appears comparatively more distant and therefore, given temporal discounting, less attractive: $(x_1, t_{now}) > (x_2, t_{later})$.

Pro-environmental policies and actions typically incur present costs for the sake of future rewards. For instance, green products are on average more expensive than conventional products. Choosing a green product thus has significant short-term costs. On the other hand, the expected reward, i.e. avoiding catastrophic climate change, is located relatively far in the future. The pay-off structure of such decisions thus makes them amenable to the above described influence of temporal displacement and discounting. Speakers of weak-FTR languages are expected to value the future benefits of pro-environmental actions and policies higher than speakers of strong FTR languages, as they appear closer to the present and are thus less subject to temporal discounting. Given their different preferences, speakers of weak-FTR languages are expected to engage in more pro-environmental behavior than speakers of strong-FTR language. This is indeed what our study finds.

Furthermore, in a standard median voter model, which assumes the presence of electoral motives, political decisions reflect the preferences of the electorate (Downs, 1957). Hence, given the different intertemporal preferences of individual voters, we expect places with weak-FTR languages to adopt more stringent climate change policies. The same result is predicted if we alternatively assume a 'citizen candidates' model. Politicians who speak weak-FTR languages have stronger pro-environmental preferences. Therefore, they are more likely to implement policies consistent with those preferences once elected (Osborne and Slivinski, 1996; Besley and Coate, 1997). Both scenarios are consistent with our findings; distinguishing between them is beyond the scope of the current paper.

3. Data

Most of the empirical evidence on the determinants of policies concerning climate change and other environmental problems are based on large country-level datasets (e.g., Damania et al., 2003; Fredriksson and Neumayer, 2013; Fredriksson and Wollscheid, 2015; Ang and Fredriksson, 2017). Cross-country data provide a general picture, but they may conceal important behavioural mechanisms underlying aggregate outcomes. Yet, not all questions are amenable to sub-national analysis; understanding the drivers of climate change policies is particularly hard to achieve using micro-level data. With these considerations in mind, the paper combines aggregate-level data to perform cross-country comparisons of climate change policies with individual-level analysis that employs survey data from a large sample of countries to compare pro-environmental behaviours of individuals.

Measurement of FTR. Our classification of languages into those which require a dedicated marking of the future, *strong-FTR* languages, and those that do not require to grammatically mark future time reference, *weak-FTR* languages, is based on the data from Chen (2013). Chen's classification relies on the criterion of whether a language requires an obligatory FTR in 'prediction-based contexts' adopted from the European Science Foundation's Typology of Languages in Europe (EUROTYP) project (Dahl, 2000). To justify this criterion, Dahl (2000) notes that "whether FTR is overtly and obligatorily marked in prediction-based sentences can be used as one of the major criteria for whether it is grammaticalized in language or not" (Dahl, 2000, p. 310). The data itself comes from EUROTYP and, in the case of non-European languages, other established cross-linguistic analyses (e.g., Dahl and Dienes, 1984; Dahl, 1985; Bybee et al., 1994; Nurse, 2008; Cyffer et al., 2009) (see Appendix B in Chen (2013) for further discussion on coding of languages). Chen (2013) demonstrates the validity of this measure using frequency analysis of future-marking in weather forecast texts retrived from the web.[6]

Country-level data. The cross-country analysis is based on data from multiple sources including Steves et al. (2011); Keefer (2012); Chen (2013); Marshall et al. (2016); World Bank (2016). Together, they result in a sample of 68 countries.[7] Table 1 specifies the sources and presents descriptive statistics for all variables used in the baseline cross-country analysis by weak- and strong-FTR language groups. The FTR marker is assigned to a country's most widely spoken language—identified based on the information collected by Alesina et al. (2003)—following other studies in the literature (e.g., Licht et al., 2007; Santacreu-Vasut

[6] The sample of languages from this analysis is too small to be useful for the current study.

[7] The countries in the sample include: Albania, Argentina, Armenia, Australia, Austria, Azerbaijan, Bahrain, Belarus, Belgium, Bolivia, Bosnia & Herzegovina, Brazil, Canada, Colombia, Congo Republic, Costa Rica, Czech Republic, Denmark, Dominican Republic, Egypt, Estonia, Fiji, Finland, France, Georgia, Germany, Greece, Hungary, Iceland, India, Indonesia, Ireland, Italy, Japan, Jordan, Korea Republic, Kyrgyz Republic, Latvia, Lithuania, Macedonia, Madagascar, Malta, Mauritania, Mexico, Mongolia, Morocco, New Zealand, Niger, Norway, Peru, Poland, Portugal, Romania, Russian Federation, Saudi Arabia, Slovak Republic, Slovenia, South Africa, Spain, Sweden, Switzerland, Turkey, United Kingdom, United States, Uruguay, Uzbekistan, Venezuela, Vietnam.

et al., 2013; Bhalotra et al., 2015).[8] Seventy-six percent of the countries in the sample speak a strong-FTR language, while the remaining 24% are weak-FTR language-speaking countries.

We analyse the relationship between the FTR system of a country's majority language and its climate change policies as captured by Climate Laws, Institutions and Measures Index (CLIMI) developed by Steves et al. (2011) and used in several published studies (e.g., Fredriksson and Neumayer, 2013, 2016).[9] CLIMI measures the climate change mitigation policies adopted by countries based on the 2005-2010 annual national communications to the UNFCCC. CLIMI is based on 12 components grouped into four key policy areas, with subweights and weights used to reflect the contribution of each of the components/areas to climate change mitigation: (i) international cooperation (0.1) [components: Kyoto ratification (0.5), Joint Implementation or Clean Development Mechanism host (0.5)]; (ii) domestic climate framework (0.4) [components: cross-sectoral climate change legislation (0.33), carbon emissions target (0.33), dedicated climate change institution (0.33)]; (iii) significant sectoral fiscal or regulatory measures or targets (0.4) [components: energy supplies/renewables (0.3), transport (0.13), buildings (0.07), agriculture (0.13), forestry (0.17), industry (0.2)]; and (iv) additional cross-sectoral fiscal or regulatory measures (0.1) [components: cross-sectoral policy measures (1)]. CLIMI ranges from 0 and 1, with higher values representing stricter policies.

As Table 1 demonstrates, the average CLIMI score in the entire sample is 0.410.[10] In the sample of countries with a weak-FTR majority language it is 0.517, while in the sample of countries with a strong-FTR language it is 0.376. This gap of 0.141 points suggests a negative effect of STRONG FTR on CLIMI.

Our analysis of the link between language FTR and climate change policies controls for a range of observable characteristics of countries that have been accounted for in previous studies on determinants of environmental policies. Since CLIMI is derived from information collected over the period 2005-2010, we use explanatory variables averaged over this time period.

Four groups of covariates are included in baseline models. The first includes economic characteristics of countries. We expect the demand for environmental quality to increase

[8] To reflect the heterogeneity in multilingual countries, a weighted measure with weights given by the share of the population speaking each language is used in robustness checks (e.g., Tabellini, 2008; Mavisakalyan, 2015).

[9] In robustness checks we employ an alternative dependent variable measuring the degree of global environmental cooperation (Esty et al., 2005).

[10] Saudi Arabia has the lowest CLIMI score in the sample at 0.023, while the UK has the highest score at 0.801.

with GDP PER CAPITA (e.g., Fredriksson and Neumayer, 2013, 2016). Following these studies, we also control for OPENNESS, defined as imports plus exports divided by GDP. On the one hand, more open countries may cooperate more on environmental problems (Neumayer, 2002). On the other hand, it is possible that the interests of exporting countries are threatened by environmental agreements. Under such a scenario, higher openness for trade may decrease the willingness to commit to stringent environmental policies. The sectoral structure of the economy may also influence the stringency of environmental policies. We include manufacturing value added as a percentage of GDP, MANUFACTURING %, to account for that possibility. According to Cole et al. (2006) and Fredriksson and Vollebergh (2009), this measure may capture the lobbying pressures from workers in the manufacturing sector for lower regulations to protect jobs. Alternatively, it may measure the degree to which an economy consists of pollution-intensive manufacturing, positively affecting the regulatory stringency.

The second group of covariates included in the analysis are demographic characteristics of countries. We control for the size of the country, as captured by the number of its population, POPULATION SIZE (e.g., Fredriksson and Wollscheid, 2014). Additionally we control for the share of immigrants in the total population, IMMIGRANT % (averaging at 8.2% in the sample) as a measure of ethnic diversity. Previous research has highlighted the difficulty in agreeing on public goods and policies in diverse societies (e.g., Easterly and Levine, 1997; Alesina et al., 1999). Accounting for ethnic diversity is particularly important in our context, given our interest in isolating the effect of language from other confounders, and including the immigrant share of the population to that end appears to be appropriate. Furthermore, the share of population of 65 or more years of age, POPULATION AGE 65+ % (averaging at 10.9% in the sample) is included as an additional demographic control. As Farzin and Bond (2006) argue, young people may have larger stakes in environmental quality, and therefore may have stronger demand for stringent environmental policies. On the other hand, older people may feel the environmentally induced health problems more directly, and thus may be more willing to extend support for such policies. Intergenerational environmental altruism and greater access to time and resources to support environmental initiatives may further contribute to higher demand for environmental policies by older people (Farzin and Bond, 2006).

The third group of covariates are measures for institutions. We control for the characteristics of the countries' political regimes based on polity score measure available from the Polity IV data set (Marshall et al., 2016). The polity score captures the regime authority spectrum on a 21-pont scale ranging from -10 (hereditary monarchy) to +10 (consolidated democracy), and is converted into three regime categories to distinguish between autocracies (-10 to -6), 10% in the sample, democracies (+6 to +10), 69% in the sample, and other regime types (Marshall et al., 2016). A strand of literature shows that democracies are more conducive to enactment of environmental regulations compared to autocracies (e.g., Murdoch and Sandler, 1997; Farzin and Bond, 2006). As an additional control, we include an indicator for LEFT GOVERNMENT, with its prevalence being 26.5% in the sample, based on information on the political orientation of the national leader's party available from Keefer (2012).[11] An implication that follows from a number of studies is that left-wing parties are more pro-environmental than their right-wing counterparts. (e.g., Neumayer, 2003, 2004).

Finally, dummies for continents are included throughout the analysis. Fourty-five percent of the countries in the sample are based on the European continent, followed by 22% country representation from Asia. Africa and South America contribute each 10% of the countries in the sample, while North American countries comprise 7%. The smallest share of countries in the sample, 4.4%, is in Oceania.

[Table 1 about here.]

Individual-level data. The data source for individual-level analysis of pro-environmental behaviour is the World Values Surveys, a collection of nationally represenattive, individual-level surveys conducted in nearly 100 countries (almost 90 percent of the world's population) containing rich information on a variety of attitudes and preferences as well as standard socio-economic and demographic characteristics of individuals. Six waves of the survey, with the latest covering the years 2010-2014 have been conducted since its inception in 1981-1984. Cross-country comparability, representativeness, richness and relevance of the data make WVS highly appropriate for the purposes of individual-level analysis in this study.[12]

The language FTR measure is linked to the language spoken at home by the individual. This information has been collected since wave 3 conducted in years 1995-1998. The FTR of the language spoken by individuals is linked to their pro-environmental behaviour, ENVIRONMENTAL ACTION, as captured by affirmative responses to a question on whether in

[11] According to the source for this data, the parties have been classified as left if their names reveal them to be communist, socialist, or social democratic or if the sources label them as left-wing (Beck et al., 2001).

[12] An alternative approach to individual-level analysis of the effect of language structures on economic outcomes of individuals is to study the behaviour of immigrants (e.g., Hicks et al., 2015; Gay et al., 2017) within a single immigrant-hosting country, applying an 'epidemiological approach' (see e.g. Gay et al., 2016 for a discussion). We were not able to identify a data source that would contain appropriate information on pro-environmental behaviours and languages spoken by individuals to allow for such study.

the preceding 12 months, 'out of concern for the environment', they have chosen household products that they think are better for the environment. Capturing individuals' willingness to incur short-term costs for the sake of future rewards, this measure is highly appropriate for understanding individual support for climate change policies adopted at national level. This question was asked in wave 3 of WVS conducted in years 1995-1998. The study therefore is restricted to this wave. Following Chen (2013), our analysis excludes first-generation immigrants to isolate the effect of differences in language from native-immigrant differences. We drop observations with missing outcome data, arriving at a baseline sample of 34,461 individuals in 35 countries.[13]

Table 2 provides the definitions and descriptive statistics for all variables used in the baseline analysis by language FTR. Eighty-seven percent of individuals in the sample speak a strong FTR language. The incidence of ENVIRONMENTAL ACTION is 62% among speakers of weak FTR languages and 41% among speakers of strong FTR languages suggesting a negative effect of STRONG FTR on pro-environmental action.

The individual-level analysis controls for standard observable demographic and socio-economic characteristics of individuals included in similar studies (e.g., Gelissen, 2007; Franzen and Meyer, 2010; Bechtel et al., 2016). The demographic controls include gender, age and family circumstances. Fourty-eight percent of individuals in the sample are male—a gender that has been linked to unecological attitudes (Blocker and Eckberg, 1997; Gelissen, 2007). We control for age, to account for associated differences in environmental preferences, as discussed above. In particular, it has been suggested that intergenerational environmental altruism, linked with older age, may contribute to pro-environmental behaviour (Farzin and Bond, 2006). Intergenerational altruism is also more likely to be observed among those with families and children—additional characteristics of individuals we control for. The average age in the sample is around 41 years old; sixty-five percent of individuals are married and only 26% of all individuals have no children. Furthermore, we account for standard socio-economic characteristics of individuals. These include educational attainment expected to be positively correlated with pro-environmental behaviour (e.g., Gelissen, 2007; Franzen and Meyer, 2010). Primary and secondary school attainment comprise 21% and 30% of the sample, with the remaining 49% having tertiary education. We further control for individuals'

[13] The countries in the sample include: Albania, Azerbaijan, Australia, Armenia, Bosnia & Herzegovina, Bulgaria, Belarus, Chile, China, Czech Republic, Estonia, Finland, Georgia, Germany, India, Latvia, Lithuania, Macedonia, Mexico, Montenegro, New Zealand, Nigeria, Peru, Puerto Rico, Romania, Russian Federation, Serbia, Slovak Republic, South Africa, Spain, Sweden, Taiwan, United States, Uruguay, Venezuela.

employment status (54% prevalence in the sample) and income, captured in deciles, both expected to result in increased propensity for environmental action (e.g., Franzen and Meyer, 2010; Bechtel et al., 2016).

[Table 2 about here.]

4. EMPIRICAL APPROACH

Our empirical analysis proceeds in several steps. First, we evaluate a baseline effect of language FTR on climate change policies across countries. We then extend it, by including additional variables that could be correlated with hitherto unexplained parts of climate change policies. Clearly, this approach cannot fully account for all confounding influences. Therefore we also assess the extent of the bias following the partial identification approach proposed by Oster (2016). Finally, we complement the cross-country analysis with an analysis of individual-level determinants of pro-environmental behaviour. The description of these steps follows.

Cross-country model. To establish the baseline relationship between language FTR and climate change policy of country i, we estimate variants of the following model using ordinary least squares (OLS):

$$CLIMI_i = X_i\alpha + \beta StrongFTR_i + \varepsilon_i \text{ for all } i = 1, ..., N. \tag{1}$$

where $StrongFTR_i$ is an indicator of strong-FTR language spoken in the country, X_i is a vector of controls for economic, demographic, institutional and geographic characteristics of countries defined in section 3, and ε_i is a disturbance term.

Estimating the effect of language FTR on climate change policies requires that it is exogenously determined and uncorrelated with the error term in (1). However, this is unlikely to hold due to unobserved heterogeneity: both linguistic features and environmental policy outcomes may be the product of deeper, unobserved factors.[14]

Existing attempts to isolate the effect of linguistic measures on various economic outcomes have taken into account the historical and geographic relatedness of languages (e.g., Chen et al., 2015; Mavisakalyan, 2015; Roberts et al., 2015). We follow these approaches as a first step to mitigate the influence of unobserved heterogeneity, and include proxies for such relatedness. We sequentially introduce these proxies into the estimations of equation (1).

[14] We largely exclude the possibility of reverse causality. Tabellini (2008) points out: ‘As a classic example of network externalities, language evolves slowly over time. Linguistic innovations are costly because until they are widely adopted communications is more difficult.’ (p. 273). In support of this, Roberts et al. (2015) show that future-time reference variable, in particular, is very stable over time.

The intention in so doing is to reveal the extent to which the estimated effect of STRONG FTR on CLIMI captures the correlation between STRONG FTR and these variables that have been omitted from equation (1), by comparing the estimated parameters from baseline and comprehensive specifications.

Despite our efforts to control for relevant observable variables, we cannot rule out that some omitted variable is correlated with both STRONG FTR and CLIMI. To evaluate how concerned we should be about omitted variables, we exploit an approach proposed by Oster (2016), which builds on the work of Altonji et al. (2005) to use the amount of selection on the observables as a guide to the amount of selection on the unobservables. To that end, we evaluate the bias-adjusted coefficient derived by Oster (2016):

$$\beta^* \approx \tilde{\beta} - \delta[\dot{\beta} - \tilde{\beta}]\frac{R_{max} - \tilde{R}}{\tilde{R} - \dot{R}} \tag{2}$$

where $\dot{\beta}$ and $\dot{R}$ are the coefficient and R-squared from a parsimonious model including STRONG FTR but no other controls, and $\tilde{\beta}$ and $\tilde{R}$ are the coefficient and R-squared from a regression with STRONG FTR and a set of other controls. δ denotes the relative importance of observable relative to unobservable variables in generating bias while R_{max} is the R-squared from a hypothetical regression of CLIMI on all observable and unobservable variables.

Since δ and R_{max} are not known, Oster (2016) proposes a bounding approach: the estimated effect of STRONG FTR should range from $\tilde{\beta}$ to β^* estimated under an assumtion of $\delta = 1$, i.e. observables and unobservables have the same explanatory power in CLIMI, and given values of $R_{max} \in [\tilde{R}, 1]$. We take two approaches to specifying plausible values for R_{max}. First, we assume $R_{max} = 0.90$ which is sensible for a cross sectional sample that potentially has considerable noise in the outcome variable. Second, we follow Oster (2016) in setting $R_{max} = min\{1.3\tilde{R}, 1\}$.[15] Estimated coefficients can be considered as robust if the identified set, $[\tilde{\beta}, \beta^*]$ excludes zero. Furthermore, following Oster (2016) we also calculate the value of δ that would be needed to explain away the entire causal effect of STRONG FTR on CLIMI. Values of $\delta > 1$ suggest that the results are robust, i.e. the unobservables would have to be more important than the observables in explaining CLIMI.

[15] Oster (2016) tests the robustness of treatment parameters from ransomized control studies published in reputable economics journals from 2008-2013 and finds that using $R_{max} = 1.3\tilde{R}$ reproduces 90% of randomized results.

Individual-level model. To establish the effect of STRONG FTR at the individual level, we estimate variants of a model of propensity for ENVIRONMENTAL ACTION, EA^*_{ij} for an individual j in country l of the following form:

$$EA^*_{jl} = K_{jl}\gamma + \zeta StrongFTR_{jl} + \omega_{jl} \text{ for all } j = 1, ..., M; l = 1, ..., P. \tag{3}$$

where $StrongFTR_{jl}$ is the indicator of a strong FTR language, K_{jl} is a vector of controls for gender, age, family status, education, employment and income characteristics and ω_{jl} is a disturbance term. Observed environmental action EA_{jl} is assumed to relate to latent propensity through the criterion $EA_{jl} = 1(EA^*_{jl} \geq 0)$, which under an assumption of normality for ω_{jl} gives rise to the standard probit model of the form:

$$Pr(EA_{jl} = 1|K_{jl}, StrongFTR_{jl}) = \Phi(K_{jl}\gamma + \zeta StrongFTR_{jl}) \tag{4}$$

with marginal effects of STRONG FTR derived from the estimated model thus:

$$\frac{\partial Pr(EA_{jl} = 1|K_{jl}, StrongFTR_{jl})}{\partial StrongFTR_{jl}} = \zeta\phi(K_{jl}\gamma + \zeta StrongFTR_{jl}). \tag{5}$$

Marginal effects such as those described in (5) can be evaluated either at the sample means or for specified values of each explanatory variable.

5. RESULTS

Cross-country results.

Baseline results. The OLS estimates of the effect of STRONG FTR on our baseline measure of climate change policies, CLIMI, given in equation (1) are presented in Table 3. The specification reported in column (1) excludes other controls. Consistent with the descriptive statistics reported in Table 1, the estimates identify a negative relationship between STRONG FTR and CLIMI. Compared to countries with a WEAK FTR majority language, stringency of climate change policies, as captured through CLIMI, is 0.15 points lower in STRONG FTR majority language countries.

Next, we examine the relationship between STRONG FTR and CLIMI controlling for economic characteristics of countries (column (2)). The magnitude of the effect of STRONG FTR is smaller, however it preserved its significance. As expected, GDP PER CAPITA is positively correlated with CLIMI. Conversely, OPENNESS is negatively correlated with CLIMI, possibly reflecting the lack of willingness to commit to stringent environmental policies by exporting countries whose interests may be threatened by such policies. This variable, however, loses its significance once other characteristics of countries are controlled for in columns (3)-(6). Meanwhile, we estimate a significant positive coefficient on MANUFACTURING %, a measure that potentially captures the pollution-intensity of economies.

We further control for demographic characteristics of countries. The results reported in column (3) demonstrate that the significance of the estimated coefficient on STRONG FTR is robust to inclusion of this controls, although its magnitude is smaller. In the spirit of previous findings on the link between ethnic diversity and public policies (e.g., Easterly and Levine, 1997; Alesina et al., 1999) we show that the share of a country's immigrant population is negatively related to the stringency of its climate change policies. This potentially reflects the difficulties in agreeing on public policies in diverse communities. This effect does not persist, however, once additional controls are included in estimations reported in columns (4)-(6). We also find that the share of a country's elderly population, defined as those aged 65 and above, is positively correlated to the stringency of climate change policies. Among possible scenarios consistent with this finding, Farzin and Bond (2006) suggest that older people may feel the environmentally induced health problems more directly, and thus have a greater willingness to extend support for such policies.

In column (4) we control for institutional characteristics of countries. The estimated coefficient on STRONG FTR is hardly affected by this. Furthermore, we find that the stringency of climate change policies is higher in democracies—a result that is consistent with other findings in the literature (e.g., Murdoch and Sandler, 1997; Farzin and Bond, 2006). Autocracies and other non-democratic regimes do not appear to significantly differ in their climate change policy outcomes. The estimated coefficient on LEFT GOVERNMENT, while positive, is alsi insignificant.

Finally, in column (5) we control for economic, demographic and institutional characteristics of countries, and also include dummies for continents where the countries are based. Our finding on significant negative effect of STRONG FTR on CLIMI persists: we estimate that CLIMI is 0.06 points lower in countries with a STRONG FTR relative to a WEAK FTR majority language. In column (6) we evaluate the sensitivity of this finding to the potential presence of influential observations calculated based on DFbetas for STRONG FTR from baseline regression in column (5). We drop those observations for which $|\text{DFbeta}|>2/\sqrt{N}$ (Belsley et al., 1980). The results are even stronger compared to those in column (5) in the sense that the magnitude of the estimated coefficient on STRONG FTR is larger.

[Table 3 about here.]

Robustness checks. We have established a statistically significant negative relationship between STRONG FTR and CLIMI. An important question is whether language simply acts as a marker of unobserved characteristics, or whether language itself has a direct causal effect (Mavisakalyan and Weber, 2016). In Table 4, we explore this issue by including several additional controls (to allow for comparisons, column (1) repeats the estimate from baseline specification in column(5) of Table 3).

First, we run a placebo regression with a different linguistic feature which is irrelevant to the outcome of our study, as an additional control (e.g., Mavisakalyan, 2015). The feature we control for is LANGUAGE GENDER, a measure of grammatical gender intensity in a language that comes from Gay et al. (2017) (the study provides the details on how this measure is constructed). Reassuringly, the results presented in column (2) show that this linguistic feature is unrelated to CLIMI while the estimated significant negative effect on STRONG FTR persists.

Existing attempts to isolate the economic effect of linguistic measures have considered the relevance of historic origins of countries. These may potentially confound the estimated effect of STRONG FTR, as they may influence linguistic and cultural evolution (Galor et al., 2016), while also being relevant for policy outcomes either through affecting these directly or through other channels. To mitigate the effect of associated bias, we next introduce controls for the nine language families covering the languages in the sample. Roberts et al. (2015) highlight the significance of controlling for language families in studying the economic effects of linguistic structures. The estimate on STRONG FTR is robust to the inclusion of these controls (which in turn are jointly significant) (column 3).

Another possibility to consider is that linguistic features of countries are spatially correlated, i.e. that there is a concentration of linguistic features in certain areas. The estimated effect on STRONG FTR may then be due to correlated geographical and climatic factors. To address this concern, our baseline estimates include continent fixed effects. In column (4) we additionally control for countries' LANDLOCKED status and their LATITUDE—features that have been linked to countries' economic development (e.g., Hall and Jones, 1999) as well as having been used in previous attempts to isolate the effect of linguistic measures on various outcomes (e.g., Mavisakalyan, 2015). Our estimates on LANDLOCKED and LATITUDE are insignficant, while the significant negative effect of STRONG FTR remains.

Lastly, we control for institutional relatedness of countries in the sample by introducing controls for the origins of their legal systems. These have been included in other attempts to mitigate the effect of unobserved heterogeneity in studying the effect of linguistic measures on economic outcomes (e.g., Chen et al., 2015; Roberts et al., 2015). Furthermore, there is evidence to suggest that they might affect climate change policies (Fredriksson and Wollscheid, 2015). Most sources distinguish between two main secular legal traditions: common law and civil law, and several subtraditions—French, German, socialist, and Scandinavian—within civil law (Porta et al., 1998; La Porta et al., 2008). French civil law and common law are the most common internationally, and dummies for these legal systems are included in the regressions reported in column (5). The estimated coefficients on these dummies are insignficiant, while the effect of STRONG FTR is significant and sizeable.

[Table 4 about here.]

The above shows that the effect of STRONG FTR persists, even when proxies for unobserved heterogeneity are included. Still, unobserved heterogeneity can never be completely excluded. The standard approach to address the problem of omitted variable bias is to use an instrumental variable. In the absence of a persuasive instrument for STRONG FTR, we apply the partial identification approach proposed by Oster (2016). The results of this test are presented in Table 5.

In columns (2) and (4) we report the coefficient bounds $[\tilde{\beta}, \beta^*]$ for models with baseline and comprehensive lists of controls (reported in column (5) of Table 3 and column (5) of Table 4 respectively). The first bound $\tilde{\beta}$ comes from the specifications controling for all baseline/comprehensive observables. The second bound β^* is evaluated using equation (2) by setting $\delta = 1$ and applying two assumptions on the value of R_{max}. First, we assume $R_{max} = 0.90$. i.e. that the measurement error in CLIMI accounts for 10% of the variation therein (column (2)). Second, we apply the rule of thumb proposed by Oster (2016) in setting R_{max} equal to the minimum of one or to the R-squared from the regression controlling for all observables multiplied by a factor of 1.3 (column (4)). Furthermore, in columns (1) and (3) we report the corresponding estimates of δ that would be needed to explain away the entire causal effect of STRONG FTR on CLIMI.

None of the estimated bounds include 0. This suggests that at least part of the estimated effect on STRONG FTR is likely to be causal. Moreover, in all cases $\delta > 1$, i.e. the unobservables would have to be more important than the observables in explaining CLIMI. This provides further assurance that the results are robust to omitted variables.

[Table 5 about here.]

As a final robustness check of the cross-country results, we exploit alternative measures of dependent and independent variables. The results are reported in Table 6. For ease of comparisons, column (1) reports the results with the baseline measures of independent and dependent variables corresponding to the estimates with a comprehensive list of controls presented in column (5) of Table 4.

In the baseline models, STRONG FTR is assigned to a country's majority language. This potentially conceals the differences across linguistically distinct groups in diverse societies. To address this, we introduce a refinement in the assignment of STRONG FTR: we replace the STRONG FTR dummy with a continuous variable, STRONG FTR %, measuring the total population share speaking a STRONG FTR language. Data on language FTR for some of the minority languages is missing. Similar to the approach in Mavisakalyan (2015), we restrict the sample to countries where information on language FTR is available for at least 80% of the population, and additionally control for the share of the population with unknown language FTR. The results of the regression of CLIMI on this measure of language FTR and comprehensive list of controls are presented in column (2). The estimated coefficient on STRONG FTR % is negative and significant, albeit small in magnitude, while that on UNKNOWN FTR % is insignificant.

We also employ an alternative measure of dependent variable, Global Environmental Cooperation Index, GLOBAL, that comes from Esty et al. (2005) and has been used in published studies on the subject (e.g., Fredriksson and Neumayer, 2013, 2016). This index combines information on a countrys memberships in environmental intergovernmental organizations, contribution to international and bilateral funding of environmental projects and development aid, and participation in international environmental agreements. In columns (3) and (4) we present the results of regressions where GLOBAL is the dependent variable. This variable is available for more countries, which means that our sample sizes are larger. First, we employ the baseline measure of language FTR, STRONG FTR dummy as our independent variable of interest. The estimated coefficient on this measure, reported in column (3) is highly significant and negative. We obtain consistent results using the alternative measures of language FTR instead, as reported in column (4).

[Table 6 about here.]

Individual-level results. As a final step, we explore the consequences of speaking a STRONG FTR language at the individual level. We estimate probit models of the effect of STRONG FTR on the probability of taking an ENVIRONMENTAL ACTION given in equation (4). We present the results of this analysis in Table 7. For ease of interpretation the marginal effects such as those described in equation (5) are reported.

Starting with a parsimonious specification reported in column (1), we estimate a significant negative effect of the STRONG FTR language spoken at home by an individual on their probability of acting pro-environmentally. This is consistent with the descriptive statistics reported in Table 2. In column (2) we control for strandard demographic and socio-economic characteristics of individuals. We estimate a negative significant marginal effect on STRONG FTR, although its magnitude is smaller. Additionally, we find that males are less likely to act pro-environmentally; this is in line with other studies on this issue (e.g., Blocker and Eckberg, 1997; Gelissen, 2007). Conversely, and consistent with cross-country evidence reported in the previous sub-section, age is positively correlated with the probability of taking an ENVIRONMENTAL ACTION. We find that the probability of acting pro-environmentally is higher for individuals who don't have children, potentially due to additional financial constraints faced by these individuals, although this result is not robust to inclusion of additional controls in subsequent models. Socio-economic characteristics are important determinants of ENVIRONMENTAL ACTION. In particular, similar to others (e.g., Gelissen, 2007; Franzen and Meyer, 2010), we find a positive link between educational attainment and the probability of acting pro-environmentally. In column (3) we repeat this regression additionally including dummies for countries in the sample. The estimated marginal effect on STRONG FTR, while of considerably smaller magnitude, remains significant.

In columns (4)-(6) we expand the list of control variables in an effort to mitigate the possibility of omitted variable bias in the estimates of STRONG FTR. First, we control for TRUST, a dummy that takes 1 if the respondent believes that most people can be trusted and 0 otherwise. This is a potentially important determinant of individuals' willingness to engage in action in support of a collective need. Indeed, we estimate a positive significant marginal effect on TRUST. However, the estimate on STRONG FTR is largely unaffected by the inclusion of this variable (column (4)). In column (5) we report the results of the regression that includes two further controls. The first is a dummy for LEFT VIEWS, calculated based on the individual's self-positioning on a political scale. The second is IDEALIST, a dummy that takes 1 if the respondent has the view that less emphasis on money and material possessions in the future would be a good thing and 0 otherwise. As expected, we find that both LEFT VIEWS and IDEALIST are positively correlated with the probability of taking an ENVIRONMENTAL ACTION; the estimated negative marginal effect on STRONG FTR remains significant. The final group of additional predictors for ENVIRONMENTAL ACTION includes three variables. We control for individuals who are OPTIMIST, defined as a dummy to indivate those who believe the humanity has a bright future and 0 for those who believe otherwise. In addition we include a dummy for HIGH LOCUS OF CONTROL defined based on the individuals judgement on the degree of free choice and control they have over their lives. Our last variable is a dummy for EXISTENTIALIST, defined as those who often or sometimes think about meaning and purpose of life in contrast to those who do so rarely or never. We estimate strong positive marginal effects on HIGH LOCUS OF CONTROL and EXISTENTIALIST. The marginal effect on OPTIMIST, however, is indistinguishable from 0. This regression also confirms the negative significant effect of STRONG FTR on the probability of acting pro-environmentally. Moving from a WEAK FTR to a STRONG FTR language leads to a 8.2 percentage point decrease in the probability of taking an ENVIRONMENTAL ACTION. This is a sizeable effect. It is larger, for example, than the effect of moving from tertiary to secondary level of education or from male to female gender identity.

[Table 7 about here.]

6. CONCLUSION

Our findings support the idea that future tense marking in language affects speakers' future-oriented behaviour. The evidence presented here indicates that this effect includes pro-environmental action: at the country level, nations with weak-FTR language, i.e. that speak about the future as it were present, have more stringent environmental policies; at the individual level, speakers of weak-FTR languages are more willing to engage in costly pro-environmental actions. We have proposed that the mechanism behind both phenomena is the joint effect of two forces: temporal displacement and temporal discounting. First, by presenting future events in the same way as present ones, weak-FTR languages subjectively locate the future closer to the agent's *now*. Second, human agents have a general tendency to discount costs and rewards as a function of their perceived temporal distance. Together, these two factors influence agents' preference structure such that speakers of weak-FTR language care more about the future, and therefore do more to address the expected costs of climate change. We have described two possible ways in which this effect on individuals' intertemporal preferences translates into an effect at the level of nations' environmental policies.

Why assume that the effect of future tense marking is causal, rather than a mere symptom of deeper, underlying forces that influence both language and environmental behaviour? The case for the claim that future tense marking might indeed influence pro-environmental behaviour and policies is twofold. First, we show that the effect persists after controlling for geographic and historical relatedness of languages. Second, applying a partial identification approach also yields support for some causal effect. Furthermore, we demonstrate an influence of future tense marking based on individual-level analysis of pro-environmental behaviour.

Our results have potential implications for policy making. They show that pro-environemental governments or lobby groups face particular obstacles in countries with strong-FTR languages. It seems unrealistic to expect countries to engage in linguistic reforms with the aim of turning strong-FTR languages into weak-FTR language, at least in the short term. But there are other possible consequences. One may, for instance, conclude that environmental campaigns in strong-FTR countries should especially aim to counterbalance the linguistic effect of temporal displacement and portray the risks of climate change as real and urgent. Further, international organisations may decide that investing in environmental projects in weak-FTR countries (that are otherwise equal) has a better payoff, as their citizens will be more receptive for environmental concerns.

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List of Tables

Table 1: Cross-country descriptive statistics

Variables	Source	Mean (s.d.) WEAK FTR	STRONG FTR	All
STRONG FTR	Chen (2013)	0	1	0.765
				(0.427)
CLIMI	Steves et al. (2011)	0.517	0.376	0.410
		(0.253)	(0.205)	(0.224)
GDP PER CAPITA	World Bank (2016)	9.965	9.587	9.676
		(1.098)	(0.873)	(0.936)
OPENNESS	World Bank (2016)	0.943	0.834	0.860
		(0.312)	(0.438)	(0.412)
MANUFACTURING	World Bank (2016)	15.963	15.564	15.658
		(6.079)	(5.164)	(5.348)
POPULATION SIZE	World Bank (2016)	15.853	16.558	16.392
		(1.763)	(1.560)	(1.625)
IMMIGRANT %	World Bank (2016)	8.647	8.122	8.246
		(7.143)	(10.128)	(9.463)
POPULATION AGE 65+ %	World Bank (2016)	12.816	10.372	10.947
		(6.513)	(5.103)	(5.514)
AUTOCRACY	Marshall et al. (2016)	0.000	0.135	0.103
		(0.000)	(0.345)	(0.306)
DEMOCRACY	Marshall et al. (2016)	0.750	0.673	0.691
		(0.447)	(0.474)	(0.465)
OTHER REGIME	Marshall et al. (2016)	0.25	0.192	0.205
		(0.447)	(0.397)	(0.407)
LEFT GOVERNMENT	Keefer (2012)	0.375	0.231	0.265
		(0.500)	(0.425)	(0.444)
CONTINENT AFRICA	World Bank (2016)	0.125	0.096	0.103
		(0.342)	(0.298)	(0.306)
CONTINENT ASIA	World Bank (2016)	0.188	0.231	0.221
		(0.403)	(0.425)	(0.418)
CONTINENT EUROPE	World Bank (2016)	0.625	0.404	0.456
		(0.500)	(0.495)	(0.502)
CONTINENT NORTH AMERICA	World Bank (2016)	0.000	0.096	0.074
		(0.000)	(0.298)	(0.263)
CONTINENT OCEANIA	World Bank (2016)	0.063	0.038	0.044
		(0.250)	(0.194)	(0.207)
CONTINENT SOUTH AMERICA	World Bank (2016)	0.000	0.135	0.103
		(0.000)	(0.345)	(0.306)
N		16	52	68

Note.— Standard deviations in parentheses. Variables are defined in section 3. The countries in the sample are listed in footnote 7.

Table 2: Individual-level descriptive statistics

Variables	Mean (s.d.)		
	Weak FTR	Strong FTR	All
Strong FTR	0	1	0.869
			(0.338)
Environmental action	0.617	0.411	0.438
	(0.486)	(0.492)	(0.496)
Male	0.500	0.477	0.480
	(0.500)	(0.499)	(0.500)
Age	40.840	40.990	40.970
	(14.920)	(15.980)	(15.850)
Married	0.721	0.643	0.653
	(0.448)	(0.479)	(0.476)
No children	0.252	0.260	0.259
	(0.434)	(0.439)	(0.438)
Primary	0.286	0.196	0.208
	(0.452)	(0.397)	(0.406)
Secondary	0.284	0.307	0.304
	(0.451)	(0.461)	(0.460)
Tertiary	0.430	0.497	0.488
	(0.495)	(0.500)	(0.500)
Employed	0.692	0.514	0.537
	(0.462)	(0.500)	(0.499)
Income decile 1	0.077	0.127	0.121
	(0.268)	(0.333)	(0.326)
Income decile 2	0.105	0.174	0.165
	(0.307)	(0.379)	(0.371)
Income decile 3	0.136	0.151	0.149
	(0.343)	(0.358)	(0.356)
Income decile 4	0.149	0.129	0.132
	(0.356)	(0.335)	(0.338)
Income decile 5	0.169	0.114	0.121
	(0.375)	(0.317)	(0.326)
Income decile 6	0.123	0.084	0.089
	(0.329)	(0.278)	(0.285)
Income decile 7	0.094	0.074	0.077
	(0.292)	(0.262)	(0.267)
Income decile 8	0.063	0.062	0.062
	(0.243)	(0.240)	(0.241)
Income decile 9	0.038	0.046	0.045
	(0.190)	(0.209)	(0.207)
Income decile 10	0.046	0.038	0.039
	(0.208)	(0.192)	(0.194)
N	4,528	29,933	34,461

Note.— Standard deviations in parentheses. Variables are defined in section 3. Source: World Values Survey Wave 3 (1995-1998). The sample is restricted to non-immigrants. Thirty-five countries listed in footnote 13 are included.

Table 3: Baseline cross-country regressions — OLS coefficients

Control variables	All	All	All	All	All	No outliers
	(1)	(2)	(3)	(4)	(5)	(6)
STRONG FTR	-0.146**	-0.097**	-0.076**	-0.082**	-0.062*	-0.098***
	(0.068)	(0.039)	(0.034)	(0.034)	(0.035)	(0.036)
GDP PER CAPITA		0.132***	0.108***	0.071**	0.079**	0.060*
		(0.025)	(0.031)	(0.032)	(0.032)	(0.031)
OPENNESS		-0.095**	-0.064	-0.017	-0.061	-0.062
		(0.042)	(0.059)	(0.054)	(0.059)	(0.056)
MANUFACTURING %		0.012***	0.009**	0.006*	0.008**	0.009**
		(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
POPULATION SIZE			0.003	0.001	-0.003	-0.001
			(0.016)	(0.017)	(0.018)	(0.018)
IMMIGRANT %			-0.005**	-0.003	-0.003	-0.002
			(0.002)	(0.002)	(0.002)	(0.002)
POPULATION AGE 65+ %			0.013***	0.010**	0.003	0.003
			(0.005)	(0.004)	(0.006)	(0.006)
AUTOCRACY				0.047	0.053	0.052
				(0.069)	(0.076)	(0.073)
DEMOCRACY				0.190***	0.219***	0.227***
				(0.054)	(0.060)	(0.059)
LEFT GOVERNMENT				0.010	0.028	0.022
				(0.046)	(0.051)	(0.053)
Constant	0.517***	-0.894***	-0.803**	-0.540	-0.466	-0.305
	(0.062)	(0.216)	(0.383)	(0.398)	(0.402)	(0.398)
Continents	No	No	No	No	Yes	Yes
R^2	0.075	0.537	0.647	0.722	0.748	0.755
N	70	68	68	68	68	64

Note.— Dependent variable is CLIMI. Columns (1)-(5) report the results based on the full sample. Column (6) reports the results in a sample where outliers are removed; these are identified by predicting DFbetas for STRONG FTR from the full sample regression and then dropping those observations for which $|\text{DFbeta}|>2/\sqrt{N}$. *Denotes significance at 10 percent; **at 5 percent; ***at 1 percent levels.

Table 4: Cross-country regressions with additional controls—OLS coefficients

Control variables	(1)	(2)	(3)	(4)	(5)
STRONG FTR	-0.062*	-0.076**	-0.095*	-0.086*	-0.112*
	(0.035)	(0.036)	(0.050)	(0.049)	(0.061)
LANGUAGE GENDER		0.018	0.031	0.028	0.026
		(0.014)	(0.025)	(0.029)	(0.029)
LANDLOCKED				-0.043	-0.030
				(0.050)	(0.060)
LATITUDE				0.024	0.024
				(0.216)	(0.248)
COMMON LAW					0.073
					(0.123)
FRENCH CIVIL LAW					0.058
					(0.072)
Constant	-0.466	-0.523	-0.647	-0.383	-0.014
	(0.402)	(0.417)	(0.444)	(0.439)	(0.550)
Language families	No	No	Yes	Yes	Yes
Baseline controls	Yes	Yes	Yes	Yes	Yes
R^2	0.748	0.755	0.804	0.822	0.827
N	68	68	65	64	64

Note.— Dependent variable is CLIMI. *Denotes significance at 10 percent; **at 5 percent; ***at 1 percent levels.

Table 5: Test of robustness of cross-country results to omitted variables

Specification	$\delta_{R_{max}=0.90}$	$\left[\tilde{\beta}, \beta^*_{(R_{max}=0.90,\delta=1)}\right]$	$\delta_{R_{max}=min\{1.3\tilde{R},1\}}$	$\left[\tilde{\beta}, \beta^*_{\left(R_{max}=min\{1.3\tilde{R},1\},\delta=1\right)}\right]$
	(1)	(2)	(3)	(4)
Baseline Control	2.501	$[-0.062, -0.040]$	1.614	$[-0.062, -0.043]$
Comprehensive Controls	2.058	$[-0.112, -0.075]$	1.016	$[-0.112, -0.003]$

Note.— δ indicates the value of proportional selection of unobservables to observables assuming the maximum value of theoretical R^2 is R_{max}. The coefficient bounds are calculated assuming the unobservables are as important as the observables in explaining the outcome variable (i.e. $\delta = 1$).

Table 6: Cross-country regressions with alternative measures of independent and dependent variables — OLS coefficients

Control variables	(1)	(2)	(3)	(4)
STRONG FTR	-0.112*		-0.982***	
	(0.061)		(0.286)	
STRONG FTR %		-0.001*		-0.013***
		(0.001)		(0.004)
UNKNOWN FTR %		0.006		-0.020
		(0.005)		(0.018)
Constant	-0.014	-0.105	-4.085*	-3.207
	(0.550)	(0.719)	(2.073)	(2.819)
Baseline controls	Yes	Yes	Yes	Yes
Additional controls	Yes	Yes	Yes	Yes
R^2	0.827	0.825	0.609	0.654
N	64	58	76	62

Note.—Dependent variable is CLIMI in columns (1) and (2), and GLOBAL, a measure of global environmental cooperation, in columns (3) and (4). STRONG FTR % is the share of population speaking a language with FTR. UNKNOWN FTR % is the share of population speaking a language with missing FTR data. The regressions in columns (2) and (4) are restricted to countries with UNKNOWN FTR % ≤ 20. *Denotes significance at 10 percent; **at 5 percent; ***at 1 percent levels.

Table 7: Individual regressions with baseline and additional controls — Probit marginal effects

Control variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)
STRONG FTR	-0.206**	-0.197**	-0.089***	-0.086***	-0.083**	-0.082**	-0.139***
	(0.0927)	(0.089)	(0.027)	(0.029)	(0.032)	(0.034)	(0.030)
MALE		-0.086***	-0.074***	-0.075***	-0.075***	-0.074***	-0.074***
		(0.014)	(0.007)	(0.007)	(0.008)	(0.007)	(0.007)
AGE		0.005*	0.007***	0.007***	0.007***	0.007***	0.007***
		(0.003)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
MARRIED		0.008	0.024***	0.028***	0.028***	0.029***	0.027***
		(0.012)	(0.007)	(0.008)	(0.008)	(0.008)	(0.008)
NO CHILDREN		0.036***	0.016**	0.014*	0.014*	0.005	0.004
		(0.011)	(0.007)	(0.007)	(0.007)	(0.008)	(0.008)
PRIMARY		-0.118**	-0.140***	-0.141***	-0.140***	-0.134***	-0.128***
		(0.046)	(0.012)	(0.012)	(0.012)	(0.012)	(0.010)
SECONDARY		-0.040	-0.059***	-0.058***	-0.057***	-0.052***	-0.050***
		(0.025)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)
EMPLOYED		0.079	0.024***	0.021***	0.021***	0.017***	0.019***
		(0.048)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
TRUST				0.031***	0.030***	0.035***	0.036***
				(0.010)	(0.010)	(0.010)	(0.010)
LEFT VIEWS					0.027**	0.027**	0.031***
					(0.012)	(0.013)	(0.012)
IDEALIST					0.022*	0.021*	0.018*
					(0.012)	(0.012)	(0.011)
OPTIMIST						0.000	0.005
						(0.012)	(0.010)
HIGH LOCUS OF CONTROL						0.049***	0.047***
						(0.013)	(0.012)
EXISTENTIALIST						0.093***	0.092***
						(0.009)	(0.009)
Income deciles	No	Yes	Yes	Yes	Yes	Yes	Yes
Countries	No	No	Yes	Yes	Yes	Yes	Yes
Language families	No	No	No	No	No	No	Yes
Pseudo R^2	0.014	0.046	0.178	0.177	0.178	0.180	0.183
N	34,461	34,461	34,461	33,087	33,087	28,084	28,080

Note.— Dependent variable is ENVIRONMENTAL ACTION. *Denotes significance at 10 percent; **at 5 percent; ***at 1 percent levels.

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