Economics Bulletin

Volume 41, Issue 3

The impact of environmental economics class on college students` future temperature expectations

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Abstract

This paper explores how college students` expectations for future temperatures change after taking an environmental economics class. As an empirical examination, survey data was collected from two groups of students, students who are taking environmental economics course and students who are not. I obtain regional temperature expectations initially from both groups. By the end of the semester, I obtain temperature predictions once more. Only the group of participants who are taking environment-related courses update their temperature predictions. Learning economic information on climate change shifts the mean of future temperature predictions up by 2 degrees Fahrenheit. The survey participants who went through formal training on climate change have about 3.6% higher prediction than participants with similar backgrounds who did not go through this learning experience. This suggests that climate change education is effective in changing perceptions.

Citation: Onur Sapci, (2021) "The impact of environmental economics class on college students` future temperature expectations", *Economics Bulletin*, Vol. 41 No. 3 pp. 1887-1897
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Submitted: March 29, 2021. **Published:** September 17, 2021.

1. Introduction

This paper explores how college students` expectations for future temperatures change when economic information is introduced into the climate change debate. More specifically, "how does learning scientific and economic information about climate change affect students` future temperature expectations?" In order to analyze the impact of education on students` beliefs about this topic, I conduct the following empirical examination. A control group consisting of students who have not taken environment-related courses yet are shown information about climate change and are asked to predict the temperature in 2040. After a semester, the control group is shown more precise information and is again asked to predict. Similarly, the treatment group of students who will be taking environment-related courses during the semester predict before and after the class. Thus, the experiment measures the impact of taking environment-related classes on how expectations change in response to new information.

According to the survey results, learning economic information on climate change shifts the mean predictions up by 2 degrees Fahrenheit and survey participants who went through formal training on climate change have about 3.6% higher prediction than participants with similar backgrounds who did not go through this learning experience. Individuals modify their beliefs after having received formal education. The survey participants are shown less precise information that is intended to create uncertainty about climate change in the beginning of the semester. The participants are exposed to more precise information at the end of the semester. But only the group of participants who have taken environment-related courses (treatment group) updated their temperature predictions. This result suggests that it does not matter how information is framed at a given instant but the intensity and duration of exposure to scientific education matter.

How people update their prior expectations after learning new information in the context of climate change has been studied in the literature. (Few examples include Kotchen and Costello 2018, Chambers and Melkonyan 2017, Levin *et al*. 2016, Sapci *et al*. 2016, Van Wijnbergen and Willems 2015, Kelly and Tan 2015, Deryugina 2013, Webster *et al*. 2008, Charness *et al*. 2007, Charness and Levin 2005, Newbold and Marten 2004, Kelly and Kolstad 1999).

More relevant to this research, a few papers previously looked at the impact of undergraduate environmental studies classes on the environmental values of students (Kuo and Jackson 2014, Woodworth *et al*. 2011, Cordero *et al*. 2008, Anderson *et al*. 2007, McMillan *et al*. 2004), but to the best of my knowledge, this study is among the first investigation within economics students on environmental economics classes.

2. Empirical Design

I administer a survey of economics students who have taken Environmental Economics classes from 2019 to 2020 (including summer sessions) in a large Midwestern U.S. university. First, I conduct a survey at the beginning of the semester to obtain their future temperature predictions. These are the prior expectations. I obtain their best guesses once more after they have learned scientific and economic facts about climate change in the same semester, about a month later than the priors. These are the posterior expectations.

The details of the empirical design are as follows. First, I show them a figure (Figure 1) that shows average yearly temperatures in their city since 1955 to today at the beginning of the semester. I also show Table 1 to the participants together with Figure 1.

Students have different backgrounds and beliefs. Most Americans get their climate change information from the news media (Dagnes 2010) and depending on the media`s political orientation, climate change is presented quite differently. Public opinion is polarized on the existence or importance of climate change (Drummond and Fischhoff 2017, Bohr 2014, Hamilton 2011). The survey at the beginning of the semester tries not to make strong statements on the climate change issue in order not to distort prior beliefs. It provides basic definitions and for and against views on the issue. The first survey (Appendix Figure 1) provides a very general assessment of climate change risk as well as economic costs of mitigation. The survey after climate change topic is covered (Appendix Figure 2) tries to simulate the post-education period by directly citing the literature and providing clearer assessment. The second stage (Appendix Figure 2) is done after participants learnt about the science and economics behind climate change in their course work. The second survey references technical aspects of climate change economics and directly cites information that are covered in class (topics like Stern vs Nordhaus debate, damage estimations, emission reduction policies, rapid cuts vs steady cuts in emissions to hold global warming to the low end of 4 degrees F, The DICE (Dynamic Integrated Climate-Economy) model). Consequently, the students who are taking the environmental economics class should immediately recognize the direct references. I ask participants to identify their best guess temperature average in their city in the year of 2040.

Figure 1: Average Yearly Temperatures and the trend

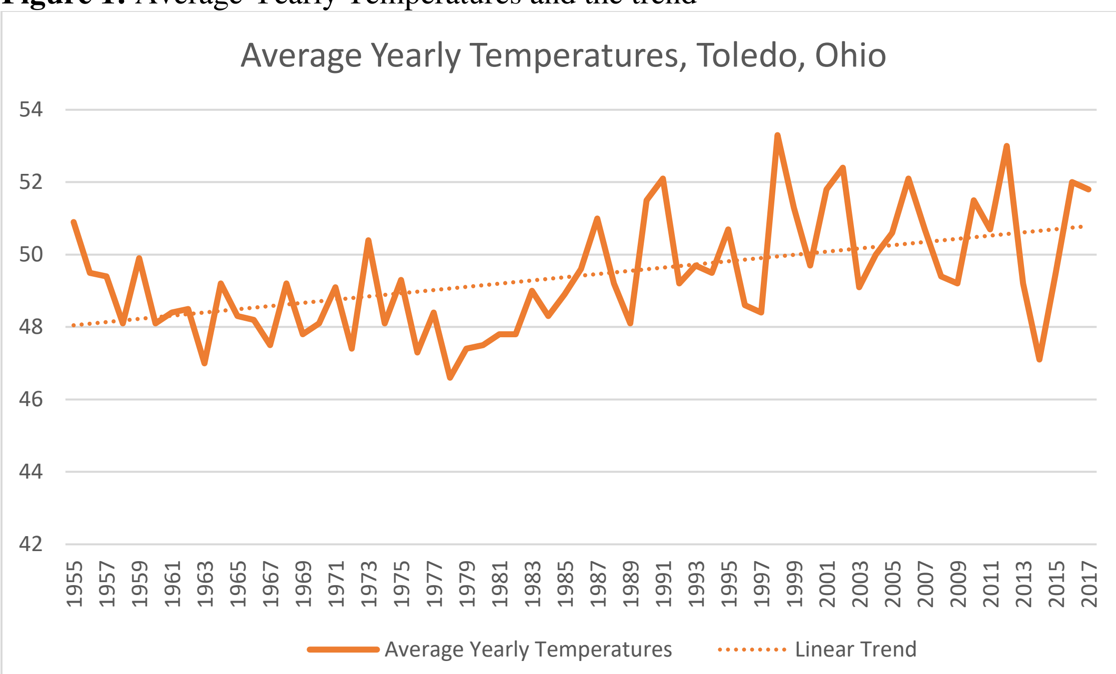


Table 1: Temperature Data between 1955 and 2017

Average	49.4
Maximum	53.3
Minimum	45.6
Std. Dev.	1.60

This first group is the treatment group (N=162), the students who have taken Environmental Economics class, the second group is the control group (N=165). The control group consists of students who volunteer and have not taken any environment related courses yet in college but planning to take at least one in later semesters. These students are mostly from principles of microeconomics and macroeconomics, intermediate microeconomics, intermediate macroeconomics, econometrics I and econometrics II courses. It should be noted that almost all of these students will eventually take environmental economics course later in their course work except the ones who might drop or change majors, and the reason that they did not take any this course yet is that they are in an earlier semester in college not that they delay taking it. In summary, I have two groups and two observation periods, and first group is exposed to economics education on climate change while the other one is not. I estimate the expected temperature (T) by using the following difference-in-difference equation,

$$Log(T_i) = \beta_0 + \beta_1(dummy1)_i + \beta_2(dummy2)_i + \beta_3(dummy1 * dummy2)_i + \beta_4\eta_i + \varepsilon_i \quad (1)$$

Dummy 1 equals to 1 if the observation is from the treatment group. Dummy 2 is 1 if the observation is a posterior expectation (expectation after climate education). The interaction variable (dummy1*dummy2) is the coefficient of interest which shows if scientific training triggers an updating process.

Table 2: Descriptive Statistics

Variable	Describtion	Mean	Std. Dev.
T^n_{treat}	Prior subjective mean temp. in the treatment group (Temperature prediction at the beginning of the semester)	50.7	2.9
T^v_{treat}	Posterior subjective mean temp. in the treatment group (Temperature prediction at the end of the semester)	52.3	2.4
T^n_{cont}	Prior subjective mean temp. in the control group (Temperature prediction at the beginning of the semester)	50.9	3.2
T^v_{cont}	Posterior subjective mean temp. in the control group (Temperature prediction at the end of the semester)	50.8	2.8
$T_{regional}$	Regional temperature trend between 1950-2017	0.044	0.009
Age	Age of Respondents	20.1	1.6
Female	Gender (Male=0, Female=1)	0.40	
Infor	I am well informed about climate change issues (Str Disagree=1, Str. Agree =5)	3.8	
Politic	Political Views (Democrat=1, Republican=2, Independent, Other)	1.3	
Intens	Intensity of political beliefs (Very strong=1, Very Weak=5)	3.0	
School	How many years of schooling completed	12	
Year	What year are you in college (Freshman=1, Fifth year and above=5)	2.8	
Science	How many science classes have you taken?	4.1	
Major	What is your college major?		
Income	What is your parents' income? (category)	3.1	
Mobility	Twenty years from now, I expect to live in the same region (NE) as I do now (Str Disagree=1, Str. Agree =5)	3.2	

η_i is the set of control variables, these are age, gender, years in college, GPA, information level about climate change, political views, and plans to live in the same region (North East United States). Environmental economics class is offered only in the Spring and Summer sessions, about 20% of the data was obtained in the online summer sessions. The survey was administered in the classroom (or in online meetings) to students who regularly attend classes. I include a dummy variable for the observations that are collected during summer term. Table 2 presents the descriptive statistics about the main variables and control variables.

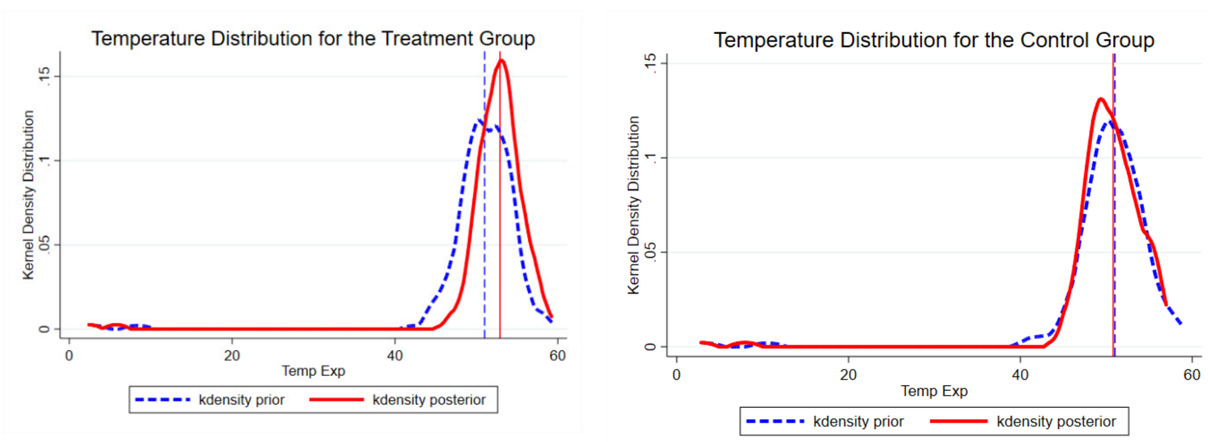
A basic *t*-test for mean comparison shows that the prior subjective mean in the control group is not statistically different than the prior subjective mean in the treatment group. Furthermore, the prior and posterior means for the control group are not statistically different, only the prior and posterior means for the treatment group are statistically significant. This *t*-test for mean comparison shows that there is no difference between the control group and treatment group in regards to prior T expectation. Furthermore, I separate all demographic info by treated/control to do a *t*-test to see if they are significantly different. The only significant difference is age, where the treatment group is 1 year older.

In the next section, I show the kernel distributions and do a regression analysis that includes the control variables for a more complete analysis.

3. Results

Figure 2 shows the kernel distribution of temperature predictions of the control and treatment groups. From the distribution of the temperature expectations, it is clear that the treatment group assigns a larger value after climate change topic is covered. We do not observe this difference in the control group. Interestingly, prior distributions both in the control and treatment groups are very similar; however, posterior distributions differ in these groups.

Figure 2: Kernel Density Distribution of Temperature Expectations for Control and Treatment Groups



Notes: In the left side picture, red line (solid line) shows the temperature expectations distribution after climate education, blue line (dashed line) shows the temperature expectations distribution at the beginning of the semester for the treatment group (for students who are taking climate related courses). In the right side picture, dashed line is for the beginning of the semester from the control group (students who have not taken climate related classes yet) and solid line is the posterior distribution of the control group. The vertical lines represent the mean of each distribution.

I use the non-parametric Wilcoxon-Mann-Whitney test to compare distributions in Figure 2. First, when I compare the prior predictions (the first survey) in the treatment group to prior predictions in the control group, the test result suggests that prior distributions (predictions in the first survey) in the two groups are statistically equal. When I compare the posterior distributions (predictions in the second survey), the test predicts that the populations are statistically not equal. Finally, when I compare prior predictions in the treatment group (students who are taking an environmental economics class) to the posterior predictions in the same group, the test result suggests that prior distributions are statistically different than posterior distributions in the treatment group. However, when I compare prior predictions to the posterior predictions for the control group, I find that the prior and posterior distributions are statistically equal in the control group. According to Figure 2, the new information shifts the mean belief by 2 degrees in the treatment group but the mean prediction does not change in the control group[1].

After this, I present the main estimation results in Table 3, which are the coefficients of equation (1). Table 3 demonstrates that the future temperature predictions increase by 3.6% on average for participants who went through a scientific training.[2] The two groups are similar in many observable characteristics and the mean of prior temperature predictions are similar. They take a second survey in a relatively short time in the middle of the same semester and the second group revises the mean predictions up after learning economics information on climate change and its potential consequences. We observe a shift in the mean temperature only in the group of students who are taking environmental economics class. The students in the control group do not change their expectations in the two surveys. This suggests that learning new materials lead them to revise their expectations. As a robustness check, I compare the results with different prior distributions and parameters to the original estimation with Gaussian Priors. For instance, to assume non-informative priors, I estimate the model with an inverse gamma distribution for priors. When I use inverse gamma priors, the estimated coefficients do not change substantially from Table 3. For a further robustness check, I analyze the effect of outliers on estimations, however as all survey responses are within the two standard deviations of the group mean, I do not find a significant impact of outliers on estimation results. Gender and political views are the only significant control variables. Looking at the coefficients, gender plays a more economically significant impact on future expectations, where females predict relatively hotter climate in the future. Even though very few control variables are significant, it is interesting to consider the characteristics of people whose assessment are changed more. People with more liberal political views change their assessment relatively more compared to people that are more conservative when receiving this kind of information. Participants that are more conservative expect relatively smaller increases in the temperatures. Other control variables are not statistically significant, which may be due to the lower variation in these variables.

[1] I obtained the same result when I regress temperature predictions from the second survey on temperature predictions from the first survey by including control variables. The estimated intercept coefficient suggests that the mean prediction is increased by 2 degrees and it is statistically significant at the 1% level.

[2] Bayesian estimation is the linear Bayesian regression. The presented results are obtained through Random-walk Metropolis-Hastings sampling with Markov Chain Monte Carlo iterations. Bayesian standard errors are Monte Carlo standard errors. In line with the kernel distributions, Gaussian priors are used. In a sensitivity analysis, I find that the results are robust to using Gibbs sampling or using gamma priors. Efficiency is achieved in every case with acceptance rate of around 0.37 and small autocorrelation.

Table 3: Difference in Difference Estimation: Equation (1)

Dependent Var: Log (Ti)		
Regressors	Coefficients	
	Equation 1	
	OLS	Bayes
Interaction Variable	0.0342**	0.0361**
	(0.009)	(0.051)
Constant	2.321	−0.32
	(0.230)	(0.230)
Income	0.438	0.436
	(0.357)	(0.357)
Number of Science Classes	0.04	0.04
	(0.03)	(0.03)
Political View (1= less conservative)	−0.02**	−0.02**
	(0.008)	(0.008)
Intens	−0.301	−0.300
	(0.24)	(0.24)
Infor	0.004	0.004
	(0.04)	(0.04)
Gender (Female=1)	0.059**	0.059**
	0.001	0.001
Age	0.09	0.09
	(0.082)	(0.080)
Mobility	0.362	0.361
	(0.341)	(0.341)
GPA	0.04	0.04
	(0.03)	(0.03)
Year in College	−0.02	−0.02
	(0.8)	(0.8)
School	0.003	0.003
	(0.003)	(0.003)
Summer Session Dummy	0.04	0.04
	(0.03)	(0.03)
N	648	648
Prob > F	0.001	

Standard Errors in Parentheses.

**Statistical Significance at 1%

4. Discussion and Concluding Remarks

These results imply important public policy recommendations. Governmental efforts to strengthen climate education, awareness, training and public engagement in achieving the goal of limiting global temperature rise[3] are contingent on how information is provided. A simple paragraph or a short talk is not enough and only by examining the science more deeply will people respond and change expectations. This result has a policy conclusion in favor of climate education and advice for the news media to avoid one sentence statements ("the science says....") and dive more deeply into the topic.

An initial survey elicits participants` prior beliefs, and a subsequent survey elicits their posterior beliefs, after the classes have covered material related to climate change. Paper finds that after covering materials related to climate change, student predictions of future temperature changes in their area by 2040 rise by 2 degrees Fahrenheit.

In this set up, naturally people have some prior beliefs about climate change and future temperatures. In the first stage, people are exposed to noisy and somewhat conflicting information treatment, which includes both for and against broad views about the issue. Two conflicting views were presented in the first survey and that the information was more general, participants elicit their temperature predictions under this noisy information treatment. In the second stage, people are given more precise information treatment, and asked their temperature expectations.

According to survey results, learning under scientific information shifts the mean predictions by 2 degrees F. The survey participants who went through economic training on climate change have about 3.6% higher prediction than participants with similar backgrounds who did not go through learning experience. However, the participants in the treatment group sit in some semester-long environment-related classes before updating their prior prediction to a higher posterior prediction. The control group does not change initial prediction over the semester regardless of the framing of information in the surveys. This result suggests that tailored information campaigns can only be effective policy tools in achieving global climate policies, as long as the duration and intensity of exposure are strong.

The caveats of the paper are two-folds. It is natural to question if the control group was randomly assigned. Students that are more concerned about environmental issues might be more likely to take environmental courses earlier. However, given that the initial priors were very similar, this is unlikely, and all participants reveal that they either have taken or will take environment-related courses. Furthermore, descriptive statistics comparisons in two groups suggest that the control and treatment groups do not differ in any measurable way except one-year age difference between groups.

The second caveat is that there is about a month in between priors and posteriors (time required to finish climate change topics), and over this time period, both the treatment and control groups might be exposed to different climate information in the news. The implicit assumption is that the intertemporal preferences do not change much in this short period of time and control variables in the estimations are able to capture some aspects of this. Given these caveats, this paper

[3] United Nations Action for Climate Empowerment (ACE) recognizes the importance of climate change education, and public access to information, and asks parties to cooperate in taking appropriate measures in their June 2019 meeting in Bonn. This action will be considered for formal adoption at the upcoming UN Climate Change Conferences. (https://unfccc.int/news/governments-agree-to-strengthen-climate-education-awareness-and-public-engagement).

demonstrates the real-life situation in which people are subject to conflicting information and how the type of information they obtain can frame their opinions on scientific facts.

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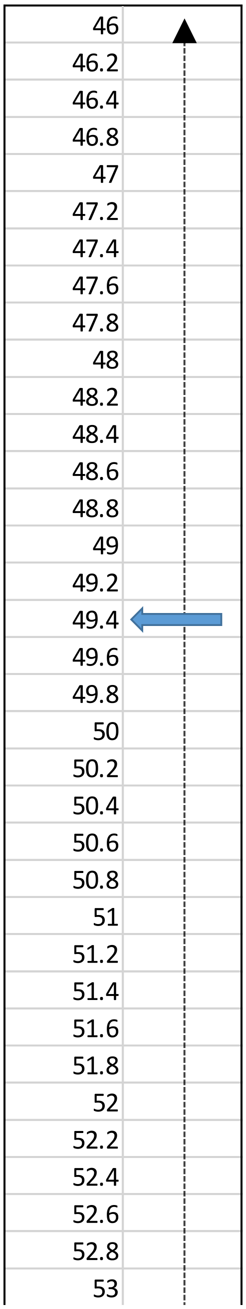
Appendix

Appendix Figure 1: Survey before climate education



The scientific data clearly shows that from 1955 to 2017, there was an increase of 2.4F in annual temperatures in your city. This means each year 0.04F over 63 years. Scientist argue that climate change is real and human driven. Their findings reflect global scientific consensus. Global warming poses catastrophic risks to humanity such as reductions in agricultural output due to rainfall, major changes in natural ecosystems, higher disease rates, sea level rise and many others.

This arrow shows the annual average temperature in your city in the last 63 years.

On the other hand, there are opponents to aggressive policies towards climate change. They claim that we just have to adapt to rising temperatures if climate change is real, the larger impact would be if we were forced to cut production in the present to reduce our greenhouse gas emissions. This would mean additional unemployment and reduced production, so all people, poor and rich, would suffer if we decreased our emissions of greenhouse gases. Also, there is so much fluctuation even in the last 5 decades (very short period of time considering the age of the earth) so we cannot be certain what factors human, non-human are contributing to this.

Appendix Figure 2: Survey after climate education

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Increases in average global temperatures are expected to be within the range of 0.5°F to 8.6°F by 2100, with a likely increase of at least 2.7°F for all scenarios except the one representing the most aggressive mitigation of greenhouse gas emissions. As we discussed in class, these projections are done with certain versions of the DICE model.

This arrow shows the annual average temperature in your city in the last 63 years.

Global warming would reduce global output of goods and services from 5% to 20% according to Stern (2006). Nordhaus (2013) thinks by 2100, the impacts would be closer to 3% of world output. Two researchers suggest two different policy prescriptions but both researchers recommend holding further global warming to the low end of 4 degrees F. Global warming more than 4 degrees F dramatically increases the probability of catastrophic outcomes (recall Weitzman). In all scenarios, benefits of climate protection exceed costs. 2015 and 2016 were the hottest years in record. The last decade was probably the hottest in the last several thousand years. There is a global consensus in the scientific community that global warming is human driven.