Final_Paper

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Introduction and Motivation

Climate change is undoubtedly a global problem, but this fact means it is also, in a way, a classic tragedy of the commons. No country wants to put itself at an economic disadvantage by restricting the use of cheap fossil fuels so all continue to emit, deteriorating the "commons" of the Earth's protective atmosphere. This can make it difficult to get citizens to identify with the problem and take responsibility; people will more likely act when something affects them individually. In this paper we want to explore this aspect: how much do people feel, consciously or unconsciously, the effects of green house gas emissions? More specifically, do emissions affect their reported health, well-being, or life satisfaction?

Theoretical Framework

Since the conventional theory on life satisfaction has largely been focusing on economic (income, unemployment, inflation) and social (health, demographics, education) determinants, an environmental component is missing from the standard theoretical framework (**???**). Therefore, the theoretical basis of the main hypothesis builds on both climate and subjective well-being literature.

In light with the rising pressure of climate change, the mankind has been facing twin challenges of expanding economic and development opportunities for the fast growing population, while also staying within the boundaries of the environmental constraints. During the onset of the climate discourse in the 1990s and 2000s, the global community labeled the twin challenges as the notion of "sustainable development" (**???**). Recently, the issue of reconciling development with natural resources adopted a fresh theoretical notion of "green growth", advocated by the major international organizations (World Bank, United National Environmental Protection, Organization for Economic Cooperation and Development) (Ibid). The strong green growth proponents argue that stringent environmental policies would have positive impact on economic growth even in the short-term, while their more moderate counterparts emphasize that the sound climate actions are necessary to undertake in order to preserve the world for the future generations, but also avoid devastating changes in the present world (Ibid).

Although the green growth theory does not explicitly juxtapose climate economics with the theory of life satisfaction, it recognizes "natural factor as a factor of production and its role in enhancing well-being" and points at the adverse effects of climate change and environmental degradation on the human progress (**???**). The OECD has lately added a group of socio-economic indicators to its scorecard of the green growth strategy in order to link it to the social goals, such as poverty reduction, social inequity and inclusion (**???**). Moreover, the OECD have initiated guidelines for measuring subjective well-being as a proxy of quality of life alongside other social and economic dimensions to have a potential framework for measuring the progress of green growth policies on individual happiness (Ibid). These developments give ground for the main hypothesis of the given research: "greener" performance reflected in lower GHG emissions and weaker environmental concerns will likely increase individual well-being due to the benefits of the green growth approach in the current climate situation.

Simultaneously, the traditional social outlook on life satisfaction justifies the inclusion of other variables (age, gender, employment, and family status) into the empirical model, as these individual-level characteristics play an inextricable part in one's quality of life and thus should be included as controls in regression analysis to avoid generating biases in the estimations (**???**). Furthermore, these socio-demographic factors may pose as life-changing events, which either potentially can permanently impact life satisfaction (ex.: divorce, unemployment due to acquirement of disability, etc.) (Ibid). This research papers anticipates that older age negatively affects life satisfaction, as older individuals tend to report worse health conditions and more unfortunate life events (ex.: death of a partner and relatives). There are empirical studies claiming U-shaped effect of age on happiness based on the Western experiences (???; ???; ???). Nevertheless, a number of other factors and cohort effects should be included in the model to observe robust U-shaped relationships. For the simplicity reasons, this research assumes negative linear relationship between age and happiness. While gender appears in the model for exploratory reasons, the anticipated effects of employment and family statuses are intuitively positive.

On the other hand, the inclusion of individual income as one of the economic factors is more contentious. Easterlin found a positive effect of individual income on life satisfaction, although with rapidly diminishing returns (???). However, the same study also established the "Easterlin Paradox", as on the aggregate national happiness over time was stable despite increasing GDP per capita. Therefore, a separate model is run on a reduced sample of solely employed respondents in order to test whether or not at the individual-level income plays a positive role.

Literature Review

In recent years, there has been a large body of empirical literature on the happiness of individuals and the effects of climate and pollution variables. In general, the findings highlight the importance of environmental conditions on individual's happiness. A significant share of the studies find a negative correlation between pollution or negative environmental conditions and overall life satisfaction, or happiness.

Welsch (2002) published an initial happiness-related study on how self-reported well-being fluctuates with different levels of prosperity and environmental quality. The study used cross-sectional data on 54 countries to illustrate how individuals are willing to calculate the trade-off between wealth and environmental conditions (Welsch 2002). The study found a negative effect of poor air quality on overall happiness of individuals, however was unable to control for heterogeneity across countries as the analysis was conducted on an aggregate level (Welsch 2002; Goetzke and Rave 2015). Welsch (2006) used a combined cross-section time-series framework to address this problem with annual data for 10 European countries from 1990-1997. By using this panel method, he was able to use country-fixed effects to eliminate problems of unobserved heterogeneity across countries. In this more robust study, Welsch (2006) finds that air pollution has a statistically significant function in predicting inter-temporal and inter-country differences in levels of happiness.

Rehdanz and Maddison (2008) used the SOEP (German Socio-Economic Panel) surveys to analyze the relationship between perceived noise and air pollution, and self-reported well-being in Germany. The evidence suggests that even when controlling for a range of variables such as demographic differences, economic status and neighborhood individualities, higher levels of noise and air pollution reduce overall levels of happiness (Rehdanz and Maddison 2008). Similarly, Brereton, Clinch, and Ferreira (2008) conducted a similar study in Ireland using data at the individual level and found that overall climate conditions had a statistically significant influence on individual happiness. The study found that proximity to waste facilities and transport routes was highly relevant in explaining the variation in happiness levels.

MacKerron and Mourato (2009) conducted a case study on London focusing on Nitrous Oxide pollutants, and the willingness of inhabitants to pay for various levels of air quality. The study collected pollutant concentrations in the immediate proximity to residents' homes, and found that both subjective perception of air quality and scientific measurements of air quality both had negative statistically significant impacts on self-reported happiness levels (MacKerron and Mourato 2009). Luechinger (2009) and Ferrer-i-Carbonell and Gowdy (2007) find similar results in their individual-data country-level analyses. Luechinger (2009) estimates the effect of SO2 concentration on life satisfaction in residents in Germany using pollution data and the SOEP data. In order to control for simultaneity between air quality, economic downturns, and declining industrial production, Luechinger (2009) uses the estimated improvement in air quality caused by mandated power plant scrubbers as an instrumental variable (IV). The study finds that IV-estimates produce larger negative statistically significant impacts of pollution on happiness. Ferrer-i-Carbonell and Gowdy (2007) study the relationship between well-being and individual environmental attitudes. The authors use a probit model to study the relationships with specific focus on ozone pollution and species extinction using the British Household Panel Survey and find a negative correlation of ozone pollution on individual's well being (Ferrer-i-Carbonell and Gowdy 2007). The study finds that the correlations are constant even when controlling for pollution conditions, engagement in outdoor activities and regional conditions.

In another study, Menz and Welsch (2010) further estimate the effect of air pollution on life satisfaction using 25 OECD countries and the World Database of Happiness between 1990 and 2004. The study finds that, using particulate matter concentration as a proxy for overall pollution levels, the correlation between overall happiness and pollution levels is negative. Further, Menz and Welsch (2010) find that the effects are greater in older and younger individuals, and less significant for middle-aged individuals.

Cuñado and Gracia (2013) use Spanish regions to further explore the relationship between pollution, climate and subjective happiness. The authors use the European Social Survey to provide information on individual well-being, and data on pollution and climate data from the regional ministries and agencies. By controlling for socio-economic variables that potentially affect happiness levels, Cuñado and Gracia (2013) find that there are significant regional differences in happiness levels which can be explained by the role of climate and pollution variables. The results illustrate that environmental variables better explain regional differences in happiness than socio-economic regional variables.

Most recently, Goetzke and Rave (2015) expand on the ideas of Van Praag and Baarsma (2005), MacKerron and Mourato (2009) and Ferreira and Moro (2010) to account for the endogeneity problem between perceived air pollution and happiness. The endogeneity inherent in this analysis is that individuals bothered by air pollution are less happy, but simultaneously that unhappy people are more disturbed by air pollution (Goetzke and Rave 2015). Using the German socio-economic panel data along with annual sulfur dioxide readings, Goetzke and Rave (2015) analyze the impact of air pollution on happiness in Germany based on both the subjective perceptions of pollution and the objectively measured environmental conditions. Using the IV-ordered probit model developed by Rivers and Vuong (1988), they find in controlling for simultaneity that perceived environmental conditions do not have a statistically significant effect on happiness (Goetzke and Rave 2015).

Hypotheses

Germany is a leader in protecting the environment while also having a long history as an industrial power and coal producer. One one hand, its energy transition (*Energiewende*) is considered one of the most ambitious climate policy projects in the world. On the other hand, it has struggled with appropriate incentives, a drop in oil prices—not to mention coal's continued role as a cheap and reliable fuel—and how to transform the transportation sector. Germany therefore still does emit large amounts of green house gases. We will look at green house gas emissions data by federal state (*Bundesland*) and compare that with life satisfaction data to examine our first hypothesis:

> *H1: Bundeslaender with higher emissions inversely affect reported levels of life satisfaction.*

On the other hand, it may not be the emissions themselves that affect people's life satisfaction. People who are more concerned about the environment would be more concerned with emissions and may feel less satisfied with life than those who are less concerned about the environment. Therefore our second hypothesis is:

> *H2: Reported individual concerns with the environment are, likewise, negatively reflected in the life satisfaction.*

Data

The individual-level data is provided by the German Socio-Economic Panel Data GSOEP conducted by the German Institute for Economic Research DIW. Due to confidentiality restrictions, DIW could only supply a shortened sample with prior specified variables in a *.dta* format. Therefore, the GSOEP dataset is stored on the local drives and GitHub Climate-Happiness Repository. The original GSOEP file is cleaned and transformed into a shorter dataset with the help of the Stata Do-File. The short dataset contains the information on the main satisfaction and personal characteristic variables: reported levels of life satisfaction (on a scale from 0 to 10), subjective concerns about the environment, age, gender, employment, family status, and state residence of a respondent. Detailed labels and descriptions of the variables are given in the GSOEP codebook. All GSOEP-related files are stored on the GitHub server.

The state-level data, on the other hand, is gathered from web-based sources: Statista.com, Environmental-Economic Accounting of the Bundeslaender UGRdL Agency for Renewable Agency of North Rhine-Westphalia AfEE, Federal Statistical Office and Statistical Offices of the Bundeslaender, and Laenderarbeitskreis.

A university subscription to *Statista.com* enabled access to historic state emissions per capita from 1990 to 2012 for most of the Bundeslaender, except North Rhine-Westphalia (NRW). Since the website allows data downloads only in *Excel* and provides no unique URLs for each of them, 15 individual files were downloaded manually on a local machine, while manipulations were conducted with the help of R loops. The information on NRW involved more intensive research and data handling but were finally gathered and combined from the UGRdL (from 1990 to 2000) and *AfEE* (from 2000 to 2012) with R web-scraping functions. Fortunately, emissions are measured in the same units (annually emitted carbon dioxide tons per capita). Hence, the yielded data frame of emissions per capita is comprehensive and consistent, although there are missing observations on some years.

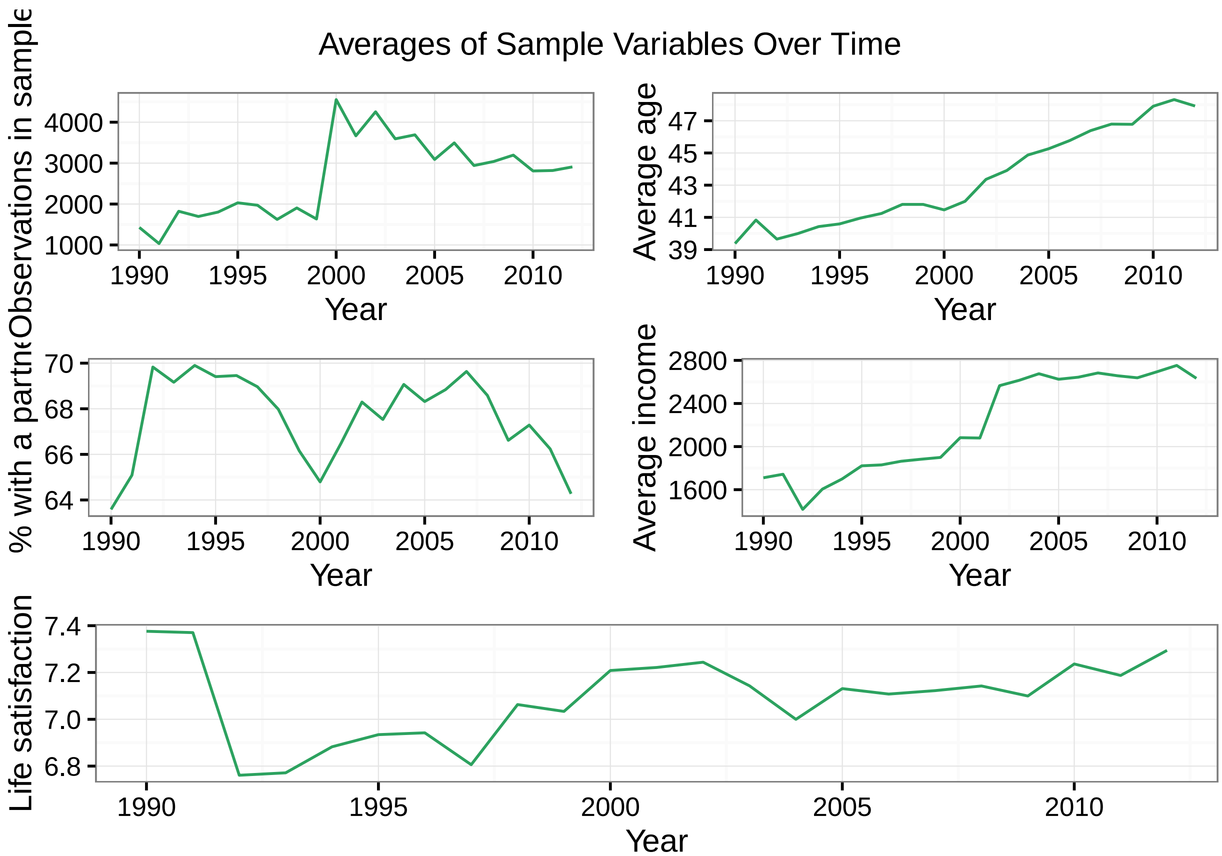
Because the Bundeslaender vary so much in geographic size as awell as population, we also added emissions data by square kilometer for each state, since that might better represent the concentration of emissions. The *Laenderarbeitskreis* maintains a publicly available database of CO2 emissions in total tons per state and per year, which can be downloaded as CSV or Excel files. The states' areas in square kilometers were then pulled from an table on the website of the Federal Statistical Office and Statistical Offices of the Bundeslaender and merged to create a dataset, in which CO2 emissions per square kilometer could be calculated.

Once the names of the Bundeslaender and the time frame of the resulting data frames were matched, they were merged in R into a final data set. The variables in our data set are listed below.

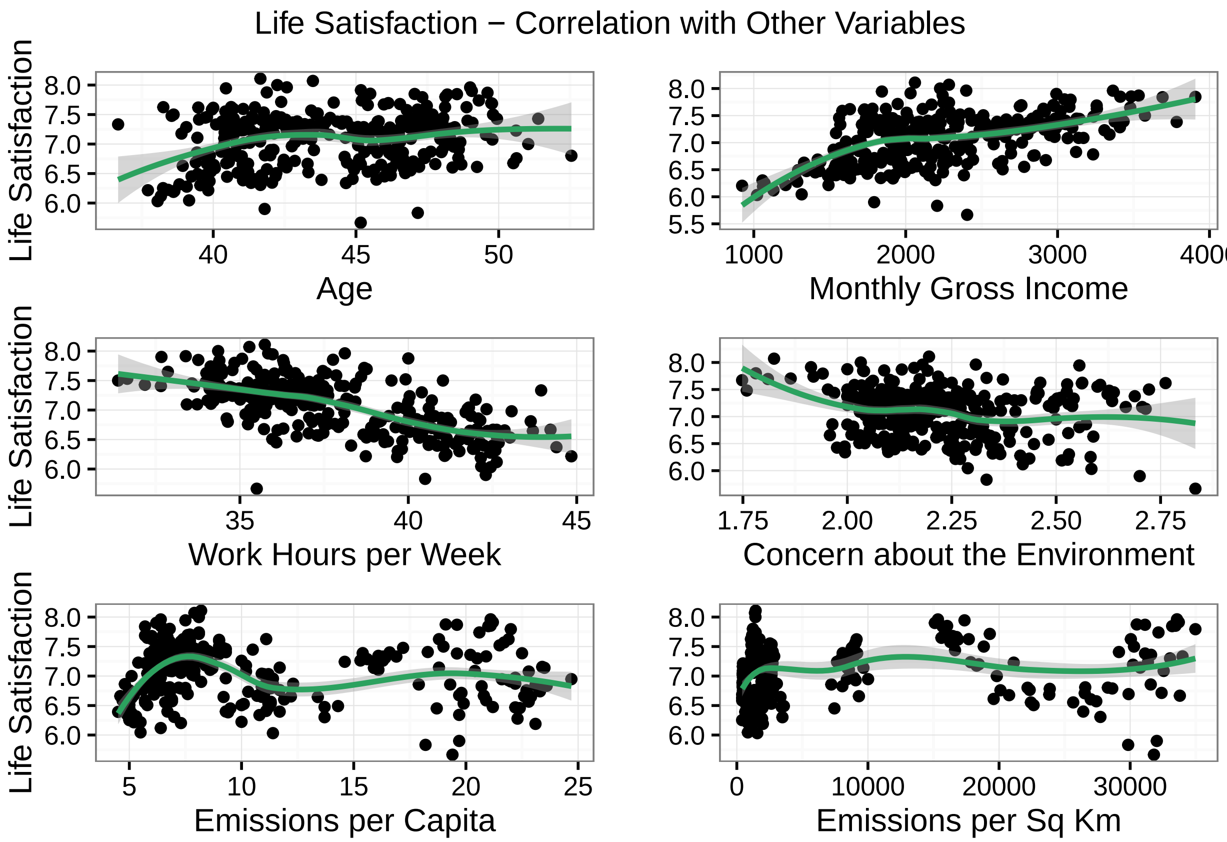
Variables	Descriptions
Year	Year
State	State
WorkHours	Hours worked per week
GrossIncome	Gross monthly income (before taxes)
NetIncome	Net monthly income (after taxes)
GermanBorn	Born in Germany (1 if yes, 2 if no)
satis_labels	Life satisfaction, labeled on a scale of 1 (low) to 10 (high)
satis	Life satisfaction, numeric values (1-10) only
environ	Concern about the environment on a scale from 1 (not concerned at all) to 3 (very concerned)
gender	Gender
age	Age
emp	Employment status (1 if not employed, 2 if employed)
fam	Family status (1 if single, 2 if with a partner)
CO2Tons	Total tons of CO2 emitted in each state, in 1000 tons
sqkm	State area in square kilometers
CO2perSqKm	Tons of CO2 emitted per square kilometer for each state
Emissions	Tons of CO2 emitted per capita in each state

Individual descriptive statistics

Examining our individual-level variables, there are some trends to keep in mind, as shown in the graphs below. The graphs represent calculated means, either of the whole sample for the line graphs or by each state for each year for the scatterplots.

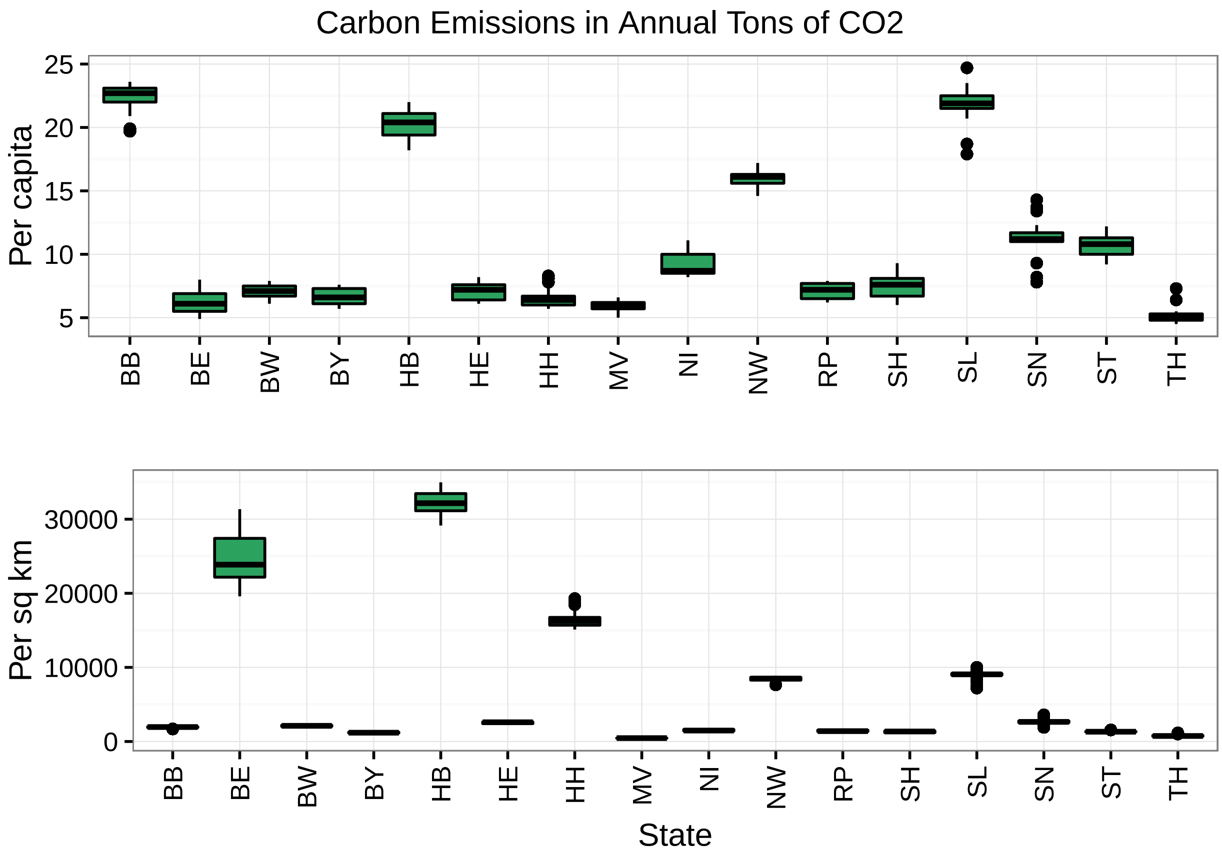


First, we see that a large number of individuals were added to the sample in 2000; though the number declined again in the following years, there are significantly more observations after 2000 then prior to 2000. Also, the overall average age of our sample increased over the time under observation; the range for all obversations was 17 to 89. It makes sense that it would increase over time for a longitudinal study, but the unevenness of the increase confirms that there are dropouts and additions. The drop in average age at the year 2000 would be accounted for by the large number of additional observations, but the steeper rise after the 2000 might confirm that younger people are less availabe and willing to respond to surveys, a well-known problem for traditional data collection. The same patterns could also account for the sharp drop in the percentage of the sample whose family status indicates that they have a partner around 2000 (assuming younger individuals in the survey were less likely to have a partner), though it does not explain the decline after 2007. Similarly, an older sample would also explain the higher monthly income after 2000, though the steepness of the increase is puzzling. Finally, the average life satisfaction shows a steep drop in the early 1990s



Looking at some correlations with our dependent variable of interest,

State level descriptive statistics



% Table created by stargazer v.5.2 by Marek Hlavac, Harvard University. E-mail: hlavac at fas.harvard.edu
% Date and time: Fri, May 13, 2016 - 12:48:32 AM

Table 1: Summary statistics

Statistic	N	Mean	St. Dev.	Min	Max
age	61,009	43.903	11.935	17	86
gender	61,009	1.464	0.499	1	2
WorkHours	61,009	37.306	14.843	−3.000	99.900
GrossIncome	61,009	2,322.308	2,132.031	0	80,000
environ	61,009	2.185	0.613	1	3
Emissions	61,009	9.923	4.789	4.500	24.700
CO2perSqKm	61,009	4,183.186	5,809.731	403.210	34,973.060

Methodology

The analysis will focus on a mixture of two levels of interest: *Federal State*, e.g. reported emissions and *the individual*, e.g. the socioeconomic status of the respondent, gender, and age. In order to account for such clustering and track differences between the German States, multilevel modelling will be applied in this project. Multilevel modelling aims to identify and understand the variance among groups and identify sources of non-independence in the data *Bliese2013 - add to bibliography*. This approach, unlike the traditional multivariate regression, partitions the residual variance into a between-state component (the variance of the state-level residuals) and a within-state component (the variance of the individual-level residuals). It does so by first finding the differences in the intercepts of groups on the dependent variable and then finding the variations in the slopes across groups (the between variance) and within a group (the within variance). Such grouping will produce more robust and reliable results, which could be potentially inferred to a larger population. Therefore, multilevel modelling is preferred over a fixed effects model, which cannot separate out effects due to observed and unobserved characteristics. *Include?:* In addition, the model can be extended by exploring the temporal effects and overtime change in the individual and state level attitudes. Time-varying components of the model, consequently, will be possible to track.

Analysis

Inferential Statistics

We first test basic inferential statistics. For the models below, X1 represents the explanatory variables of interest: emissions (both per capita and per square kilometer), gross income, work hours per week, concern for the environment, gender, and age. Emissions has a wide range: from 4.5 up to 31.6 annual tons of CO2 per capita. Observations in the upper range may be outliers that need to be removed; half of the observations fall between 6.5 and 13.7 tons, and the median is 7.6 compared to a mean of 10.2 tons. Energy use also varies widely, from 79.3 to 337.0 annual gigajoules (GJ) per capita, with a median of 164.0 and mean of 172.3 GJ. Concern for the environment, measured on a scale from 1 (very) to 3 (not very), has an average of 1.8. Gender is almost evenly split between males and females, and the average age is about 50 years old.

```
## serie emp  is constant and has been removed
```

Y1 represents "satis" (life satisfaction), measured on a scale ranging from 0 (low) to 10 (high). The data is skewed toward the upper range, with the majority of responses being more than 6 and with a mean of 6.9.

```
##      satis
##  Min.   : 0.0
##  1st Qu.: 6.0
##  Median : 7.0
##  Mean   : 7.1
##  3rd Qu.: 8.0
##  Max.   :10.0
```

Below, we tested various types of panel data models on our individual-level data. The data set is unbalanced because we don't have information for all years in all the states.

series emp is constant and has been removed Oneway (individual) effect Pooling Model

Call: plm(formula = Y1 ~ X1, data = pdataind, model = "pooling")

Unbalanced Panel: n=12461, T=1-23, N=61009

Residuals : Min. 1st Qu. Median 3rd Qu. Max. -9.360 -0.976 0.130 0.982 3.820

Coefficients : Estimate Std. Error t-value Pr(>|t|)
(Intercept) 7.7670e+00 4.8666e-02 159.5986 < 2.2e-16 ***X1Emissions -7.5003e-03 1.3687e-03 -5.4800 4.270e-08*** X1environ -6.2185e-02 1.0734e-02 -5.7934 6.932e-09 ***X1gender 3.9761e-02 1.4322e-02 2.7762 0.005501*** *X1age -8.8424e-03 5.7141e-04 -15.4746 < 2.2e-16* **X1WorkHours -1.1679e-02 5.0121e-04 -23.3019 < 2.2e-16** *X1GrossIncome 1.3766e-04 3.5108e-06 39.2095 < 2.2e-16* ** — Signif. codes: 0 '' ***0.001*** '' *0.01* '' 0.05 '.' 0.1 '' 1

Total Sum of Squares: 164370 Residual Sum of Squares: 159710 R-Squared: 0.028352 Adj. R-Squared: 0.028348 F-statistic: 296.663 on 6 and 61002 DF, p-value: < 2.22e-16 series emp is constant and has been removed Oneway (individual) effect Between Model

Call: plm(formula = Y1 ~ X1, data = pdataind, model = “between”)

Unbalanced Panel: n=12461, T=1-23, N=61009

Residuals : Min. 1st Qu. Median 3rd Qu. Max. -7.3400 -0.5170 0.0617 0.6970 3.9300

Coefficients : Estimate Std. Error t-value Pr(>|t|)
(Intercept) 7.8131e+00 1.0324e-01 75.6759 < 2.2e-16 ***X1Emissions -6.4665e-03 2.0267e-03 -3.1906 0.001423*** *X1environ -5.6719e-02 2.3210e-02 -2.4437 0.014551*
X1gender 6.8858e-02 3.1300e-02 2.1999 0.027830 *
X1age -9.1841e-03 1.2295e-03 -7.4696 8.578e-14 ***X1WorkHours -1.5751e-02 1.0956e-03 -14.3771 < 2.2e-16*** X1GrossIncome 1.7349e-04 7.8442e-06 22.1170 < 2.2e-16 *** — Signif. codes: 0 ‘***’ 0.001 ’’*** *’’ 0.01* ” 0.05 ‘.’ 0.1 ‘’ 1

Total Sum of Squares: 16059 Residual Sum of Squares: 15350 R-Squared: 0.044165 Adj. R-Squared: 0.044141 F-statistic: 95.9086 on 6 and 12454 DF, p-value: < 2.22e-16 series emp is constant and has been removed Oneway (individual) effect First-Difference Model

Call: plm(formula = Y1 ~ X1, data = pdataind, model = “fd”)

Unbalanced Panel: n=12461, T=1-23, N=61009

Residuals : Min. 1st Qu. Median 3rd Qu. Max. -10.3000 -1.2500 -0.0082 1.2500 9.9200

Coefficients : Estimate Std. Error t-value Pr(>|t|)
(intercept) 8.9628e-03 1.0241e-02 0.8752 0.3815
X1Emissions 4.0723e-03 1.8429e-02 0.2210 0.8251
X1environ -4.8533e-02 1.2186e-02 -3.9826 6.826e-05 ***X1gender 7.5709e-02 1.5928e-02 4.7531 2.009e-06*** X1age -8.9724e-03 6.4562e-04 -13.8972 < 2.2e-16 ***X1WorkHours -7.6686e-03 5.6921e-04 -13.4722 < 2.2e-16*** X1GrossIncome 1.1293e-04 4.0340e-06 27.9951 < 2.2e-16 *** — Signif. codes: 0 ‘***’ 0.001 ’’*** *0.01* ” 0.05 ‘.’ 0.1 ‘’ 1

Total Sum of Squares: 251590 Residual Sum of Squares: 247130 R-Squared: 0.017716 Adj. R-Squared: 0.017713 F-statistic: 145.909 on 6 and 48541 DF, p-value: < 2.22e-16 series emp is constant and has been removed Oneway (individual) effect Within Model

Call: plm(formula = Y1 ~ X1, data = pdataind, model = “within”)

Unbalanced Panel: n=12461, T=1-23, N=61009

Residuals : Min. 1st Qu. Median 3rd Qu. Max. -7.5100 -0.7210 0.0681 0.9160 5.1100

Coefficients : Estimate Std. Error t-value Pr(>|t|)
X1Emissions -5.9563e-03 9.8139e-03 -0.6069 0.5438998
X1environ -5.4328e-02 1.2218e-02 -4.4467 8.739e-06 ***X1gender 5.8591e-02 1.5931e-02 3.6777 0.0002356*** X1age -8.8566e-03 6.4408e-04 -13.7508 < 2.2e-16 ***X1WorkHours -7.4820e-03 5.6728e-04 -13.1891 < 2.2e-16*** X1GrossIncome 1.0855e-04 4.0168e-06 27.0244 < 2.2e-16 *** — Signif. codes: 0 ‘***’ 0.001 ’’*** *0.01* ” 0.05 ‘.’ 0.1 ‘’ 1

Total Sum of Squares: 125450 Residual Sum of Squares: 123350 R-Squared: 0.016765 Adj. R-Squared: 0.013339 F-statistic: 137.949 on 6 and 48542 DF, p-value: < 2.22e-16

```
F test for individual effects
```

data: Y1 ~ X1 F = 2.4127, df1 = 48548, df2 = 12454, p-value < 2.2e-16 alternative hypothesis: significant effects

Regression Estimates of Life Satisfaction

Dependent variable:

Y1

(1)

(2)

(3)

(4)

Constant

7.77***

7.81***

(0.05)

(0.10)

X1Emissions

-0.01***

-0.01***

0.004

-0.01

(0.001)

(0.002)

(0.02)

(0.01)

X1environ

-0.06***

-0.06**

-0.05***

-0.05***

(0.01)

(0.02)

(0.01)

(0.01)

X1gender

0.04***

0.07**

0.08***

0.06***

(0.01)

(0.03)

(0.02)

(0.02)

X1age

-0.01***

-0.01***

-0.01***

-0.01***

(0.001)

(0.001)

(0.001)

(0.001)

X1WorkHours

-0.01***

-0.02***

-0.01***

-0.01***

(0.001)

(0.001)

(0.001)

(0.001)

X1GrossIncome

0.0001***

0.0002***

0.0001***

0.0001***

(0.0000)

(0.0000)

(0.0000)

(0.0000)

Constant

7.77***

7.81***

(0.05)

(0.10)

Observations

61,009

12,461

48,548

61,009

R2

0.03

0.04

0.02

0.02

Adjusted R2

0.03

0.04

0.02

0.01

F Statistic

296.66*** (df = 6; 61002)

95.91*** (df = 6; 12454)

145.91*** (df = 6; 48541)

137.95*** (df = 6; 48542)

Note:

p<0.1; ***p<0.05;*** p<0.01

In terms of explanatory power, the first difference and within estimators might be less useful than the between or pooled OLS estimators, based on their low R-squared and adjusted R-squared Values. Interestingly, gender does not appear to have a significant effect on reported life satisfaction in any of the models. The other variables are statistically significant in all the models. For variables other than gender, the directions of the relationships are also the same across models: emissions and age have negative coefficients, while concern about the environment and energy use have positive coefficients.

We can compare the fixed effects/within and pooled OLS models using an F-test for individual and/or time effects:

```
##
##  F test for individual effects
##
## data:  Y1 ~ X1
## F = 1.1484, df1 = 12460, df2 = 48542, p-value < 2.2e-16
## alternative hypothesis: significant effects
```

The test is set up so that the null hypothesis is that OLS pooled is better than the within estimator. The small resulting p-value indicates that despite the larger R-squared values with OLS pooling, we should reject the null hypothesis that OLS pooling is better.

Discussion

This paper presents a multilevel analysis that adds to the increasing number of studies that evaluate the effects of air pollution and emissions on people's life satisfaction. In fact, in our data the potential negative impacts on happiness associated with emissions levels was non-existent when we controlled for state-level and individual characteristics. We approached the problem of estimating the reduction in satisfaction by examining a number of regressions based on life-satisfaction that include a variety of socio-economic data to justify a person's stated level of life satisfaction on a subjective 1-10 scale.

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