Effects of Sea Level Rise in the United States and Climate Change Perception in the United Kingdom

Monika Novackova

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Declaration

I hereby declare that this thesis has not been and will not be submitted in whole or in part to another University for the award of any other degree.

This thesis consists of three papers. I produced the three papers under the guidance of my main supervisor Prof. Richard Tol and my second supervisor Dr Alexander Moradi.

The first paper, which is entitled Effects of Sea Level Rise on the Economy of the United States, is co-authored with my main Supervisor, Prof. Richard Tol, and it is published in Journal of Environmental Economics and Policy (Novackova and Tol, 2017). The final publication is available via http://www.tandfonline.com/doi/full/10.1080/21606544.2017.1363667. I hereby declare that the entire analysis was carried out by me under the guidance of Prof. Richard Tol. Except for the Introduction, I wrote the first draft independently and incorporated the edits and amendments suggested by him. The Introduction of the first paper was mostly written by Prof. Richard Tol. I wrote the last two paragraphs of the Introduction and I incorporated a few additional minor changes.

The second paper entitled 'Effects of Sea Level Rise on Agricultural Land Values in the United States' is single-authored. I hereby declare that the entire analysis was carried out by me under the guidance of my Supervisors. I produced the first draft independently and I included edits and amendments suggested by my Supervisors.

The third paper named 'Climate Change Awareness and Willingness to Pay for its Mitigation: Evidence from the United Kingdom' is co-authored with my main Supervisor Prof. Tol. I hereby declare, that the entire analysis was carried out by me under the guidance of Prof. Richard Tol. I wrote the first draft independently and I incorporated edits and amendments suggested by him.

For all three papers I obtained valuable advice and feedback from my second supervisor Dr Alexander Moradi. I incorporated few edits and amendments suggested by him into each paper.

Signature:

Monika Novackova

UNIVERSITY OF SUSSEX

Monika Novackova, Doctor of Philosophy in Economics

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Summary

This thesis has three separate parts. In the first part I report the first ex post study of the economic impact of sea level rise. I apply two econometric approaches to estimate the past effects of sea level rise on the economy of the USA, viz. Barro type growth regressions adjusted for spatial patterns and a matching estimator. The unit of analysis is 3063 counties of the USA. I fit growth regressions for 13 time periods and I estimate numerous varieties for both growth regressions and matching estimator. Although there is some evidence that sea level rise has a positive effect on economic growth, in most specifications the estimated effects are insignificant. Therefore, I cannot confirm the implicit assumption of previous ex-ante studies, in particular that sea level rise has in general negative effect on economies.

In the second part I fit Ricardian regressions of agricultural land values for 2830 counties of the USA on past sea level rise, taking account of spatial autocorrelation and heteroscedasticity. I find a significant, hill-shaped relationship. Hence, the outcomes are mixed. Mild sea level rise increases, while more pronounced sea level rise causes land values to fall. The results are robust to a set of variations.

In the third part I explore an unprecedented dataset of almost 6,000 observations to identify main predictors of climate knowledge, climate risk perception and willingness to pay (WTP) for climate change mitigation. Among nearly 70 potential explanatory variables I detect the most important ones using a multisplit lasso estimator. Importantly, I test significance of individuals' preferences about time, risk and equity. The study is innovative as these behavioural characteristics were recorded by including experimental methods into a live sample survey. This unique way of data collection combines advantages of surveys and experiments. The most important predictors of environmental attitudes are numeracy, cognitive ability, inequity aversion and political and ideological world-view.

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Chapter 1

Introduction

Climate change has been observed for decades and we are beginning to observe its widespread consequences. Many of the resulting changes have affected humans all around the world in harmful ways. Climate related changes include change in precipitation patterns, droughts, sea level rise, acidification of oceans, melting of ice sheets and the increased frequency and intensity of extreme weather events such as storms and floods (Zachariadis, 2016). Although future consequences of climate change could be disastrous, we can mitigate them substantially by adopting adequate measures (Church et al., 2013; Hinkel et al., 2014; Seneviratne et al., 2012). For the whole of humankind, it is therefore crucial to acquire as much knowledge and information in this area as possible. Whether and how well climate change will be tackled does not only depend on what scientists know but also on the understanding and perception of global warming by the general public. Public attitudes play a key role in policy decision-making (Slaymaker, 1999; Tierney et al., 2001). Therefore, besides investing into high quality research, it is important for this climate science to be communicated to public in efficient, comprehensive and understandable way.

This thesis consists of three papers. Climate change is the fundamental topic of all of them. The first two papers contribute to our understanding of effects of global warming and its underlying mechanisms while the third one improves understanding of environmental attitudes and climate knowledge of general public. The first two papers are focused on the contiguous US and the third one is based on a survey conducted in the UK.

The first two papers of this essay are focused on one of the most costly and most certain results of climate change, namely sea level rise. This phenomenon has the potential to have damaging consequences for regional and even national economies. There are two main channels through which sea level rise affects economies, in particular land loss and expensive coastal protection (Fankhauser and Tol 2005).

Global sea levels have risen by 14 meters since the beginning of the Holocene with most of it happening before the Common Era (Fleming et al. 1998; Milne et al. 2005). Although global sea level change has been relatively muted in recent past, in some parts of the world local sea level rise has been serious enough to have disastrous consequences. For example, parts of Bangkok and Tokyo fell five meters during the $20th$ century (Hinkel et al. 2014; Nicholls and Cazenave 2010; Sato et al. 2006).

A large literature has focused on estimation and predicting future impacts of sea level rise, mostly by means of simulation models (e.g., Nicholls et al., 1999; Nicholls and Tol, 2006; Anthoff et al., 2010b; Hinkel et al., 2010, 2013; Spencer et al., 2016). However, to the best of my knowledge, nobody has attempted to quantify the consequences of past sea level rise. The first two papers of this essay fill this gap. In the first study, I examine effects of sea level rise on economic growth and in the second one I study effects of sea level rise on agricultural land prices. Both studies are based on county level cross-sectional data. If the underlying assumption of the prediction studies is correct, I should be able to detect significant negative effects.

In the first paper, I use two different methods to estimate past effects of sea level rise on economic growth. These are Barro type growth regressions with spatial adjustment and a matching estimator. The Barro type regressions explain economic growth rate during the period $1990-2012$. Besides sea level rise, the regressions include a usual set of covariates.[1] I estimate the Barro type regressions using a standard procedure suggested by Evans (1997), namely three stage least squares with instrumental variables (3SLS-IV). Surprisingly, I do not find any meaningful significant effect of sea level rise. I obtain the same outcome using a matching estimator and a large set of robustness tests.

A possible reason why I do not find significant effects in the first study can be the fact that sea level rise is a very slow and gradual process and its effects on economic growth are only apparent after a much longer period, i.e. decades or centuries. Estimating a model for a period of hundred years or more would not be possible due to lack of data. Instead of that, I decided to use a different indicator, one which is likely to be more sensitive to sea level rise. Hence, in the second paper, I use average land values as a dependent variable.

Although the econometric model utilized in the second paper appears to be analogous to the model used in the first study, the underlying methodology is different. In the second paper I estimate a hedonic regression of 2007 land values on a set of explanatory variables including rates of sea level rise. This approach is based on the theory of Ricardo

[1] Their values are from year 1990 or 1992.

(1817), which was first developed by Mendelsohn et al. (1994) in the relevant context. The fundamental assumption is that under perfect competition, value of land will be the same as the net profits from the best usage of land (Ricardo, 1817). Also in the second paper I adjust for spatial patterns.

In contrary to the first paper, I detect a significant effect of sea level rise on land prices. The relationship is hill-shaped. Small sea level rise has a positive effect on land values and large sea level rise affects land values negatively. The results are robust for a number of robustness checks. This outcome is in accordance with my hypothesis, which is that past sea level rise had negative effect on land values.

The third paper seeks to identify the main factors influencing climate knowledge, climate risk perception and willingness to pay (WTP) for climate change mitigation. This topic is particularly important because there is a large discrepancy between scientific and public opinions on human caused climate change. In spite of the fact that most relevant scientific studies accept existence of anthropogenic climate change, public opinion on global warming is far away from consensus (Leiserowitz et al., 2012; Pew, 2012; Cook et al., 2013). What actually drives the public opinion is, therefore, a very interesting question.

A large majority of earlier studies which aim to identify predictors of climate knowledge and climate change risk perception are either based on survey data (e.g. Lee et al., 2015; Morrison et al., 2015; Carlsson et al., 2013), or on experimental methods (e.g. Braaten, 2014; Glenk and Colombo, 2013). Each of these techniques, however, has its limitations. Surveys often lead to hypothetical bias and experiments are usually conducted in an artificial environment over small, non-representative sample, therefore they have low external validity. The third paper of this thesis seeks to overcome some of these issues. It contributes by exploring a unique dataset of almost $6,000$ observations which combines advantages of survey and experimental methods. Economic experiments are usually computer based and they involve participants responding to various situations on a computer screen. This set-up was replicated in a large live sample survey (Dolton and Tol, 2016). In particular, experimental methods were used to elicit preferences on time, equity, risk and social value orientation. The survey also collected data on large number of demographics and other characteristics including numeracy or ideological world-view.

Because of a lack of scientific consensus on what are the main predictors of climate knowledge, climate attitudes and climate risk perception, I utilize a least absolute shrinkage and selection operator (lasso) to identify the most influential factors. Among nearly 70 potential explanatory variables, I find the most important ones for each of the three climate variables. The most important factors associated with climate knowledge are cognitive ability and gender. The most significant factors affecting climate risk perception are climate knowledge, gender, political/ideological world-view and numeracy. Regarding WTP for climate change mitigation, the most influential predictors include age, inequity aversion, climate risk perception, perception of intergenerational allocation of resources, numeracy and financial literacy.

The rest of this thesis is organised as follows. Each of the following three sections presents one of the papers briefly described above. Section 2 is dedicated to *Effects of Sea Level Rise on Economy of the United States*, Section 3 includes paper *Effects of Sea Level Rise on Agricultural Land Values in the United States* and Section 4 presents *Climate Change Awareness and Willingness to Pay for its Mitigation: Evidence from the UK*. Finally, Section 5 concludes.

Chapter 2

Effects of Sea Level Rise on Economy of the United States

2.1 Introduction

Sea level rise features among the more important economic impacts of climate change (Tol 2009), particularly because of its potential to overwhelm regional and even national economies, either through massive land loss or exorbitantly expensive coastal protection (Nicholls and Tol 2006). Better understanding of past effects of sea level rise should help to predict future sea level rise effects more precisely and find optimal policies to face this consequence of climate change.

Studies of the future impact of climate change typically rely on simulation models that are applied far outside their domain of calibration (Hinkel et al. 2014). Model validation and parameter estimation are rare (Mendelsohn et al. 1994). This is to a degree unavoidable – climate change is part of a yet-to-be-observed future – but should be minimized to gain more confidence in future projections of the effects of climate change. This paper contributes by studying the economic impacts of sea level rise on the economic development of the USA in the recent past. To the best of our knowledge, no one has yet attempted to test model-based impact estimates of sea level rise against observations. This paper does not do that either. Instead, we take a key prediction from these ex ante models —that sea level rise would decelerate economic growth —and test it against the data.

Our starting point is that sea level rise is a common phenomenon. Indeed, since the start of the Holocene, global sea level rise has been 14 metres, although the bulk of it happened between seven and eight thousand years ago and most of the rest before the start of the Common Era (Fleming et al. 1998; Milne et al. 2005). Global sea level rise has been muted in more recent times – relative to both the more distant past and future projections, but relative sea level rise has been pronounced in some locations. Thermal expansion, ice melt and ice displacement cause the sea to rise, but subsidence and tectonics can cause the land to fall (Church et al. 2013). This effect can be large. Parts of Bangkok and Tokyo, for instance, fell by five metres in a few decades during the 20$^{\text{th}}$ century (Hinkel et al. 2014; Nicholls and Cazenave 2010; Sato et al. 2006).

We focus on the contiguous USA for three reasons. (*i*) There are excellent data on relative sea level rise and pronounced regional differences in sea level rise. (*ii*) There are also excellent data on economic growth with fine spatial detail. (*iii*) Finally, regional growth patterns are well-studied in the USA (e.g. Goetz and Hu 1996; Higgins et al. 2006; Latzko 2013) so that we minimize the risk of ascribing to sea level rise what is caused by something else.

We hypothesize that relative sea level rise has a negative effect on economic growth. There are two main channels —see Fankhauser and Tol (2005) for a more thorough treatment. First, sea level rise causes damage in the form of erosion and floods, which reduce the productivity of land, labour and capital. Second, protection against coastal hazards implies that capital is diverted from productive to protective investment. On the other hand, if coastal protection is subsidized by inland areas (which may be the case in the USA), then areas with high relative sea level rise would record the economic activity of dike building etc. without suffering the costs, and would thus grow faster than other areas.

It is also worth noting that increase in sea level is likely to magnify future seasonal amplitudes and sea level extremes (Church et al. 2013; Lowe et al. 2010); which, together with long term sea level rise can have considerable consequences on flood risk and state of marine ecosystems in coastal areas. Seneviratne et al. (2012) and Wahl et al. (2014) found a substantial amplification of seasonal sea level cycle around US Gulf coast from 1990s onwards. The damage caused by Hurrican Katrina is an infamous example of a combined impact of sea level rise and increase in sea level extremes (Lowe et al. 2010).

The paper proceeds as follows. Section 2.2 describes the two main methods used in this study. The methods include a Barro type conditional growth regressions and a matching estimator. Section 2.3 discusses data sources. Section 2.4 presents empirical results. In Section 2.5, different variants of the Barro type economic growth regressions are discussed to verify robustness of results. Section 2.6 concludes.

2.2 Methodology

One of the most important reasons that motivated us for conducting this study is the number of existing papers focused on prediction of effects of future sea level rise of 25 cm or more (Anthoff et al. 2010a; Bigano et al. 2008; Bosello et al. 2007). It would be particularly insightful to fit a model to empirical sea level rise data of comparable magnitude and compare our results with the results of the above mentioned studies. However, average sea level rise measured at a gauge station is 2.764 mm per year, hence we would have to fit a model for a period of about 100 years. The availability of all required data for 100 years back would be a real problem, especially at county level. Therefore, we restrict our study for periods of maximum of 22 years. Thus, we are considering total sea level rise of about 6 cm on average, which is significantly smaller than the sea level rise considered in the above mentioned studies. One may argue that the effects of 6 cm sea level rise will differ from those of 25 cm and while it is very likely that sea level rise of 25 cm or more will have measurable effects on economies, the sea level rise which happened during the recent 22 years in the US was much smaller, hence there may not be any detectable impacts on the US economy during this period. We, however, believe that the effects are linearly scalable at least to some degree. The area of land loss is assumed to be linear in sea level rise (Anthoff et al. 2010a; Nicholls et al. 2008) and in case with protection, the costs are assumed to be linear in dike height (thus also in sea level rise) and therefore readily scaled (Bosello et al. 2007). With 6 cm sea level rise, we also expect other impacts including sea water infiltration, adaptation costs, change in agricultural prices or reducing investments from producing assets which can result in decrease in household consumption. In some areas, for example, increased frequency of coastal storms and floods caused by increase in sea levels can have considerable damaging effects on rail transportation (Dawson et al. 2016). We expect all these impacts to be proportionally smaller than in the case of sea level rise of 25 cm or more. In spite of being aware that some other effects, such as certain impacts on agriculture or tourism (which can happen for example due to beach erosion) may not be exactly linear in sea level rise, we deem the linear scalability assumption reasonable and we adopt it for the purpose of comparison of our results with the results of the above mentioned prediction studies. Hence, our working hypothesis is that we will find much smaller (yet detectable) negative effects than those predicted by the above mentioned studies. We compare our estimated sea level rise impacts to scaled predicted impacts of two example studies (Bigano et al. 2008 and Bosello et al. 2007) in Table 2.6 at the end of

Section 2.4.1.

2.2.1 *Barro type growth regressions*

The rate of sea level rise changes only very slowly over time and its estimates do not vary during the relatively recent period for which economic data are available. Therefore, we opted for cross-sectional regressions rather than panel data analysis. Conventional growth regressions are fitted according to Barro and Sala-i-Martin (1991) and Barro and Sala-i-Martin (1992). As a staring point, the average growth rate of per capita income is regressed on the initial logarithm of per capita income and on sea level rise without other covariates. After that, other covariates are added that have been found to be important in previous studies. The regression equation can be written as:

$$g_n = \alpha + \beta y_{n,0} + \gamma' x_n + v_n, \tag{2.1}$$

where $y_{n,0}$ is the initial logarithm of per capita income in county n, $g_n = (y_{n,T} - y_{n,0})/T$ is average growth rate of per capita income between years 0 and T for county n, $y_{n,T}$ is the logarithm of per capita income in year T, x_n is a vector of controls capturing regional differences and v_n is an error term which is assumed to have zero mean and finite variance. The controls in x_n are listed in Table A.1 in Appendix A and discussed below. Coefficient β is typically found to be negative, that is, poorer regions grow faster than richer.

Evans (1997) shows that the OLS estimator of (2.1) is consistent only if the following conditions are satisfied: (*i*) The dynamical structures of economies can be expressed by identical AR(1) processes; (*ii*) every economy affects every other economy symmetrically; and (*iii*) all permanent cross-economy differences are captured by control variables. As these conditions are highly implausible, Evans (1997) suggested a three stage least squares with instrumental variables (3SLS-IV) to obtain consistent estimates.[1]

The first step of the 3SLS-IV procedure involves differencing of (2.1). The reason why equation (2.1) needs to be differenced follows from the autoregressive representation of the data-generating process of $y_{n,t}$ (see equations (2) and (3) in Evans, 1997). In every time period, $y_{n,t}$ depends on its previous value and on a time invariant intercept that is specific to each county. The county-specific intercept can be partially explained by x_n but it also includes a component that cannot be explained by x_n. If the component, which cannot be

[1] This method is not the same as the typical 3SLS used for estimation of simultaneous equations models, which is described for example in Greene (2002). Therefore, the residuals do not need to be corrected as in case of typical 2SLS or 3SLS (expect of adjustment for heteroscedasticity, which we discuss in Section 2.5.1 and adjustment for spatial patterns which we discuss below).

explained by x_n, has a positive cross-sectional variance, the OLS estimates of (2.1) are inconsistent. Evans (1997) suggests eliminating the problematic county-specific invariant component by differencing (2.1). The differenced equation can be written as:

$$\Delta g_n = \omega + \beta \Delta y_{n,0} + \eta_n, \tag{2.2}$$

where Δ denotes first difference. As it further follows from the autoregressive representation of the data-generating process of $y_{n,t}$, the error term η_n in (2.2) is correlated with $\Delta y_{n,0}$. Hence, (2.2) can be estimated consistently using instrumental variables correlated with $\Delta y_{n,0}$ but uncorrelated with η_n. Thus, in the first stage, we estimate:

$$\Delta y_{n,0} = \delta' z_n + \xi_n, \tag{2.3}$$

where z_n is a vector of instruments, δ is a vector of parameters to be estimated and ξ_n is the error term. We will denote the OLS estimates of δ from (2.3) as $\hat{\delta}$. Then the predicted values of $\Delta y_{n,0}$ from (2.3) can be denoted as $\widehat{\Delta y}_{n,0} = \hat{\delta}' z_n$ and we use them to estimate the second stage:

$$\Delta g_n = \kappa + \beta \widehat{\Delta y}_{n,0} + \zeta_n. \tag{2.4}$$

As shown in Evans (1997), the above described procedure provides a consistent estimator of β and we will denote the resulting estimate as $\hat{\beta}$.

We are particularly interested in estimating the parameter vector γ from (2.1) as it includes the sea level rise coefficient. To get the estimates of γ, the estimate $\hat{\beta}$ can be substituted into (2.1). After subtracting $\hat{\beta} y_{n,0}$ from both sides of (2.1), we get:

$$g_n - \hat{\beta} y_{n,0} = \tau + \gamma' x_n + \epsilon_n, \tag{2.5}$$

where τ and γ are parameters and ϵ_n is the error term.

In practice, we create a new variable $\pi_n = g_n - \hat{\beta} y_{n,0}$ after obtaining the estimate $\hat{\beta}$ and our final stage can be written as:

$$\pi_n = \tau + \gamma' x_n + \epsilon_n. \tag{2.6}$$

Evans (1997) shows that the resulting estimators for α and γ are consistent.

The model estimated in this paper explains economic growth during the period 1990-2012, thus year zero is 1990 and $T = 22$. As in Higgins et al. (2006), asymptotic conditional convergence rates are calculated by substituting estimate of β from equation (2.4) into the formula $c = 1 - (1 + T\beta)^{1/T}$. Estimates of γ from (2.6) represent initial effects on economic growth rate rather than partial effects on average growth rate. However, if β is negative – as assumed by the neoclassical growth hypothesis – the signs of these estimates will be the same as the signs of partial effects of the elements in x_n on average economic growth rate. Also, under the assumption that β is identical across the counties, the magnitude of the coefficients relative to one another is the same as the magnitude of the partial effects of the variables in x_n relative to one another.

Matrix x_n includes the control variables that are important to achieve conditional convergence. If they were not included, the model would represent the hypothesis of absolute convergence rather than the hypothesis of conditional or club convergence (Higgins et al. 2006). It was found by previous literature (Goetz and Hu 1996; Rupasingha and Chilton 2009) that these covariates have an effect on economic growth – hence they can affect the relationship between growth and sea level rise if correlated with sea level rise. Furthermore, the inclusion of control variables reduces the risk of omitted variables bias and the standard errors of estimates are smaller.

An important covariate is distance from coast as the absolute value of its correlation coefficient with sea level rise is extremely high compared to other covariates, because sea level rise is zero for all inland counties. The value of the correlation coefficient is -0.336 and its p-value is lower than 2.2×10^{-16}. Furthermore, the coastal counties are different because of their transport facilities and natural amenities. Other important covariates are per capita highway and education expenditures and per capita tax income, which accounts for the total taxes imposed by local government. The highway and education expenditures are included as a measure of local government expenditure and the tax income is a measure of local government activities. These controls are relevant, because they are related to decisions about funding of dikes and other forms of coastal protection. Besides, it is believed that higher taxes tend to deter potential immigrants and discourage people from starting a business which may slow down economic growth. On the other hand, higher government infrastructure expenditure might attract entrepreneurs.

Whereas we assume that sea level rise affects the economy negatively on average, in some locations, where coastal protection is subsidised, the total effect of sea level rise might be positive because of these subsidies. Therefore, it would be insightful to include data on coastal protection expenditures and subsidies among explanatory variables to disentangle these two effects. However, to the best of our knowledge, county level data on coastal protection expenditures or budgets are not available. Therefore, we adopt a reduced form model to estimate the total net effect of sea level rise. Using this model, we test whether the negative or the positive effect prevails. As a robustness test, we include various public finance variables and their combinations in Section 2.5.6. Public funds are likely to be correlated with coastal protection expenditures; therefore, this robustness check can serve as a rough test of potential confounding effects of coastal protection budgets. As we conclude in Section 2.5.6, the estimates are reasonably stable and robust with respect to government finance variables.

We sort the other covariates into four groups, particularly measures of agglomeration, measures of religious adherence, regional dummy variables and other socioeconomic and environmental indicators.

The measures of religious adherence are included because Rupasingha and Chilton (2009) show that religious adherence has significant impact on economic growth. Moreover, the included religious variables are correlated with a dummy variable which indicates presence of interstate highways which can be associated with the construction of levees. Building of both interstate highways and levees was funded from the public funds, mostly from the federal finance; they were both built in the approximately same time period (American Society of Civil Engineers, 2017; Elmendorf, 2011; Poole Jr, 2013). More details about included covariates can be found in Table A.1 in Appendix A. Descriptive statistics of these variables are summarized in Tables 2.1 and A.2 in Appendix A.

The instruments in z_n in equation (2.3) are chosen from the set of 1980 values of the explanatory variables. The criterion for the choice of instruments was the Sargan test of overidentifying restrictions. It turns out that the test is insignificant when per capita religious adherence and population density are used as instruments. These two covariates are therefore used in z_n in (2.3). Although the Sargan test is not considered as a very strong criterion, it is clear that all possible instruments are exogenous as they are from year 1980 and the dependent variable is economic growth for the period starting in year 1990. In order to confirm the appropriateness of the IV estimation we used the Wu-Hausman test which is described for example in Davidson and Mackinnon (2009). The value of the test statistic is 9.502 and the corresponding p-value is 0.002, thus the null hypothesis of exogenity is rejected, which is in accordance with the growth model estimation theory presented by Evans (1997).

As the analysis is based on cross county data, we may expect the data to be spatially dependent. According to LeSage and Pace (2009), spatial dependence in the dependent variable causes OLS estimates to be biased and spatial dependence in error terms causes OLS estimates to be inefficient. To obtain unbiased and efficient estimates an approach which takes the spatial dependency into account is needed.

As in LeSage (1998), the general spatial model for (2.6) can be written as follows:

$$\begin{aligned} \pi &= \rho W\pi + X\beta + u, \\ u &= \lambda W u + \epsilon, \\ \epsilon &\sim N(0, \sigma^2 I_n), \end{aligned} \tag{2.7}$$

where π is a $n \times 1$ vector of dependent variables, scalar ρ is a spatial lag parameter, scalar λ is a spatial error parameter, W is the known $n \times n$ spatial weight matrix, X is an $n \times k$ matrix of explanatory variables that determine the growth, β is $k \times 1$ vector of parameters and ϵ is the error term.

In this study, the binary contiguity matrix W is constructed as a symmetric matrix where $W_{ij} = 1$ if county i and county j have a common border and $W_{ij} = 0$ otherwise. Since it is unrealistic to assume that no spillover effects exist between island counties and counties which are close to them, the island counties are treated as if they had common borders with coastal counties which surround them. Matrix W is row standardised, which means that the sum of all W_{ij} is equal to n.

Model (2.7) considers two spatially autoregressive processes, in particular a spatial process in the dependent variable and a spatial process in error terms. Imposing restrictions on (2.7), more specific spatial models can be derived. Setting $\rho = 0$ produces a spatial error model, which can be written as in LeSage (1998):

$$\begin{aligned} \pi &= X\beta + u, \\ u &= \lambda W u + \epsilon, \\ \epsilon &\sim N(0, \sigma^2 I_n). \end{aligned} \tag{2.8}$$

Imposing the restriction $\lambda = 0$ on equations (2.7) results in a spatial autoregressive model (SAR). According to LeSage (1998) this model can be written as:

$$\begin{aligned} \pi &= \rho W\pi + X\beta + \epsilon, \\ \epsilon &\sim N(0, \sigma^2 I_n). \end{aligned} \tag{2.9}$$

As is shown in Section 2.4, specification (2.9) is the most appropriate, therefore we estimate this specification and use it as the basis for further variations and robustness tests. The model is estimated via maximum likelihood estimation. First the parameter ρ is found applying a one dimensional optimization procedure; β and the other parameters are subsequently found by generalized least squares.

Models (2.9) were estimated for various time periods to verify whether the results remain the same. In particular, we estimated 13 models with T from 10 to 22 and we discuss them in Section 2.4. Year zero is 1990 in all of these models. Matrix X in (2.9) contains the same set of covariates for all 13 models. Each covariate in these 13 models is from the same year (which is stated in Table A.1 in Appendix A for individual covariates).

2.2.2 Matching estimator

Matching is a technique used to estimate the effect of a treatment (see Caliendo and Kopeinig 2008 and Myoung-jae 2005). In this study we use it to verify our results obtained by the Barro type growth regressions. An advantage of matching is that a functional form does not need to be specified, thus it is not susceptible to misspecification bias. Furthermore, as only matched cases are used, less weight is put on outliers.

The treatment effect estimator, which assumes that suitable matching has already been found, is described in the next few paragraphs. After that, we discuss a procedure of creating a suitable matching and its assessment.

Let y_0 denote the outcome of interest without treatment, y_1 the outcome of interest with treatment and d a dummy variable which is equal to 1 for treated and 0 for untreated individuals. As shown in Myoung-jae (2005), if $E(y_0|d, X) = E(y_0|X)$ the mean treatment effect on the treated $E(y_1 - y_0|d = 1)$ is identified with $E\{y - E(y|X, d = 0)|d = 1\}$. The estimator used in this study can be written as:

$$T_N \equiv N_u^{-1} \sum_{i \in T_u} (y_i - |C_i|^{-1} \sum_{m \in C_i} y_{mi}), \tag{2.10}$$

where N_u is the number of successfully matched treated subjects, T_u is the set of the successfully matched treated subjects, y_i is a response variable in treated i, C_i is a group of controls assigned to treated i, $|C_i|$ is a number of controls in comparison group C_i and y_{mi} denotes a response variable in C_i. The standard errors are estimated according to Abadie and Imbens (2006).

Instead of matching on X, one may get around the dimensionality problem by matching on one dimensional propensity score $\pi(X)$ for which it holds $\pi(X) \equiv P(d = 1|X)$. The propensity score is the probability for an individual to participate in a treatment given his observed covariates X. Myoung-jae (2005) shows that if d is independent of (y_0, y_1) given X, it is also independent of (y_0, y_1) given just $\pi(X)$.

To estimate a propensity score, we have to choose a model to be estimated and a set of variables to be included in the model. We fitted several types of models, including a binomial logistic regression (logit), a probit and a linear probability model. According to quality of matching, the most suitable is logistic regression and probit. The models are fitted by iteratively reweighted least squares.

The literature suggests several ways to select explanatory variables for the propensity score (see e.g. Caliendo and Kopeinig 2008; Myoung-jae 2005). Here, the variables are chosen according to their statistical significance and according to quality of matching.

Using the measures of imbalance, we compared various matchings obtained by different methods. We put the main emphasis on the p-values of two sided t-tests of equality of means of the successfully matched treated and successfully matched controls and on p-values of Kolmogorov-Smirnov tests of the null hypothesis that the probability density of the successfully matched treated is the same as density of successfully matched controls. The test statistics are calculated for each variable in X separately.

In this case, the treatment is sea level rise and the variables to be matched on are the covariates from model (2.9) listed in Table 2.4. We considered all inland counties and four counties with negative sea level rise as controls. Since the sea level rise is not a binary variable, we decided to consider all coastal counties with difference of the sea level rise and its 95% confidence interval higher than a certain value as treated. We omitted the rest of the counties with very small sea level rise from this part of analysis (these observations are not omitted from the Barro type growth regressions). The 95% confidence intervals were obtained from the same source as the mean sea level trends and they are inversely related to length of sea level data collection period. The data sources are discussed in Section 2.3. As the length of confidence intervals is independent of sea level rise and economic growth, the use of confidence intervals to define the set of treated should not cause the matching estimator to be biased.

Since the dataset contains only 274 coastal counties, which is much less than the number of controls, we chose the threshold for defining the treated observations to be equal to a ten percent sample quantile of sea level rise of coastal counties, which is 1.8 mm/year. [2]

[2] We also tried other matching algorithms besides the propensity score matching. These include Mahalanobis distance and its generalization, where the optimal weights of each covariate are found by a generic search algorithm (Diamond and Sekhon 2014). However, we obtained the best matchings (in terms of balance) applying the propensity score method, therefore we do not present results of the other matchings.

2.3 Data

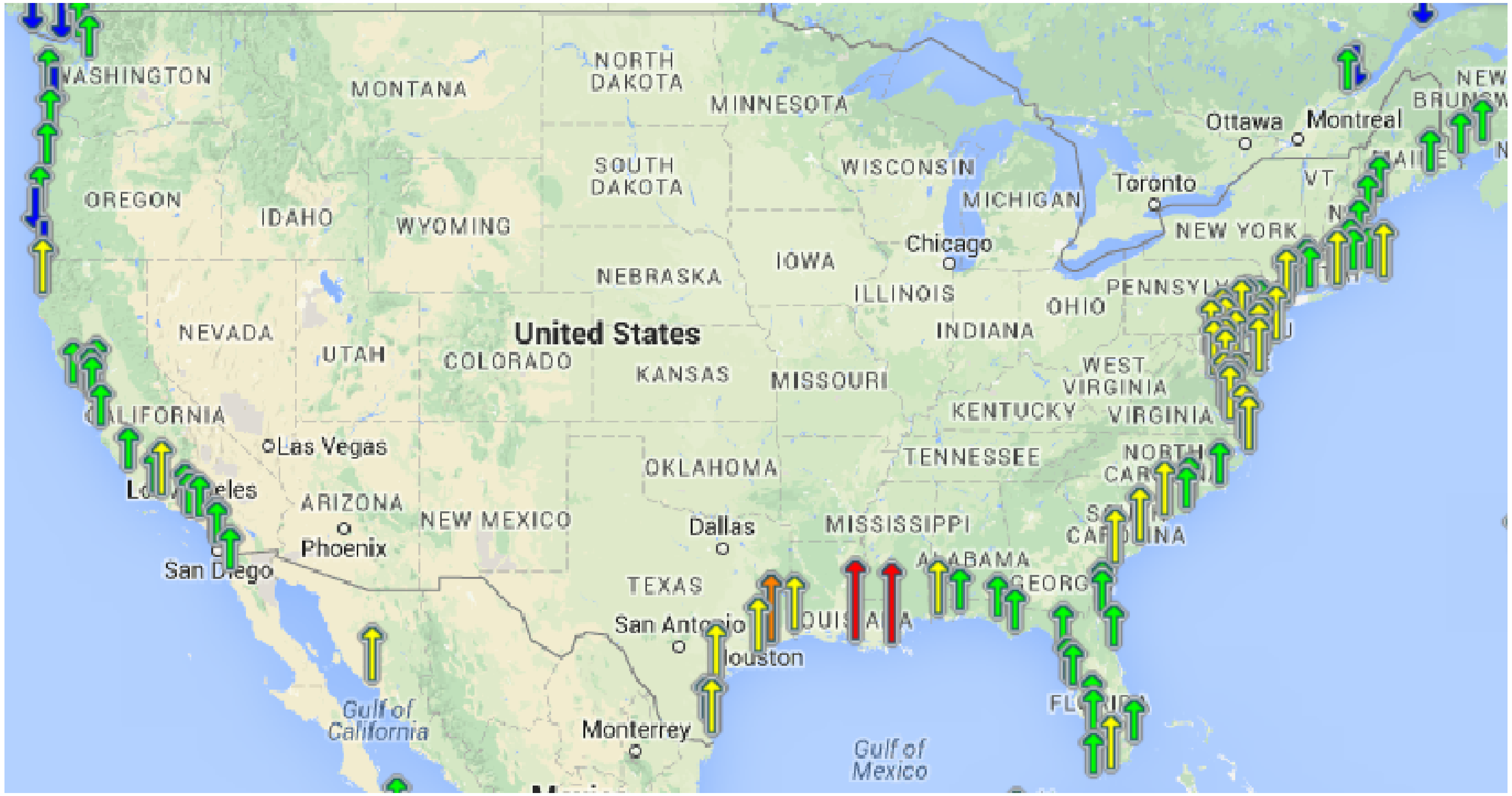
All control variables used in this study are listed in Table 2.1 or Table A.1 in Appendix A. Since values of some of these covariates are not available for all counties, most of the models are estimated using a dataset which includes 3063 counties for which all data are available, while the total sample size is 3072. Descriptive statistics of sea level rise, average growth rate of per capita income and the most relevant covariates are summarized in Table 2.1. Descriptive statistics of the other covariates can be found in Table A.2 in Appendix A. The statistics are calculated for the sample of complete cases.

Table 2.1: **Descriptive Statistics**

Variable	**Mean**	**Std. dev.**
Sea level rise - stations average (mm/year)	2.764	1.768
Sea level rise - coastal counties (mm/year)	3.376	2.068
Average growth rate of per capita income 1990-2012 (Income in log of dollars)	0.041	0.008
Coast distance (km)	600.914	463.532
Gov. expenditures per capita (Thousands of US$)	1071.411	376.838
Tax income per capita (Thousands of US$)	652.926	434.457

The sea level rise data are available at the website of the Center for Operational Oceanographic Products and Services (2016) (CO-OPS). The water level data were collected at 94 CO-OPS water gauge stations located within the contiguous United States. The locations of the stations are illustrated in Figure 2.1. The stations are represented by arrows of different colours that illustrate spatial variation in sea level trends. As we can see, the stations are distributed along the coast approximately evenly. A relatively long stretch of coast without a station is in northern California, but the total number of stations and their layout in central and southern parts of California is adequate. The number of water stations is somewhat lower around the coast of Texas and the east coast of Florida, while the stations appear to be relatively more frequent around Virginia and Maryland, probably because of the more rugged character of the coast along the Chesapeake Bay. Overall, the stations are located relatively evenly along the US coastline.

Figure 2.1: Location of water gauge stations and sea level trends



9 – 12 mm/year 6 – 9 mm/year 3 – 6 mm/year 0 – 3 mm/year -3 – 0 mm/year

Source: Center for Operational Oceanographic Products and Services (2016)

Based on the colours of arrows in Figure 2.1, the spatial variation in sea level trends does not seem to be large as only five levels of average sea level trends are distinguished by different colours. Nevertheless, after more detailed examination of the data and their descriptive statistics, we conclude that the spatial variation is reasonable. The sea level trends range from -0.72 to 9.65 mm per year and their variance is 3.126. Relatively large spatial variability is along the Gulf of Mexico where the sea level rise is the most rapid.

Water levels have been captured at these stations for a span of at least 30 years. The fact that the sea level data collection period varies across the water gauge stations may make the analysis more complicated. This issue is addressed in Section 2.5.4. According to information provided by CO-OPS, the sea level trends were obtained by the decomposition of the sea level variations into a linear secular trend, an average seasonal cycle, and residual variability at each station. For most of the stations, water level data up to the year 2007 were used for estimation of mean sea level trend.

Land surface topography is an important factor that needs to be considered when analysing the effects of sea level rise. The topography of coastal areas could potentially affect the relationship between sea level rise and economic growth. Agricultural activity and land use is likely to differ across areas with different land surfaces. Furthermore, the area of land directly affected by sea level rise depends on coastal land slope. Hence, in the following we discuss the topography of the coastal counties.

The United States Department of Agriculture (USDA) provides a dataset that classifies US counties into 21 categories based on their land surface topography.[3] According to this classification, the biggest part of the East Coast (135 out of the 232 East Coast counties included in our sample) is classified as flat plains. Most of the remaining part of the East Coast consists of irregular plains or tablelands with moderate relief. In particular, the coasts of Alabama, Florida, Massachusetts, Mississippi, District of Columbia, most of coastal Virginia, some parts of Maryland, New York and Rhode Island are classified as irregular plains. Tablelands with moderate relief can be found on the coast of Virginia and Maryland. A small part of the East Coast consists of plains with hills (New Jersey, Rhode Island) and plains with high hills (Maine, New Hampshire).

The topography of the West Coast is relatively less homogeneous. Coastal Washington, Oregon and California consist mostly of low or high mountains. Very small areas of the

[3] The dataset can be downloaded from `https://www.ers.usda.gov/data-products/natural-amenities-scale/`. The topography scale originally comes from *The National Atlas of the United States of America.* U.S. Department of Interior, U.S. Geological Survey, Washington, DC., 1970.

West Coast are classified as tablelands with moderate relief or plains with low mountains.[4]

A potential data related problem could be due to the fact that the long term sea level rise signal is relatively weak in comparison to other phenomena which affect the water level measure at a tide gauge (for example seasonal or tidal sea level changes). Hence, the noise from the measurement error could possibly lead to attenuation bias. Although we believe that this is unlikely as the measurement errors are mostly random and they usually average out over an yearly or monthly average (Parker 1992), we perform statistical tests to further eliminate the possibility of occurrence of problematic measurement errors. Measurement error only produces inconsistent OLS estimates when the error is correlated with the measure which we observe and this situation is called classical measurement error or classical errors-in-variables (Wooldridge 2002). According to Parker (1992), the potential sea level rise measurement problem is much more likely to occur if the gauge station is located inside of an estuary or in a shallow bay. This is due to a nonlinear interaction between storm surge and the tide and slowly varying annual precipitation patterns which can result in low-frequency sea level signal. Therefore, we use a t-test of equality of means to test whether the sea level trends measured at the gauge stations located inside of an estuary or in a shallow bay are significantly different from the trends measured at the other stations. The test statistic is insignificant with p-value equal to 0.978[5]; hence, the measured sea level trends are not significantly different at the gauge stations located in shallow water bodies. The measurement error could be also correlated with the data collection range, so we tested correlation between measured sea level trends and data sample range. The p-value of the correlation coefficient is 0.328; hence, the statistic is insignificant. We did not find any evidence indicating occurrence of classical measurement error.

The sample of complete data includes 274 coastal counties and 2789 inland ones. The 94 CO-OPS stations are located in 86 coastal counties. We considered the sea level rise to be equal to zero in the inland counties. For the coastal counties extrapolation is needed. We adopt a simple extrapolation as follows. For a few coastal counties with more than one station, the sea level rise is calculated as the arithmetic average of the sea level trend captured at different stations in county. For counties with one CO-OPS station, the mean

[4]To confirm that variability in land surface topography does not confound our results, we estimated a set of models with the categories of land surface topography as additional control variables. The results are not qualitatively different from our main results. Nearly all categories of surface topography are insignificant in the vast majority of the relevant models. Also the F-tests of joint significance of all topographical categories are insignificant in nearly all cases (the joint F-test is significant in only one of our 26 models with the topographical categories). We also estimated a set of models with interactions of the topography categories and sea level rise. In almost all of these models, the sea level rise variables, topography and their interactions are insignificant as well as the F-tests of their joint significance. We do not present these results here to keep the length of this thesis within reasonable limit.

[5]Assuming unequal variance in the two groups.

sea level trend measured at this station is used. For counties with no CO-OPS station, the sea level rise is obtained as mean sea level trend, measured at the station which is closest to the centroid of the county. The distance is calculated as the shortest Euclidean distance.

Since most of the counties are landlocked with zero sea level rise, it makes little sense to present descriptive statistics of sea level rise of the whole sample. Therefore, Table 2.1 shows the mean and standard deviation of sea level rise for the sample of 94 CO-OPS stations and the mean and standard deviation of sea level rise of the subsample of coastal counties using the extrapolation described above.

The per capita income growth data are drawn from the Bureau of Economic Analysis. Descriptive statistics of per capita income growth rates for the 13 time periods are summarized in Table A.3 in Appendix A. Distance from coast was obtained as the shortest Euclidean distance from centroids of counties to coast. Details about the data sources of the other covariates can be found in Appendix A.2.

2.4 Empirical results

In Section 2.4.1, the empirical results of several variants of Barro type growth models are presented. The empirical results of the matching estimator discussed in Section 2.2.2 are presented in Section 2.4.2.

2.4.1 Barro type growth regressions

As a starting point, we fitted a single OLS regression of economic growth g_n on sea level rise without any other covariates and an OLS regression of economic growth g_n on sea level rise and its square without any other covariates. Estimates of these two regressions and estimates of a 3SLS-IV model characterised by equations (2.2) to (2.6) without other covariates are summarized in Table 2.2.

We also included sea level rise squared. If the squared term is not included, the linear term will be positive and slightly significant in some of the models. This is not in accordance with our expectation and the reason could be the nonlinearity of the relationship. Therefore, the quadratic term of sea level rise is included and it turns out to be negative in most cases and often significant. We also test for joint significance of the quadratic and linear sea level rise terms in the estimated models. The tests of joint significance confirm that if at least one sea level rise coefficient is significant, then the quadratic and linear sea level rise terms are jointly significant as well. Hence, the specifications with quadratic sea level rise term are the preferred ones. We report the results of the tests of joint significance below (see Tables 2.2, 2.4 and 2.7).

In the first column of Table 2.2, the effect of sea level rise is positive and significant, whereas the literature has assumed the opposite effect. However, as mentioned above, the OLS estimate of Barro type growth regression is not consistent in most cases. Furthermore, the possible relationship between sea level rise and economic growth can be non-linear. The peculiar result may also be due to omitted variable bias. When the squared sea level rise is included, both linear and squared terms are positive and insignificant. However, as we can see in Table 2.2, the coefficients are jointly significant. This is likely to be due to the inevitable collinearity between sea level rise and its quadratic term.

Things change for the 3SLS-IV estimate. As we can see in Table 2.2, income diverges, as the log of initial per capita income in the third column is positive. The linear term of sea level rise is negative and insignificant, while the quadratic term is positive and slightly significant. According to the F-test, the two sea level rise terms are jointly significant.

Table 2.2: **Income growth model for period 1990-2012 - First estimates**

	OLS 1	OLS 2	3SLS-IV equation (2.6)
Dependent variable	g	g	π
Constant	0.077 (0.011)***	0.077 (0.011)***	−1.390 (0.008)***
Log of initial per capita income (US$)	−0.004 (0.001)***	−0.004 (0.001)***	0.146 (0.036)***
Sea level rise (m/year)	0.828 (0.145)***	0.565 (0.497)	−4.077 (3.875)
Sea level rise (m/year) - squared	− − −	0.026 (0.048)	0.902 (0.368)*
Measures of agglomeration	**No**	**No**	**No**
Measures of religious adherence	**No**	**No**	**No**
Other socioeconomic and environmental indicators	**No**	**No**	**No**
Regional dummy variables	**No**	**No**	**No**
Joint significance of sea level rise and its squared term - F-test	− − −	1.732×10^{-7} *** ($p-value$)	2.895×10^{-6} *** ($p-value$)
Convergence rate	0.004	0.004	0.004
Observations	274	274	274

Notes: Standard errors in brackets

*p<0.05; **p<0.01; ***p<0.001

These results might be biased as other covariates are omitted and spatial patterns are not taken into account, therefore more accurate models are estimated.

OLS estimates of model (2.1) for period 1990-2012 with covariates can be found in Table A.4 in Appendix A. The 3SLS-IV estimates of equation (2.6) for the same period including covariates can be found in the first column of Table 2.4. Adjusted R-squared is 0.492 for this model and value of F-statistic is 119.8 with a p-value lower than 2.2×10^{-16}. Estimates of the first stage (2.3) and the second stage (2.4) of this model are summarized in Table A.5 in Appendix A. However, as possible spatial relationships are not taken into account, these estimates may be biased and inconsistent.

Moran's I confirms spatial dependence for the economic growth rate g_n. The test statistic equals 0.500 with a p-value lower than 2.2×10^{-16}, thus the null hypothesis of no spatial dependence is rejected. Moran's I was calculated also for the variable π_n from equation (2.6). Its value is 0.532 and the corresponding p-value is lower than 2.2×10^{-16}. Also in this case, the null hypothesis of no spatial dependence is rejected. One of the forms (2.7), (2.8) or (2.9) should therefore be fitted instead of applying the straightforward 3SLS-IV procedure.

As an additional check whether the use of the spatially adjusted model is justified, we used the Lagrange Multiplier (LM) diagnostic tests for spatial dependence as proposed by Anselin et al. (1996). Specifically, we used the LM test for spatial error dependence and the LM test for a missing spatially lagged dependent variable. We also calculated variants of these tests, which are robust to presence of the other. These include the LM test for spatial error dependence in the presence of omitted spatially lagged dependent variable and the other way around. Distributions of these test statistics are well known for the case of OLS residuals, therefore we applied them to residuals from (2.1) and to residuals from (2.6). The values of the LM statistics for spatial error dependence and for missing spatially lagged dependent variable and its robust versions are summarized in Table 2.3.

All statistics in Table 2.3 are highly significant, suggesting that a general spatial model (2.7) could be a suitable form. Estimates of this form are summarized in the first column of Table A.8 in Appendix A. Parameter λ is insignificant while ρ is highly significant which indicates that specification (2.9) is more suitable. Estimates of (2.9) are summarized in the second column of Table 2.4, the estimates of all its coefficients can be found in the second column of Table A.6 in Appendix A. Also according to the LM test for residual autocorrelation, specification (2.9) is appropriate. The value of this test statistic is 0.826 and its p-value is 0.364, thus the null hypothesis of uncorrelated error terms is not rejected.

Table 2.3: **LM tests for spatial dependence in residuals**

		Error dependence		**Missing spatially lagged dependent variable**	
		Test statistic	***p*-value**	**Test statistic**	***p*-value**
OLS (2.1) **residuals**	**Standard**	625.270	$< 2.2 \times 10^{-16}$	631.655	$< 2.2 \times 10^{-16}$
	Robust	22.527	2.072×10^{-6}	28.912	7.575×10^{-8}
3SLS-IV (2.6) **residuals**	**Standard**	553.635	$< 2.2 \times 10^{-16}$	533.797	$< 2.2 \times 10^{-16}$
	Robust	41.802	1.010×10^{-10}	21.964	2.779×10^{-6}

Therefore, we take model (2.9) as a starting point for further analysis and for estimation of different variants of this model.

Table 2.4: **Income growth model for period 1990-2012**

	3SLS-IV model (2.6)	SAR model (2.9)
Constant	0.348 (0.002)***	0.185 (0.007)***
Log of initial per capita income (US$)	-0.033 (0.005)***	-0.033 (0.005)***
Sea level rise (m/year)	0.947 (0.277)***	0.594 (0.252)*
Sea level rise (m/year) - squared	-0.059 (0.037)	-0.044 (0.034)
Coast distance (thousands km)	-0.007 (0.001)***	-0.005 (0.001)***
Coast distance (thousands km) - squared	0.008 (0.001)***	0.005 (0.001)***
Gov. expenditures per capita (billion US$)	-0.710 (0.451)	-0.596 (0.411)
Tax income per capita (billion US$)	4.171 (0.399)***	3.370 (0.368)***
ρ (SAR)	—	0.458 (0.021)***
Measures of agglomeration	**Yes**	**Yes**
Measures of religious adherence	**Yes**	**Yes**
Other socioeconomic and environmental indicators	**Yes**	**Yes**
Regional dummy variables	**Yes**	**Yes**
Joint significance of sea level rise and its squared term - F-test	8.588×10^{-6} *** $(p - value)$	$0.011^{*\ a}$ $(p - value)$
Convergence rate	0.058	0.058
Observations	3,063	3,063

Notes: Standard errors in brackets

*p<0.05; **p<0.01; ***p<0.001

[a] To test joint significance of the sea level rise terms in our SAR models, we use a likelihood ratio test for comparing spatial autoregressive models rather than a typical F-test. In particular, we use a function called anova.sarlm in the **R** programming system (R Core Team, 2017).

As we can see in the second column of Table 2.4, the sea level rise is positive and slightly significant, while the squared sea level rise is negative and insignificant in spatial autoregressive model (2.9). The two sea level rise terms are jointly highly significant.[6]

As explained in LeSage and Pace (2009), impact measures are needed for correct interpretation of coefficients of models with spatially lagged dependent variable. Because of the spillover effects, a change in explanatory variable in one observation can potentially effect value of dependent variable of all other observations. Therefore, the coefficients can not be interpreted in the same way as typical OLS coefficients.

The impact measures for our model (2.9), which are summarized in Table 2.5, were calculated according to equation (2.46) in LeSage and Pace (2009) using an exact dense matrix. A direct impact is an impact of an explanatory variable in county i on the dependent variable in county i, an indirect impact is an impact of an explanatory variable in county i on the dependent variable in all counties but i and total impact is a sum of direct and indirect impact. The impacts of all covariates included in this model can be found in Table A.7 in Appendix A.

[6]We use the same methodology as Higgins et al. (2006) and Rupasingha and Chilton (2009). We attempted to replicate the results of Rupasingha and Chilton (2009), but we did not obtain precisely the same estimates as we do not have their dataset available. However, our estimates are not qualitatively different from those of Rupasingha and Chilton (2009) and as in their paper, some of our estimates turned out to be insignificant or having different sign than expected. These include for example per capita highway and education expenditures (see Section 2.5.6).

Table 2.5: **Income growth model for period 1990-2012 - Impact measures**

	SAR model (2.9)		
	Direct	Indirect	Total
Sea level rise (m/year)	0.6218	0.4753	1.0971
Sea level rise (m/year) - squared	−0.0465	−0.0355	−0.0820
Coast distance (thousands km)	−0.0048	−0.0036	−0.0084
Coast distance (thousands km) - squared	0.0047	0.0036	0.0084
Gov. expenditures per capita (billion US$)	−0.6232	−0.4764	−1.0996
Tax income per capita (billion US$)	3.5257	2.6948	6.2205
Measures of agglomeration		**Yes**	
Measures of religious adherence		**Yes**	
Other socioeconomic and environmental indicators		**Yes**	
Regional dummy variables		**Yes**	

The coefficients in Table 2.4 are barely significant but we show effect size nonetheless. Estimated total initial impacts of sea level rise on the economies of coastal counties and their confidence intervals are depicted in Figures 2.2 and 2.3. We obtained the counties' impacts by multiplying the sea level rise and its square of each county with the estimated total impacts of sea level rise (which can be found in the first two rows of Table 2.5) and the confidence intervals were obtained accordingly using the standard errors of model (2.9) in the second column of Table 2.4. In Figures 2.2 and 2.3, the counties are ordered according to their location along the coast. In Figure 2.2, west coast counties are depicted from north to south and Figure 2.3 represents counties along the Gulf of Mexico and east coast counties from south to north. The alternating gray and white groups of bars represent groups of counties in each coastal state. The impacts are only negative in the four counties where sea level is falling, but the confidence intervals are far below zero in many states including Texas, Louisiana and Virginia.

We compare the impacts of past sea level rise to predictions of two example studies (Bigano et al. 2008 and Bosello et al. 2007) in Table 2.6. Both Bigano et al. (2008) and Bosello et al. (2007) present effects of increase of 25 cm, hence we scale their estimates downwards. More specifically, we compare the effects of sea level rise of 0.302 mm and 2.764 mm (the average yearly sea level rise over all counties and over the gauge stations,

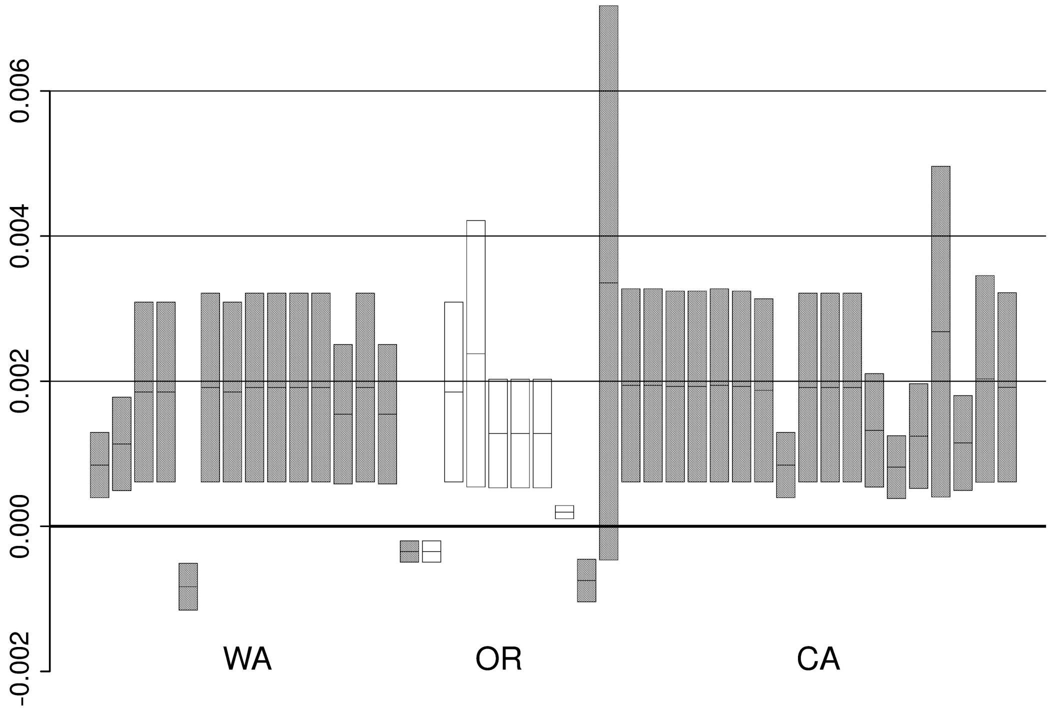


Figure 2.2: Initial total impacts of sea level rise on economic growth rate - West coast

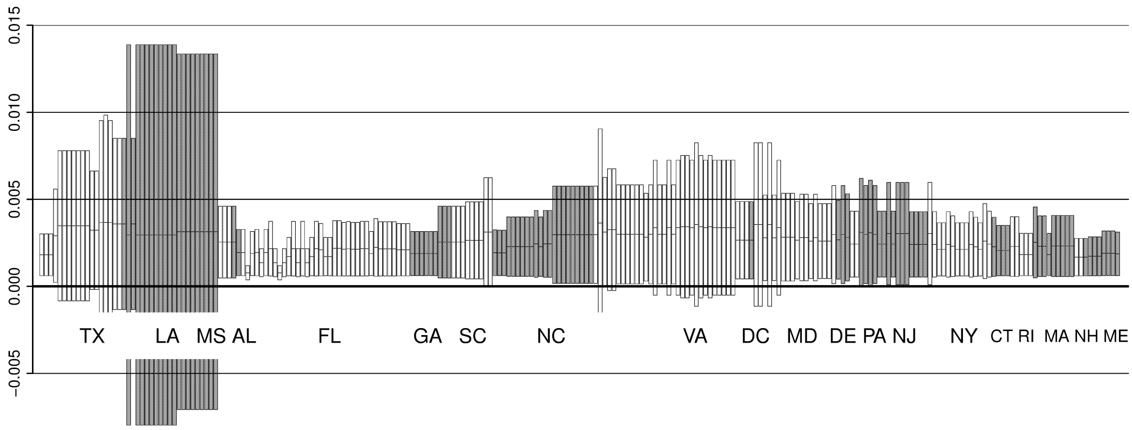


Figure 2.3: Initial total impacts of sea level rise on economic growth rate - East coast

respectively) on annual GDP. Our estimates (in the fourth column of Table 2.6) were obtained using the total impact measures presented in Table 2.5. Our results differ from those of Bigano et al. (2008) and Bosello et al. (2007) as our estimates are relatively small but positive whereas theirs are negative. This result does not support our hypothesis.

Table 2.6: **Estimated impacts of sea level rise**

Sea level rise (mm)	**Bigano et al. (2008)**	**Bosello et al. (2007)**	**Our estimate**
0.302[a]	-1.57×10^{-6}	-1.09×10^{-5}	3.24×10^{-4}
2.764[b]	-1.44×10^{-5}	-9.95×10^{-5}	2.41×10^{-3}
250.000[c]	-0.001	-0.009[d]	—

The values expressed as % changes of GDP with respect to 'without climate change' scenario.

[a] sample average
[b] average per station
[c] Bigano et al. (2008) and Bosello et al. (2007) show the estimated effects of 25 cm (=250 mm) increase in sea level. We show these estimates in the last row of this table. The first two columns of the first two rows include the estimates of Bigano et al. (2008) and Bosello et al. (2007) after being scaled down.
[d] Total protection scenario, the change in GDP is equal to additional GDP growth stimulated by additional demand for investment triggered by coastal protection building minus protection expenditure. The loss is even bigger for the no protection scenario.

As mentioned above, we estimated model (2.9) for different time periods of economic growth. In total, we estimated 13 different models for 13 different time periods, which are listed in the first column of Table 2.7. The first row relates to time period 1990-2012, hence this row depicts the same estimates of sea level rise and coast distance as those in the second column of Table 2.4.

As one can see in Table 2.7, for the period 1990-2006 and the shorter periods both linear and quadratic sea level rise terms are significant and the linear term is positive while the quadratic term is negative. The period 1990-2003 is the exception: sea level rise is insignificant. However, for most of the longer periods both linear and quadratic sea level rise terms are insignificant, therefore it can not be generally claimed that sea level rise has a significant effect on economic growth. The third column of Table 2.7 includes significance levels of the likelihood ratio tests of joint significance of sea level rise and its quadratic term. The results of the joint tests are mostly consistent with the significance levels of the individual t-tests. If at least one of the sea level rise coefficients is individually significant, then the joint test is also significant. Thus, the tests of joint significance of the sea level rise coefficients do not affect the interpretation of our results. The relationship between sea level rise and economic growth is unstable over time. As the growth rates are averaged over the periods in Table 2.7, we see that the relationship reverses in 2003, 2007 and 2011. The only interpretation is therefore that the earlier significance is a fluke.

Table 2.7: **Sea level rise and coast distance estimates**

SAR models (2.9) for different time periods

Period	**SLR**			**Coast distance**	
	Linear	**Squared**	**Joint significance** [a]	**Linear**	**Squared**
1990 – 2012	+ *	-	*	- ***	+ ***
1990 – 2011	+	+		-	+ ***
1990 – 2010	+ •	-	*	- **	+ ***
1990 – 2009	+ ***	- **	***	- **	+ ***
1990 – 2008	-	+		- •	+ **
1990 – 2007	-	+		-	+ *
1990 – 2006	+ ***	- **	***	- •	+ *
1990 – 2005	+ ***	- ***	***	- *	+ ***
1990 – 2004	+ ***	- ***	***	- *	+ ***
1990 – 2003	+	-		- **	+ ***
1990 – 2002	+ ***	- ***	***	- *	+ **
1990 – 2001	+ ***	- ***	***	- **	+ ***
1990 – 2000	+ ***	- ***	***	- **	+ ***
Observations:					3063

Notes: Standard errors in brackets

All models include all covariates from Table A.6.

•p<0.1; *p<0.05; **p<0.01; ***p<0.001

+ estimate is positive; − estimate is negative

[a] To test joint significance of the sea level rise terms in our SAR models, we use a likelihood ratio test for comparing spatial autoregressive models rather than a typical F-test. In particular, we use a function called anova.sarlm in the **R** programming system (R Core Team, 2017).

2.4.2 Matching estimator

We compared a number of different propensity score matchings. Methods used to obtain these matchings differ in variables in balance matrix, caliper, number of controls assigned to one treated, propensity score model, whether the matching is with replacement or not and in way how ties are treated. Specifically, we found three different matchings with balance achieved on all covariates listed in Table A.6 except for sea level rise and coast distance. We excluded coast distance from the balance matrix as all treated counties are coastal, while most of the controls are inland, thus it would be impossible to obtain matching balanced on this variable. For the three balanced matchings, two sided t-tests of equality of means and both naive and bootstrap Kolmogorov-Smirnov tests are insignificant for all the covariates. All these three matchings are paired matchings with one control assigned to each treated and without replacement. Ties are randomly broken.

The estimated treatment effect and some features of the three completely balanced matchings are summarized in Table 2.8. The explanatory variables in each propensity score model estimated in this study are covariates of the corresponding balance matrix. Regarding the first matching in Table 2.8, the balance matrix and the propensity score model include all covariates listed in Table A.6 with the exception of sea level rise and coast distance. It also includes the square of government expenditures, nonwhites, and amenities. The propensity score model of the second and the third matching in Table 2.8 includes also squared percentage of Catholics besides the explanatory variables included in the propensity score model for the first matching.

The estimated treatment effect for the treated is positive for the first and third matching, and negative for the second matching. In all three cases the effect is insignificant. Besides these three matchings we estimated a number of other matchings, however balance was not achieved on all relevant covariates for them. For almost none of these not completely balanced matchings, the estimate of the treatment effect is significantly different from zero. As in the case of the economic growth model, no significant effect of sea level rise on economy of the United States was found applying the matching estimator.

Table 2.8: **Balanced propensity score matchings**

Matching	Estimated treatment effect	Std. error	p-value	Treated matched cases	Propensity score model	Caliper
1	8.60×10^{-5}	2.12×10^{-4}	0.684	131	Logit	0.035
2	-6.46×10^{-5}	1.85×10^{-4}	0.726	136	Probit	0.035
3	1.88×10^{-5}	1.89×10^{-4}	0.921	126	Probit	0.020

Notes: Estimated effect: Treatment effect for the treated
Caliper in multiples of standard deviation for each covariate

2.5 Robustness

Variants of the models discussed in Section 2.4.1 are estimated to test the robustness of our findings.

2.5.1 Heteroscedasticity

We estimated heteroscedasticity robust White estimates to find out whether the model does not suffer from more general types of heteroscedasticity. Specifically, we fitted the following spatial lag model:

$$\pi = \rho W \pi + X\beta + \epsilon. \tag{2.11}$$

The model was estimated by performing a generalized two stage least square procedure (Kelejian and Prucha 1998b) with a heteroscedasticity correction to the covariances of coefficients to obtain a White consistent estimator. We used the spatially lagged values of variables in X as instruments for the spatially lagged dependent variable. The White estimates are compared with the estimates of the spatial autoregressive lag model (2.9) in Table 2.9. They do not differ substantially. The full set of estimates can be found in the second column of Table A.8 in Appendix A.

The impact measures for model (2.11) calculated according to equation (2.46) in LeSage and Pace (2009) using exact dense matrix can be found in Table A.9 in Appendix A.

Table 2.9: **Income growth model for period 1990-2012**

	SAR model (2.9)	White errors (2.11)
Constant	0.185 (0.007)***	0.177 (0.019)***
Log of initial per capita income (US$)	−0.033 (0.005)***	−0.033 (0.005)***
Sea level rise (m/year)	0.594 (0.252)*	0.577 (0.244)*
Sea level rise (m/year) - squared	−0.044 (0.034)	−0.044 (0.032)
Coast distance (thousands km)	−0.005 (0.001)***	−0.004 (0.001)***
Coast distance - squared (thousands km squared)	0.005 (0.001) ***	0.004 (0.001)***
Gov. expenditures per capita (billion US$)	−0.596 (0.411)	−0.590 (0.570)
Tax income per capita (billion US$)	3.370 (0.368)***	3.330 (0.543)***
ρ (SAR)	0.458 (0.021)***	0.481 (0.054)***
Measures of agglomeration	**Yes**	**Yes**
Measures of religious adherence	**Yes**	**Yes**
Other socioeconomic and environmental indicators	**Yes**	**Yes**
Regional dummy variables	**Yes**	**Yes**
Convergence rate	0.004	0.004
Observations	3,063	3,063

Notes: Standard errors in brackets

*p<0.05; **p<0.01; ***p<0.001

2.5.2 Outliers

We estimated the spatial autoregressive models without outliers for all 13 periods. We classify as outliers all observations with negative sea level rise or with sea level rise above 5.5 mm per year (approximately 90th sample percentile of the subsample of coastal counties)[7] and also all observations with average growth rate of per capita income higher or equal to its 95th sample percentile or lower or equal to its 5th sample percentile. The outliers which were removed because of very high sea level rise are mostly coastal counties around the Gulf of Mexico (in Louisiana and Texas) and we also removed four counties with negative sea level rise (in California, Oregon and Washington). Estimates of sea level rise and coast distance coefficients of the models without outliers are compared with estimates of the models based on the whole sample in Table 2.10. Columns (2) − (5) summarise estimates of the models using the whole sample and estimates of the models without outliers are presented in columns (6) − (9). The sea level rise coefficients of the second variety do not differ substantially in their significance levels or signs from the estimates of the full sample. The significance levels are somewhat lower for some of the periods without outliers, probably as a result of the smaller sample size. However, there is only one period for which sea level rise is significant for the full sample and not significant for the sample without the outliers at any significance level. This confirms that the results are not driven by outliers and that sea level rise has no significant impact on economic growth.

[7] We found it more sensible to choose the cut-offs 0 mm/yr and 5.5 mm/yr than using quantiles because the distribution of the sample sea level rise is very specific. For most counties, sea level rise is equal to zero or to a very small positive value, for few cases it is extremely high and for even fewer cases it is negative and close to zero.

Table 2.10: **SAR models** (2.9) **without outliers**

Sea level rise and coast distance estimates for different time periods

Period	**Whole sample**				**Without outliers**			
	SLR		**Coast distance**		**SLR**		**Coast distance**	
	Linear	**Sq.**	**Linear**	**Sq.**	**Linear**	**Sq.**	**Linear**	**Sq.**
1990 – 2012	+ *	-	- ***	+ ***	+ *	- *	- **	+ ***
1990 – 2011	+	+	-	+ **	+	-	-	+ **
1990 – 2010	+ •	-	- **	+ ***	+ •	- •	- •	+ ***
1990 – 2009	+ ***	- **	- **	+ ***	+ **	-	- *	+ ***
1990 – 2008	-	+	- •	+ **	+	- •	-	+ *
1990 – 2007	-	+	-	+ *	+ •	- •	-	+ •
1990 – 2006	+ ***	- **	- •	+ *	+ **	-	- *	+ **
1990 – 2005	+ ***	- ***	- *	+ ***	+ ***	- *	- *	+ ***
1990 – 2004	+ ***	- ***	- *	+ ***	+ ***	- *	- *	+ ***
1990 – 2003	+	-	- **	+ ***	+	-	-	+ **
1990 – 2002	+ ***	- ***	- *	+ **	+ *	-	- **	+ ***
1990 – 2001	+ ***	- ***	- **	+ ***	+ **	- *	- **	+ ***
1990 – 2000	+ ***	- ***	- **	+ ***	+ •	-	- ***	+ ***
Obs.:	3063				Varies between 2718 and 2730			

Notes:

- For each period, the outliers are defined as observations with sea level rise higher than 5.5 mm/yr or with negative sea level rise or with per capita income growth rate above its Q95 or below its Q05
- All models include all covariates from Table A.6
- + estimate is positive; − estimate is negative
- $^{\bullet}p<0.1$; $^{*}p<0.05$; $^{**}p<0.01$; $^{***}p<0.001$

All models in Table 2.10 include the covariates listed in Table A.6, but the estimates are not presented here to save space. The signs and significance levels of the coast distance coefficients are depicted as they are highly correlated with sea level rise.

2.5.3 Groundwater depletion

One reason why no significant negative effect was found can be a reverse causality due to groundwater depletion. An alternative hypothesis is that excessive ground water withdrawal has led to land subsidence which appears as relative sea level rise. More water is being extracted in more populated areas with higher economic growth, thus higher economic growth can be positively correlated with relative sea level rise, which may cancel the negative effects of sea level rise on the economy.

Groundwater depletion has only been an issue in some coastal areas in United States (Konikow 2013). As a robustness test we estimated the spatial autoregressive models (for the 13 time periods) for subsamples without the coastal areas that experience groundwater depletion. We used the estimates of Konikow (2013) to sort the states where groundwater has been depleted into four groups according to volume of depleted water during the relevant time period. Then, the model was estimated for four subsamples. First the model was estimated for the subsample without the states in the group with the highest levels of depletion, then for the subsample without the two groups with the highest levels of depletion, after that the three groups of states with the highest levels of depletion were excluded and finally all four groups were excluded. For the subsample without the first group, the estimates of sea level rise coefficients do not differ significantly from the complete sample for almost all time periods. For the other three subsamples, previously significant sea level rise coefficients are not significant any more, which can be also due to decreased sample size. These results are in accordance with the above conclusion that no significant effect of sea level rise was detected.

2.5.4 Sea level data sample range

The period of sea level data collection varies across the CO-OPS stations. Since the length of data collection period is independent of sea level rise or economic growth, it should not cause a measurement error or bias. However, the unequal length of collection periods may cause a heteroscedasticity problem. The possible heteroscedasticity issue is discussed in Section 2.5.1 and as one can see in Table 2.9, the heteroscedasticity robust White estimates do not differ substantially from the estimates of (2.9) thus heteroscedasticity is not an issue.

As a further robustness test, we fitted the models for all 13 time periods of economic growth using the mean sea level trend estimated for identical 28 years long time periods using water level data available at the website of Permanent Service for Mean Sea Level (2016) (PSMSL). The maximum length of time period for which the data are available for most of the stations is 28 years, specifically from the year 1979 to 2007. These data are only available for water gauge stations in 57 counties, thus we used extrapolated values of sea level rise for the other counties. The same way of extrapolation is applied as described in Section 2.3. In Table 2.11, the signs and significance levels of coefficients obtained by our basic variant of (2.9) (using the whole sea level rise data collection periods) are compared with the estimates obtained using the 28 years long time period of sea level rise data collection. The table summarises 13 models for the 13 time periods of economic growth, each row corresponds to one time period. Although these models include also all other covariates from Table A.6, only the sea level rise and coast distance coefficients are presented in Table 2.11 to save space. The results do not differ substantially, significance levels and signs of the sea level rise are the same for most of the time periods.

All coefficients of the two models in the first row of Table 2.11 are compared in Table A.10 in Appendix A. Thus, Table A.10 compares estimates of (2.9) using the sea level rise data from the whole data collection ranges (our basic specification summarised in the second column of Table 2.4) with estimates of the same specification using sea level rise data from the shortened 28 years long time period. In both of these models the time period of economic growth is 1990-2012. We can see that the estimates and their significance levels are very similar in these two specifications. Regarding the models for the other 12 periods of economic growth in Table 2.11, estimates of other coefficients not presented in Table 2.11 are also very similar to estimates obtained using the whole ranges of sea level rise data collection. However, they are not presented here to save space.

We can conclude that the results are robust with respect to time period of the sea level rise data collection.

Table 2.11: **SAR models** (2.9) **- alternative data range**

Sea level rise and coast distance estimates for different time periods

Period	**Full range of SLR data**				**SLR data from** 1979 – 2007			
	SLR		**Coast distance**		**SLR**		**Coast distance**	
	Linear	**Sq.**	**Linear**	**Sq.**	**Linear**	**Sq.**	**Linear**	**Sq.**
1990 – 2012	+ *	-	- ***	+ ***	+ •	-	- ***	+ ***
1990 – 2011	+	+	-	+ ***	-	+	-	+ ***
1990 – 2010	+ •	-	- **	+ ***	+	-	- ***	+ ***
1990 – 2009	+ ***	- **	- **	+ ***	+ ***	- *	- ***	+ ***
1990 – 2008	-	+	- •	+ **	-	+	- •	+ ***
1990 – 2007	-	+	-	+ *	-	+	-	+ *
1990 – 2006	+ ***	- **	- •	+ *	+ ***	- **	- **	+ **
1990 – 2005	+ ***	- ***	- *	+ ***	+ ***	- ***	- **	+ ***
1990 – 2004	+ ***	- ***	- *	+ ***	+ ***	- ***	- **	+ ***
1990 – 2003	+	-	- **	+ ***	+	-	- **	+ ***
1990 – 2002	+ ***	- ***	- *	+ **	+ ***	- ***	- **	+ ***
1990 – 2001	+ ***	- ***	- **	+ ***	+ ***	- **	- ***	+ ***
1990 – 2000	+ ***	- ***	- **	+ ***	+ **	- *	- ***	+ ***
Obs.:	3063				3063			

Notes: All models include all covariates from Table A.6

+ estimate is positive; − estimate is negative

•p<0.1; *p<0.05; **p<0.01; ***p<0.001

2.5.5 Coastal and near coast counties

According to Pearson's product-moment correlation coefficient, sea level rise and distance from coast are significantly correlated. The value of the test statistic is -0.335 and the corresponding p-value is lower than 2.2×10^{-16}. Because this may cause one of these coefficients to capture the effect of the other, spatial autoregressive models (2.9) with all covariates are re-estimated for the subsample of counties which are near the coast and for the subsample of coastal counties. Another reason why comparison of models for these subsamples with models for all counties can be revealing, is the fact that sea level rise only directly affects the coastal counties.

Models estimated using the whole sample are compared with the models estimated for the subsample of counties which are near the coast in Table 2.12. Columns (2) – (5) include estimates of the models using the whole sample, therefore they are the same as those in Table 2.7. Columns (6) – (9) in Table 2.12 describe models estimated for the subsample of counties which are near the coast. These counties were defined based on the shortest Euclidean distance between coast and centroid of each county. The subsample of near coast counties includes 761 counties for which the distance between centroid and coast is shorter than 189km, which is the first quartile of the sample distribution of the shortest distances between counties' centroids and the coast.

In Table 2.13 models estimated using the whole sample are compared with models estimated for the subsample of coastal counties which includes 274 counties. Columns (2) – (5) include estimates of models based on the whole sample and they are the same as the estimates in Table 2.7. Estimates of models based on subsample of coastal counties are in columns (6) and (7) in Table 2.13. These models do not need spatial correction, therefore equation (2.6) is used. The models for coastal counties do not include distance from coast either.

We can see in Tables 2.12 and 2.13 that both quadratic and linear sea level rise terms are only highly significant when the models are estimated for all counties. As displayed in Table 2.12, the sea level rise terms are not significant at all for almost all models of the near coast counties while they remain slightly significant in models for coastal counties in Table 2.13, which do not include the coast distance terms. This suggests that the reason why the sea level rise coefficients are significant in models for all counties, is because they partially capture the effects of distance from the coast.

Table 2.12: **SAR models** (2.9) **- near coast counties**

Sea level rise and coast distance estimates for different time periods

Period	**All counties**				**Near coast counties**			
	SLR		**Coast distance**		**SLR**		**Coast distance**	
	Linear	**Sq.**	**Linear**	**Sq.**	**Linear**	**Sq.**	**Linear**	**Sq.**
1990 – 2012	+ *	-	- ***	+ ***	+	+	- •	+ •
1990 – 2011	+	+	-	+ ***	+	-	+	-
1990 – 2010	+ •	-	- **	+ ***	+	+	-	+
1990 – 2009	+ ***	- **	- **	+ ***	-	+	- **	+ *
1990 – 2008	-	+	- •	+ **	+	+	+	-
1990 – 2007	-	+	-	+ *	+	-	+	-
1990 – 2006	+ ***	- **	- •	+ *	-	+	- *	+ *
1990 – 2005	+ ***	- ***	- *	+ ***	+	-	- *	+ *
1990 – 2004	+ ***	- ***	- *	+ ***	+	-	- *	+ *
1990 – 2003	+	-	- **	+ ***	+ *	- *	-	+
1990 – 2002	+ ***	- ***	- *	+ **	+	-	- *	+ *
1990 – 2001	+ ***	- ***	- **	+ ***	+	-	- *	+ •
1990 – 2000	+ ***	- ***	- **	+ ***	+	-	- *	+ *
Obs.:				3063				761

Notes: All models include all covariates from Table A.6 except for dummy variables for the following regions: Great Lakes, Plains, Southwest and Rocky Mountain, which are not included in the models for the near coast counties to avoid perfect multicollinearity

+ estimate is positive; − estimate is negative
•p<0.1; *p<0.05; **p<0.01; ***p<0.001

Table 2.13: **SAR models** (2.9) **- coastal counties**

Sea level rise and coast distance estimates for different time periods

Period	**All counties SAR models** (2.9)				**Coastal counties 3SLS**	
	SLR		**Coast distance**		**SLR**	
	Linear	**Sq.**	**Linear**	**Sq.**	**Linear**	**Sq.**
1990 – 2012	+ *	-	- ***	+ ***	+ •	-
1990 – 2011	+	+	-	+ ***	+	-
1990 – 2010	+ •	-	- **	+ ***	+	+
1990 – 2009	+ ***	- **	- **	+ ***	+ *	-
1990 – 2008	-	+	- •	+ **	+	+
1990 – 2007	-	+	-	+ *	+	+
1990 – 2006	+ ***	- **	- •	+ *	- •	+ *
1990 – 2005	+ ***	- ***	- *	+ ***	+ *	- •
1990 – 2004	+ ***	- ***	- *	+ ***	+ *	- *
1990 – 2003	+	-	- **	+ ***	+ **	- *
1990 – 2002	+ ***	- ***	- *	+ **	+ **	- *
1990 – 2001	+ ***	- ***	- **	+ ***	+ **	- *
1990 – 2000	+ ***	- ***	- **	+ ***	+ *	- *
Observations:				3063		274

Notes: All models include all covariates from Table A.6 except for coast distance variables which are not included in the model for the coastal counties and dummy variables for the following regions: Great Lakes, Plains, Southwest and Rocky Mountain, which are not included in the models for the coastal counties to avoid perfect multicollinearity

+ estimate is positive; – estimate is negative

•p<0.1; *p<0.05; **p<0.01; ***p<0.001

2.5.6 Government finances

The government finances variables are important as coastal protection is usually funded by federal, state or county government. As we can see in Table 2.4, the estimates of per capita local tax income and per capita highway and education expenditures have different signs than expected. The estimate of per capita local tax income is positive and highly significant, and the estimate of per capita highway and education expenditures is negative and insignificant.

Previous research, for example Bartik (1992) and Becsi (1996), indicate that the state and local tax income have negative and statistically significant effects on economic growth. Reverse causality is one explanation for the opposite sign of tax income. In richer counties more taxes are paid, so it might appear as if higher taxes cause higher economic growth. Another explanation is the existence of one or more omitted covariates which are correlated with per capita local tax income and per capita income growth. The omitted variables can be other government expenditures and taxes not captured in the model. The positive impact on location and production provided by improved quality of services can be higher than negative impact of higher taxes when the revenue from taxes is used to finance public services (Helms 1985).

Comparing estimates of per capita tax income for the 13 time periods, it turns out that the positive and significant effect is not consistent over time. As we can see in Table 2.14, the coefficient is negative and significant in two cases and in two other cases it is negative and insignificant.

The negative sign of per capita highway and education expenditures which was obtained by fitting (2.9) for the longest time period $1990 - 2012$ also contradicts our expectations. However, as we can see in Table 2.14, for almost half of the time periods including the longest one the coefficient is not significant and in one case it is positive. The negative and significant estimates of the other periods could be explained by the existence of one or more omitted covariates which are correlated with per capita government expenditures and per capita income growth similarly as in the case of per capita tax income.

Because the government finances and their effects on economic growth are not the main focus of this study, we decided not to search for all of the data which would reflect the government finances more accurately. Instead, we estimated model (2.9) without the government finances variables and we also estimated several variants of (2.9) which include other local government revenue variables instead of per capita tax income to verify whether

Table 2.14: **Estimates of local government finances variables**

SAR models (2.9) for different time periods

Local government finances variables (per capita)				
Period	**Direct expenditures for highways and education**		**Total taxes**	
1990 – 2012	-		+	***
1990 – 2011	+		-	
1990 – 2010	-		+	*
1990 – 2009	-	***	+	***
1990 – 2008	-		-	***
1990 – 2007	-		-	***
1990 – 2006	-	***	+	***
1990 – 2005	-	***	+	***
1990 – 2004	-	***	+	***
1990 – 2003	-		-	
1990 – 2002	-	***	+	***
1990 – 2001	-	***	+	***
1990 – 2000	-	***	+	***
Observations:				3063

Notes: All models include all covariates from Table A.6

+ estimate is positive; − estimate is negative

$^{\bullet}p<0.1$; $^{*}p<0.05$; $^{**}p<0.01$; $^{***}p<0.001$

Table 2.15: **Sea level rise and government finances estimates**
SAR models (2.9) with various local government finances variables

Government finances variables included (per capita)		**Period** 1990 – 2012						
		SLR		**SLR sq.**	**Government finances**			
Direct Expenditures	**General Revenue**				**Exp.**		**Revenue**	
For highway and edu.[a]	Total taxes	+	*	-	-		+	***
For highway and edu.[a]	Total intergov.	+	**	-	+	***	-	***
For highway and edu.[a]	Intergovernmental from state gov.	+	**	-	+	***	-	***
– – –	Total taxes	+	*	-	– – –	– – –	+	***
– – –	Total intergov.	+	**	-	– – –	– – –	-	***
– – –	Intergovernmental from state gov.	+	**	-	– – –	– – –	-	***
– – –	Property taxes	+	*	-	– – –	– – –	+	***
– – –	– – –	+	**	-	– – –	– – –	– – –	– – –
Observations:		3063						

Notes: **a** education

All models include all covariates from Table A.6 (except for government expenditures and tax income unless listed in the table)

– – – if no government finances variable included; *$p<0.05$; **$p<0.01$; ***$p<0.001$

+ estimate is positive; – estimate is negative

the results remain robust. The per capita highway and education expenditures variable is omitted in some of these variants. The signs and significance levels of the estimates of sea level rise and local government finances variables of these variants are summarised in Table 2.15. The economic growth rate variable in all models in Table 2.15 reflects time period 1990 – 2012. Each row represents one variant and all government finance variables are per capita, for fiscal year 1992. Though we estimated each variant for all 13 time periods and each of these models include also all other covariates from Table A.6 (except for government expenditures and tax income unless listed in Table 2.15), estimates of the other periods and the other coefficients are not presented here to save space as they do not differ substantially. The first row represents the same specification as the second column of Table 2.4 and it is included for comparison.

Sea level rise and coast distance coefficients obtained by fitting two variants of spatial autoregressive model (2.9) are summarized and compared in Table 2.16. The variant in columns (2) – (5) was obtained by fitting our basic variant of (2.9) with all covariates including total per capita taxes and per capita highway and education expenditures and the one in columns (6) – (9) was obtained by (2.9) with all covariates excluding the

Table 2.16: **SAR models (2.9)- Sea level rise and coast distance estimates**

Comparison of models with and without local government finances variables

Period	Including per capita taxes and expenditures for highways and education				Without per capita taxes and expenditures for highways and education			
	SLR		Coast distance		SLR		Coast distance	
	Linear	Sq.	Linear	Sq.	Linear	Sq.	Linear	Sq.
1990 – 2012	+ *	-	- ***	+ ***	+ **	-	- ***	+ ***
1990 – 2011	+	+	-	+ ***	-	+	-	+ ***
1990 – 2010	+ •	-	- **	+ ***	+ •	-	- **	+ ***
1990 – 2009	+ ***	- **	- **	+ ***	+ ***	- **	- **	+ ***
1990 – 2008	-	+	- •	+ **	-	+	-	+ **
1990 – 2007	-	+	-	+ *	-	+	-	+ •
1990 – 2006	+ ***	- **	- •	+ *	+ ***	- **	- •	+ *
1990 – 2005	+ ***	- ***	- *	+ ***	+ ***	- ***	- *	+ ***
1990 – 2004	+ ***	- ***	- *	+ ***	+ ***	- ***	- *	+ **
1990 – 2003	+	-	- **	+ ***	+	-	- **	+ ***
1990 – 2002	+ ***	- ***	- *	+ **	+ ***	- ***	- *	+ *
1990 – 2001	+ ***	- ***	- **	+ ***	+ ***	- ***	- **	+ **
1990 – 2000	+ ***	- ***	- **	+ ***	+ ***	- ***	- **	+ **
Obs.:	3063				3063			

Notes: All models include all covariates from Table A.6
(except for the government finances variables for the second model)
+ estimate is positive; − estimate is negative
•p<0.1; *p<0.05; **p<0.01; ***p<0.001

government finances variables. We can see that the signs and significance levels do not differ for most periods.

Estimates of all coefficients of the spatial autoregressive model (2.9) without any government finances variables are summarized in Table A.11 in Appendix A. The period of economic growth of this model is 1990 – 2012. We can see that the estimates are similar to our basic variant in the second column of Table 2.4. Also the coefficients of the other specifications from Table 2.15 are very similar as well as its estimates for the other time periods. However, these are not presented in this paper to keep its length within reasonable limit.

We can conclude that the estimates are reasonably robust with respect to government finances variables.

2.6 Conclusion and discussion

A common assumption in numerous studies is that sea level rise has negative effects on the economy. Here, in the first empirical test, we did not find a statistically robust and significant effect of sea level rise on economic growth in the contiguous USA.

A growth model and a matching estimator were used to investigate the effects of sea level rise on the economy of the United States. We applied a 3SLS-IV method with spatial correction to estimate the economic growth model. The model was estimated for 13 different time periods, each of them starting in year 1990 and ending in a year between 2000 and 2012. In some of these models, in particular for period 1990-2006 and some shorter periods, we found a statistically significant relationship, however it is not present for all periods. In almost half of the models presented in Table 2.7 both sea level rise coefficients are insignificant. Further, different variants of the economic growth model were estimated to verify whether the results remain unchanged. We found that in models for near coast and coastal counties the sea level rise coefficients are less significant. The results of the other robustness tests do not differ substantially from the estimates of spatial autoregressive models (2.9) presented in Tables 2.7 and A.6.

Comparing our predicted impacts to the results of Bigano et al. (2008) and Bosello et al. (2007), we found that our estimates are not in accordance with the predictions of the earlier studies. However, the available data cover sea level rise of 6 cm, whereas Bigano et al. (2008) and Bosello et al. (2007), as well as other prediction studies, assume a sea level rise of 25 cm or more. It could be that the functional form changes for more pronounced sea level rise. Therefore it is possible that if we had data describing a sea level rise comparable in magnitude to the sea level rise assumed by Bigano et al. (2008) and Bosello et al. (2007), our estimates would be comparable to the results of the ex-ante studies.

We used three different matchings that are balanced on all relevant covariates in our dataset. The estimated treatment effect is insignificant in all three cases, which is in accordance with the results of the economic growth model. There is therefore no statistically discernible impact of past sea level rise on economic growth in the USA.

While we assume the total average effect of sea level rise to be negative, in some locations coastal protections may be subsidised and this may work as a positive effect of sea level rise in our model. Disentangling these two effects would bring a notable insight into our understanding of the economic effects of sea level rise. Unfortunately, obtaining the required data would be particularly challenging. One could possibly account for coastal protection budgets using data from the National Levee Database (NLD) developed by the U.S. Army Corps of Engineers (USACE)[8]. However, although this database lists the majority of levees within the USACE program, it does not include information on protection expenditures or subsidies. Furthermore, as is stated on their official website, the database includes the majority of levees in the USA, but does not include all of them. Hence, using the NLD data would provide only limited additional information while the cost of data work, which would need to be done to match the NLD data to our county level dataset, would be relatively high.

One reason why we did not find a stable significant effect may be the fact that sea level rise is a gradual and slow process, developing over decades and centuries if not millennia, and its effects can be apparent only for a longer time period. The longest period for which the effects are analysed in this study is 22 years. A logical continuation of this study would be an extension long-term growth, however data from more than 60 or 70 years ago are hardly available for all required covariates. A possible solution could be the use of sparse regression without the unavailable covariates. This is a topic for future research.

Instead of economic growth, alternative indicators could be used, such as land prices as it is plausible that they are affected by sea level rise, or the composition of public investment as that is plausibly affected by coastal protection.

It may also be that, as with other impacts of climate change, sea level rise has a minimal effect on a developed economy like that of the USA, but a more substantial impact on less developed economies. In order to test this hypothesis, the current study would need to be repeated either for currently poor countries or for sea level rise in the distant past. In either case, data availability may be a real problem.

Another direction of further research could be analysis of natural seasonal variability of sea levels and its consequences which could be helpful for better understanding of impacts of long term sea level rise. The seasonal variability is two or three times larger than average sea level rise over 1990 – 2012 and there is a substantial regional variation in seasonal sea level variability across the US coasts (Zervas 2009). Besides contiguous United States, the US affiliated Pacific Islands are one of the areas worth investigating consequences of local seasonal sea level changes as they experience substantial seasonal variations in sea levels caused by the El Niño-Southern Oscillation (Chowdhury et al. 2007). Nevertheless, it is important to emphasise, that although some of the consequences of seasonal sea level changes (e.g. increased storminess, coastal surges and subsequent higher risk of coastal

[8] http://nld.usace.army.mil/egis/f?p=471:1:

flooding) are similar to effects of long term sea level trends, other impacts including effects on soil properties and its fertility are likely to be different from effects of long term sea level rise and this limits the potential of using the natural seasonal sea level variability for better understanding of effects of long term sea level rise.

To conclude, no stable, significant effect of sea level rise on economic growth was found. More research should be done on this topic as possible significant effects could be found for different regions or different time periods.

Chapter 3

Effects of Sea Level Rise on Agricultural Land Values in the United States

3.1 Introduction

Sea level rise is a serious consequence of climate change (Tol, 2009), which affects the economy mostly through massive land loss and diversion of investments from production to coast protection (Nicholls and Tol, 2006). A comprehensive understanding of how sea level rise affects the economy is crucial to mitigate the losses; therefore, a number of recent papers seek to estimate and predict future effects of sea level rise on economies (e.g., Nicholls et al., 1999; Nicholls and Tol, 2006; Anthoff et al., 2010b; Hinkel et al., 2010, 2013; Spencer et al., 2016). For example, Hinkel et al. (2010) predict that up to $780,000$ people per year will be affected by coastal flooding by year 2100 and the total monetary damage caused by flooding, salinity intrusion, erosion and migration will be about 17 billions US$ without any adaptation. However, the prediction studies mostly suggest that the future losses can be substantially mitigated or even prevented by making adequate adaptations. Therefore, it is crucial to exploit all possible means which can help to understand how sea level rise affects the economy and verify assumptions made in the number of the prediction studies. A large and unexplored domain, which can provide a valuable insight and improve understanding of mechanisms of impacts of sea level rise, is the analysis of the effects of sea level rise on the economy in the past. If the impacts of future sea level rise are as dire as some predict them to be, then surely I should be able to detect them in the observed record.

To the best of my knowledge, no one has attempted to quantify past effects of sea level rise on the economy before. An exception is Novackova and Tol (2017), who attempt to estimate past effects of sea level rise on the economic growth in the US over a period of 22 years. They do not find a stable, significant effect, perhaps because sea level rise is a slow, gradual process which develops over decades or even centuries. Hence, the effect on the economic growth over a period of just 22 years is too small to be detected. For the distant past, data availability is a real problem, thus I decided to use a different indicator (rather than the economic growth), one more sensitive to impacts of sea level rise even during a relatively short time period. Mendelsohn et al. (1994) develop the Ricardian approach (Ricardo, 1817) to estimate value of climate characteristics as they show that the value of change in the environmental variable is exactly captured by change in the land value between the different environmental conditions (Mendelsohn et al., 1993). The main advantage of this method is, that it captures adjustments to the climate change made by economic agents (Mendelsohn et al., 1994; Fezzi and Bateman, 2015). In this study, I adopt the Ricardian approach based on hedonic regression of land values on a set of explanatory variables including rates of sea level rise.

Since the beginning of Holocene, the global sea level has risen by 14 meters with most of it happening before the start of the Common Era (Fleming et al., 1998; Milne et al., 2005). The causes and pace of sea level rise vary across time as do its consequences. During the recent period, the global sea level rise has been relatively muted, though in many areas local sea level rise has been a serious issue. The anthropogenic causes of sea level rise include thermal expansion, ice melt and ice displacement. Moreover, subsidence and tectonics can cause the land to fall or rise (Church et al., 2013), which appears as local sea level rise. In some areas, this effect is large. For example, parts of Tokyo and Bangkok fell by five meters during the $20th$ century (Sato et al., 2006; Nicholls and Cazenave, 2010; Hinkel et al., 2014).

Availability of excellent data on both relative sea level rise and land values is not the only reason why I focus on the contiguous USA. Another motive is the fact that the rates of sea level rise vary substantially along the US coasts. In particular, the range of sea level rise is between -0.72 to 9.65 mm per year along the US coast and its variance is 3.126. The variability of sea level trends along the US coast is illustrated in Figure 2.1, which can be found together with a brief discussion of spatial variability of sea level trends in Section 2.3.

Furthermore, sea level rise can have huge, damaging effects on the US coasts as they are heavily populated with increasing number of inhabitants and continuous growth of development (Savonis et al., 2008). For example, sea level rise increases storm frequency and severity on the US coasts, which in turn cause huge property and economic damage but also threaten human health and safety. Sea level rise also increases the salinity of ground water which can make it undrinkable and harm plants and animals. Due to the human induced changes in the sediment of Mississippi River and sea level rise, coastal Louisiana has lost approximately 2,000 square miles and its local wetlands do not receive enough sediment to keep up with rising seas which seriously jeopardise their ability to function as natural buffers to flooding. Hence, my hypothesis is that sea level rise has negative effect on agriculture (and thus it decreases the land values) as it reduces productivity of land, mostly as a consequence of intensified floods and erosion.

The results of this study indicate that mild sea level rise increases land values thus it is beneficial for agriculture, while more rapid sea level rise decreases land values and it is harmful to the agriculture. The results remain robust for a set of variations of the Ricardian regression. The main contribution of this paper is, that as the first empirical study, it associates changes in sea level rise with changes in land values based on the past data. Hence, this is also the first analysis of this type that supports the assumption made in the number of projection studies (some of them are listed above), that the rapid sea level rise is harmful to the economy. On the other hand, the results indicate that mild sea level rise is beneficial for the economy.

The structure of the paper is as follows. In the next section, I discuss the methodology, specifically the Ricardian cross-sectional regression and its modification which accounts for spatial autocorrelation and is robust to spatial heterogeneity and heteroscedasticity. Section 3.3 describes data sources and the results are presented in Section 3.4. In Section 3.5, I present different variations of the cross-sectional regression to show that the results are robust. These include linear functional form, controlling for population growth and state fixed effects, historical data, restriction to the subsample of coastal counties, different Kernel function used for the heteroscedasticity and autocorrelation variance-covariance matrix (HAC) estimator and different coding scheme of the spatial contiguity matrix. In Section 3.6 I discuss policy implications and Section 3.7 includes summary and comparison of the results to the previous relevant literature.

3.2 Methodology

In Section 3.2.1 I describe theory which is fundamental for the application of Ricardian method for evaluation of effect of change in a climate variable (Mendelsohn et al., 1993). Then, I explain how I account for spatial autocorrelation and heteroscedasticity in Section 3.2.2 and in Section 3.2.3 I discuss explanatory variables including the variable of interest and (possible) confounders.

3.2.1 Ricardian approach

In this subsection I describe the Ricardian approach citing equations and derivations as first developed by Mendelsohn et al. (1993).

Under the assumption that consumers maximise their utility functions given n available products, after aggregation, a system of inverse demand functions can be written as follows:

$$\begin{aligned} P_1 &= D^{-1}(Q_1, Q_2, \ldots, Q_n, Y) \\ \vdots & \qquad\quad \vdots \\ P_n &= D^{-1}(Q_1, Q_2, \ldots, Q_n, Y) \end{aligned} \tag{3.1}$$

where P_i is the price and Q_i is the quantity of good $i, i = 1, .., n$ and (3.1) is assumed to be integrable. It is further assumed, that purchased and environmental inputs are linked into the firm's production of outputs by well-behaved production functions as follows:

$$Q_i = Q_i(\boldsymbol{K_i}, \boldsymbol{E}), i = 1, .., n \tag{3.2}$$

where bold symbols denote vectors or matrices, Q_i is the output of good i, $\boldsymbol{K_i} = (K_{i1}, .., K_{ij}, .., K_{iJ})$ where K_{ij} denotes the purchased input $j (j = 1, .., J)$ for the production of good i, and $E = (E_1, .., E_l, .., E_L)$ with E_l denoting the exogenous environmental input $(l = 1, ..., L)$, for example climate, soil quality or water quality. Cost minimisation leads to a cost function as follows:

$$C_i = C_i(Q_i, \boldsymbol{R}, \boldsymbol{E}) \tag{3.3}$$

where C_i is the cost of production of good i, $\boldsymbol{R} = (R_1, ..., R_J)$ is the set of prices of purchased inputs R_j for K_j and $C_i(*)$ denotes the cost function. Given market prices, it is assumed that firms maximise their profit as follows:

$$\max_{Q_i} P_i Q_i - C_i(Q_i, \boldsymbol{R}, \boldsymbol{E}) \tag{3.4}$$

The maximization implies that firms equate prices and marginal costs. The first-order conditions can be obtained by setting first derivatives of (3.4) with respect to purchased inputs equal to zero:

$$P_i \delta Q_i(\boldsymbol{K_i}, \boldsymbol{E})/\delta K_{ij} - R_j = 0 \tag{3.5}$$

Assuming the environmental change from initial point $\boldsymbol{E_A}$ to new point $\boldsymbol{E_B}$, the change in value caused by the environmental changes can be expressed as:

$$\begin{aligned} V(\boldsymbol{E_A} - \boldsymbol{E_B}) = \textstyle\int_0^{\boldsymbol{Q_B}} \sum D^{-1}(Q_i) dQ_i - \sum C_i(Q_i, \boldsymbol{R}, \boldsymbol{E_B}) - \\ [\textstyle\int_0^{\boldsymbol{Q_A}} \sum D^{-1}(Q_i) dQ_i - \sum C_i(Q_i, \boldsymbol{R}, \boldsymbol{E_A})] \end{aligned} \tag{3.6}$$

where $\int \sum$ is the line integral evaluated between the vector of quantities and the zero vector, $\boldsymbol{Q_A} = [Q_1(\boldsymbol{K_1}, \boldsymbol{E_A}), ...Q_i(\boldsymbol{K_i}, \boldsymbol{E_A}), ...Q_n(\boldsymbol{K_n}, \boldsymbol{E_A})]$, $\boldsymbol{Q_B} = [Q_1(\boldsymbol{K_1}, \boldsymbol{E_B}), ...Q_i(\boldsymbol{K_i}, \boldsymbol{E_B}), ...Q_n(\boldsymbol{K_n}, \boldsymbol{E_B})]$, $C_i(Q_i, \boldsymbol{R}, \boldsymbol{E_A}) = C_i(Q_i(\boldsymbol{K_i}, \boldsymbol{E_A}), \boldsymbol{R}, \boldsymbol{E_A})$, and $C_i(Q_i, \boldsymbol{R}, \boldsymbol{E_B}) = C_i(Q_i(\boldsymbol{K_i}, \boldsymbol{E_B}), \boldsymbol{R}, \boldsymbol{E_B})$.

In Mendelsohn et al. (1993) and in the present study, the impacts of changes in environment are analysed through values of one particular purchased input, agricultural land. Hence, land can be separated out from the firm's profit function (3.4) as follows:

$$\max_{Q_i} P_i Q_i - C_i(Q_i, \boldsymbol{R}, \boldsymbol{E}) - P_{LE} L_i \tag{3.7}$$

where P_{LE} denotes the annual rent per unit of land given the environment $\boldsymbol{E}$ and L_i is the amount of land used to produce Q_i.

Assuming that production of good i is the best usage of the land given the environmental inputs $\boldsymbol{E}$ and factor prices $\boldsymbol{R}$ and if there is perfect competition, the market rent of the land will be the same as the net yearly profits from production of good i and pure profits will be equal to zero:

$$P_i Q_i - C_i(Q_i, \boldsymbol{R}, \boldsymbol{E}) - P_{LE} L_i = 0 \tag{3.8}$$

Further, under the assumption of fixed market prices, (3.6) can be rewritten as:

$$V(\boldsymbol{E_A} - \boldsymbol{E_B}) = \boldsymbol{PQ_B} - \sum C_i(Q_i, \boldsymbol{R}, \boldsymbol{E_B}) - [\boldsymbol{PQ_A} - \sum C_i(Q_i, \boldsymbol{R}, \boldsymbol{E_A})] \tag{3.9}$$

where $\boldsymbol{P} = (P_1, .., P_i, .., P_n)$. Substituting (3.8) into (3.9) leads to:

$$V(\boldsymbol{E_A} - \boldsymbol{E_B}) = \sum_i (P_{LEB} - P_{LEA}) L_i \tag{3.10}$$

where P_{LEB} is P_{LE} at $\boldsymbol{E_B}$ and P_{LEA} is P_{LE} at $\boldsymbol{E_A}$. Equation (3.10) implies that the value of the change in the environmental value is captured exactly by the change in land rent given the assumptions above and it is known as the definition of the Ricardian estimate of the value of environmental changes.

As it is discussed in Mendelsohn et al. (1993), market land rents are usually not observed as most land is occupied by its owners. Nevertheless, assuming that the interest rate and rate of capital gains on the lands are the same for all plots, the land rent is proportional to the land price which can be observed. Therefore, the value of the change in the environmental inputs can be estimated using change in the agricultural land prices.

The Ricardian model of agricultural land values can be written as a single cross-section (Massetti and Mendelsohn, 2011):

$$ln(v_i) \quad = \quad \boldsymbol{X_i \beta} + u_i \tag{3.11}$$

where $\boldsymbol{v}$ is a vector of values of farmland per acre (in this paper I am using the word farmland or land in farms as a synonym to agricultural land), $\boldsymbol{X}$ is a matrix of explanatory variables, $\boldsymbol{\beta}$ is a parameter vector to be estimated, $\boldsymbol{u}$ is an error term and i varies across space.

The present study investigates the impact of a particular environmental variable, sea level rise. Since the rate of sea level rise changes very slowly over time, the sea level trends data used in this study are long term averages estimated based on sea level data captured for decades. On the contrary, the land prices are captured at specific point of time. In spite of this, the impacts of long term sea level rise can be estimated using change in the agricultural land prices because the land price is equal to the present value of the land rents which means that future interest rates are implicitly captured in the land prices. The future interest rates account for risk related with uncertainty about future productivity of land. Hence, also the risk related with long-term sea level rise (which is expected to continue far into the future) is reflected in the present land prices.

Changes in the prices of agricultural land not only capture patterns of future sea level rise, but also reflect past sea level trends. Local sea level trends are combinations of the global sea level rise and the local vertical land motion which is relatively constant over time(Zervas, 2001). Hence, rates of sea level rise are approximately constant per location. Therefore, the sea level rise that has already occurred in a location carries some information about future sea level rise at the location. Therefore, the information conveyed by past sea level change is reflected in future interest rates, which are captured in agricultural land prices. The estimates should, therefore, be interpreted assuming that future sea level trends will be approximately the same as past local sea level trends. That is, no sudden extreme tectonic movement, which would affect the geographical area of this analysis, will happen.

The models estimated in this study are cross-sectional rather than panel regressions. I opted for the cross-sectional structure because sea level rise is a very slow and gradual process and rates of local sea level change are stable during the period of my interest. Furthermore, the local sea level rise data are only available as long-term averages over several decades. Therefore, the panel model structure is unlikely to provide additional information. I chose year 2007 because obtaining consistent data for all relevant variables turned out to be problematic for the more recent years.

According to more recent studies built upon Mendelsohn et al. (1993) (e.g., Mendelsohn et al., 2011; Massetti et al., 2015; Schlenker et al., 2006), a loglinear functional form is a better fit for land values than a linear form and thus I opted for loglinear models. However, I also present estimates of a linear functional form as a robustness check (see Section 3.5.1).

3.2.2 Spatial autocorrelation and heteroscedasticity

In a cross-sectional analysis, taking spatial relationships into account can be necessary for consistency of estimates and it can also improve their efficiency (Piras, 2010). As explained in LeSage and Pace (2009), spatial patterns can occur for example due to adjustments of the economic agents to previous decisions of neighbouring agents. LeSage and Pace (2009) give the example that government may rise tax rates after observing a tax increase in neighbouring regions which would lead to the spatial dependence patterns in the cross-sectional tax rates. Another motivation for the spatial adjustment is spatial heterogeneity which causes spatial error dependence.

According to Kelejian and Prucha (1999), one of the most widely referred model that adjusts for spatial autocorrelation is the one introduced by Cliff and Ord (1973, 1981). This model is commonly referred to as the spatial autocorrelation (SAR) model and it can be written as follows:

$$\begin{aligned} \boldsymbol{y} &= \rho \boldsymbol{W} \boldsymbol{y} + \boldsymbol{X}\boldsymbol{\beta} + \boldsymbol{\epsilon} \\ \boldsymbol{\epsilon} &\sim N(0, \sigma^2 \boldsymbol{I_n}) \end{aligned} \tag{3.12}$$

where $\boldsymbol{y}$ is a $n \times 1$ vector of independent observations, ρ is a spatial lag parameter to be estimated, $\boldsymbol{W}$ is an $n \times n$ spatial weight matrix, $\boldsymbol{X}$ is a matrix of $n \times k$ covariates, $\boldsymbol{\beta}$ is a $k \times 1$ vector of parameters to be estimated and $\boldsymbol{\epsilon}$ is the error term.

Piras (2010) argues that the generalized method of moments (GMM) estimation of the Cliff-Ord type models is preferred to the maximum likelihood (ML) estimation as it requires considerably weaker assumptions. Further, there are still various unsolved problems related to the ML approach (Kelejian and Prucha, 1998a, 1999). Kelejian and Prucha (1999) proposed a GMM estimator of these models consistent under the usual assumption that the innovations in the disturbance process are homoscedastic. Since the spatial units usually differ in size and other important characteristics, the homoscedasticity assumption is often implausible in the spatial context (Arraiz et al., 2010). Kelejian and Prucha (2010) extend their results for models with spatial autoregressive disturbance process with heteroskedastic innovations by suggesting a new modified GMM estimator. However, this estimator assumes that the disturbances follow a specific SARMA(p,q) process, hence, one can still be concerned about possible misspecification, e.g. due to an incorrect specification of the weight matrix (Piras, 2010). I have no reason to assume any particular process of the disturbances, therefore I opt for the HAC estimator of the variance covariance matrix proposed by Kelejian and Prucha (2007). This HAC estimator is robust towards possible misspecification of the process in disturbances. Not only it allows for heteroscedastic innovations but also for the distance between spatial units to be measured with error (Piras, 2010). The disturbances are assumed to be generated by a very general process (Piras, 2010):

$$\boldsymbol{\epsilon} = \boldsymbol{T}\boldsymbol{\xi} \tag{3.13}$$

where $\boldsymbol{T}$ is an $n \times n$ unknown non stochastic matrix and $\boldsymbol{\xi}$ is a vector of innovations.

More details about the estimation procedure can be found in Kelejian and Prucha (2007) and Piras (2010).

My specification can be written down by combining (3.11), (3.12) and (3.13) as follows:

$$\begin{aligned} ln(\boldsymbol{v}) &= \rho \boldsymbol{W} ln(\boldsymbol{v}) + \boldsymbol{X\beta} + \boldsymbol{\epsilon} \\ \boldsymbol{\epsilon} &= \boldsymbol{T\xi} \end{aligned} \tag{3.14}$$

where $\boldsymbol{v}$ is a vector of values of farmland per acre, ρ is a spatial lag parameter to be estimated, $\boldsymbol{W}$ is an $n \times n$ spatial weight matrix, which is constructed such that $W_{i,j} = 1$ if counties i and j have a common border and $W_{i,j} = 0$ otherwise, $\boldsymbol{X}$ is a matrix of explanatory variables including the sea level rise, $\boldsymbol{\beta}$ is a parameter vector to be estimated, $\boldsymbol{T}$ is an $n \times n$ unknown non-stochastic matrix and $\boldsymbol{\xi}$ is a vector of innovations.

I estimated the specification (3.14) for year 2007 and also for 1900 as a robustness check. The unit of analysis is 2830 counties of the contiguous United States.

3.2.3 Explanatory variables

Besides sea level rise I consider also effects of the water level changes at the Great Lakes, because despite being fresh, they have many sea-like characteristics including rolling waves, great depths and strong currents (Williamson, 1854). Hence, I treat the counties lying at the shore of the Great Lakes as coastal counties. However, there are also differences between sea water bodies and the Great Lakes, for example in salinity. Also the Great Lakes level trends are substantially different from the sea level trends. Therefore, I capture the lake level changes at the Great Lakes in a separate variable from the sea level rise. This variable is equal to zero for all counties except for those lying on the shore of the Great Lakes.

Apart from sea level rise, matrix $\boldsymbol{X}$ from (3.14) includes control variables to decrease the risk of omitted variable bias and to get smaller standard errors of estimates. In order to present the results in a more comprehensible way, I organise the control variables into two groups, specifically geoeconomic characteristics and soil characteristics. The geoeconomic characteristics include per capita income, coordinates of counties' centroids, distance of the counties' centroids from coast, coast length, volume of groundwater depletion, area of farmland and a dummy variable which is equal to one for the counties which are situated on shore of a brackish or tidal water bodies and zero otherwise.

Distance from coast is an important covariate because it is likely to be a predictor of the land values and it is also highly correlated with sea level rise as sea level rise is zero in inland counties. The value of the correlation coefficient is -0.283 and its p-value is lower than 2.2×10^{-16}. The coefficient is in absolute value extremely high in comparison to the correlation coefficients of sea level rise and the other covariates. Thus, not including the distance from coast would lead to an omitted variable bias (Kennedy, 2003; Greene, 2002). I also control for the length of coast as the coastal area which is directly exposed to the sea level rise and its effects varies considerably across counties. Obviously, counties with different length of coast can be affected by sea level rise differently. [1]

Another confounding factor is the volume of groundwater depletion. Groundwater depletion can cause land to fall and land subsidence contributes to relative sea level rise (Konikow, 2013). Higher economic and agricultural activity leads to higher volumes of groundwater to be withdrawn which may lead to reverse causality as the economic and agricultural activity is likely to be positively correlated with the land values. Therefore, I include the groundwater withdrawals as a proxy for the groundwater depletion to avoid this confounding.

Coast distance and groundwater withdrawals are immediate confounders. Therefore, in Section 3.4 I discuss a variation without these two covariates to compare it with the main specification which includes them.

The brackish/tidal dummy variable is included as the environmental characteristics, such as soil properties, tidal patterns, fauna and flora and others differ at the brackish shore from the environments at the salt water coast (Pine, 2008; Wieski et al., 2010). This can motivate to different economic use of the land thus the land prices around the brackish or tidal water bodies are likely to be affected differently by sea level change.

Previous studies (e.g., Mendelsohn et al., 1994; Massetti and Mendelsohn, 2011; Massetti et al., 2015) find income per capita, coordinates of the centroids, area of farmland, groundwater withdrawals, and the soil characteristics (listed in Appendix B.1) to be important determinants of land values in environmental economic models. It is plausible that per capita income is correlated with land prices and it can also be affected by sea level rise directly. The soil characteristics can determine the local extent and pace of sediment compaction which is likely to be correlated with sea level rise (or land subsidence which contributes to regional relative sea level rise as explained in Konikow (2013)) and this can affect the relationship between sea level rise and land values. Obviously, the centroids' coordinates can be correlated with the local sea level rise and also the effect of sea level rise on land prices is likely to vary with area of farmland in each county. Therefore, I include also these covariates. Although I do not control for temperature and precipitation, omitting

[1] The interaction of sea level rise and coast length is insignificant thus it is not included in the model.

these variables should not cause an omitted variable bias. My identification strategy is based on spatial differences in sea level trends rather than on their temporal changes and according to Church et al. (2013), the local fluctuations in sea levels and its rates are due to sediment compaction, tectonic movement and gravitational field of the Earth. Therefore, the temperature and precipitation are unlikely to be significantly correlated with long term sea level trends and their omission should not cause an omitted-variable bias.

The soil characteristics include salinity, flooding, wet factor, K-factor (= erodibility factor), slope length, sand, clay, moisture level and permeability and for these covariates I use the same dataset as Massetti and Mendelsohn (2011). Their description can be found in the data appendix of Massetti and Mendelsohn (2011) and it is also included in Appendix B.1 of the present study for the sake of integrity of this paper.

3.3 Data

The sample includes 2830 counties of the United States for which the required data are available. Unless otherwise stated, the variables measure data from year 2007. The descriptive statistics of the geoeconomic variables (including the dependent variable) can be found in Table 3.1 and the descriptive statistics of the soil characteristics are summarised in Table B.1 in Appendix B.

Table 3.1: ***Descriptive statistics****, Geoeconomic variables, year* 2007

Observations: 2830

Variable:	**Units**	$\bar{x}$[a]	$\hat{s}(x)$[b]	**Min**	**Max**
Sea level rise - coastal[c]	mm/year	2.213	2.200	−0.650	9.650
Lake level rise - Great Lakes[d]	mm/year	−6.224	3.688	−9.380	0.000
Agricultural land value	dollars per acre	3095.000	2960.605	169.000	56520.000
Agricultural land value	log, dollars per acre	7.760	0.751	5.130	10.940
Per capita income	log, dollars per person per year	10.330	0.218	9.578	12.030
X centroid coordinate	decimal degrees	-91.860	11.281	-124.220	-67.610
Y centroid coordinate	decimal degrees	38.450	4.841	26.100	48.830
Coast distance	km	385.891	303.383	0.000	1272.538
Length of coast[c]	km	55.072	41.195	0.000[e]	266.271
Brackish or tidal (dummy)[c]	0/1	0.305	—	—	—
Groundwater withdrawals	l/ha/day	0.403	1.226	0.000	16.091
Land in farms	thousands of acres	305.301	375.817	0.000	6101.943

[a] $\bar{x}$ indicates the sample mean
[b] $\hat{s}(x)$ indicates the sample standard deviation
[c] Descriptive statistics of the subsample of 256 coastal counties as the value of this variable is zero for all the inland counties. For most of the stations, the sea level trends cover period starts between 1940 and 1980 and ends in 2007.
[d] Descriptive statistics of the subsample of 90 counties on the coast of the Great Lakes as the value of this variable is zero for the other counties. The lake level trends cover period is between 1860 and 2013.
[e] The subsample of the coastal counties includes two counties which are not directly on coast but they are very close to it and they are located on shore of a brackish lake or river. The length of coast of these two counties is therefore zero.

As in Mendelsohn et al. (1994), Massetti et al. (2015) and other above referred studies, the dependent variable is the county average of agricultural land prices including buildings in dollars per acres and the data are drawn from the United States Department of Agriculture.[2] In this study, land in farms is used as a synonym to agricultural land and it consists primarily of land used for crops and grazing. Agricultural land also includes woodland and wasteland that is not currently used for growing, pasture or grazing given that it was a part of the farm operator's total operation (Vilsack and Clark, 2009).

As one can see in Table 3.1, the range of agricultural land values is notably large. In particular, the average land values vary between 169 and $56,520$ dollars per acre. The sample distribution of land values is asymmetric with a long right tail. That is, values below mean are distributed much more evenly than values above mean. Hence, the large range is due to extremely high land values rather than extremely low values. The locations with the highest agricultural land prices include areas in the north of New Jersey, Westchester and Rockland counties in New York, Napa, Ventura, Santa Cruz and some other, mostly coastal, counties in California, counties Broward and Pinellas in Florida, Newport county in Rhode Island, Cuyahoga in Ohio and a group of counties in east of Massachusetts. The areas with the lowest agricultural land prices include most of New Mexico, north of Arizona, Sweetwater in Wyoming and Hudsdepth and Pecos counties in the south-west of Texas.

Possible reasons behind the large variation in agricultural land values include diversity in natural amenities, ratio of land in agriculture (the ratio is relatively small in counties with the highest average land prices) and number and value of buildings on agricultural land, because the land values are actually prices of land areas including the buildings on it. Another factor contributing to the broad range of land prices is soil quality. Simple correlation coefficients between the average land values and the soil characteristics listed in Appendix B.1 are significant with p-values lower than 0.001. The only exception is land slope, for which the p-value is 0.1.

Agricultural landscape provides many benefits with characteristics of public goods and this leads to underallocation of land to agriculture in many locations of the US (Plantinga and Miller, 2001; Lopez et al., 1994). For example, Lopez et al. (1994) estimate that the acreage of agricultural land is 20% below its optimum accounting for external benefits in a group of counties in Massachusetts. According to the basic supply-demand model, an under-supplied good should be overpriced. This is supported by data for the case of

[2] National Agricultural Statistical Service, available at https://quickstats.nass.usda.gov/results/8B28D500-4AE5-3FEC-A6C4-D985EBE3292D.

Massachusetts: the average land values in all counties of Massachusetts are in the top decile of the sample distribution of all US counties. To preserve agricultural land, states and local governments have used land use controls, tax and other policies (Sokolow, 2006; Daniels, 2004; Plantinga and Miller, 2001; Lopez et al., 1994). Therefore, another possible explanation of the broad range of the agricultural land prices is the usage of different tools for agricultural land protection and the varying extent of their usage across states and counties.

For the inland counties, the sea level rise is zero. For the coastal counties, the sea level change data are available at the website of the Center for Operational Oceanographic Products and Services (CO-OPS).[3] The water level has been captured at 94 CO-OPS water level stations at the coast of US and at 53 CO-OPS water level stations on the Great Lakes for a span of at least 30 years. The CO-OPS specifies that the sea level trends were constructed by decomposing of sea level variations into a linear secular trend, an average seasonal cycle, and residual variability at each station. For discussion about the locations of the observation stations and coastal topography, see Section 2.3 and Figure 2.1.

The analysed dataset includes 256 coastal counties and more than half of them does not have a water gauge station; therefore, the sea level trends data (measured at the 94 water level stations) are extrapolated as follows. For each coastal county the sea level trend is considered to be equal to the trend captured at the gauge station which is closest to the inner centroid of the county. For the outer ocean and sea coasts I use the trends constructed based on the water level data from the first year of data collection of each station up to year 2007.[4] For most of the stations, the first year of data collection is a year between 1940 and 1980. The exact period of data collection for each station can be found on the CO-OPS website. Regarding the Great Lakes, the lake-wide yearly water level averages are constructed using the data from selected water level stations for the period from year 1860 until 2013 and they are available at the website of the National Oceanic and Atmospheric Administration[5]. Using these data I derived the average changes in the levels of the Great Lakes per year. As one can see from the descriptive statistics in Table 3.1, the lake level falls at all lakes thus the variable is negative for all counties

[3] Retrieved from http://tidesandcurrents.noaa.gov/about.html.

[4] Although more recent water level data are available, according to the CO-OPS the most recent trends may not be more accurate than the previous ones. Actually, if the most recent sea levels differ anomalously from the previous ones, the newest sea level trend values can move slightly away from the true long-term trends. Hence, the estimates of the regression models with the more recent sea level trends are not presented here but they do not differ significantly.

[5] Great Lakes Environmental Research Laboratory. Available at https://www.glerl.noaa.gov/data/wlevels/levels.html.

surrounding the Great Lakes.

The source of the per capita income data is the Bureau of Economic Analysis (CA1).[6] The coordinates of the counties' centroids were retrieved from a US county map and its shapefile is accessible from the Census Bureau's MAF/TIGER database.[7] The coordinate system of this map is the projected GCS North American system 1983.[8] This county map is also used for construction of distance from coast and length of the coast. The area of land in farms was drawn from the USA Counties database.[9] The county level water use data are published every five years by the United States Geological Survey and since the ground water use data are not available for 2007, I use the data from 2000. Alike Massetti et al. (2015), I use the ground water use data divided by the amount of farmland in census 2002. Regarding the soil characteristics, I use the same data as Massetti and Mendelsohn (2011), which were originally retrieved from the National Resources Inventory (NRI), developed by the United States Department of Agriculture.[10]

[6] Retrieved from http://www.bea.gov/itable/.

[7] TIGER/Line Shapefile, 2012, nation, U.S., Current county and Equivlaent National Shapefile. Available at https://catalog.data.gov/dataset/tiger-line-shapefile-2012-nation-u-s-current-county-and-equivlaent-national-shapefile.

[8] The datum of the coordinate system is D North American 1983, the central meridian is -96, standard parallel 1 is 33, standard parallel 2 is 45, latitude of origin is 39, the prime meridian is Greenwich.

[9] Available at http://www.census.gov/support/USACdataDownloads.html.

[10] The soil characteristics data are from year 2002 rather than 2007 due to availability issues. However, this should not cause any problems as the soil characteristics are very stable in time.

3.4 Results

As a starting point, I fit an ordinary least squares (OLS) regression of agricultural land prices on sea level rise without any other covariates. This regression is estimated for the subsample of coastal counties because the distance from coast, which is a strong confounder in the whole sample cross-section, is not controlled for. Furthermore, only the coastal counties are affected by sea level rise directly. The estimates are summarised in the first two columns of Table 3.2. The first column includes the estimated sea level rise coefficient and for easier interpretation I present also the exponent of the coefficient in the second column as the model has a loglinear form. The sea level rise coefficient is negative and strongly significant which is in accordance with my hypothesis. The squared sea level rise term is insignificant thus it is not included.

Next, I fit an OLS regression with all covariates for the full sample of 2830 US counties. The estimates of the sea level rise coefficients are summarised in the third column of Table 3.2, their exponents can be found in the fourth column of Table 3.2. The squared sea level rise term is negative and significant while the linear term is positive and marginally significant, which indicates that small sea level rise increases agricultural land prices and more pronounced sea level rise has negative effect on them. We will see that these estimates are very similar to those obtained from the main SAR specification discussed below. The estimates of all coefficients of the OLS model and their exponents are tabulated in the first two columns of Table B.2 in Appendix B.

Moran's I confirms presence of spatial autocorrelation in the agricultural land values. The value of this statistic is 73.741 for the logarithm of the raw data and its value is 52.602 for the OLS residuals (I use the adjusted Moran's I for residuals). Both these values are highly significant. Hence, as explained in Section 3.2.2, the OLS specification does not satisfy all desirable properties as the spatial patterns need to be taken into account to reach consistency and to improve efficiency. Thus, as the next step I estimate model (3.14) with the covariates discussed in Section 3.2.3 and the Kelejian-Prucha HAC estimator of the variance-covariance matrix. The sea level rise estimates obtained from this model are summarised in Table 3.3 and the estimates of all its coefficients can be found in Table B.3 in Appendix B. As one can see in Table 3.3, the spatially lagged dependent variable (coefficient ρ) is positive and highly significant (although it is relatively small in magnitude); hence, the agricultural land prices are indeed highly spatially correlated and the spatial autoregressive model is a correct specification.

Table 3.2: ***Ordinary least squares***, *year* 2007

Sample:	**Coastal counties** (n=187)		**All counties** (n=2830)	
Coefficient:	**estimate**	**in exponent**	**estimate**	**in exponent**
Sea level rise (mm/yr)	−0.149 (0.028)***	0.861 (1.028)	0.057 (0.029)*	1.058 (1.029)
Sea level rise (mm/yr) - sq.	Not included		−0.015 (0.004)***	0.985 (1.004)
Lake level rise (mm/yr) - Great Lakes	Not included		0.018 (0.007)*	1.018 (1.007)
Coast distance	Not included		Included	
Groundwater withdrawals	Not included		Included	
Geoeconomic characteristics	Not included		Included	
Soil characteristics	Not included		Included	
Adjusted R^2:	0.129		0.650	

Notes: •p<0.1; *p<0.05; **p<0.01; ***p<0.001, Standard errors in brackets,

As discussed in LeSage and Pace (2009), the coefficients of regression models with spatially lagged dependent variable can not be interpreted in the same way as the usual OLS coefficients. As a result of spillovers, a change in a value of any explanatory variable of one observation affects values of the dependent variable of all observations. The effect of a change in a value of explanatory variable of one observation on the observation itself is a direct impact while the effect of a change in value of an explanatory variable of one observation on all other observations (but the observation itself) is an indirect impact (LeSage and Pace, 2009). The sum of the direct impact and the indirect impact is a total impact. However, my focus of interest is not on the individual impacts of each single observation, but on summary impacts of the variables over the whole sample and their measures. Therefore, I use the impact measures computed according to formula (2.46) in LeSage and Pace (2009) as cited immediately below. Model (3.12) can be expressed as:

$$
\begin{aligned}
(\boldsymbol{I_n} - \rho \boldsymbol{W})\boldsymbol{y} &= \boldsymbol{X\beta} + \boldsymbol{\imath_n \alpha} + \boldsymbol{\epsilon} \\
\boldsymbol{y} &= \textstyle\sum_{r=1}^{k-1} \boldsymbol{S_r(W)x_r} + \boldsymbol{Z(W)\imath_n\alpha} + \boldsymbol{Z(W)\epsilon} \\
\boldsymbol{S_r(W)} &= \boldsymbol{Z(W)I_n\beta_r} \\
\boldsymbol{Z(W)} &= (\boldsymbol{I_n} - \rho\boldsymbol{W})^{-1} = \boldsymbol{I_n} + \rho\boldsymbol{W} + \rho^2\boldsymbol{W^2} + \rho^3\boldsymbol{W^3} + ...
\end{aligned}
\tag{3.15}
$$

where α is the intercept of the SAR model, r is an index of explanatory variables in $\boldsymbol{X}$ and otherwise the same notation is used as in Section 3.2. The impact measures are calculated as follows (LeSage and Pace, 2009):

$$
\begin{aligned}
\bar{M}(r)_{direct} &= n^{-1} tr(\boldsymbol{S_r(W)}) \\
\bar{M}(r)_{total} &= n^{-1} \boldsymbol{\imath_n' S_r(W)\imath_n} \\
\bar{M}(r)_{indirect} &= \bar{M}(r)_{total} - \bar{M}(r)_{direct}
\end{aligned}
\tag{3.16}
$$

For the sake of easier interpretation, the second column of Table 3.3 includes exponents of the estimates and exponents of their standard errors in brackets and in the third column are exponents of the direct impact measures rather than the impact measures itself. As one can see in Table 3.3, the squared sea level rise term is highly significant and negative (the exponent of the estimate is smaller than one) while the linear sea level rise term is positive (the exponent of the estimate is higher than one). The direct impact measures are almost equal to the coefficients (their exponents are equal to the exponents of the coefficients after rounding), that means that the exponent of the direct impact is smaller than one for the squared term and it is higher than one for the linear term. Hence, minor sea level rise increases the agricultural land prices while more pronounced sea level rise causes them to fall. Besides the coefficients' estimates, Table B.3 in Appendix B summarises exponents of the total impacts as well as exponents of the direct impacts of all coefficients in this model. It is noticeable, that these two impact measures are very similar for all the coefficients. Since total impact is equal to the sum of direct and indirect impact, it can be concluded, that the indirect impacts are negligible relatively to the direct impacts, although the spatially lagged dependent variable is highly significant. The SAR estimates are compared with the OLS estimates in Table B.2 in Appendix B. The signs and significance levels are equal for most of the coefficients, hence the estimates are robust.

As depicted in Table 3.3, the effect of lake level rise is positive and marginally significant for the Great Lakes, which is different from my hypothesis and from the total effect of sea level rise. It is obvious from the descriptive statistics in Table 3.1 that the Great Lakes' level rise is negative for the whole sample in contrary to the sea level rise which is positive for most of the coastal counties.

High amenity areas are often converted into recreation or retirement destinations (Stephens and Partridge, 2015). Therefore, a possible explanation for the positive lake level rise coefficient could be the higher attractiveness of areas with smaller lake level fall as recreational destinations or locations for living or retirement houses. This would result in higher land prices in areas with smaller lake level fall. Indeed, proximity to the Great Lakes was associated with rising rents in the 1990s (Stephens and Partridge, 2015). Considering the positive effect of natural amenities, one should bear in mind that recreation or retirement housing are not agricultural uses, while this analysis is based on agricultural land values. Nevertheless, if rents from an alternative future use of current agricultural land exceed agricultural rents in the future, the higher rent from the alternative use will be capitalized into the current price of agricultural land (Plantinga and Miller 2001). In other words, the agricultural land values reflect the scope for conversion to other uses and the value of such other uses might be partly determined by sea level rise. Assuming, that agricultural land is convertible to recreational or residential housing use, the current land value is likely to be affected by impacts of anticipated sea level rise on the future value of the land in residential or recreational uses.

The future land convertibility is likely to be affected by planning/zoning frameworks and decisions. Hence, one needs to assume that the planning and zoning decisions will not restrict the conversion of agricultural land to other uses when interpreting the positive lake level rise coefficient as a result of amenity-based migration. In Section 3.5.3, I present the results of a specification with state level dummy variables. It turns out that the relationship is somewhat different from the results of the main specification without the state fixed effects. This is in accordance with the above-described theory that agricultural land values reflect the expected effects of sea level rise on future land use. Scope for converting agricultural land into housing and recreational areas depends on planning and

Table 3.3: ***Spatial autoregressive model*** (3.14)

Loglinear functional form, year 2007

	Coefficient estimate	**Coefficient - exponent**	**Direct impacts - exponent**
ρ (SAR)	0.062 (0.011)***	1.064 (1.011)	—
Sea level rise (mm/year)	0.081 (0.049)•	1.085 (1.050)	1.085
Sea level rise (mm/year) - squared	−0.017 (0.006)**	0.983 (1.006)	0.983
Lake level rise (mm/year) - Great Lakes	0.017 (0.008)*	1.017 (1.008)	1.017
Coast distance		Included	
Groundwater withdrawals		Included	
Geoeconomic characteristics		Included	
Soil characteristics		Included	

Notes: •p<0.1; *p<0.05; **p<0.01; ***p<0.001, Spatial HAC standard errors in brackets

zonal decisions, which are affected by state-level factors.

Table 3.4 summarises predicted total, direct and indirect impacts of sea level rise at mean, 10*th* and 90*th* percentiles of its sample distribution (only the coastal counties excluding the Great Lakes are considered here as the sea level rise is zero for the other counties). For the 10*th* percentile and the mean, the total impact is positive while it is negative for the 90*th* percentile as the effect became negative for sea level rise of approximately 5 mm per year and more. It is also apparent from Table 3.4, that the indirect impacts are very small in comparison to the direct impacts.

Table 3.4: ***Predicted impact of sea level rise on farmland values***

	Change in farmland values (%)		
Sea level rise	**Total**	**Direct**	**Indirect**
$Q10$[a] (1.60 mm/yr)	9.65	9.03	0.57
Mean[a] (3.19 mm/yr)	9.57	8.95	0.56
$Q90$[a] (5.29 mm/yr)	-4.94	-4.65	-0.31

[a] Sample statistics of the subsample of the coastal counties excluding the counties at the shore of the Great Lakes

Only some of the geoeconomic variables are significant, specifically per capita income and groundwater withdrawals which are positive and coast distance and land in farms

Table 3.5: ***Spatial autoregressive model*** (3.14) *without immediate confounders*

Loglinear functional form, year 2007

	Coefficient estimate	**Coefficient - exponent**	**Direct impacts - exponent**
ρ (SAR)	0.119 (0.013)***	1.126 (1.014)	—
Sea level rise (mm/yr)	0.144 (0.056)*	1.154 (1.058)	1.155
Sea level rise (mm/yr) - squared	−0.022 (0.007)**	0.978 (1.007)	0.978
Lake level rise (mm/yr) - Great Lakes	−0.001 (0.009)	0.999 (1.009)	0.999
Coast distance		Not included	
Groundwater withdrawals		Not included	
Geoeconomic characteristics		Included	
Soil characteristics		Included	

Notes: •p<0.1; *p<0.05; **p<0.01; ***p<0.001, Spatial HAC standard errors in brackets

which are negative. Regarding the soil characteristics, only three of them are significant, specifically percentage of sand, percentage of clay and permeability. The first two have negative effect on land prices and the third one affects the land prices positively (see Table B.3 in Appendix B).

As discussed in Section 3.2.3, coast distance and groundwater withdrawals are immediate confounders. Therefore, I further estimate SAR model (3.14) without these two covariates. The sea level rise estimates, their exponents and exponents of the direct impacts are summarised in Table 3.5. The signs of the sea level rise coefficients are the same as those obtained from the main specification presented in Table 3.3, and the magnitude and significance levels are also very similar to those from the main specification. In contrary to the main specification presented in Table 3.3, the linear sea level rise term is marginally significant without the immediate confounders while it is marginally insignificant in the specification which includes them. Nevertheless, the signs and significance levels of the squared sea level rise term do not differ, thus in general I can conclude that the relationship of sea level rise and land prices does not change significantly after excluding the coast distance and groundwater withdrawals.

It is, however, remarkable that the lake level rise coefficient is negative and insignificant in the variant without the immediate confounders (see Table 3.5) while it is positive and slightly significant if coast distance and groundwater withdrawals are included (see Table 3.3). To investigate which of the two immediate confounders affects the sign of the

Table 3.6: ***Spatial autoregressive model*** (3.14) *without coast distance*

Loglinear functional form, year 2007

	Coefficient estimate	**Coefficient - exponent**	**Direct impacts - exponent**
ρ (SAR)	0.119 (0.013)***	1.127 (1.013)	—
Sea level rise (mm/yr)	0.137 (0.055)*	1.146 (1.056)	1.147
Sea level rise (mm/yr) - squared	−0.021 (0.007)**	0.979 (1.007)	0.979
Lake level rise (mm/yr) - Great Lakes	−0.001 (0.009)	0.999 (1.009)	0.999
Coast distance		Not included	
Groundwater withdrawals		Included	
Geoeconomic characteristics		Included	
Soil characteristics		Included	

Notes: •p<0.1; *p<0.05; **p<0.01; ***p<0.001, Spatial HAC standard errors in brackets

lake level rise I estimate two other variants such that one of the two immediate confounders is omitted in each of them (other covariates from the main specification in Table B.3 are present in both of them). It turns out that the variable affecting the sign and significance of the lake level rise is distance from coast. The simple correlation coefficient of the lake level rise and distance from coast is 0.197 and it is highly significant indicating strong positive correlation. The sea level rise and lake level rise estimates of the variant with all covariates from Table B.3 except for distance from coast are summarised in Table 3.6. The lake level rise coefficient is negative and insignificant, hence it is clear that the confounder which affects its sign and significance level is distance from coast. It is plausible, that the lake level rise coefficient is picking the effect of distance from coast (if distance from coast is not included) as the two variables are strongly positively correlated and value of the land decreases with distance from coast of the Great Lakes.[11]

The estimates of all coefficients of the SAR model (3.14) without distance from coast and groundwater withdrawals are summarised in Table B.4 in Appendix B.

[11] As one may notice in Table B.3 in Appendix B, the distance from coast is negative and strongly significant in the main specification indicating that land values indeed drop with distance from coast.

3.5 Robustness

Modifications of model discussed in Section 3.4 are examined in this section to check the robustness of my findings.

3.5.1 Linear functional form

It is a common practice to use a loglinear functional form when modelling effects of environmental factors on land prices (Mendelsohn et al., 2011; Massetti et al., 2015). Nevertheless, in this section I discuss a linear functional form as a robustness check.

The linear specification can be written down as model (3.14) without the logarithm of the dependent variable:

$$\begin{aligned} \boldsymbol{v} &= \rho \boldsymbol{W} \boldsymbol{v} + \boldsymbol{X} \boldsymbol{\beta} + \boldsymbol{\epsilon} \\ \boldsymbol{\epsilon} &= \boldsymbol{T} \boldsymbol{\xi} \end{aligned} \tag{3.17}$$

The estimates of the linear specification (3.17) can be found in Table B.5 in Appendix B. Comparing the estimates of the linear model in Table B.5 with the estimates of the loglinear form in Table B.3 in Appendix B, it is apparent that in both cases the spatial autoregressive coefficient ρ is positive and highly significant and the squared sea level rise term is negative and highly significant. The linear sea level rise term is positive in both cases, it is significant in the linear form and insignificant but very close to significant in the loglinear form. The significance levels of the geoeconomic characteristics of the linear model are the same as in the loglinear model and the signs are also the same with the exception of Y coordinate of the centroids which is insignificant, thus the change in sign is not alarming. Regarding the soil characteristics, the same coefficients are significant in the linear specification as in the loglinear specification with the exception of soil permeability which is highly significant in the loglinear model, while it is insignificant in the linear model (its p-value is 0.053 in the linear model, thus it is still very close to significant). Hence, the results are in general robust with respect to the functional form. It is further remarkable that the indirect impacts are larger relatively to the direct impacts in the linear form than in the loglinear form.

3.5.2 Population growth

Sea level rise has damaging effect on agriculture which explains the negative impact of pronounced sea level rise on land prices detected in this study. On the other hand, my results also indicate that small sea level rise causes land values to rise. Explanation of the positive effect of small sea level rise is not so straightforward. It is possible, that coasts which are subject to subsidence are more attractive as places to live and this drives land values up. Therefore, as a robustness check I re-estimate the model controlling also for population growth.

County level population data are accessible from the website of the Bureau of Economic Analysis (CA1)[12] for every year from 1969 onwards. I calculated the compound annual population growth rate for period between 1969 and 2007 as follows:

$$G = ((P_{2007}/P_{1969})^{(1/38)} - 1) * 100 \tag{3.18}$$

where G is the compound annual population growth rate in percent, P_{2007} is the county level population in 2007 and P_{1969} is the county level population in 1969. Then I included growth rate G as an explanatory variable in specification (3.14).

The estimates of sea level rise coefficients, their exponents and exponents of their direct impacts are summarised in Table 3.7. In spite of the fact, that the population growth is highly significant, estimates of sea level rise are very similar to the sea level rise estimates obtained from the main specification without population growth rate (summarised in Table 3.3). Their signs and significance levels are the same. Hence, the positive effect of minor sea level rise is not due to higher population growth in the coastal areas exposed to sea level rise. Other possible explanations of the positive effect of mild sea level rise are discussed in Section 3.7.

The estimates of all coefficients of the variation with population growth rate are summarised in Table B.6 in Appendix B. Table B.6 also includes exponents of the estimates and exponents of the direct and total impacts of all covariates. They do not differ substantially from the estimates of the main specification without the population growth rate.

[12] Retrieved from http://www.bea.gov/itable/.

Table 3.7: ***Spatial autoregressive model*** (3.14) *with population growth*

Loglinear functional form, year 2007

	Coefficient estimate	**Coefficient - exponent**	**Direct impacts - exponent**
ρ (SAR)	0.073 (0.010)***	1.076 (1.010)	—
Sea level rise (mm/yr)	0.069 (0.048)	1.072 (1.049)	1.072
Sea level rise (mm/yr) - squared	−0.015 (0.005)**	0.985 (1.005)	0.985
Lake level rise (mm/yr) - Great Lakes	0.019 (0.007)**	1.020 (1.007)	1.020
Population growth rate (% - yearly average)	0.141 (0.010)***	1.151 (1.010)	1.151
Coast distance		Included	
Groundwater withdrawals		Included	
Geoeconomic characteristics		Included	
Soil characteristics		Included	

Notes: •p<0.1; *p<0.05; **p<0.01; ***p<0.001, Spatial HAC standard errors in brackets

3.5.3 State fixed effects

I include state level dummy variables to compare the estimates with and without state fixed effects. I did not include state dummy variables in the main specification because to the best of my knowledge, there was a priori no state specific factor which can affect relationship between land prices and sea level rise.

It turns out that if the state level dummy variables are included, the squared sea level rise term is not significant and the linear term is negative and significant, implying that sea level rise causes agricultural land prices to fall over the whole range of sea level rise. This is in accordance with my original hypothesis. Also the Great Lakes' level rise is not significant if the state fixed effects are included.

The estimates of sea level rise coefficients, their exponents and exponents of their direct impacts obtained from model (3.14) which (besides the above discussed covariates) includes state dummy variables are tabulated in Table 3.8. The estimates and exponents of all covariates included in this model can be found in Table B.7 in Appendix B. The base category of the state fixed effects is Alabama.

A possible reason why the relationship differs when fixed effects are included can be existence of few water level stations with relatively extreme rate of sea level rise. Rate of

Table 3.8: ***Spatial autoregressive model*** (3.14) *with state fixed effects*

Loglinear functional form, year 2007

	Coefficient estimate	**Coefficient - exponent**	**Direct impacts - exponent**
ρ (SAR)	0.048 (0.008)***	1.049 (1.008)	—
Sea level rise (mm/year)	−0.034 (0.014)*	0.967 (1.014)	0.967
Lake level rise (mm/year) - Great Lakes	−0.001 (0.006)	0.999 (1.006)	0.999
State fixed effects		Included	
Coast distance		Included	
Groundwater withdrawals		Included	
Geoeconomic characteristics		Included	
Soil characteristics		Included	

Notes: •p<0.1; *p<0.05; **p<0.01; ***p<0.001, Spatial HAC standard errors in brackets

sea level rise is higher than 9 mm per year at two stations and at two other stations it is above 6 mm per year. In contrary to that, at most of the stations the rate of sea level rise is around 3 mm per year. Controlling for state fixed effects means that the extreme values are also controlled for which causes the quadratic effect to vanish.

Another possible explanation is the 2006-2007 real estate bubble and housing crisis which considerably affected economy of over half of the US states and was followed by 2007-2008 financial crisis. Since intensity of its effects varied across states, the relationship between sea level rise and land prices can be different if the state fixed effects are controlled for.

As discussed in Section 3.4, agricultural land values might be partly determined by future use of land and by the scope of its conversion to other uses. The scope of land conversion to other uses is dependent on planning/zoning frameworks and decisions, which are dependent on state-level factors. This could be another reason why the effects of sea level rise and lake level change differ if state fixed effects are included.

3.5.4 Historical data - year 1900

As a further robustness test, I estimated model (3.14) for the 1900 agricultural land values. The model is estimated for a sample of 2600 US counties for which the required historical data are available. The sea level trends, which are available from the CO-OPS, were constructed from the sea level data measured at the water gauge stations. Almost all these stations started to operate after 1900; hence, the sea level rise data are not available for any period before 1900. However, the local sea level trends are combinations of the global mean sea level rise and the local vertical land motion (Zervas, 2001). Since the local land movement is relatively constant over time, I constructed the sea level trends for a period before 1900 by subtracting the global mean sea level rise from the local sea level trends retrieved from the CO-OPS (which I use for the modern period).[13] Church and White (2006) reconstruct the monthly global sea level back to 1870 and find a significant acceleration of sea level rise of 0.013 ± 0.006 mm yr^{-2}. On average, the periods of sea level rise data collection used for 2007 are centred around year 1975. Thus, I need to shift the modern local sea level trends 75 years back to obtain the estimates of the sea level trends in 1900. Therefore, the constant that I subtract from the 1900 sea level trends is equal to $75 \times 0.013 = 0.975$.

The Great Lakes water level trends were constructed in the same way as for the 2007 models, using the same source of data, but I used a subset of data for a period of time between 1860 and 1900.

The dependent variable is an average value of farmland and buildings per acre in 1900 and the county level data are from the Census of Agriculture.[14] To the best of my knowledge, per capita income data at county or state level are not available for the year 1900; therefore, I used average monthly wages to a farm hand with board in 1860 as a proxy. Unfortunately, the historical data are not available for any other year between $1860 - 1900$ and they are only available at the state level. Coordinates of the centroids, distance from coast and length of the coast are constructed based on a 1900 US county map.[15] The acres of farmland data come from the 1900 Census. To the best of my knowledge, neither groundwater withdrawals or groundwater depletion data are available for year 1900 or before. However, Konikow (2013) constructs estimates of US groundwater depletion for time period between $1900 - 1950$ and I used these estimates as a proxy for groundwater depletion in my 1900 model.[16] The soil characteristics data are from year 1978 and they come from the same dataset as those I used for the 2007 model. I was not able to obtain these data for any earlier period, however this is not an issue as the soil characteristics only change very slowly in time (Massetti and Mendelsohn, 2017; Jenny, 1994). The descriptive

[13]Subtraction of a constant does not change the regression estimates except for the intercept.

[14]Both 1900 farmland values and acres of farmland are available at (https://data2.nhgis.org/main).

[15]The 1900 US county map is available from the Integrated Public Use Microdata Series https://usa.ipums.org/usa/index.shtml.

[16]As a robustness test I estimate the 1900 model with the 2007 groundwater withdrawals data and the results do not differ significantly.

Table 3.9: ***Spatial autoregressive model*** (3.14) - *year* 1900*, loglinear functional form*

	Coefficient estimate	**Coefficient - exponent**	**Direct impacts - exponent**
ρ (SAR)	0.447 (0.031)***	1.564 (1.032)	—
Sea level rise (mm/year)	0.053 (0.051)	1.055 (1.052)	1.057
Sea level rise (mm/year) - squared	−0.011 (0.006)•	0.989 (1.006)	0.989
Lake level rise (mm/year) - Great Lakes	−0.015 (0.004)***	0.985 (1.004)	0.984
Coast distance		Included	
Groundwater withdrawals		Included	
Geoeconomic characteristics		Included	
Soil characteristics		Included	

Notes: •p<0.1; *p<0.05; **p<0.01; ***p<0.001
Spatial HAC standard errors in brackets

statistics of the geoeconomic covariates used for the 1900 model can be found in Table B.8 in Appendix B and the descriptive statistics of the soil characteristics used for the 1900 model can be found in Table B.9 in Appendix B.

The estimates and the direct impacts of the 1900 sea level rise coefficients (as well as their exponential functions) are presented in Table 3.9. All estimated coefficients, their exponential functions and exponential functions of the total and direct impacts are summarized in Table B.10 in Appendix B. Table 3.10 depicts sea level rise estimates of the 1900 linear specification.

As one can see in Table 3.9, the spatial autoregressive coefficient ρ is positive and highly significant and the linear sea level rise term is positive and insignificant which is analogous to the 2007 estimates. Also the magnitudes of the coefficients are quite comparable considering the price level difference between 1900 and 2007. Similarly as in the 2007 model, the squared sea level rise term is negative but in contrary to the 2007 model (where the squared sea level rise term is highly significant) the coefficient is insignificant, although its p-value is 0.089; hence, it is very close to significant. In spite of this, the exponents of both sea level rise terms and their impact measures are almost the same in 2007 and 1900. More specifically, the exponential function of the total impact of the linear sea level rise term is equal to 1.091 in 2007 and it is equal to 1.102 in 1900 and as for the quadratic sea level rise term, the exponential function of the total impact is equal to

Table 3.10: ***Spatial autoregressive model*** (3.14) - *year* 1900*, linear functional form*

	Coefficient estimate	**Direct impacts**
ρ (SAR)	0.798 (0.039)***	—
Sea level rise (mm/year)	1.860 (1.003)•	2.336
Sea level rise (mm/year) - squared	−0.344 (0.122)**	−0.432
Lake level rise - Great Lakes (mm/year)	−0.517 (0.174)**	−0.649
Coast distance	Included	
Groundwater withdrawals	Included	
Geoeconomic characteristics	Included	
Soil characteristics	Included	

Notes: •p<0.1; *p<0.05; **p<0.01; ***p<0.001
Spatial HAC standard errors in brackets

0.982 in 2007 and it is equal to 0.981 in 1900. A possible explanation for the difference in significance can be the smaller sample size in 1900 or a misspecification of the functional form of the historical cross-section. In Table 3.10, one can see that the squared sea level rise term is highly significant in the 1900 linear functional form (alike for the 2007 linear functional form), thus it might be possible that the linear functional form is correct for 1900 and the linearity forced by the log-linear transformation introduce additional noise, which makes the squared sea level rise term insignificant.

It is further noticeable, that the sign of the Great Lakes' level rise is negative and significant in 1900 while it is positive and slightly significant in 2007. Regarding the linear functional form, the coefficient is still negative and significant in 1900 and it is positive and insignificant in 2007. A possible explanation can be a difference in the domains of the sea level rise as all values of the Great Lakes' level rise are negative and quite big in absolute values while in 1900 the variable is positive for almost one third of the counties lying at the shore of the Great Lakes and the functional form can be different for negative values of the sea level rise.

To sum up, the sea level rise estimates are reasonably robust when compared to the 1900 estimates.

3.5.5 Coastal counties

Only coastal counties are affected by sea level rise directly. Therefore, as another robustness test, I fitted equation (3.14) for the subsample of 256 coastal counties including the counties lying at the shore of the Great Lakes. The variable which measures the distance of the centroids from coast is not included as its interpretation would be different from the interpretation of this variable in the model fitted for the whole sample. The estimated sea level rise coefficients, their exponential function and the exponential function of the direct impacts can be found in Table 3.11. The sea level rise estimates remain mostly the same for the coastal counties, only the linear term changes from marginally insignificant to slightly significant. Also the impact measures and their exponential functions remain almost identical for the subsample. The Great Lakes' level rise estimates are quite similar in magnitude to the whole sample estimates. However, the coefficient is slightly significant for the whole sample but insignificant for the coastal counties. The reason can be the substantially smaller sample size of the latter.

Table 3.11: ***SAR model* (3.14) *- Coastal counties***

Loglinear functional form, year 2007

	Coefficient estimate	**Coefficient - exponent**	**Direct impacts - exponent**
ρ (SAR)[a]	0.032 (0.026)	1.032 (1.026)	—
Sea level rise (mm/year)	0.154 (0.067)*	1.166 (1.069)	1.166
Sea level rise (mm/year) - squared	−0.016 (0.006)**	0.984 (1.006)	0.984
Lake level rise (mm/year) - Great Lakes	0.013 (0.017)	1.013 (1.017)	1.013
Coast distance		Not included	
Groundwater withdrawals		Included	
Geoeconomic characteristics		Included	
Soil characteristics		Included	

•p<0.1; *p<0.05; **p<0.01; ***p<0.001, Spatial HAC standard errors in brackets

[a] The spatial autoregressive coefficient is insignificant. The results remain robust when the lagged dependent variable is excluded (OLS). According to the Moran's I test (adjusted for residuals), the OLS residuals are spatially autocorrelated.

All coefficients, their exponential functions and impact measures are tabulated in Table B.11 in Appendix B.

3.5.6 Epanechnikov Kernel

When implementing the HAC estimator proposed by Kelejian and Prucha (2007), a Kernel function needs to be specified. The Kernel function determines weights for different covariance elements of the HAC matrix and it is defined for each pair of observations in terms of a distance measure between the pair of observations (depending on a bandwidth which can vary across the observations, the Kernel function is usually zero for a set of pairs of more distant observations). After e-mail consultation with Harry H. Kelejian, I opted for the Euclidean distance measure with the bandwidths defined such that for each observation the distance measure is non-zero only for its k nearest neighbours, where k is equal to the square root of the total number of observations rounded downwards. In all previously discussed models, I use the Triangular kernel and as a robustness test I re-estimate the model with the Epanechnikov kernel. Definitions of these Kernel functions can be find in Piras (2010). The estimates of coefficients do not differ when using a different Kernel function, however the standard errors are different and also the significance levels can vary. The standard errors obtained using the Triangular kernel are compared with those obtained using the Epanechnikov kernel in Table B.12 in Appendix B. The first column includes the estimated coefficients which are equivalent for both kernels (hence, they are also the same as those in Table B.3 in Appendix B). In the second column are the standard errors and significance levels obtained using the Triangular kernel (which are again equivalent to the standard errors in Table B.3) and in the third column are the standard errors obtained using the Epanechnikov kernel. It is apparent, that the standard errors are almost the same for these two kernels and the significance levels are the same for all the coefficients; hence, the estimates are robust.

3.5.7 Globally standardised contiguity matrix

A spatial weight matrix needs to be specified to estimate a spatial autoregressive model. The spatial weight matrix is an $n \times n$ square matrix, where n is the number of observations and each row and each column corresponds to one observation (LeSage and Pace, 2009). I am using a simple contiguity matrix where all elements are equal to one or zero, more specifically, an element is equal to one if the corresponding pair of counties has a common border and it is equal to zero if the corresponding pair of counties does not have a common border. In spatial econometrics, it is a common convention to convert a general spatial weight matrix using a coding scheme. Tiefelsdorf et al. (1999) introduce a variance-stabilizing coding scheme S. They argue that this coding is superior to other traditionally used coding schemes because in contrary to the S-coding, the traditional coding schemes emphasize either objects with relatively large number of connections or objects with relatively small number of connections and this introduce a topology induced heterogeneity. According to Tiefelsdorf et al. (1999), with the S-coding scheme the topology induced heterogeneity can be substantially alleviated. Therefore, I am using the S-coding scheme in the all previously discussed models. As a robustness test, I use a globally standardised C-coding. A formal definition of both the S-coding scheme and the C-coding scheme can be found in Tiefelsdorf et al. (1999).

The estimated coefficients of model (3.14) with the globally standardised weight matrix (C-coding) are tabulated in Table B.13 in Appendix B. Table B.13 also includes exponents of the estimates and exponents of direct and total impact measures of the explanatory variables. Comparing the estimates with those obtained using the S-coding scheme in Table B.3 in Appendix B, it is apparent that the coefficient estimates and also the impact measures and their exponential functions are almost identical. The significance levels are the same for all explanatory variables and also the signs correspond with exception of length of coast, which is positive with the S-coding scheme and negative with the C-coding scheme, but in both cases the estimate is insignificant. In summary, the estimates are robust.

3.6 Policy implications

Sea level rise shows a delayed response to present-day atmospheric warming and greenhouse gas (GHG) emissions (Mengel et al., 2018). As it follows from the present study, today's rate of sea level rise has positive effects on agricultural land values in most counties of the United States. A possible interpretation of this result is that mild sea level rise is beneficial for agriculture. However, as it further follows from this study, the positive effect disappears as the rate of sea level rise increases and for more pronounced sea level rise the effect becomes negative. Hence, it is advisable to keep implementing GHG reduction policies as we do not currently observe a full response to current GHG emissions in terms of sea level rise. Furthermore, increase in agricultural land values does not imply net benefits to the whole economy or increase in the total utility of the society.

Based on the results of this study, it is further advisable to take sea level rise and its effects into consideration in planning/zoning decision-making. Adding state level fixed effects in Section 3.5.3 reveals that these decisions are likely to affect the relationship between local sea level rise and agricultural land prices. However, more research should be conducted to identify how planning decisions in particular affect the relationship. This is beyond the scope of this study.

Great Lakes water levels have been falling during recent years. It follows from the results of this study that the Great Lakes level fall is related to a decrease in land prices in the affected counties. As discussed in Section 3.4, a decrease in agricultural land values is likely to reflect a decrease in alternative future uses of agricultural land. The alternative uses are, for example, recreation or retirement housing. It is therefore likely that the water level decline negatively affects the recreational and retirement housing value of the counties surrounding the Great Lakes. Hence, more research should be done about the dynamics of Great Lakes levels and how we can affect them.

Another possible use of the results of this study could be the utilization of the estimates as inputs for simulation studies on the future effects of climate change.

3.7 Summary and conclusion

Recent studies focused on prediction of economic and social consequences of climate change mostly assume that sea level rise has negative impacts on the economy. However, to the best of my knowledge, no previous study except for Novackova and Tol (2017) has attempted to identify or evaluate the possible effects of sea level rise on the economy in the past. Novackova and Tol (2017) did not find any significant effect of sea level rise on economic growth. In the present paper, I seek to quantify past effects of sea level rise on the economy of the United States by identifying impacts of sea level rise on agricultural land prices. More specifically, I fit a hedonic cross-sectional regression of agricultural land prices on sea level rise and other relevant covariates including soil characteristics. To address spatial autocorrelation, possible autoregressive or heteroscedastic patterns in disturbances and also possible occurrence of measurement errors, I use the HAC estimator of the variance covariance matrix proposed by Kelejian and Prucha (2007).

My estimates suggest that the effect of sea level rise is significant and there is a hill-shaped relationship between log of land values and sea level rise. Hence, slight sea level rise has positive effect on land prices which diminishes as sea level rise become more pronounced and the effect becomes negative for sea level rise of 4.76 mm per year and above. When I control for state fixed effects, the effect of sea level rise on agricultural land prices is purely negative: the linear sea level rise term is significant and negative and the quadratic sea level rise term is not significant and therefore not included. Estimates of this specification are therefore in line with my original hypothesis. One explanation of the different relationship could be an occurrence of several water gauge stations with extreme sea level rise. When the state level dummy variables are included, they pick the effect of these extreme values. Another reason could be the housing crisis in 2006-2007, as its intensity and impacts varied across the states of the US.

The main results are robust to a large set of variations of the above discussed model. Excluding distance from coast and groundwater withdrawals, which are immediate counfounders, does not change signs and significance levels of the sea level rise substantially. The linear sea level rise term becomes marginally significant, while it is marginally insignificant when the immediate confounders are included. However, this small difference does not in general affect the hill-shaped relationship between sea level rise and land prices. The linear functional form yields mostly the same signs and significance levels of the estimates as the loglinear functional form and also the relationship between sea level rise and agricultural land prices is hill-shaped as in the case of the loglinear specification.

Neither controlling for population growth changes signs and significance levels of the sea level rise coefficients and most of the covariates.

The evidence suggests that the effect of sea level rise was less apparent in year 1900 as the p-value of the quadratic sea level rise term, which is equal to 0.089, is just above the significance threshold (p-value smaller than 0.1 can be sometimes considered significant depending on how the significance level is specified). Nevertheless, the magnitude of the sea level rise coefficients, the impact measures and its exponential functions for 1900 are very comparable to those obtained for the modern period considering the price level difference. Further, the sea level rise estimates are very similar to the results obtained from the main specification if the sample is restricted to the coastal counties. Especially the estimate of the squared sea level rise term is almost equivalent to that obtained for the full sample. As a further robustness check, I estimated the Kelejian and Prucha (2007) HAC consistent standard errors with a different Kernel function. The significance levels of all coefficients hold same with exception of one control variable (permeability). Finally, I find out that the significance levels and signs of all coefficients remain the same also with a different coding scheme which is used to convert the spatial weight matrix. The only exception is length of coast, which is insignificant in both cases but positive with the S-coding scheme and negative with the C-coding scheme.

In spite of the fact that the evidence of the beneficial impacts of mild sea level rise is quite surprising, the shape of the relationship detected in the present study is noticeably similar to the results of Novackova and Tol (2017). Although, for the more recent time period they do not find any significant negative or hill-shaped relationship between sea level rise and economic growth, for the period between $1990 - 2005$ and some earlier periods the authors detect a strongly significant and negative squared sea level rise term and a strongly significant and positive linear sea level rise term (see Table 6 in Novackova and Tol (2017)), implying that mild sea level rise has positive effect on economic growth while more pronounced sea level rise affects economic growth negatively, which is analogous to the results of the present study.

Possible explanation of the hill-shaped relationship can be the fact, that the negative impact of sea level rise on coastal land values drives up prices of land further inland. For mild sea level rise, the positive inland effect is stronger than the negative effect on coast, but for more rapid sea level rise, the negative effect prevails. Unfortunately, I can not test for this as the available land values data are county averages and the areas of counties are large, including both inland and coastal zones.

More details about the relationship between sea level rise and land values can be explored using plot specific land values. This is a topic for further research, however availability of more detailed property data can be a problem.

Chapter 4

Climate Change Awareness and Willingness to Pay for its Mitigation: Evidence from the United Kingdom

4.1 Introduction

According to scientific consensus, climate change does exist and it is human caused (Oreskes, 2004; McCarthy et al., 2001; Cook et al., 2013). However, public opinion on global warming is not so unified. For example, nearly 50% of Americans did not believe in human caused climate change in 2010 (Leiserowitz et al., 2012; Pew, 2012). Without taking actions to prevent or mitigate climate change and its consequences, the effects of global warming could be disastrous (Church et al., 2013; Hinkel et al., 2014; Seneviratne et al., 2012).

Public attitudes towards natural hazards and risk perception are important drivers of policy decision making (Slaymaker, 1999; Tierney et al., 2001). Whether and how well climate change will be tackled depends heavily on public opinion. But what are the main factors influencing climate change perception and awareness among the general population? A large literature examines the role of personal characteristics, demographics and behavioural variables in climate change awareness and risk perception by means of survey or experimental methods. Recent survey-based studies include Lee et al. (2015), who exploits the Gallup World Poll data and conclude that civic engagement, communication access and education are the most important predictors of climate change awareness while beliefs about causes and perception of local temperature changes are the main predictors of climate risk perception. Another example of a survey-based analysis of environmental attitudes is Morrison et al. (2015), who use ordered logit models to investigate the relationship between religion and climate change attitudes and behaviour. They conclude that Buddhists, atheists and agnostics are the most engaged with climate change while Christian literalists are the least engaged. Also Carlsson et al. (2013) use survey data to estimate preferences of the redistribution of the burden caused by CO_2 emissions in China and in the United States. Understandingly, both Chines and Americans prefer rules of redistribution which are less costly for their country. However, these rules differ for the two countries. US respondents prefer the current emissions rule while in China, the historical emissions rule is preferred.

As for papers based on experiments, for instance Braaten (2014) analyses motivation of a good feeling from giving in contrast to 'pure altruism' in climate change context. He concludes that this 'warm glow' is important for motivating of environmentally friendly behaviour. Another example of a study which uses experimantal methods is Glenk and Colombo (2013), who conduct a choice experiment in Scotland. Based on the results, they claim that an outcome related risk is an important attribute in choice of land-based climate change mitigation project.

Not so many studies have been focused on willingness to pay (WTP) for climate change mitigation in terms of gas and electricity tax in the UK. However, some authors have addressed the valuation of environmental or other non-market goods or ecological services in the UK using a contingent valuation or choice experiment (CE) formats. The UK-based contingent valuation studies include one by O'Garra and Mourato (2016), who estimate UK respondents' WTP towards climate change adaptation projects in developing countries. The authors conclude that UK residents would be willing to pay less than one-third of what would be needed according to an estimate based on the World Bank's recommendation. Another UK-focused contingent valuation study is one by Hanley et al. (2009), who contribute by allowing for negative and zero WTP preferences for prospective changes in two UK national parks. Christie et al. (2007) combine a frequency-based choice experiment and a contingent behaviour model to estimate the valuation of improvements to recreational facilities in forests and woodlands in the UK. In their study, the contingent behaviour models fit better than the choice experiments.

As for the choice experiment studies, Sheremet et al. (2017) investigate public preferences and WTP for forest disease control measures. Scarpa and Willis (2010) use a choice experiment to elicit WTP for micro-generation renewable energy technologies in the UK. The authors conclude that renewable energy is valued relatively highly in the UK but still not enough to cover the capital cost of micro-generation energy technologies. Also Tatchley et al. (2016) focus on renewable energy sources. In particular, they examine the level of acceptance of small wind turbines in the UK. Colombo et al. (2009) and Hanley et al. (2007) analyse how people value upland farmlands in the North-West region of England using CE survey data. Tinch et al. (2015) find out that stated preferences associated with environmental goods are highly context dependent. The Department of Energy and Climate Change (DECC) set up a tracking survey in early 2012. The survey includes questions about perception of climate change and energy security. Based on the resulting report, climate change and energy security are not seen as key problems or risks in the UK. However, after being asked directly, the respondents show rising concerns about energy security (DECC, 2013).

A number of environmental evaluation studies have been focused on public perceptions in Scotland. For example, Hunter et al. (2012) conducted a contingent valuation study that estimates WTP for reduction of health risks caused by toxic cyanobacterial blooms in Loch Leven. Kuhfuss et al. (2016) use a contingent valuation method to elicit WTP for conservation of historic sites in terms of higher income taxes. Another example of a Scotland based contingent valuation study is by MacMillan et al. (2006), who analyse differences between WTP for a familiar good (energy from wind power) and WTP for an unfamiliar good (red kite reintroduction). Jobstvogt et al. (2014) utilize discrete-choice survey data to estimate public valuation of deep-sea biodiversity. Bergmann et al. (2008, 2006) estimate public valuation of renewable energy projects.

Another group of environmental and other non-market goods valuation papers have been focused on Ireland. An example of a contingent valuation study is by Hynes and Hanley (2009). The choice experiment based papers include, for example, van Osch et al. (2017), Hynes et al. (2013), Stithou et al. (2012) and Campbell (2007).

As discussed in the previous few paragraphs, a number of surveys, choice experiments and contingent valuation studies have been conducted to analyse public opinion and attitudes towards climate change in the UK. However, to the best of our knowledge, none of these studies has attempted to estimate WTP in terms of gas, electricity or fuel duty. They focus mostly on public valuation of renewable energy, preservation of natural landscape or valuation of other non-market goods or services. A big portion of the studies has been focused on Scotland or Ireland rather than on the population of England or the entire United Kingdom. Furthermore, to the best of our knowledge, there is no study that relates climate knowledge and attitudes towards climate change, especially the desired effect of climate policy on utility bills and fuel duty, to behavioural measures such as risk and time preferences or social value orientation elicited in choice experiments in the UK. Here we present a first analysis of climate knowledge and attitudes towards climate change including desired climate tax rates and how they are affected by behavioural variables elicited using experimental methods on the population of the UK.

Since the effects of climate change will mostly be apparent in relatively distant future and they will particularly affect the next generations, we hypothesize that people with smaller time discount rates and those who are rather pro-social or altruistic will show higher concerns about climate change than respondents with higher discount rates and those with an individualistic or a competitive world-view. Similarly, we expect that people who are particularly risk averse will be more concerned about climate change than risk-takers.

The previous studies of public attitudes and knowledge about environment are usually based either on survey or on experimental methods. Surveys can be conducted over large, reasonably representative samples and experiments are powerful tools to infer parameters of utility functions, measures of risk and time preferences or social value orientation (Ifcher and Zarghamee, 2011; Murphy et al., 2011; Tanaka et al., 2010). Each of these methods, however, suffers from serious drawbacks. Surveys often lead to hypothetical bias while experimental data tend to be affected by artificial settings and small, non-representative samples which often consist of students. We contribute by overcoming some of these shortcomings as we use a dataset which was created by surveying a large sample of respondents in an experimental, interactive and dynamic way. Experiments are usually computer based and their participants respond to various situations on a screen. We replicate this set-up in a live sample survey by including the experimental methods as a part of the survey (Dolton and Tol, 2016). The experimental set-up covers attitudes towards risk, attitudes towards equity including altruism and time preferences. We will explore effects of these attitudes on stances towards climate change and climate knowledge.

We also investigate the influence of other characteristics on environmental attitudes including standard demographic data such as age, sex, race, ethnicity, religion, education, sector, occupation, date of birth, siblings, questions about assets, debts and family income. We further examine the role of financial literacy and numeracy and we also investigate preferences regarding government spending and income redistribution, cultural and political ideology and world-view. As there is no general consensus on what are the main determinants of climate change perception and climate literacy, we start the explanatory analysis using a least absolute shrinkage and selection operator (lasso) to select significant predictors from almost 70 candidates.

We further contribute by showing substantially different results from those of Newell and Siikamaki (2015), who experimentally measure individual discount rates and analyse their role in energy efficiency decisions of US households. The study of Newell and Siikamaki (2015) is particularly relevant to our analysis as the authors use the same experimental framework to obtain individual time discount rates and they analyse them as possible predictors of households' energy efficiency decisions and valuation of future energy savings. They find a negative and significant effect. More specifically, Newell and Siikamaki (2015) conclude that WTP for annual operating energy cost savings decrease in discount rates. This disagrees with our results as we do not find any evidence of significant effects of individual discount rates on any of our dependent variables, including WTP. We argue that our estimates are more precise than those of Newell and Siikamaki (2015) as our sample size is substantially larger.[1] We also cover much broader spectrum of potential predictors and we use a more precise estimator, in concrete multisplit lasso with resampling.

Our additional contribution is a partial replication of Kahan (2015). We believe that the research of Dan Kahan presents the frontiers of knowledge in his area of expertise[2] and that the author is one of the most respected scientists in his field of study, not least because his papers have been published in prestigious scientific journals (e.g. Kahan and Carpenter 2017; Kahan and Corbin 2016; Kahan 2015). This is one of the reasons why we decided to use the 'ordinary climate science intelligence' (OCSI) questions that were developed by Kahan (2015) to measure climate knowledge in the present study. A more detailed description of the OCSI instrument and a discussion about its validity, strengths and weaknesses is in Section 4.3.1. The OCSI questions can be found in Appendix C.1.

Consistently with the results of Kahan (2015), we find that climate knowledge measured by the OCSI instrument does not depend on measures of personal ideology and cultural world-view as opposed to other, previously used measures of climate knowledge (Hamilton, 2011; Kahan, 2012; Kellstedt et al., 2008). In accordance with Kahan (2015), our results show that climate knowledge is positively correlated with numeracy. We also detect association between the measure of climate knowledge and gender.

In accordance with previous research (Kahan et al., 2012; Kahan, 2015; Kellstedt et al., 2008) we find that stated climate change risk perception does not increase with numeracy and financial literacy (we use these variables as proxies for ability of analytical reasoning and capacity to make use of quantitative information although they can also be interpreted as tests of the respondents' attentiveness during the survey) as one may intuitively assume

[1]Our estimation samples include between 5659 and 5749 respondents while the estimation sample of Newell and Siikamaki (2015) has 879 observations.

[2]or at least it did at the time when the survey that we used for our analysis was conducted

(Weber and Stern, 2011). As a matter of fact, we find that individuals' concerns about climate change decline as numeracy and financial literacy increase and it is also closely related to respondents' gender and cultural and ideological world-view. This is consistent with previous literature (Kahan, 2015; Kellstedt et al., 2008; Whitmarsh, 2011). We particularly show that the respondents, who agree with the statement that 'Government should redistribute income from the better off to those who are less well off' (we will further refer to this statement as 'government should redistribute income', 'degree of agreement with income redistribution' or simply 'income redistribution'), which we use as a measure of cultural or ideological world-view, are more likely to take climate change more seriously and have higher WTP for its mitigation than those not agreeing with this statement. Consistently with recent literature (e.g. Kahan, 2015; Kahan et al., 2012; Hamilton, 2011; Hamilton and Keim, 2009), we find evidence suggesting that the ideological polarization over climate change is stronger among people who are more proficient in numeracy and comprehension of quantitative information.

We detect other significant predictors of WTP for climate change mitigation by means of gas and electricity tax. These are age, inequity aversion, perception of equality of intergenerational allocation of resources and risk assessment consistency. Expectedly, the respondents who consider themselves to be more affected by climate change than by climate policy have higher WTP than those who feel to be more affected by climate policy. Consistently with previous literature, we find a negative and significant effect of age (Hamilton, 2011; Kellstedt et al., 2008; Hayes, 2001). The impacts of inequity aversion are mixed. WTP also depends on the respondent's perception of her standard of living and income in comparison to the standard of living and income of her parents and the standard of living and income of her children at the same age as the respondent currently is. We estimate an analogous model for WTP by means of transport fuel duty as a robustness test and the results are very comparable. The estimates are robust.

Perhaps surprisingly, we did not find the behavioural characteristics to be significant predictors of our climate perception or climate knowledge measures. The only exception is inequity aversion, which has significant effects on WTP for climate change mitigation.

The paper proceeds as follows. In Section 4.2 we discuss methods, in particular multisplit lasso and jackknife ordinary least squares (OLS). Section 4.3 describes the dataset used for our analysis and how the important variables were obtained. In Section 4.4 we present and discuss the results. More specifically, Section 4.4.1 is focused on climate knowledge, in Section 4.4.2 we present estimates of climate seriousness perception models and Section 4.4.3

describes models for WTP. In Section 4.5 we estimate alternative specifications for each dependent variable to verify robustness of our results. We summarise our findings in Section 4.6 and in Section 4.7 we discuss caveats. Section 4.8 includes policy implications and concluding remarks.

4.2 Econometric methodology

Prior empirical studies detected large number of miscellaneous predictors of climate change knowledge and concerns (e.g. Lee et al. 2015; Hamilton 2011; McCright 2010; Morrison et al. 2015). There is, however, a lack of consensus about which are the most important ones. Since our dataset includes almost 70 potential predictors, we decided to start with an explanatory regression analysis using a model selection estimator.

Stepwise-like procedures were found to be problematic as it was shown that large portion of selected variables is often noise and the adjusted R^2 is biased upwards (Flack and Chang, 1987). There are also other problems with these methods. For example, a forward stepwise regression selects in each step the predictor having largest absolute correlation with the response y, say x_{j1}. Then a simple linear regression of y on x_{j1} is performed and a residual vector from this regression is considering to be the new response variable. Then the procedure is repeated and we eventually end up with a set of selected predictors $x_{j1}, x_{j2}, ..., x_{jk}$ after k steps. This method can, however, eliminate a good predictor in second step if it happens to be correlated with x_{j1}. Furthermore, these methods frequently fail to identify the correct data-generating process, even in large samples (Austin, 2008). A possible alternative is the best subset selection approach. Given a collection of possible predictors, the best subset approach compares all possible subsets of predictors based on some well-defined objective criterion, usually having the largest adjusted R^2. However, besides being excessively computationally demanding, also this method often fails to identify the true predictors (Flack and Chang, 1987). On the other hand, sparse estimators such as lasso (Tibshirani, 1996) are usually more stable than stepwise procedures and they are commonly better in prediction accuracy (Bühlmann and Van De Geer, 2011). Because lasso has been shown to be very powerful for high-dimensional variable selection in general (Meinshausen et al., 2009), we opt for this estimator.

Using the same notation as Friedman et al. (2010), our dependent variable is $Y \in \mathbb{R}$ and our vector of explanatory variables is $X \in \mathbb{R}^p$. We assume that the relationship between them can be approximated by a linear regression model $E(Y|X = x) = \beta_0 + x^T\beta$. Lasso estimator selects the predictors by setting some of the coefficients β_j to be equal to zero.

We consider four distinct models for the four response variables and one additional model as a robustness test. The dependent variables are: (i) Knowledge about climate change (ii) Perceived seriousness of climate change (iii) Perception of effects of climate change policy relatively to effects of climate change and (iv) WTP for climate change mitigation, which we measure by preferred tax rates on gas and electricity. We also estimate an additional model for petrol duty as a robustness test for the WTP model. How we measure the dependent variables is described in Section 4.3.1. The potential predictors included in x, which are not the behavioral variables and which were not selected into any model by multisplit lasso are listed in Tables C.6 and C.7 in Appendix C. How we measure the behavioural variables is discussed in Section 4.3.2 and their descriptive statistics are summarised in Table C.8 in Appendix C with the exception of inequity aversion as this variable is considered as categorical and its frequencies are summarised in Table C.10 in Appendix C. The predictors, which were selected into some model can be found in a table of estimates of the relevant models and their descriptive statistics or frequencies are summarised in Tables C.8, C.9, C.10, and C.11 in Appendix C.

The estimation function can be written as (Friedman et al., 2010):

$$\min_{(\beta_0,\beta)\in\mathbb{R}^{(p+1)}} \boldsymbol{R}_\lambda(\beta_0,\beta) = \min_{(\beta_0,\beta)\in\mathbb{R}^{(p+1)}} \left[\frac{1}{2N}\sum_{i=1}^{N}(y_i-\beta_0-x_i^\intercal\beta)^2+\lambda\sum_{j=1}^{p}(|\beta_j|)\right] \tag{4.1}$$

where y_i is the value of one of our four dependent variables for an individual i, x_i includes potential predictors listed in Tables C.6 to C.11 in Appendix C, N is the number of observations and $\lambda \geq 0$ is the penalty parameter. Without loss of generality, we assume that the potential predictors in (4.1) are standardized: $\sum_{i=1}^{N} x_{ij} = 0$, $\frac{1}{N}\sum_{i=1}^{N} x_{ij}^2 = 1$, for $j = 1, ..., p$. [3]

In line with common practice, we compute estimator (4.1) for a series of λ and then we choose a preferred value of λ using cross-validation (Bühlmann and Van De Geer, 2011). In particular, we use a sequence of 100 values of λ and 10-fold cross validation.[4] We opt for the value of λ which is recommended by Friedman et al. (2010) and is probably the most common choice. More specifically, we use the largest value of λ such that the mean cross-validated error (CVM) is still within one standard error of its minimum.[5]

Determining significance levels is problematic with lasso. Classical p-values are not valid and there is no simple approximation. Therefore, we adopt a concept of Meinshausen et al. (2009), who introduce an approach based on multiple random splits of data, repeated

[3]Both x_{ij} and y_j are standardized automatically in the implementation of the algorithm we use. However, the estimated coefficients are always returned and presented on the original scale.

[4]For estimation of lasso (4.1) we use function cv.glmnet in the **R** programming system (R Core Team, 2017) and we use default settings and values of arguments, unless otherwise stated.

[5]In case of WTP we use the value of λ which minimises the CVM. This value is also suggested by Friedman et al. (2010). The only difference from the model estimated using the one standard error based λ is that for the latter, a dummy variable for male becomes significant and gets into the model. The effect of male is positive and this contradicts predominant conclusions in previous relevant literature (e.g. Hamilton 2011; McCright 2010; Hamilton and Keim 2009; Flynn et al. 1994).

estimation and aggregated inference. In particular, Meinshausen et al. (2009) build on the proposal of Wasserman and Roeder (2009), who suggest to split the dataset randomly into two subsets. One of the subsets is used for variable selection via lasso and the other one is for estimating OLS with the predictors selected by lasso and calculating their p-values in a usual way. This procedure allows asymptotic error control under minimal conditions. The problem is that the results depend on a one-time arbitrary split and they are therefore irreproducible. Meinshausen et al. (2009) further develop the single-split method. They suggest to split the sample repeatedly, obtain a set of p-values for each split and then aggregate them. In each split, the p-values of the variables which are not selected are considered to be equal to one and the p-values of the selected variables are multiplied by the number of variables selected in the current split. If a p-value multiplied by the number of selected variables happens to be larger than one, it is considered to be equal to one. Let's assume that we have $h = 1, ..., H$ splits. A p-value for predictor j obtained in split h adjusted as described above will be further denoted $P_j^{(h)}$. Meinshausen et al. (2009) suggest to aggregate the adjusted p-values using quantiles. In particular, a suitable aggregated p-value is defined for any predictor j and for any fixed $0 < \gamma < 1$ as

$$Q_j(\gamma) = min\left\{1, q_\gamma(\{P_j^{(h)}/\gamma; h = 1, ..., H\})\right\}, \tag{4.2}$$

where and $q_\gamma(\cdot)$ is the (empirical) γ-quantile function. We will further refer to this procedure as a multisplit lasso.

Meinshausen et al. (2009) show that for any predefined value of $\gamma \in (0, 1)$, the p-values defined in (4.2) can be used for control of family-wise error rate[6] and also for regulation of false discovery rate.[7] Moreover, the multisplit method improves the power of estimates.

For simplicity, we set γ in (4.2) to be equal to 0.5 for every application of a multisplit lasso in this study. Each time we perform $H = 100$ splits (we believe that this number is sufficient as Meinshausen et al. (2009) use 50 sample splits per simulation) and we always use one third of the sample for the variable selection using lasso and the rest for the OLS estimation and obtaining p-values.

A large fraction of our potential predictors are categorical variables because large part of the survey data was collected by multiple choice questions. However, the multisplit lasso selects individual predictors rather than groups of variables. Therefore, it can happen that a model specified by a multisplit lasso includes a dummy variable for one category of a

[6] Probability of making at least one incorrect rejection of a true null hypothesis (type 1 error).

[7] Expected proportion of incorrect rejections of a true null hypothesis (type 1 errors). False discovery rate controlling procedures are less stringent than family-wise error rate controlling methods.

particular categorical variable but it does not include dummy variables for its remaining categories. An obvious way how to overcome this issue would be to add the remaining dummy variables and use an F-test to determine the joint significance of the group. If the F-test implies that the categories are jointly significant, they should all stay in the model and they should be left out otherwise. However, the solution is not so straightforward with a multisplit lasso as it is not obvious on which subsample we should perform the F-test. Therefore, for each model specified by a multisplit lasso, we decided to perform a following procedure which is sometimes called jackknife resampling. We will further refer to the procedure as a jackknife OLS. We again randomly split the dataset into two subsamples. The bigger subsample has size of two thirds of the original sample and it is used for OLS estimation and calculation of p-values of the model with predictors selected by multisplit lasso.[8] In addition, if the model specified by multisplit lasso includes a binary indicator which represents a category of a nominal variable, we include also all other categories of this variable among the set of predictors. Besides individual t-tests we perform an F-test of joint significance of the categories of the nominal variable. Similarly as in the case of multisplit lasso, we repeat the resampling and OLS estimation 100-times. Each time we perform t-tests and also a joint F-test for each group of dummy variables representing one categorical variable. The p-values of the t-tests are then aggregated in the same way as in case of multisplit lasso (see above). Further, we calculate mean and median of p-values of each joint F-test over the 100 subsamples and according to these statistics we determine whether the dummy indicators of the particular categorical variable should be included. It turns out that every time when a dummy variable representing a category of a nominal variable is chosen by a multiple lasso, both average and median p-values of the corresponding F-tests are below the significance level ($\alpha = 0.05$). Hence, we include the dummy variables for categories of each nominal variable selected by lasso (see Section 4.4).

[8]Sample splitting can generally result in loss of efficiency. We, however estimated all models also for the whole sample as robustness checks and the results do not differ in signs or significance levels.

4.3 Data and survey methodology

All data used in this study except for predicted income and population density, which we use in robustness tests, were collected in the online survey conducted by Dolton and Tol (2016).

In Section 4.5 we use an alternative measure of income as a robustness test. In particular, this estimated income is obtained from a regression model based on data from Annual Survey of Hours and Earnings (ASHE). More specifically, the predicted income is based on age, gender, occupation, sector and education.

We use two measures of population density, in particular average density per Lower Layer Super Output Areas (LSOA) estimated by the Office for National Statistics for year 2015 and average density for Local Authority Districts (LAD) obtained from the 2011 Census.

The survey that generated data for our study is reproduced in Appendix C.4. An important part of the survey is a section on public policy which consists of four domains, in particular pensions, health care, education and climate. Each respondent was randomly assigned two of the four domains. Our dataset consists of the respondents who were assigned the climate domain; hence we have around $6,000$ observations.[9] The parts of the survey that include questions about pensions, health care and education are not included in Appendix C.4 as we do not use them in this study. The questionnaire was created using SurveyGizmo and two pre-testing rounds were conducted. The first pre-testing round was done by members of the faculty and PhD students of the Department of Economics of the University of Sussex. The second pre-testing round was conducted online using social media. The main survey was carried out online by the company GlobalTestMaker and it ran from 9 September to 14 October 2015. The respondents were sampled according to gender and age to correspond to the UK population. Participants are residents in the United Kingdom and they are rewarded £1.50 for responding to a 30-minute survey (Dolton and Tol, 2016).

The survey is reasonably geographically representative taking into account population density in the UK (Dolton and Tol, 2016).[10] As the survey was conducted online, the initial sample is representative for UK adults with internet access rather than for the entire UK population. The questionnaire was partially filled out by $17,053$ interviewees (including those not selected for the climate domain and therefore not included in our dataset). $12,028$

[9] We had to exclude some observations from various parts of analysis as they included missing values for some important variables. However, we have at least $5,500$ observations for each model.

[10] For map with location of respondents see Figure 1 in Dolton and Tol (2016)

of the $17,053$ participants completed the survey. The most respondents dropped out on pages with relatively difficult questions; that is, questions about time preferences and about how the government is spending money and how it should be spending money. The third highest drop out rate was on the financial literacy questions. Hence, although the survey was designed such that more difficult questions are spaced out relatively evenly across the whole questionnaire, the final sample is biased towards people who are not afraid of hard questions (Dolton and Tol, 2016).

The median length of time taken to complete the questionnaire (including the parts not relevant for the present study) was 17.6 minutes for the whole sample and 18.18 minutes for the subsample of participants who answered the climate domain. The spread of time taken to complete the survey was relatively wide across the sample. The vast majority of respondents finished the questionnaire within 45 minutes.

There has been an active debate regarding the issue of hypothetical bias from stated-preference methods (e.g., Murphy et al., 2005; Aadland and Caplan, 2003). Hypothetical bias can be defined as a bias that has the potential to occur when respondents are asked about a maximum value they are willing to pay for a good without actually having to pay the stated value (Aadland and Caplan, 2003). In our survey, many of the measures were elicited by stated preferences methods. Therefore, we need to consider potential hypothetical biases in the results. Several factors have been associated with the occurrence and magnitude of hypothetical bias in previous literature. For example, the magnitude of the hypothetical value and the laboratory setting were found to be positively related with an increase in the magnitude of hypothetical bias. On the other hand, individual setting and choice-based eliciting formats were found to be effective for reducing hypothetical bias (Murphy et al., 2005). To reduce potential hypothetical bias in our study, choice-based methods were used to elicit preferences about time, risk and social value orientation in the survey (see Section 4.3.2, Appendix C.4 and Dolton and Tol, 2016). However, WTP for climate change mitigation was elicited using answers in the form of a slider (scale) rather than choice-based eliciting. Including a series of choice questions about climate policies would considerably increase the length of survey. This would not only increase the cost of survey but it would also lead to less reliable answers as capacity and motivation to focus usually decline with the length of a questionnaire. Furthermore, there is an ongoing debate about the superiority of choice-based eliciting over scale payment or open-ended methods in various contexts (Kőszegi and Rabin, 2007; Frew et al., 2003).

To investigate the potential occurrence of hypothetical bias in our WTP variables, we asked about preferred tax rate on fuel in addition to asking about preferred tax rate on gas and electricity. The median preferred petrol duty is 10 pence, which is relatively small in magnitude and much smaller than the values of WTP on gas and electricity. The estimates of regression with WTP on fuel instead of WTP on gas and electricity as a dependent variable are not significantly different (see Section 4.5.3).

To reduce the possible effect of a laboratory setting on potential hypothetical bias, some of the participants completed the survey in group sessions at the University of Sussex, while the majority of interviewees participated online. We did not find any significant difference in responses between the two groups.

Another way in which to reduce potential hypothetical bias is ex-post calibration, which involves multiplying of stated willingness to pay by a calibration factor. We do not apply this method, as we believe that hypothetical bias is not a substantial issue to confound our results and multiplying by a coefficient would not change the regression results. Furthermore, estimating the calibration coefficient can be problematic (Murphy et al., 2005).

Another type of bias that can result from stated WTP methods is strategic bias. This type of bias can occur when a respondent understates or overstates WTP in the hope of influencing policy. We believe that there is very little incentive for giving untruthful strategic answers, as the respondents were informed that the research was being conducted for academic purposes and the chances of influencing policy are small. However, to ensure that we will not get extremely high or extremely low unrealistic values, we opted for a scale payment rather than an open-ended format.

In Table 4.1 we compare distribution of our sample over sex and age with the distribution of the UK population. The age data are only available as a categorical variable in our survey. As we can see in Table 4.1, the youngest category is slightly over-sampled while the two categories of the highest age are slightly under-sampled, probably because the survey was conducted online. Otherwise the distributions are relatively comparable.[11]

Table 4.1: ***Sex and age distribution*** *of the sample and the population*

	Sample		UK population[a]	
Age range	**Male**	**Female**	**Male**	**Female**
18 – 24	9.3%	9.4%	6.2%	6.0%
25 – 34	10.0%	10.3%	9.0%	9.1%
35 – 44	7.8%	8.3%	8.6%	8.8%
45 – 54	8.1%	9.4%	9.3%	9.6%
55 – 64	7.4%	8.4%	7.5%	7.8%
65 – 74	4.1%	4.8%	6.2%	6.7%
75 – 80	0.1%	0.1%	2.4%	2.8%
Observations	8,541[b]		48,189,434	

[a] Population data are from the Office of National Statistics, Population Estimates of UK, England and Wales, Scotland and Northern Ireland Mid 2014, Table MYE2.
[b] Half of the total number of respondents, more specifically those who were selected for the climate change module. The number is higher than the number of observations of the individual models as the models include many variables and some of them have missing values.

More details about the methodology of the survey, sample and descriptive statistics can be found in Dolton and Tol (2016).

In the rest of this section we focus on how we obtained the data for our climate (dependent) variables and the behavioural characteristics.

4.3.1 Climate variables

Descriptive statistics of our climate variables are summarised in Table 4.2.

Table 4.2: ***Dependent variables:*** *Descriptive statistics*

Variable:	**Mean**	**St. dev.**	**Min**	**Max**
Climate change knowledge	3.851	1.266	1	8
Climate change seriousness perception	6.622	2.249	0	10
Climate versus policy effects perception	5.370	2.315	0	10
WTP - gas and electricity tax (£ per year)	123.900	105.459	0	500
WTP - duty on transport fuel (pence per year)	20.530	22.518	0	100

[11] One way how to deal with sample selection is to use sampling weights. We, however decided not use weights given the modest nature of our bias. Weighting usually increases standard errors and leads to less precise estimates and there is lack of consensus on whether or not to use weights in regression methods (Gelman, 2007; Kott, 2007; Winship and Radbill, 1994). Winship and Radbill (1994) for example recommend not to use weights if they are solely a function of independent variables.

It was previously shown, that questions which are intended to measure climate science comprehension often measure who people are rather than what they know about climate change as the strongest predictor is often respondents' ideology and cultural and political world-view (Hamilton, 2011; Kahan et al., 2012; Kahan, 2015). To avoid picking of effect of cultural or political world-view instead of climate knowledge, we use questions from the OCSI instrument developed by Kahan (2015) as a measure of climate knowledge. Kahan (2015) shows that these questions are indeed a measure of climate science comprehension rather than an indicator of who one is. The values of climate knowledge are integers from 1 to 8 and they stand for counts of correctly answered questions about climate change (Kahan, 2015). An example of one of the 8 climate knowledge questions is: 'Climate scientists believe that if the North Pole icecap melted as a result of human-caused global warming, global sea levels would rise. Is this statement true or false?' The list of all climate knowledge questions can be found in Appendix C.1. The relative frequencies of counts of the correctly answered questions are summarised in Table 4.3.

One may argue that the OCSI quiz that we use in this analysis (see Appendix C.1) is relatively difficult in comparison to previously used climate knowledge questions and that answering the OCSI questions correctly would require a high level of expertise in climate knowledge, which can only be possessed by a small part of the population. In this paragraph, we explain why these questions, which appear to be relatively tricky, were used to create the OCSI instrument and why we use them in the present study. Previous studies have found that climate questions commonly used to measure climate knowledge are often indicators of political and ideological world-views rather than measures of climate knowledge. It is not clear whether the main factors that affect the respondents decision to affirm or reject factual statements about climate change is her level of knowledge and comprehension of climate science or the correspondence between each proposition and the respondent's affective orientation towards climate change (Hamilton 2011; Kahan 2007, 2015; Reynolds et al. 2010). Kahan (2015) aims to develop an instrument that would truly capture a person's climate knowledge without being confounded by her political and ideological world-views and affective orientation towards climate change risk. He takes two steps to remedy this potential issue. The first step is balancing the number of questions that are likely to be answered correctly by those respondents whose affective orientation is consistent with greater concern about climate change risk (for example, a true or false statement: 'Climate scientists believe that human-caused global warming will result in flooding of many coastal regions') and those that are more likely to be answered correctly by people whose affective orientation is consistent with being less concerned about climate change risk (for example, a true or false statement: 'Climate scientists believe that nuclear power generation contributes to global warming'). This should help to assure that only those respondents who have a corresponding level of climate knowledge and climate science comprehension will answer all questions correctly, irrespective of their affective orientation towards climate change. The second step, which should help the participants to disregard their affective orientation when answering the climate knowledge questions, is to introduce each statement with 'Climate scientists believe that...' or a similar clause.

To investigate opinions about seriousness of climate change, the respondents were asked the following question: 'How serious a problem do you think climate change is at this moment?' Using an interactive slider, the respondents answered an integer value between 0 and 10 where min = 0 and max = 10 (as it was noted just below the slider). In a similar way, the respondents were asked if they feel to be more affected by climate change or by climate policy. The wording of the question was: 'Which affects you and your way of life more, climate change or policies to reduce greenhouse gas emissions?' Again, the respondents provided answers on an integer scale from 0 (climate policy) to 10 (climate change) using a slider. Relative frequencies of climate seriousness perception and climate versus policy perception are summarised in Table 4.3.

Table 4.3: ***Dependent variables:*** *Relative frequencies (%)*

Variable:	**0**	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
Climate knowledge[a]	0.0	1.7	11.4	30.4	25.4	20.9	8.6	1.6	0.1	N/A	N/A
Climate seriousness perception	3.3	2.8	5.4	8.1	8.9	27.2	14.0	12.8	8.3	4.1	5.0
Climate vs. policy perception[b]	2.1	1.5	2.5	3.8	4.6	9.8	18.5	21.7	16.7	8.6	10.4

Notes: Total number of observations: 5749

a The first row includes the relative frequencies of numbers of correctly answered climate knowledge questions. For example, 1.7 in the second column means that 1.7% of the respondents answered one question correctly, 11.4 in the second column means that 11.4% of the respondents answered two questions correctly, and so on.

b Higher number means greater concern about climate change, lesser concern about climate policy.

Regarding the preferred gas and electricity tax rates, the respondents were first asked how much the current tax was. In particular, the question was as follows: 'The average household pays £1,369 per year for gas and electricity. Government intervention has raised the price to encourage people to use less and so reduce greenhouse gas emissions. How much of that £1,369 is for climate policy?' They indicated the response on a slider with a minimum of −50[12] and a maximum of 500. We include this variable on the right hand side as a robustness test (see Table 4.13). We refer to it as 'How much is tax gas and electricity'. After this, the respondents were told the correct answer and they were asked about they preferred tax rates: 'Actually, climate policy adds about £89 per year to the gas and electricity bill of the average household. How much do you think climate policy should add to this bill?' The respondents expressed their opinion on a slider from 0 to 500. The answer to this question is the dependent variable which we refer to as 'WTP - gas and electricity' and we use it as a proxy for WTP for climate change mitigation. Analogously, we inquired about the fuel duty. The only difference is that the slider for the actual fuel duty is limited from 0 to 60 and the one for the preferred fuel duty is from 0 to 100 as the actual fuel duty is 3 pence per litre.[13] Descriptive statistics of the respondents' estimates of actual tax rates can be found in Table C.8 in Appendix C and the descriptive statistics of the preferred tax rates are in Table 4.2.

4.3.2 Behavioural variables

One of our goals is to investigate effects of behavioural variables on climate knowledge and concerns about climate change. The behavioural variables that we consider in our study are social value orientation, time preferences, risk preferences, and attitudes towards inequality.

To estimate the social value orientation, respondents played six dictator games with the same questions as in Murphy et al. (2011). The ring measure of social value orientation which we use in our models is defined as

$$R = \arctan \frac{\sum_{i=1}^{N} P_O - 50N}{\sum_{i=1}^{N} P_S - 50N}, \tag{4.3}$$

where P_O is the pay-off given to the other party, P_S is the pay-off taken by the player herself and N is the number of games played (in our case 6).

[12] −50 was chosen as a minimum because some people believe that fossil fuels are subsidized in the UK. This was claimed by some of the most-read UK newspapers: for example, The Guardian, 7 November 2013 (see Vidal, 2013) or The Independent, 15 November 2015 (see Bawden, 2015).

[13] The wording of the fuel duty questions was: 'On every litre of petrol, there is a duty of 61 pence. The duty for diesel is 71 pence per litre. The duty is partly a fuel duty for financing road building and maintenance, and partly a carbon duty for encouraging people to drive less so that less carbon dioxide is emitted. The carbon duty is the same for petrol and diesel. How big do you think it is?' and 'Actually, the carbon duty is 3 pence per litre. How high do you think it should be?'

As one may notice in Table C.6 in Appendix C, we also include dummy variables for four types of social value orientation (altruist, prosocial, individualist, competitive) among potential predictors in the lasso estimators. These types are defined based on ring measure (4.3). Each dummy variable corresponds to one of four non-overlapping intervals of the values of ring measure (4.3). None of these dummy variables was selected by lasso into any of our models, therefore we do not discuss them in more detail.

As a basic measure of time preferences we use derived annual discount rates (in percentage), for investing now for one year from now and we refer to this variable as 'Discount rate year from now' in the present study. To obtain the data which would allow us to infer the discount rates, the respondents played games and answered questions informed by Voors et al. (2012), Ifcher and Zarghamee (2011) and Tanaka et al. (2010). In particular, the measures used to elicit time preferences are based on Question 19 in Appendix C.4. For example, if a respondent states that she would rather have £1000 in one year's time than £750 now, it implies that her discount rate is smaller than 33%:

$$\pounds 750 \quad < \quad \tfrac{\pounds 1000}{1+r} \quad \Leftrightarrow \quad r \quad < \quad 33\% \tag{4.4}$$

If the same respondent answers that she would prefer to have £850 now over £1000 in one year's time, we can derive a lower bound of her discount rate as

$$\pounds 850 \quad > \quad \tfrac{\pounds 1000}{1+r} \quad \Leftrightarrow \quad r \quad > \quad 17.6\% \tag{4.5}$$

Combining (4.4) and (4.5) we get

$$33\% \quad > \quad r \quad > \quad 17.6\% \tag{4.6}$$

Besides using discount rates for investing now and getting returns in one year, we also inferred other types of discount rates. These are discount rates for (i) investing now for getting returns in five years (ii) investing in one year for getting returns in two years from now and (iii) investing in one year from now for getting return in six years from now. None of them was found to be significant, thus we do not further discuss them.

We use two parameters which describe inequity aversion (Bergson, 1938, 1954; Samuelson, 1956), in particular the rate of inequity aversion and the subsistence or reserve income. To infer these parameters, respondents were choosing from various distributions of income between three hypothetical people. One of them was higher on average but more unequal and the other was lower on average but more equal. The respondents were asked two sets of choice questions. In one of them, the income distribution was centred on the 70^{th} percentile of the UK income distribution and in the other the distribution was centred on 40^{th} percentile of the UK income distribution. Given the respondents' answers to the two choice-sets, the rate of inequity aversion and subsistence was obtained for each respondent based on equations (4.7):

$$\begin{aligned} \sum_{i=1}^{3} \frac{(Y_{i,1}^{H} - \underline{Y})^{1-\gamma}}{1-\gamma} &= \sum_{i=1}^{3} \frac{(Y_{i,2}^{H} - \underline{Y})^{1-\gamma}}{1-\gamma} \\ \sum_{i=1}^{3} \frac{(Y_{i,1}^{L} - \underline{Y})^{1-\gamma}}{1-\gamma} &= \sum_{i=1}^{3} \frac{(Y_{i,2}^{L} - \underline{Y})^{1-\gamma}}{1-\gamma} \end{aligned} \tag{4.7}$$

where γ is the rate of inequity aversion, $\underline{Y}$ is the subsistence or reserve income and $Y_{i,j}^{H}$ is the income of a hypothetical person i according to distribution chosen by respondent in a choice set j which was centred on the 70^{th} percentile of the UK income distribution. Analogously, $Y_{i,j}^{L}$ is the income of a hypothetical person i according to distribution chosen by respondent in a choice set j which was centred on the 40^{th} percentile of the UK income distribution. To obtain the inequity parameters, equations (4.7) were solved for γ and $\underline{Y}$ while minimizing distance of $\underline{Y}$ to zero.

In theory, the rate of inequity aversion is a continuous measure. However, we consider it as a categorical one as in our dataset it is equal to one of 16 distinct values for each respondent.[14] These 16 values and the corresponding frequencies can be found in Table C.10 in Appendix C. The subsistence parameter was not selected by lasso into any of our models thus we do not discuss it in more detail.

To test significance of risk aversion, we use various risk aversion coefficients which were estimated for each person from four different utility functions using Bayesian inference (Balcombe and Fraser, 2015). The utility functions are power, logarithmic, exponential and quadratic and we use the estimates of their means and medians. None of them is significant or chosen by lasso in any of our models. For the economy of space we only present models with median or mean of power function. The estimates are very similar when we use other risk aversion coefficients.

As the behavioural variables are not significant in our study, we described their measures only briefly. For more detailed description see Dolton and Tol (2016). The descriptive statistics of these variables (except inequity aversion) can be found in Table C.8 in Appendix C. As explained above, we consider the inequity aversion rate as a categorical

[14]We also estimated variants of models where the rate of inequity aversion is considered as scale for completeness but we do not present them to save space. However, the results do not differ substantially from those presented here.

variable and its frequencies are in Table C.10 in Appendix C.

4.4 Results and discussion

In this section we describe our results and discuss their interpretation.

In the tables which summarise the estimates of lasso below, p-values of some of the explanatory variables are equal to one. These variables were not selected by the lasso in most of the sample splits. They are, however, included in the tables because they represent either a category of a nominal variable whose other category was selected by the lasso or a linear term of a variable whose quadratic term was selected by the lasso.

4.4.1 Climate change knowledge

Table 4.4 summarizes estimates of the predictors of climate change knowledge which we found to be important by means of multisplit lasso estimator. In particular, three predictors are chosen by lasso (see first column in Table 4.4). Total score on financial literacy is the number of correct answers out of three finance related mathematical problems (Dolton and Tol, 2016).[15] However, when we re-estimate the model using jackknife OLS with all relevant dummy variables, all categories of total score on financial literacy are insignificant. Furthermore, the model suffers from multicollinearity as the coefficient of correlation between cognitive reflection and total score of financial literacy is equal to 0.343 and its p-value is smaller than 2×10^{-8}. For illustration, estimates of jackknife OLS with all explanatory variables listed in Table 4.4 including financial literacy are shown in Table C.12 in Appendix C. The last column of Table C.12 includes variance inflation factors (VIF) which confirm the presence of multicollinearity. Because of the multicollinearity and insignificance of total score on financial literacy we do not further consider this variable as a predictor of climate knowledge.

The estimates of jackknife OLS without the financial literacy are summarised in the last two columns of Table 4.4. The other two variables which were found to be important in explaining climate knowledge are gender and cognitive reflection test (Frederick, 2005). We use the latter as a measure of numeracy and ability of analytical reasoning.

The cognitive reflection test is fully described in Frederick (2005) and it consists of three numerical problems. The value of our variable is the number of correct answers out of the three questions.[16] The frequencies of values of this variable are summarised in

[15] We also consider answers to each of the three problems separately as individual potential predictors. Two of them are labelled understands inflation and understands compound interest and they are identified as important predictors in other models later.

[16] The possible values are integers and half-integers between zero and three including zero and three as we also recognise if respondent solves half of a problem. Hence, if a respondent answers for example one and half problems correctly, her score is 1.5.

Table C.10 in Appendix C. To account for plausible non-linear relationship between the test score and cognitive ability we treat the variable as categorical with the base category zero. As it is apparent from Table 4.4, the respondents who solved all three problems correctly have significantly higher level of climate knowledge compared to those who did not solve any of them. According to the jackknife OLS, climate knowledge is on average higher also for respondents who answered two problems correctly. However, the effect is larger for three correctly answered problems. Expectedly, the effect of numeracy is positive.

Table 4.4: ***Climate change knowledge:*** *Multisplit lasso and jackknife OLS*

Variable	**Multisplit lasso** Aggregated adj. p-value		**Jackknife OLS** Aggregated coefficient	Aggregated adj. p-value	
Gender = male	$< 2 \times 10^{-8}$	***	0.733	$< 2 \times 10^{-8}$	***
Cognitive reflection = 0 [a]	0.038	*	*Not included - base cat.*		
Cognitive reflection = 0.5	1.000		2.071	1.000	
Cognitive reflection = 1	1.000		0.283	0.129	
Cognitive reflection = 1.5	1.000		0.895	1.000	
Cognitive reflection = 2	1.000		0.628	1×10^{-5}	***
Cognitive reflection = 2.5	1.000		1.098	1.000	
Cognitive reflection = 3	0.046	*	1.033	$< 2 \times 10^{-8}$	***
Financial literacy total score = 0.5	1.000		*Not included*		
Financial literacy total score = 1	1.000		*Not included*		
Financial literacy total score = 1.5	1.000		*Not included*		
Financial literacy total score = 2	1.000		*Not included*		
Financial literacy total score = 2.5	1.000		*Not included*		
Financial literacy total score = 3	2×10^{-5}	***	*Not included*		
Observations:			5749		

Notes: $^{\bullet}$ $p < 0.1$; * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$

For the significant predictors, the signs of the coefficients of the multisplit lasso are the same as those of the jackknife OLS and also size of most of the coefficients is very comparable for these two models.

a The estimate is negative for cognitive reflection = 0 while it is positive for cognitive reflection = 3 in this model.

We find the positive and strongly significant effect of the dummy variable for males quite peculiar. Previous research shows mixed evidence about effects of gender on climate knowledge and comprehension of science in general. For example, McCright (2010) finds that, in the United States, women demonstrate a higher level of scientific knowledge of climate change. On the other hand, Hayes (2001) analyses nationally representative survey data from the United States, Great Britain, Norway, the Netherlands, Germany and Japan, and he shows that men exhibit significantly higher level of scientific knowledge than women, even if controlling for a number of background variables. We perform additional tests to verify whether the positive effect of gender can be a result of sample selection. The tests include proportion tests, model with interactions as additional explanatory variables and a Heckman selection model. We discuss the results in detail in Appendix C.2. Based on the outcomes, we conclude that the results are not driven by sample selection.

A possible explanation why our measure of climate knowledge is significantly higher for men is that the climate knowledge test that we use in this study was developed by a man (Kahan, 2015), therefore it may be the case that these particular questions are naturally more comprehensible for men. The only way to test this would be to let a woman design another set of climate knowledge questions and then conduct a survey which would include these woman-designed climate questions. This is, however, beyond the scope of this study.

To sum up, we find that gender and cognitive ability are significant predictors of climate knowledge. Some previous studies found a similar effect of gender on climate knowledge, in particular that men tend to have a higher level of environmental knowledge than women (Arcury et al., 1986, 1987; Gendall et al., 1995; Tikka et al., 2000; Mostafa, 2007). Climate knowledge increases with higher numeracy which is consistent with Kahan (2015), who finds the climate knowledge measure to be positively correlated with ordinary science intelligence. Although various measures of climate knowledge were previously find to be correlated with social ideology or partisan identity (Hamilton, 2011; Kahan, 2012; Kellstedt et al., 2008), our measures of ideology, cultural world-view or their interactions were not chosen as predictors of climate knowledge by the lasso. This is also consistent with Kahan (2015).

4.4.2 Climate change risk perception

In this section we discuss our estimates of the models which explain individuals' perception of climate change risk. We focus on two measures of climate risk perception, in particular climate change seriousness perception and climate versus policy perception. We present the results of lasso and jackknife OLS with the climate seriousness perception as dependent variable in Table 4.5. Three predictors were selected, in particular gender, climate knowledge, and degree of agreement with redistribution of income by government. In this case, the effect of being male is negative. This is mostly consistent with results of previous research which typically finds women to take climate risk more seriously than men (Whitmarsh, 2011; McCright, 2010; Kahan et al., 2007). As we can see in Table 4.5, degree of agreement with income redistribution affects climate change seriousness perception positively as the base category is 'Strongly disagree'. This is in agreement with previous literature as we consider the degree of agreement with income redistribution as an indicator of political and ideological world-view, which was found to be significantly correlated with climate concern by large number of previous studies (e.g. Leiserowitz et al., 2013; Kahan, 2012; Whitmarsh, 2011).

We will comment on the significant effects of climate knowledge at the end of Section 4.4.2.

Table 4.5: ***Climate change seriousness perception:*** *Multisplit lasso and jackknife OLS*

Variable	**Multisplit lasso**		**Jackknife OLS**		
	Aggregated adj. *p*-value		**Aggregated coefficient**	**Aggregated adj. *p*-value**	
Gender = male	0.0002	***	−0.3658	4.45×10^{-6}	***
Climate knowledge	1.0000		0.1380	1.0000	
Climate knowledge - squared	$< 2.00 \times 10^{-8}$	***	−0.0548	0.0209	*
Redistribution of income: disagree[a]	1.0000		0.1819	1.0000	
Redistribution of income: neutral[a]	1.0000		0.2789	0.8251	
Redistribution of income: agree[a]	$< 2.00 \times 10^{-8}$	***	0.8343	8.58×10^{-8}	***
Redistribution of income: strongly agree[a]	$< 2.00 \times 10^{-8}$	***	1.0828	$< 2.00 \times 10^{-8}$	***
Observations:			5749		

Notes: • $p < 0.1$; * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$

For the significant predictors, the signs of the coefficients of the multisplit lasso are the same as those of the jackknife OLS and also size of most of the coefficients is very comparable for these two models.

a Degree of agreement with the following statement: 'Government should redistribute income from the better off to those who are less well off.' The base category is 'Strongly disagree'.

We now discuss the estimates of the model with dependent variable which answers the question whether respondent feels to be more affected by climate policy (0) or by climate change (10). The estimates are shown in Table 4.6. We can see that the selected predictors are climate knowledge, understanding of inflation and risk assessment consistency.

The level of understanding of inflation is based on respondents' answer to the following numerical problem: 'Imagine that the interest rate on your savings account was 1 percent per year and inflation was 2 percent per year. After 1 year, would you be able to buy...' The respondents should choose one of the three following answers: (*i*) 'More than today with the money in this account' (*ii*) 'Exactly the same as today with the money in this account' (*iii*) 'Less than today with the money in this account'. The correct answer is 'less'. The value of the variable is equal to one if the respondent answers 'less', it is equal to 0.5 if she answers 'the same' and it is equal to zero if she answers 'more'. The frequencies of answers are summarised in Table C.10 in Appendix C. Since it is quite possible that the effect of our measure of understanding of inflation is non-linear we treat the variable as categorical with the base category zero.

As it is apparent from Table 4.6, understanding of inflation and risk assessment consistency increase the likelihood of being subjectively more affected by climate policy than by climate change. This is likely to be because the two predictors are highly correlated with financial literacy. The correlation coefficient of understanding of inflation and financial literacy is 0.694 and the correlation coefficient of risk assessment consistency and financial literacy is 0.145. Both correlation coefficients are highly significant with p-value lower than 2.00×10^{-8}. [17] It is intuitive, that the respondents with higher level of financial literacy are more likely to see how their wealth and way of living can be affected by climate policy through environmental tax rates.

It was previously shown that interactions of measures of cognitive ability and ideological and political world-view are strong predictors of attitudes towards climate change rather than cognitive ability or numeracy itself (Kahan, 2012; Kahan et al., 2012; Hamilton, 2011; Hamilton and Keim, 2009). In accordance with this (as we discuss in more detail in Section 4.4.3 below) we detect a significant impact of interactions of an indicator of political and cultural world-view and a measure of numeracy (and ability of analytical, technical reasoning) on WTP for climate change mitigation. Therefore, we also estimated variants of the models presented in this section with the interaction terms included among the predictors but we did not find them to be significant for climate risk perception. We

[17] Risk assessment consistency is a binary variable so we also run a two sample t-test to measure correlation between risk assessment consistency and financial literacy. In particular, we applied a two sample t-test to test if mean financial literacy is statistically equal for the respondent who answered risk questions consistently and for those with inconsistent answers to risk questions. The test statistic is highly significant with p-value lower than 2.00×10^{-8}. Hence, the mean financial literacy is different in these two groups which is in accordance with the significance of the correlation coefficient

do not present the results in our study to keep its length within reasonable limits. [18]

Table 4.6: ***Climate versus policy effects perception:*** *Multisplit lasso and jackknife OLS*

Variable	Multisplit lasso: Aggregated adj. *p*-value		Jackknife OLS: Aggregated coefficient	Jackknife OLS: Aggregated adj. *p*-value	
Climate knowledge	1.0000		0.2158	1.0000	
Climate knowledge - squared	$< 2.00 \times 10^{-8}$	***	-0.0607	0.0124	*
Understands inflation = 0.5	1.0000		-0.0394	1.0000	
Understands inflation = 1	0.0130	*	-0.5759	6.27×10^{-6}	***
Consistent answers to risk questions (0/1)	1.06×10^{-8}	***	-0.5885	$< 2.00 \times 10^{-8}$	***
Observations:			5749		

Notes: $^{\bullet}$ $p < 0.1$; * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$

For the significant predictors, the signs of the coefficients of the multisplit lasso are the same as those of the jackknife OLS and also size of most of the coefficients is very comparable for these two models.

As we can see in Tables 4.5 and 4.6, the linear climate knowledge term is positive (and insignificant), but the squared term is negative and significant for both climate seriousness and climate change versus policy. That means, the effect of climate knowledge is positive but decreasing for low levels of knowledge, while for medium and high degree of climate knowledge the effect is negative. The negative effect of higher levels of climate knowledge may seem to be counter-intuitive, however it is less surprising in the light of previous literature. According to Reynolds et al. (2010), people who know less about climate change tend to ascribe unrealistic consequences (for example skin cancer) to global warming. The authors argue that it is even possible for any future ecological or political disaster to be viewed as a consequence of global warming by public (Read et al., 1994). Also the level of familiarity with causes and basic mechanisms of climate change is quite unsatisfactory. For example, members of public tend to confuse climate and weather[19] and as a result they mostly agree with the statement that climate changes from year to year (Reynolds et al.,

[18] It would probably be more revealing to test for significance of interactions of cognitive ability and political orientation, but unfortunately, the respondents were not asked about their political or partisan preferences directly in the survey.

[19] Actually, some researchers confuse climate and weather too (Hsiang et al., 2013; Deschnes and Greenstone, 2007).

2010). It is therefore understandable that individuals who are weaker in climate knowledge are more concerned about climate change and its consequences.

Another possible explanation of the negative and significant climate knowledge effect can be affective orientation towards global warming (Kahan, 2015). It was previously shown that individuals, who believe that climate change is real and caused by humans and who correctly assert, for instance, that usage of fossil fuels is one of the causes of global warming are also likely to affirm other, perhaps false statements which are consistent with higher environmental risks (Reynolds et al., 2010). An example of such a false statement is that atmospheric emissions of sulphur contribute to global warming (Kahan, 2015). The OCSI questions which we use to measure climate knowledge are true/false statements and many of them are of the same type as the sulphur emissions statement above. That is, the correct answer does not evince concerns about climate change while the incorrect one does. This could explain why the respondents who believe that climate change is quite serious are likely to score lower on climate knowledge. If this is true, the climate concern variables are predictors of climate knowledge and not the other way around. Therefore, if this is true, climate knowledge should not be included in the specifications with estimates summarised in Tables 4.5 and 4.6. As a robustness test, we estimate the models for climate seriousness perception and climate change versus climate policy not including the climate knowledge as an explanatory variable. In both cases, the estimates of the rest of the explanatory variables and their significance levels are almost the same as in the case with climate knowledge and they are summarised in Table C.13 in Appendix C.

4.4.3 Willingness to pay for climate change mitigation

This section is focused on models explaining preferred gas and electricity tax rates, which we use as a measure of WTP for climate change mitigation. The estimates of the multisplit lasso and the jackknife OLS are summarised in Table 4.7.

One of the important selected predictors is age. The age was recorded as a categorical variable with the lowest category 24 or younger, the second lowest category is $25 - 34$, the third one is $35 - 44$ and so on up to the highest category which is 75 or older. We use the lowest age group (24 or younger) as the base category. Coefficients of all higher categories are negative and with exception of $35 - 44$ and 75 or older they are all significant. Thus, WTP declines with age, perhaps because older people have lower likelihood of experiencing tougher consequences of climate change predicted for more distant future

(Hamilton, 2011).[20]

Table 4.7: ***WTP climate - gas and electricity tax:*** *Multisplit lasso and jackknife OLS*

Variable	**Multisplit lasso**		**Jackknife OLS**		
	Aggregated adj. *p*-value		**Aggregated coefficient**	**Aggregated adj. *p*-value**	
Age[a] $25-34$	1×10^{-6}	***	-13.271	0.266	
Age $35-44$	0.006	**	-29.494	3×10^{-7}	***
Age $45-54$	1.000		-34.625	$<2\times10^{-8}$	***
Age $55-64$	1.000		-40.061	$<2\times10^{-8}$	***
Age $65-74$	1.000		-46.006	$<2\times10^{-8}$	***
Age 75 or older	1.000		-26.071	1.000	
Climate versus policy effects perception	$<2\times10^{-8}$	***	10.408	$<2\times10^{-8}$	***
Inequity aversion (categorical)[a]	*negative cor.* *		*negative cor.* ***		
Equal intergenerational allocation of resources (0/1)[b]	0.011	*	20.760	0.002	**
Understands compound interest = 0.5	1.000		-2.942	1.000	
Understands compound interest = 1	1×10^{-5}	***	-39.381	3×10^{-5}	***
Understands inflation = 0.5	1.000		-15.892	0.516	
Understands inflation = 1	6×10^{-5}	***	-42.711	$<2\times10^{-8}$	***
Consistent answers to risk questions (0/1)	$<2\times10^{-8}$	***	-34.861	$<2\times10^{-8}$	***
Consistent answers within investments (0/1)[c]	0.045	*	*Not included*		
Observations:			5749		

Notes: • $p<0.1$; * $p<0.05$; ** $p<0.01$; *** $p<0.001$
The signs of the significant coefficients in the multisplit lasso are same as those of the jackknife OLS and also size of most of the coefficients is very comparable for these two models.

a Age is only available as categorical with base category '24 or younger'. Inequity aversion treated as categorical (see Section 4.3.2).

b This variable is equal to 1 for those respondents who believe that their income and standard of living generally is about equal to the income and standard of living of their parents (when they were about the respondent's age) and it is also equal to the income and standard of living of their children (when they will reach the respondent's age). The variable is equal to 0 for all other respondents.

c We eventually excluded this variable from the further analysis. Although consistency within investment was selected by lasso, it is only marginally significant and strongly correlated with risk assessment consistency. Furthermore, even after exclusion of this variable the model includes relatively large number of predictors and their signs and significance levels do not change.

[20] We also estimated the model with interactions of age and number of children and grandchildren as older people who have more offspring can obviously be more concern about future than those who do not have children. However, we did not find the interactions to be significant. We do not present the results in this study to save space.

We can see in Table 4.7 that another very strong predictor of WTP is perception of climate versus policy effects on ones way of living which we analyse as a dependent variable in Section 4.4.2. Expectedly, those who perceive effects of climate change as more serious than effects of climate policy have higher WPT for climate change mitigation. As we will discus below, this variable is a partial mediator of impact of financial literacy.

Another predictor of WTP is inequity aversion. As we explained in Section 4.3.2, we treat this variable as categorical. The values of our inequity aversion measure and their frequencies are summarised in Table C.10 in Appendix C. Although the effect of inequity aversion is largely positive and decreasing, the signs and significance levels vary across the categories without any clear pattern.

The variable that is called 'Equal intergenerational allocation of resources (0/1)' in Table 4.7 belongs to a group of binary variables, which were constructed based on Questions 21 and 22 in Appendix C.4. The wording of Question 21 is: 'Compared with your parents when they were about your age, are you better or worse off in your income and standard of living generally?' The possible answers are: 'Much better off', 'Better off', 'About equal', 'Worse off', 'Much worse off' and 'Don't know'. Analogously, Question 22 asks how respondents expect their children to compare relative to themselves. Four binary variables were generated combining the two questions as follows:

- *'Always up'*: My children are better off than me and I am better off than my parents
- *'Always down':* My parents are better off than me and I am better off than my children
- *'Up then down':* I am better off than my parents and I am better off than my children
- *'Down then up':* I am worse off than my parents and I am worse off than my children
- *'Always the same':* My standard of living and income is about the same as the standard of living and income of my parents and my children

We believe that the indicator variables that capture respondents' perceived standard of living compared to the future and previous generations are likely to be correlated with attitudes towards intergenerational allocation of resources and with perceived responsibilities towards future generations, which are related to attitudes towards climate change. Except for 'Always the same', which is referred to as 'Equal intergenerational allocation of resources (0/1)' in Table 4.7, none of the binary variables above was significant or selected by lasso into any model. Therefore, the other indicator variables listed above are not included in our preferred models.

It is apparent from Table 4.7 that WTP is higher for respondents who believe that their income and standard of living generally is about equal to the income and standard of living of their parents when they were about the respondent's age and they also believe that their income and standard of living is equal to the income and standard of living of their children when they will reach the respondent's age.

We can also see in Table 4.7 that WTP for climate change mitigation is significantly lower for individuals with higher financial literacy[21] and for those who answered the questions about risk consistently. This is similar to model with climate versus policy perception as dependent variable (see Table 4.6). It is very likely, that financial literacy and risk assessment consistency are strongly correlated with ability of analytical reasoning and comprehension of quantitative information, hence, the former can be interpreted as a measure of the latter. Because of complexity of the climate system and inherited difficulty of understanding of climate change by the public (Weber and Stern, 2011) these findings may seem to be counterintuitive as one may expect the climate concerns to intensify with increasing level of analytical reasoning and numeracy. Our evidence is, however, consistent with previous literature (Kahan et al., 2012; Kahan, 2015; Kellstedt et al., 2008).

Sunstein (2007) and Kahan et al. (2012) argue that the risks related to natural hazards caused by climate change are quite abstract and remote compared to other more salient risks such as terrorism. Hence, it is difficult to perceive the climate change risk as a relatively serious one. It was shown that attitudes towards climate change and related risks are indicators of personal world-view or political outlook rather than correlates of numeracy or science comprehension. People, who identify themselves with egalitarian, communitarian ideology tend to take climate change more seriously than those with rather hierarchical, individualistic world-view (Leiserowitz et al., 2013; Kahan et al., 2012; Whitmarsh, 2011). It can be more important for an individual to consider the climate risk questions from a cultural identity perspective than from a scientific and collective knowledge acquisition viewpoint (Kahan, 2015). Whether an individual is right or wrong has no meaningful impact on climate change. The decisions of a single consumer or voter

[21] Variable 'Understands inflation' is described in Section 4.4.2. Values of variable 'Understands compound interest' are based on respondents answer to the following numerical problem: 'Suppose you had £100 in a savings account and the interest rate was 2 percent per year. After 5 years, how much do you think you would have in the account if you left the money to grow?' The respondents should choose the correct answers from the following three options: (*i*) 'More than £102' (*ii*) 'Exactly £102' (*iii*) 'Less than £102'. Correct answer is 'more'. The value of the variable is equal to one if the respondent answers 'more', it is equal to 0.5 if she answers 'the same' and it is equal to zero if she answers 'less'. The frequencies of answers are summarised in Table C.10 in Appendix C.

can hardly make a measurable difference to the natural hazard risks caused by climate change. On the other hand, adopting a position which is not consistent with one's cultural group can have dangerous consequences (Kahan, 2012). Kahan et al. (2012) show that the ideological polarization over climate change is higher among people with the highest degrees of numeracy and science literacy. That means, for the individuals who identify themselves with hierarchical, individualistic ideology, the climate concern is negatively correlated with numeracy and science literacy while for the individuals who believe in rather egalitarian, communitarian ideology the correlation is positive. A possible interpretation is that the members of public with higher degree of numeracy and analytical reasoning are using these abilities to protect their cultural identity and they are therefore better in interpreting the scientific facts in a way which is consistent with their cultural group's ideology. Following Hamilton (2011), we test this hypothesis by including interaction terms of degree of agreement with redistribution of income and financial literacy among the set of explanatory variables. The estimates are summarised in Table C.14 in Appendix C. The interaction is positive and significant, which means that the positive effect of agreeing with income redistribution is much stronger for those who understand inflation. Similarly, the negative effect of not agreeing with income redistribution is larger in magnitude if accompanied with higher level of understanding of inflation. This is in accordance with the theory that the ideological polarization over climate change is higher among people with higher degrees of numeracy and science literacy (Kahan 2012; Kahan et al. 2012; Hamilton 2011; Hamilton and Keim 2009). Our results are robust, the estimates and their significance levels are almost the same as those of the model without the interaction term in Table 4.7.

One may notice that level of understanding of inflation is a significant predictor of both climate versus policy effects perception and WTP for climate change mitigation. In both cases the effect is negative. The two climate variables are also strongly correlated. Hence, we will now focus on disentangling the structure of relationships among these three variables.

We reveal that the measure of climate versus policy perception partially mediates effect of understanding of inflation on WTP. In Table 4.6 we can see that understanding of inflation is a significant (negative) predictor of climate versus policy perception and in Tables 4.7 and C.14 we can notice that climate versus policy effects perception is a significant (positive) predictor of WTP. In Table 4.8 we regress WTP on understanding of inflation without the mediator in order to verify whether the basic condition of mediation is satisfied, i.e. whether we can see the significant effect of the predictor when the mediator is not present. Model 1 in Table 4.8 is a regression of WTP solely on understanding of inflation while Model 2 includes also the other predictors selected by the multisplit lasso. Even without the mediator, the effect of understanding of inflation is strongly significant. Furthermore, the effect is larger in magnitude than the effect in the regressions which include the mediator (compare with the estimates in Tables 4.7 and C.14). This finding also supports the occurrence of mediation. Table 4.9 summarizes estimates of WTP regressed on the mediator without the effect of understanding of inflation. Model 1 in Table 4.9 only includes climate versus policy as explanatory variable while Model 2 in Table 4.9 also includes the other predictors selected by the multisplit lasso. If the mediation is present, the mediator should also be a significant predictor of the dependent variable itself and we can see in Table 4.9 that this is true in our case.

As we can see in Tables 4.7 and C.14, the effect of understanding of inflation is significant if the mediator is present, therefore the mediation is partial.

To verify our conclusion about the presence of mediation, we perform the Sobel test for the effect of understanding of inflation being mediated through climate versus policy variable. The test statistic is strongly significant with p-value equal to 4.21×10^{-22}, hence the Sobel test supports the occurrence of mediation.

To sum up, people who understand inflation tend to feel to be more affected by climate policy than by climate change and consequently their WTP for climate change mitigation declines. On the other hand, individuals with lower level of understanding of inflation tend to perceive more effects from climate change than from climate policy and therefore their WTP increases.

Table 4.8: ***WTP - mediation through climate versus policy perception:*** *WTP regressed on financial literacy (understands inflation) without the mediator, OLS*

Dependent variable: WTP-gas and electricity tax (£ /yr.)	Model 1 coef.	Model 1 *p*-value	Model 2 coef.	Model 2 *p*-value
Understands inflation = 1	−73.648	$< 2 \times 10^{-8}$ ***	−47.827	$< 2 \times 10^{-8}$ ***
Understands inflation = 0.5	1.912	0.712	−16.889	0.0007 ***
Age[a] 25 − 34	*Not included*		−11.520	0.003 **
Age 35 − 44	*Not included*		−27.881	$< 2 \times 10^{-8}$ ***
Age 45 − 54	*Not included*		−33.602	$< 2 \times 10^{-8}$ ***
Age 55 − 64	*Not included*		−43.684	$< 2 \times 10^{-8}$ ***
Age 65 − 74	*Not included*		−50.493	$< 2 \times 10^{-8}$ ***
Age 75 or older	*Not included*		−33.163	0.008 **
Inequity aversion (categorical)[b]	*Not included*		*negative cor.* ***	
Equal intergenerational allocation of resources (0/1)	*Not included*		19.471	4×10^{-6} ***
Understands compound interest = 0.5	*Not included*		−5.751	0.431
Understands compound interest = 1	*Not included*		−44.022	$< 2 \times 10^{-8}$ ***
Consistent answers to risk questions (0/1)	*Not included*		−39.922	$< 2 \times 10^{-8}$ ***
Adjusted R^2:	0.092		0.212	
Observations:	5749		5749	

Notes: • $p < 0.1$; * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$

a Age is only available as categorical with base category '24 or younger'.

b Inequity aversion treated as categorical (see Section 4.3.2).

Table 4.9: ***WTP - mediation through climate versus policy perception:*** *WTP regressed on the mediator (climate versus policy effects perception) without variable understands inflation, OLS*

Dependent variable: WTP - gas and electricity tax (£ /yr.)	**Model 1** coef.	**Model 1** p-value	**Model 2** coef.	**Model 2** p-value
Climate versus policy effects perception	13.847	$< 2 \times 10^{-8}$ ***	10.936	$< 2 \times 10^{-8}$ ***
Age[a] $25 - 34$	*Not included*		-14.672	0.0001 ***
Age $35 - 44$	*Not included*		-32.393	$< 2 \times 10^{-8}$ ***
Age $45 - 54$	*Not included*		-40.588	$< 2 \times 10^{-8}$ ***
Age $55 - 64$	*Not included*		-47.725	$< 2 \times 10^{-8}$ ***
Age $65 - 74$	*Not included*		-54.523	$< 2 \times 10^{-8}$ ***
Age 75 or older	*Not included*		-32.341	0.008 **
Inequity aversion (categorical)[b]	*Not included*		*negative cor.* ***	
Equal intergenerational allocation of resources (0/1)	*Not included*		21.644	1×10^{-7} ***
Understands compound interest = 0.5	*Not included*		0.396	0.956
Understands compound interest = 1	*Not included*		-40.066	$< 2 \times 10^{-8}$ ***
Consistent answers to risk questions (0/1)	*Not included*		-40.935	$< 2 \times 10^{-8}$ ***
Adjusted R^2:	0.092		0.244	
Observations:	5749		5749	

Notes: • $p < 0.1$; * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$

a Age is only available as categorical with base category '24 or younger'.

b Inequity aversion is treated as categorical (see Section 4.3.2).

4.5 Robustness

One of the important objectives of this study is to examine effects of behavioural variables on climate knowledge and climate change perception. Except for inequity aversion, none of the behavioural variables was chosen by lasso into any of our models. In spite of this, for each dependent variable we estimate a jackknife OLS with all the behavioural measures included as explanatory variables (besides the predictors selected by lasso) as robustness tests and to investigate possible changes in signs and significance levels of the previously selected predictors. We also add some other potentially confounding variables including population density, climate variables other than the dependent variable, degree of agreement with income redistribution, net assets and predicted income as an alternative to the income recorded in our survey (Dolton and Tol, 2016) since the income obtained from the survey is categorical rather than continuous. [22]

The population density serves as a proxy for rural-urban classification. We include it in the robustness tests because we believe that whether one lives in rural or urban area can have considerable impact on attitudes towards climate change.

In each model we include attitude towards income redistribution as an indicator of political and ideological world-views, as the ideological opinions were found to be especially important for the explanation of attitudes towards climate change and measures of climate knowledge by a large number of previous studies (e.g. Hamilton (2011), Kahan (2012), Kellstedt et al. (2008)).

Controlling for income and net assets is especially important for WTP as both income and assets are very likely to be correlated with WTP. However, other variables such as discount rates can also be correlated with income and net assets. Therefore, we examine whether controlling for them changes our estimates. As an alternative measure of income we use a prediction obtained from a regression model estimated using the ASHE data.

We noticed that the relationship between discount rate and each dependent variable exhibit similar, characteristic patterns. The values of dependent variables tend to be high for small values of discount rate, they are quite low for medium values of discount rate and they increase again for relatively high values of discount rate. Because of this parabolic shape, we include both linear and quadratic terms of discount rate as explanatory variables. The estimates of all coefficients are almost the same if the squared discount rate is omitted, but we only present the results of the models with both linear and quadratic term to keep the length of our paper within reasonable limit.

[22] We include these variables in the robustness tests although they were not originally chosen by lasso.

The descriptive statistics of the additional explanatory variables can be found in Table C.8 in Appendix C.

For the WTP models we also perform other robustness tests.

4.5.1 Climate change knowledge

In this section we estimate the climate knowledge model specified in Section 4.4.1 including the behavioural variables and additional potential confounders as discussed at the beginning of this Section 4.5. The estimates are summarised in Table 4.10. As we can see, all additional covariates and behavioural variables with except for climate seriousness perception and climate versus policy perception are insignificant.

Climate seriousness perception and climate versus policy perception are negative and strongly significant predictors of climate knowledge (see Table 4.10). This is not surprising given the fact that climate knowledge is negative and significant when included as an explanatory variable for both of these climate concern variables (see Tables 4.5 and 4.6 in Section 4.4.2). There are two possible explanations. (*i*) Individuals, who are less educated in climate change tend to believe to incorrect statements and mechanisms which would imply that climate change is much more serious than it actually is (Reynolds et al., 2010; Read et al., 1994). In this case, the direction of dependency would be the other way around. (*ii*) The negative correlation is caused by affective orientation towards global warming (Kahan, 2015). That is, people who believe in anthropogenic climate change and correctly assert, for example, that usage of fossil fuels is one of the causes of global warming are also likely to affirm other, perhaps false propositions which would imply higher environmental risks, for example that atmospheric emissions of sulphur contribute to global warming (Reynolds et al., 2010).

The estimates of the predictors which were originally chosen by the multisplit lasso are qualitatively the same as those in Section 4.4.1 (see Table 4.4). The estimates are robust.

Table 4.10: ***Climate change knowledge:*** *Jackknife OLS - robustness*

Variable	Model 1 Aggreg. coef.	Model 1 Aggreg. adjusted p-value	Model 2 Aggreg. coef.	Model 2 Aggreg. adjusted p-value
Gender = male	0.280	1×10^{-8} ***	0.282	$< 2 \times 10^{-8}$ ***
Cognitive reflection = 0.5	0.863	1.000	0.934	1.000
Cognitive reflection = 1	0.107	1.000	0.112	1.000
Cognitive reflection = 1.5	0.432	1.000	0.461	1.000
Cognitive reflection = 2	0.258	0.001 **	0.255	0.003 **
Cognitive reflection = 2.5	0.520	1.000	0.537	1.000
Cognitive reflection = 3	0.450	1×10^{-7} ***	0.448	5×10^{-7} ***
Income - predicted (mill. £ /yr.)	−0.273	1.000	*Not included*	
Income - reported (mill. £ /yr.)[a]	*Not included*		*varies*	1.000
Net assets (mill. £)	0.026	1.000	0.020	1.000
People per mill. km^2-LSOA level	1.416	1.000	*Not included*	
People per mill. km^2-LAD level	*Not included*		0.254	1.000
WTP-gas and electricity tax (£ / yr.)	−0.0003	1.000	−0.0001	1.000
WTP-duty on transport fuel (pence/ yr.)	0.001	1.000	0.0006	1.000
Climate seriousness perception	−0.077	$< 2 \times 10^{-8}$ ***	−0.076	$< 2 \times 10^{-8}$ ***
Climate vs. policy effects perception	−0.043	0.0009 ***	−0.044	0.001 **
Social value orientation (ring meas.)	0.0008	1.000	0.0007	1.000
Inequity aversion (categorical)	*varies*	1.000	*varies*	1.000
Discount rate yr. from now	−0.001	1.000	−0.001	1.000
Discount rate yr. from now - sq.[b]	2×10^{-6}	1.000	2×10^{-6}	1.000
Risk aversion coefficient[c]	*Not included*		−0.390	1.000
Redistribution of income (cat.)[d]	−,*varies*	1.000	−,*varies*	1.000
Mean adjusted R^2:	0.071		0.072	
Observations:	5749		5659	

Notes: • $p < 0.1$; * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$

a Self reported income is only available as categorical.
b If squared discount rate is omitted, linear discount rate remains insignificant and the estimates of the other covariates are almost the same as those presented in this table.
c The risk aversion coefficient is an estimated parameter of a utility function. In this model, the mean of power function is used. We also estimated varieties of this model with different risk aversion coefficients, particularly means or medians of various utility functions. These are power, log, exponential and quadratic. The risk aversion parameter is always insignificant and whether it is included or not (or which one) does not affect sign or significance level of any other parameter.
d A degree of agreement with the statement: 'Government should redistribute income from the better off to those who are less well off.' Included to test for significance of political opinions.

4.5.2 Climate change risk perception

In this section we discuss robustness of the climate risk perception models. The models which were specified using lasso in Section 4.4.2 are re-estimated with behavioural variables and additional potential confounders among explanatory variables. The estimates of the climate seriousness perception models are summarised in Table 4.11 and the estimates of the models for climate change versus policy perception can be found in Table 4.12.

As apparent from Table 4.11, all the behavioural variables and the additional potential confounders are insignificant for climate seriousness, with exception of the climate variables. The significance of the climate variables is in accordance with our expectation and it confirms that our climate measures are valid. The estimates of the predictors selected using lasso are qualitatively equivalent to the estimates in Table 4.5, hence our results are robust.

Table 4.12 summarises the estimates of models with climate change versus policy as a dependent variable. Alike in the case of the climate seriousness model, all the behavioural variables, income, assets and population density are insignificant while the climate variables are significant. This is what we expected for the climate measures to be valid. However, understanding of inflation is not significant in Table 4.12 while it is strongly significant in the model specified using lasso (see Table 4.6). This is probably a result of the mediation relationship structure among climate versus policy, financial literacy and WTP discussed in Section 4.4.3. Level of understanding of inflation is correlated with WTP. If we remove WTP for gas and electricity and WTP for transport fuel keeping all other variables in, understanding of inflation becomes significant. Estimates of this variety can be found in Table C.15 in Appendix C. This evidence is consistence with our mediation hypothesis. The effects of climate knowledge and risk assessment consistency are negative and significant as in the original model summarised in Table 4.6. The results are, on the whole, robust.

Table 4.11: ***Climate change seriousness perception:*** *Jackknife OLS - robustness*

Variable	Model 1 Aggreg. coef.	Model 1 Aggreg. adjusted p-value	Model 2 Aggreg. coef.	Model 2 Aggreg. adjusted p-value
Gender = male	−0.302	0.001 *	−0.285	0.001 **
Climate knowledge[a]	−0.187	$< 2 \times 10^{-8}$ ***	−0.182	$< 2 \times 10^{-8}$ ***
Redistribution of income: disagree[b]	0.297	1.000	0.298	1.000
Redistribution of inc.: neutral[b]	0.256	1.000	0.263	1.000
Redistribution of income: agree[b]	0.778	2×10^{-7} ***	0.806	8×10^{-8} ***
Redistribution of income: strongly agree[b]	0.937	$< 2 \times 10^{-8}$ ***	0.939	$< 2 \times 10^{-8}$ ***
Income- predicted (mill. £ /yr.)	2.760	1.000	*Not included*	
Income- reported (mill. £ /yr.)[c]	*Not included*		*varies*	1.000
Net assets (million £)	−0.163	1.000	−0.310	1.000
People per mill. km^2-LSOA level	9.838	1.000	*Not included*	
People per mill. km^2-LAD level	*Not included*		−6.520	1.000
WTP-gas and elec. tax (£ / yr.)	0.002	0.0003 ***	0.002	0.0005 ***
WTP-duty on transp. fuel (p./yr.)	0.005	1.000	0.005	1.000
Climate vs. policy effects perc.	0.356	$< 2 \times 10^{-8}$ ***	0.359	$< 2 \times 10^{-8}$ ***
Social value orientation (ring measure)	0.003	1.000	0.003	1.000
Inequity aversion (categorical)	+, *varies*	1.000	+, *varies*	1.000
Discount rate yr. from now	0.0003	1.000	4×10^{-5}	1.000
Discount rate yr. from now - sq.[d]	-2×10^{-6}	1.000	-1×10^{-6}	1.000
Risk aversion coefficient[e]	*Not included*		0.731	1.000
Mean adjusted R^2:	0.247		0.254	
Observations:	5749		5659	

Notes: • $p < 0.1$; * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$

a Squared term of climate knowledge is insignificant in this version, hence it is not included.

b Degree of agreement with the following statement: 'Government should redistribute income from the better off to those who are less well off.' The base category is 'Strongly disagree'.

c Self reported income is only available as categorical.

d If squared discount rate is omitted, linear discount rate remains insignificant and the estimates of the other covariates are almost the same as those presented in this table.

e The risk aversion coefficient is an estimated parameter of a utility function. In this model, the median of power function is used. We also estimated varieties of this model with different risk aversion coefficients, particularly means or medians of various utility functions. These are power, log, exponential and quadratic. The risk aversion parameter is always insignificant and whether it is included or not (or which one) does not affect sign or significance level of any other parameter.

Table 4.12: ***Climate versus policy effects perception:*** *Jackknife OLS - robustness*

	Model 1		Model 2	
Variable	**Aggreg. coef.**	**Aggreg. adjusted *p*-value**	**Aggreg. coef.**	**Aggreg. adjusted *p*-value**
Climate knowledge[a]	−0.127	8×10^{-5} ***	−0.128	0.0001 ***
Understands inflation = 0.5	0.051	1.000	0.028	1.000
Understands inflation = 1	−0.219	1.000	−0.243	1.000
Consistent answers to risk questions (0/1)	−0.310	0.019 *	−0.305	0.038 *
Income- predicted (mill. £ /yr.)	2.446	1.000	*Not included*	
Income- reported (mill. £ /yr.)[b]	*Not included*		*varies*	1.000
Net assets (million £)	−0.070	1.000	0.027	1.000
People per mill. km^2-LSOA level	−16.683	1.000	*Not included*	
People per mill. km^2-LAD level	*Not included*		15.548	1.000
WTP- gas and electric. tax (£ / yr.)	0.002	9×10^{-5} ***	0.002	9×10^{-5} ***
WTP-duty on transport fuel (p./yr.)	0.011	9×10^{-5} ***	0.010	0.001 **
Climate seriousness perception	0.382	$<2 \times 10^{-8}$ ***	0.387	$<2 \times 10^{-8}$ ***
Social value orientation (ring measure)	0.006	0.396	0.005	0.726
Inequity aversion (categorical)	*varies*	1.000	*varies*	1.000
Discount rate yr. from now	−0.001	1.000	−0.001	1.000
Discount rate yr. from now - sq.[c]	2×10^{-6}	1.000	2×10^{-6}	1.000
Risk aversion coefficient[d]	*Not included*		−0.523	1.000
Redistribution of income (categ.)[e]	+,*varies*	1.000	+,*varies*	1.000
Mean adjusted R^2:	0.254		0.257	
Observations:	5749		5659	

Notes: • $p < 0.1$; * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$

a Squared term of climate knowledge is insignificant in this version, hence it is not included.

b Self reported income is only available as categorical.

c If squared discount rate is omitted, linear discount rate remains insignificant and the estimates of the other covariates are almost the same as those presented in this table.

d The risk aversion coefficient is an estimated parameter of a utility function. In this model, the mean of power function is used. We also estimated varieties of this model with different risk aversion coefficients, particularly means or medians of various utility functions. These are power, log, exponential and quadratic. The risk aversion parameter is always insignificant and whether it is included or not (or which one) does not affect sign or significance level of any other parameter.

e A degree of agreement with the statement: 'Government should redistribute income from the better off to those who are less well off.' Included to test for significance of political opinions.

4.5.3 Willingness to pay for climate change mitigation

In this section we verify robustness of the models with dependent variable WTP for climate change mitigation. Table 4.13 summarises estimates of two varieties of the models specified in Section 4.4.3 with additional behavioural variables, climate change variables and other potential confounders discussed at the beginning of Section 4.5. The estimates of the predictors which were originally selected by the multisplit lasso (in the first 11 rows of Table 4.13) are qualitatively the same as those of the models in Table 4.7. The only exception is the dummy variable for scoring 0.5 on understanding of compound interest as its estimate is negative in Table 4.7 while it is positive in both models in Table 4.13. However, the estimate of this dummy variable is insignificant in each of these models so the difference in signs does not imply that the estimates are not robust.

Similarly as in the case of the robustness model for climate knowledge (Table 4.10) and the robustness models for climate change risk perception (Tables 4.11 and 4.12) the climate change variables are significant (with the exception of climate knowledge) while the other potential confounders and behavioural variables in the second half of Table 4.13 are insignificant. An exception is predicted income, which has a significant impact on WTP.[23] The significance of income can be explained by its diminishing marginal utility. For people with higher income, the utility of amount of money paid as climate tax is lower than for people with lower income. Therefore, preferred tax rates are higher for higher income groups. Whether or not income or the other additional explanatory variables are included does not have any significant impact on estimates of the predictors in Table 4.13 which were chosen by the means of the multisplit lasso in Section 4.4.3.

Pride may have played role in the strong significance of current tax rates estimates. As explained in Section 4.3.1, the respondents were informed about the correct tax rates after they gave their estimates and before they were asked about their preferences regarding the climate policies. It is possible that respondents tended to give preferred tax rates which were close to their estimate of the current tax rates feeling that their estimate should be

[23]Interestingly, the categorical income recorded in the survey (Dolton and Tol, 2016) is not significant. We suspect that it can be due to inaccuracy of the income variable recorded in the survey as relatively big number of participants are students and it is not clear if they stated their own income or income of their parents. The possible inaccuracy of the income measure is one of the reasons why we also use the alternative predicted income.

the preferred one.

Table 4.13: ***WTP climate - gas and electricity tax:*** *Jackknife OLS - robustness*

	Model 1		Model 2	
Variable	**Aggreg. coef.**	**Aggreg. adj. p-value**	**Aggreg. coef.**	**Aggreg. adj. p-value**
Age (categorical)[a]	*negative cor.* ***		*negative cor.* ***	
Climate vs. policy effects perc.	6.654	$< 2 \times 10^{-8}$ ***	6.534	$< 2 \times 10^{-8}$ ***
Inequity aversion (categorical)[a]	*negative cor.* **		*negative cor.* **	
Equal intergenerational allocation of resources (0/1)	18.843	0.004 **	19.646	0.004 **
Understands comp. interest = 0.5	1.276	1.000	3.870	1.000
Understands comp. interest = 1	−34.032	0.0003 ***	−32.084	0.001 ***
Understands inflation= 0.5	−12.364	1.000	−11.779	1.000
Understands inflation= 1	−31.737	$< 2 \times 10^{-8}$ ***	−29.101	$< 2 \times 10^{-8}$ ***
Consistent answers to risk (0/1)	−28.046	$< 2 \times 10^{-8}$ ***	−27.714	$< 2 \times 10^{-8}$ ***
Income- predicted (thousand £/yr.)	0.703	3×10^{-5} ***	*Not included*	
Income- reported (mill. £/yr.)[a]	*Not included*		+,*varies*	1.000
Net assets (million £)	18.033	0.133	20.072	0.151
People per mill. km^2-LSOA level	768.974	1.000	*Not included*	
People per mill. km^2-LAD level	*Not included*		594.369	1.000
Climate knowledge	0.020	1.000	0.556	1.000
How much is tax gas and el.(£ /yr.)	0.252	$<2 \times 10^{-8}$ ***	0.251	$<2 \times 10^{-8}$ ***
Climate seriousness perception	7.158	$< 2 \times 10^{-8}$ ***	7.282	$<2 \times 10^{-8}$ ***
Social val. orientation (ring meas.)	0.048	1.000	0.009	1.000
Discount rate yr. from now	−0.078	1.000	−0.084	1.000
Discount rate yr. from now - sq.[b]	0.0002	0.992	0.0002	0.908
Risk aversion coefficient[c]	*Not included*		−0.261	1.000
Redistribution of income (cat.)[d]	*varies*	1.000	*varies*	1.000
Mean adjusted R^2:	0.370		0.364	
Observations:	5749		5659	

Notes: • $p < 0.1$; * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$; **a** Age and reported income only available as categorical. Inequity av. treated as categorical (see Sec. 4.2) **b** If squared discount rate is omitted, linear discount rate remains insignificant and the estimates of the other covariates are almost the same as those presented in this table. **c** The risk aversion coefficient is an estimated parameter of a utility function. In this model, the mean of power function is used. We also estimated varieties of this model with different risk aversion coefficients, particularly means or medians of power, log, exponential or quadratic utility function. The risk aversion parameter is always insignificant and whether it is included or not (or which one) does not affect sign or significance level of any other parameter. **d** A degree of agreement with the statement: 'Government should redistribute income from the better off to those who are less well off.'

As another robustness test we use preferred tax rates on transport fuel as a measure of WTP. The estimates are summarised in Table 4.14. Model 1 in Table 4.14 only includes explanatory variables which were chosen for WTP using the lasso in Section 4.4.3. Model 2 in Table 4.14 also includes climate variables, behavioural variables and additional potential confounders to test their significance and to examine whether or not their inclusion changes signs or significance levels of the main predictors. Comparing Model 1 in Table 4.14 with the estimates of the models in Table 4.7 (Section 4.4.3), we can see that the signs and significance levels of the coefficients are the same in these two models. Also their magnitude is comparable considering the different scales of the two dependent variables. Regarding Model 2 in Table 4.14, we can see that inclusion of the additional explanatory variables does not change signs or significance levels of the main predictors (the variables in the first 11 rows of Table 4.14). An exception is dummy variable for scoring 0.5 on understanding of inflation as in Model 1 the coefficient is negative while in Model 2 it is positive. However, this change is unremarkable as these coefficients of understanding of inflation are insignificant in both models. The additional explanatory variables in Model 2 in Table 4.14 are insignificant except for the estimate of current fuel duty and climate seriousness perception. The signs of all the additional variables are the same as their signs in the model for WTP on gas and electricity in Table 4.13. Interestingly, income does not have any significant impact on preferred fuel duty although its impact on gas and electricity tax is significant. Our explanation is that individuals with lower income exhibit lower WTP through gas and electricity tax, but they are less likely to own a car (thus they are less likely to be eligible for paying transport fuel duty). Thus, when asked about their preferred rates on fuel duty, they actually impose the duty on those owning a car rather than on themselves. It is understandable that preferred tax rates imposed on others are higher than preferred tax rates paid by ourselves. Hence, people with lower income may exhibit higher preferred fuel duty as they impose it on others rather than on yourself. This may offset the significant positive impact of income, which we detected in the model for gas and electricity tax. Even lower income groups are eligible for gas and electricity tax, therefore the positive influence of income is significant as it is not offset by the fact that lower income groups impose the tax on others rather than on themselves.

We can conclude that our models are reasonable robust.

Table 4.14: ***WTP climate - duty on transport fuel:*** *Jackknife OLS*

Variable	Model 1 Aggreg. coef.	Model 1 Aggreg. adj. p-val.	Model 2 Aggreg. coef.	Model 2 Aggreg. adj. p-val.
Age (categorical)[a]	*negative cor.* ***		*negative cor.* ***	
Climate vs. policy effects perception	2.192	$< 2 \times 10^{-8}$ ***	1.494	$< 2 \times 10^{-8}$ ***
Inequity aversion (categorical)[a]	*negative cor.* **		*negative cor.* **	
Equal intergenerational allocation of resources (0/1)	4.461	0.002 **	4.824	0.0004 ***
Understands compound interest= 0.5	1.703	1.000	1.818	1.000
Understands compound interest= 1	−7.363	0.001 ***	−7.091	0.0008 ***
Understands inflation= 0.5	−0.602	1.000	0.135	1.000
Understands inflation= 1	−7.458	$< 2 \times 10^{-8}$ ***	−5.834	4×10^{-7} ***
Consistent answers to risk questions (0/1)	−6.294	$< 2 \times 10^{-8}$ ***	−5.591	$< 2 \times 10^{-8}$ ***
Income - predicted (thousands £ /yr.)	*Not included*		88.788	0.344
Net assets (million pounds £)	*Not included*		3.168	0.936
People per mill. km^2 - LSOA level	*Not included*		43.595	1.000
Climate knowledge	*Not included*		0.210	1.000
How much is duty transp. fuel (p./yr.)	*Not included*		0.311	$< 2 \times 10^{-8}$ ***
Climate seriousness perception	*Not included*		1.327	$< 2 \times 10^{-8}$ ***
Social value orientation (ring measure)	*Not included*		0.004	1.000
Discount rate year from now	*Not included*		−0.011	1.000
Discount rate year from now - sq.[b]	*Not included*		3×10^{-5}	1.000
Redistribution of income (categorical)[c]	*Not included*		*varies*	1.000
Mean adjusted R^2:	0.244		0.309	
Observations:	5749		5659	

Notes: • $p < 0.1$; * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$

a Age and self reported income are only available as categorical. Inequity aversion is treated as categorical (see Section 4.3.2).

b If squared discount rate is omitted, linear discount rate remains insignificant and the estimates of the other covariates are almost the same as those presented in this table.

c A degree of agreement with the statement: 'Government should redistribute income from the better off to those who are less well off.' Included to test for significance of political opinions.

4.6 Summary

We exploited a unique dataset of nearly 6000 observations which combines advantages of survey and experimental methods (Dolton and Tol, 2016). Among almost 70 explanatory variables and much more interactions we identified the main predictors of climate knowledge, climate risk perception and WTP for climate change mitigation. An important part of our analysis was testing of effects of four behavioural variables, in particular social value orientation, time preferences, risk preferences and attitudes towards inequality on the climate change variables. The measures of these variables were inferred using data from the survey conducted recently in the UK (Dolton and Tol, 2016).

Using a multisplit lasso we helped to understand the relationship structure among the climate variables and the behavioural measures. The lasso estimator has been shown to be very powerful in high-dimensional context as it yields sparse and interpretable results (Meinshausen et al., 2009). We used p-values proposed by Meinshausen et al. (2009) which were shown to be a good tool for control of both family-wise error and false discovery rate.

With exception of inequity aversion, we did not find any of the behavioural measures to have significant effect on the climate variables. According to our results, the rate of inequity aversion has a significant impact on WTP for climate change mitigation. The value of our inequity aversion measure is equal to one of 16 distinct values for all respondents in our dataset (given the way of its construction and the data recorded in our survey and experiments). Therefore, we treat the inequity aversion rate as categorical. We can say that its effects on WTP are largely positive and decreasing, although the impacts vary in magnitude and significance over the categories without clear pattern. Besides rate of inequity aversion, the most important predictors of WTP are age, perception of intergenerational allocation of resources, financial literacy which we also use as a proxy for numeracy, climate versus policy effects perception which is a partial mediator of understanding of inflation. Consistently with previous literature the impact of age and numeracy is negative (Hamilton, 2011). Expectedly, WTP is higher for individuals who feel to be more affected by climate change than by climate policy.

We found that climate knowledge is higher for men and for individuals with higher level of cognitive ability.

We considered two measures of climate risk perception. The first one is based on the respondents' opinion on level of climate change seriousness. The other one is referred to as climate versus policy perception and it records respondents' opinions on whether they are more affected by climate change or by climate policy. The first question is meant to be answered immediately without thinking by most people while we expected the respondents to take more time before answering the latter one. For climate seriousness, the important predictors are gender, climate knowledge and opinion on whether or not government should redistribute income from the better off to those who are less well off, which we consider a proxy for ideological or political world-views. The drivers of climate versus policy perception are climate knowledge, degree of understanding of inflation and risk assessment consistency. It is noticeable that (with the exception of climate knowledge, which is common to both) the predictors of the first climate measure which is meant to be answered without thinking (and therefore more intuitively) are likely to be correlated with personality traits. On the other hand, the predictors of the latter climate risk question, which is considered to need more time and thinking before giving an answer, are likely to be correlated with cognitive ability and analytical reasoning.

As robustness tests, we used alternative measure of WTP and for each dependent variable we re-estimated the models with additional potential confounders. Based on them we can conclude that our estimates are robust.

4.7 Limitations and further research

We conducted our research within some unavoidable constrains, mostly related to our dataset and time restriction. As a result, the study has some limitations. Caveats are discussed in this section. We also outline suggestions for further research in this section.

The sample is not exactly representative of the UK adult population as it was conducted online. The highest age category is slightly under-sampled and the lowest two age categories are slightly over-sampled. However, as we can see in Table 4.1, the age and sex distribution in our sample is relatively comparable to the age and sex distribution of the UK population. Also, more respondents tended to drop out on more complicated questions. Thus, the sample of respondents who finished the survey is slightly biased towards those who are unafraid of hard questions.

As a measure of climate knowledge we adopted the OCSI instrument developed by Kahan (2015) and we found it to be significantly higher for men. For further research, it would be particularly interesting to let a woman propose a set of similar questions which would constitute an alternative climate knowledge measure and to test whether we would find a significant effect of gender on the alternative climate knowledge measure.

The data on WTP were enquired in the survey as follows. The respondents were first asked how much they think the climate duty currently is. Then they were told the correct answer and then they were asked about their preferred tax rates. We believe that for further analysis it would be useful to ask half of the respondents about their preferred tax rates before telling them the correct answer or both before and after informing them about the actual tax rates. This could enable us to estimate effect of information.

Unfortunately, the survey which collected our data did not include direct questions about political opinions. Hence, our next suggestion for future research is to collect data about political opinions directly and test their significance as well as significance of their interactions with measures of numeracy and cognitive ability on climate knowledge, climate risk perception and WTP for climate change mitigation. Also, if a similar survey will be conducted in future, we would like to suggest including questions about method of travel to work. This information could be particularly helpful in identifying who answered the desired duty question assuming that the rate will apply to themselves and who, on the other hand, imposed the duty on others. The respondents travelling by car are probably assuming that the fuel duty will apply to themselves, while those travelling by train or bike are likely to be imposing the tax on others. If these data were available, it would also be interesting to examine the gap between desired duty imposed on others and desired climate duty imposed on oneself.

Other possible direction of further research would be to verify whether some natural disaster happened during the period of survey and if so, how did it affect public environmental attitudes. This could be also analysed using data from different surveys. Scrutinising weather data at the time of survey and investigating their possible effects on stated environmental attitudes could be another useful approach.

4.8 Concluding remarks and policy implications

Consistently with previous literature, we reveal that people who identify themselves with communitarian, pro-social world-view tend to be more concerned about climate change than those who incline towards competitive, individualistic ideology (Leiserowitz et al., 2013; Kahan, 2012; Whitmarsh, 2011). This polarization, which increases with higher degree of numeracy and cognitive ability, hinders efforts to mitigate climate change and its consequences. Reducing the association between ideological or political opinions and attitudes towards global warming would be a good step towards alleviation of climate change. In practice, this could be achieved for example by more cautious utilization of ideological and political polarization over climate change in political campaigns.

We found that cognitive reflection and financial literacy are among the most important factors affecting the climate knowledge and climate perception. Therefore, we would like to empathise importance of education in these areas. Our results further suggest that the effect of age on climate concerns is negative and significant. Possible explanation is that much less was known about climate change back in times when older people were in education system. Hence, they were not exposed to the same level of information about climate change as younger generations. In addition, older people are less likely to be proficient in working with the internet, which is probably the most common source of information today. Therefore, we believe that more information provided through media which are easily accessible for elderly people would help them to improve understanding of consequences of global warming for them and their offspring. We would like to encourage policy makers to facilitate support towards educating middle-aged and older people about climate change and towards motivating them to further educate themselves in this area.

According to our results, income has significant positive effect on preferred gas and electricity tax rates. We suggest that this should be further examined and taken into account when making decisions about climate tax rates. In particular, we suggest to investigate possibility of introducing different tax rates for different income groups.

Chapter 5

Conclusion

This thesis has provided an empirical analysis of effects of climate change on human population in the two most populated English-speaking countries, in particular the United States and the United Kingdom. The thesis consists of three separate papers, each of them examines effects of climate change from a specific point of view. In the first two papers, effects of global warming are analysed at macro level while the third paper estimates effects of climate change as perceived by individual members of public.

Besides focusing on climate change, the first two papers are interlinked in the following ways. They both address effects of sea level rise, their units of analysis are counties of the contiguous US and they are both based on cross-sectional regressions with spatial adjustments.

Sea level rise is a serious result of global warming and it is likely to have disastrous consequences unless actions are taken to mitigate and adapt to it (Church et al., 2013; Hinkel et al., 2014; Seneviratne et al., 2012). In some locations, harmful consequences of sea level rise have already been observed (Hinkel et al. 2014; Nicholls and Cazenave 2010; Sato et al. 2006). In order to tackle sea level rise it is crucial to acquire as much knowledge about this phenomenon as possible. Therefore, many previous studies were dedicated to estimating future effects of sea level rise mostly through means of simulations (e.g., Nicholls et al., 1999; Nicholls and Tol, 2006; Anthoff et al., 2010b; Hinkel et al., 2010, 2013; Spencer et al., 2016). If the fundamental assumption behind these studies is valid, effects of past sea level rise should be detectable.

In the first paper I sought to estimate effects of sea level rise on economic growth rate. In particular, I estimated Barro type growth regressions with sea level rise as one of the explanatory variables. The regressions were estimated repeatedly for various time periods of economic growth. I did not find any stable significant effect. This result was confirmed by an alternative method, namely a matching estimator. In addition, I obtained the same results for a number of robustness tests. The tests included estimating the model for the subsample of coastal counties, using heteroscedasticity robust standard errors and using an alternative sea level rise data collection range.

One limitation of this study is the fact, that sea level rise is relatively slow and gradual process and it is therefore possible that its effects on economic growth are only detectable over a period of hundreds or thousands of years. Therefore, for further research I would suggest estimating similar models based on a longer time series. A lack of historical data could possibly be overcome by using sparse regression methods without the unavailable covariates. Another explanation of why no stable significant effect was found can be the fact that sea level rise has very small effect on developed economies like that of the United States, but it has a more substantial impact on developing economies. Thus, another direction of further research would be focusing on past sea level rise effects in developing countries. Data availability for large spatial areas could be a problem in developing countries. However, insightful outcomes could be obtained, for instance by means of natural experiments in small islands.

In the second paper of this essay I aimed to identify effects of sea level rise on agricultural land prices as this indicator is likely to be more sensitive to sea level rise than economic growth. The model was based on theory of Ricardo (1817), which was first developed by Mendelsohn et al. (1994) and it involves a hedonic regression of land values on a set of explanatory variables including sea level rise. In contrary to the results of the first paper, I found a significant, hill-shaped relationship. More specifically, small sea level rise has positive effect on land prices and more pronounced sea level rise affects them negatively. If state fixed effects are included, the effects of sea level rise is purely negative, which is in accordance with my hypothesis. To test for robustness of the main results, I conducted a set of robustness checks including utilization of 1900 land values data. I found the results to be robust. The second paper of the present thesis is a first study that has associated past sea level rise with significant changes in an economic indicator.

There is a remarkable similarity in the results of the first and second paper. In the first paper I did not find any significant effects for the most recent time period. However, for some other earlier periods I identified a significant hill-shaped relationship of sea level rise and economic growth implying that moderate sea level rise has positive effect on economic growth and more intensive sea level rise affects economic growth negatively. This is analogous to the results of the first paper.

There are some limitations to the second paper which are worth mentioning. First, the land values are only available as county averages and county areas are relatively large. It is possible, that decrease in land prices caused by sea level rise in coastal locations makes inland prices to rise. Thus, an explanation of the hill-shaped relationship can be the fact that for smaller sea level rise, the effect of increase in land values inland prevails, while for more pronounced sea level rise the negative effect on coasts is dominant. This could only be tested if plot specific data were available.

A limitation, which affects both the first and the second paper is a relative sparsity of the water gauge stations. There are almost 300 coastal counties in the contiguous US and almost 3000 counties altogether. However, there are only 94 water gauge stations with complete data available. Thus, the sea level rise data had to be extrapolated for the analysis. More precise estimates could be obtained if sea level data from more locations were available.

Although the underlying topic of the three papers of this thesis is climate change and its effects on humans, the third paper is relatively different from the first two studies. In contrary to the first two papers, the third one is based on survey data and it is focused on the United Kingdom.

The aim of the third paper is to identify the main predictors of individuals' climate knowledge and attitudes towards climate change. Importantly, the third study includes analyses of effects of four behavioural characteristics on environmental knowledge and attitudes. The behavioural measures are time preferences, risk preferences, social value orientation and inequity aversion. The study contributes by exploring a unique live-sample dataset which combines advantages of survey and experiments as the behavioural variables were elicited using experimental methods (Dolton and Tol, 2016). The dataset consists of almost 6000 observations and nearly 70 possible predictors. Using a multisplit lasso estimator, I found that the most important predictors of climate knowledge are numeracy and gender and the most significant factors affecting the climate risk perception are climate knowledge, cultural/ideological world-view, gender and financial literacy. In addition, I revealed that WTP for climate change mitigation decrease with age and it is lower for individuals with higher level of financial literacy and for those with consistent attitudes towards risk. WTP also depends significantly on attitudes towards equity, climate policy perception and income.

The survey was conducted online, therefore the sample of respondents who started the questionnaire is representative for the UK population with internet access rather than for the entire UK population. The most substantial drop in participants was during the parts of survey which included more difficult questions. Hence, the final sample is slightly biased towards those who are not afraid of hard questions. This would be a limitation of this study.

I revealed that cultural/ideological world view is a significant predictor of climate risk attitudes. This finding is consistent with previous literature (Leiserowitz et al., 2013; Kahan, 2012; Whitmarsh, 2011). However, the respondents of the survey used in this study were not asked about their political opinions directly. Instead of that, questions about attitudes towards income and similar were used as measures of political/idealogical attitudes. Therefore, should a similar survey be conducted in future, I would suggest adding direct questions about political opinions. This could help to further investigate the link between political/ideological opinions and environmental attitudes.

It would be desirable for society as a whole if members of public form their attitudes towards climate change based on scientific facts rather than on their ideological beliefs or political orientation. Therefore, I would like to suggest more careful public communication about climate change and reducing utilization of political polarization over climate change in political campaigns.

My next suggestion for further research is based on the finding that income is strongly positively correlated with WTP for climate change mitigation. This could be utilized in policy decision making. Hence, I would like to suggest that more research should be conducted on this particular topic. For example, it could be useful to investigate the possibility of introducing different climate tax rates for different income groups.

In summary, this thesis has improved understanding of effects of climate change and its consequences in innovative ways. The first two papers were focused on effects of past sea level rise while the third one analysed perception of climate change by general public. To the best of my knowledge, the first two papers present the first study focused on quantifying past effects of sea level rise. Therefore, more research should be conducted on this topic. It would also be insightful to look at the public environmental concerns and climate knowledge from alternative points of view and conduct more research in this area.

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Appendix A

Appendix to Chapter 2

A.1 Control variables

The covariates used in this study are listed in Table A.1.

Population density and urban and rural dummy variables are included as measures of agglomeration as it is assumed that economic activities are attracted to metropolitan areas which further enhance economic growth.

Rupasingha and Chilton (2009) show that the percentage of religious adherents has a significant impact on economic growth as well as the percentages of adherents of individual religious denominations and religious diversity. Similarly, as in Rupasingha and Chilton (2009), we first considered two specifications, specifically a model with percentage of all religious adherents and a model without this variable, which includes percentages of adherents of the three main denominations, namely Catholics, Evangelical Protestants and Mainline Protestants. The religious diversity index is included in both these specifications. Finally, we chose the second specification as for the first specification both parameters ρ and λ are significant in the form (2.7) and also according to the LM diagnostic tests for spatial dependence (Anselin et al. 1996) the form (2.7) is correct, but Moran's I adjusted for residuals is significant for this specification. On the other hand, appropriate specification of the model with the percentages of the three main religious adherents is (2.9) (λ is insignificant in form (2.7)) and Moran's I statistic applied to residuals from this model is insignificant.

The three denominations, specifically Catholics, Evangelical Protestants and Mainline Protestants include most of the 133 Judeo-Christian church bodies listed in the Yearbook of American and Canadian Churches which responded to the invitation to participate in the study organized by the Association of Statisticians of American Religious Bodies (ASARB) in 1990. The excluded group includes all other church groups and non-affiliates. Percentage

Table A.1: **List of Covariates and their description**

	Government finances
Gov. expenditures p. capita	Per capita highway and education expenditures 1992
Tax income per capita	Per capita local tax income 1992
	Measures of agglomeration
Population density	Population density 1990
Urban	Metropolitan counties
Rural	Rural counties not adjacent to metropolitan areas
	Measures of religious adherence
Adherents	Per capita total number of religious adherents 1990
Catholics	Per capita Catholics adherents 1990
Evangelical Protestants	Per capita Evangelical Protestants adherents 1990
Mainline Protestants	Per capita Mainline Protestants adherents 1990
Religious diversity	Religious diversity index 1990
	Other socioeconomic and environmental indicators
Coast distance	Distance from coast
Education	Percent of population (25 years or older) who have bachelor's degree or higher 1990
Highway	Presence of interstate highway interchange
Right to work laws	Right to work laws
Nonwhites	Percent of population who are nonwhite 1990
Amenities	Natural amenities index by McGranahan (1999) (see note below table)
	Regional dummy variables
New England	New England region
Mideast	Mideast region
Great Lakes	Great Lakes region
Plains	Plains
Southeast	Southeast region
Southwest	Southwest region
Rocky Mountain	Rocky Mountain region

Note: Environmental qualities captured by the natural amenities index: January temperature, Days of sun in January, July temperature, July humidity, Proportion of water area, Topography of religious adherents, percentage of Evangelical Protestant adherents and percentage of Mainline protestant adherents are all negatively correlated with dummy variable interstate highway access. Their Pearson's product - moment correlation coefficients are -0.103, -0.124 and -0.074, respectively with both-sided p-values 1.009×10^{-8}, 5.25×10^{-12} and 4.523×10^{-5}, respectively. On the other hand, the percentage of Catholic adherents is weakly positively correlated with highway access dummy variable. Its value of the Pearson's product - moment correlation coefficient is 0.045 and the p-value is 0.014. Since highway construction is usually funded from the same sources as the construction of flood dikes, it is plausible that the percentage of Catholics is positively correlated with construction of dikes, while the percentage of Protestants is negatively correlated with construction of dikes. Therefore the religious variables are relevant and they are included in the model. Religious diversity is included as according to some studies, for example Barro and McCleary (2003), higher religious diversity is related to higher quality religion due to higher competition. On the other hand, in the presence of greater religious plurality societies have less social capital which may lead to a less trusting society and slower economic growth. The religious diversity index was obtained similarly as in Rupasingha and Chilton (2009) according to formula

$$Reldiv = 1 - \sum_{i=1}^{133} (Denom_i^2), \tag{A.1}$$

where $Denom_i$ denotes share of adherents of denomination i.

Education is measured as the percentage of the population who are 25 years or older and have a bachelor's degree or higher. This variable serves as a proxy for human capital. Interstate highway access is a dummy variable which is equal to 1 for counties which have interstate highway interchange and 0 for the other counties and it is included to capture accessibility of counties. Effects of right to work law on the economy and its growth have been studied extensively. In the absence of right to work laws, legislation favours labour unions which raises labour costs and discourages employers from investing. According to some studies, for example Hicks and LaFaive (2013) or Vedder and Robe (2014), there is evidence that right to work laws have a positive and significant effect on economic growth, therefore a state level dummy variable which indicates the presence of right to work laws is included. Percentage of nonwhite population was found to be associated with earning rates and overall costs of production by many labour studies therefore it is also included.

It is further expected that a higher level of natural amenities is related to higher economic growth, thus the natural amenities index derived by McGranahan (1999) is included. The index is constructed using six measures of climate, topography and water area which are explained in detail in McGranahan (1999).

The last seven covariates in Table A.1 are regional dummy variables included to capture regional effects. The omitted region is the Far West.

A.2 Data

Descriptive statistics of sea level rise, average growth rate of per capita income, coast distance, per capita government expenditures and per capita tax income can be found in Table 2.1 in Section 2.3. Descriptive statistics of the other covariates are summarized in Table A.2 below.

Per capita highway and education expenditures, per capita local tax income, population density, education and percent of population who are nonwhite were obtained from the United States Census Bureau (2016). Urban and rural dummy variables were constructed in the same way as in Rupasingha and Chilton (2009) based on Rural-Urban Continuum Codes, which are published by United States Department of Agriculture (2016) (USDA). Variable urban is equal to 1 for metropolitan counties with Rural-Urban Continuum Codes $0-3$ and variable rural is equal to 1 for counties with Rural-Urban Continuum Codes 5, 7 and 9 that are not adjacent to metropolitan areas. The excluded group includes rural counties adjacent to metropolitan areas with Rural-Urban Continuum Codes 4, 6 and 8.

The religious variables are available online by the Association of Religion Data Archive (2016) (ARDA). The data set provided by ARDA contains percentages of religious adherents of 133 religious denominations who responded to an invitation to participate in the study organized by ASARB in year 1990. The invitation was sent to 246 denominations that included all Judeo-Christian church bodies listed in the Yearbook of American and Canadian Churches, plus a few others for whom addresses could be found. The 133 denominations were grouped into three groups, in particular Catholics, Evangelical Protestants and Mainline Protestants in the same way as Rupasingha and Chilton (2009). These three groups include almost all 133 participating denominations, the rest is in the excluded category.

Table A.2: **Descriptive Statistics**

Variable	**Mean**	**Std. dev.**
Population density (rate per km^2)	64.3236	338.9815
Urban $(0, 1)$	0.2635	0.4406
Rural $(0, 1)$	0.4146	0.4927
Measures of religious adherence		
Adherents (Percentage)	59.7319	19.8822
Catholics (Percentage)	13.0005	15.1542
Evangelical Protestants (Percentage)	31.4110	20.5496
Mainline Protestants (Percentage)	12.9707	8.6508
Religious diversity (Formula (A.1)) Rupasingha and Chilton (2009)	0.8697	0.1296
Other socioeconomic and environmental indicators		
Education (Percentage)	13.3918	6.4250
Highway $(0, 1)$	0.4084	0.4916
Right to work laws $(0, 1)$	0.6202	0.4853
Nonwhites (Percentage)	12.7202	15.4563
Amenities (Scale McGranahan (1999))	0.0505	2.2876
Regional dummy variables		
New England $(0, 1)$	0.0219	0.1463
Mideast $(0, 1)$	0.0568	0.2315
Great Lakes $(0, 1)$	0.1423	0.3495
Plains $(0, 1)$	0.2018	0.2018
Southeast $(0, 1)$	0.3356	0.4723
Southwest $(0, 1)$	0.1224	0.3278
Rocky Mountain $(0, 1)$	0.0702	0.2555

A.3 Tables

Adjusted R-squared is 0.374 for the OLS estimate of regression (2.1) in Table A.4 and the F-statistic is 71.36 which is significant with a p-value lower that 2.2×10^{-16}.

The F-statistic of the first stage regression in the first column of Table A.5 is 85.82 and its p-value is lower than 2.2×10^{-16}. The F-statistic of the second stage in the second column of Table A.5 is 46.14 and the corresponding p-value is 1.319×10^{-11}. Value of Sargan test statistic of over-identifying restrictions in the IV estimation is 0.796 and its p-value is 0.372, thus the test is insignificant and the over-identifying restrictions are valid.

Table A.3: Descriptive statistics - growth rate

Average growth rate of per capita income g_n, various time periods:

Period	Mean	Standard deviation
1990 – 2012	0.0413	0.0076
1990 – 2011	0.0415	0.0075
1990 – 2010	0.0402	0.0070
1990 – 2009	0.0408	0.0072
1990 – 2008	0.0443	0.0075
1990 – 2007	0.0435	0.0069
1990 – 2006	0.0423	0.0074
1990 – 2005	0.0427	0.0071
1990 – 2004	0.0429	0.0076
1990 – 2003	0.0425	0.0077
1990 – 2002	0.0418	0.0085
1990 – 2001	0.0453	0.0088
1990 – 2000	0.0439	0.0098

Table A.4: **OLS** (2.1) - *Growth rate between 1990-2012*

Constant	0.2250 (0.0084)***
Log of initial income pp. (US$)	−0.0200 (0.0009)***
Sea level rise (m/year)	0.5337 (0.2677)*
Sea level rise (m/year) - squared	−0.0184 (0.0357)
Coast distance (thousands km)	−0.0072 (0.0012)***
Coast distance (thousands km) - squared	0.0080 (0.0001)***
Gov. expenditures per capita (US$)	−0.3145 (0.4336)
Tax income per capita (bn. US$)	2.4300 (0.4001)***
Measures of agglomeration	
Population density (rate per m^2)	0.0356 (0.0531)
Urban (dummy)	0.00002 (0.0003)
Rural (dummy)	0.0005 (0.0003)
Measures of religious adherence	
Catholics (percentage)	0.0001 (0.00001)***
Evangelical Protestants (percentage)	0.0001 (0.00001)***
Mainline Protestants (percentage)	0.0001 (0.00002)**
Religious diversity (Formula (A.1))	0.0031 (0.0012)*
Other socioeconomic and environmental indicators	
Education (percentage)	0.0002 (0.00003)***
Highway (dummy)	−0.0004 (0.0002)
Right to work laws (state level dummy)	0.0012 (0.0003)***
Nonwhites (percentage)	−0.00004 (0.00001)***
Amenities (scale McGranahan (1999))	−0.0003 (0.0001)***
Regional dummy variables	
New England (dummy)	−0.0006 (0.0010)
Mideast (dummy)	−0.0017 (0.0008)*
Great Lakes (dummy)	−0.0045 (0.0009)***
Plains (dummy)	−0.0027 (0.0009)**
Southeast (dummy)	−0.0033 (0.0007)***
Southwest (dummy)	0.0001 (0.0008)
Rocky Mountain (dummy)	−0.0012 (0.0008)

Notes: *p<0.05; **p<0.01; ***p<0.001, Standard errors in brackets

Table A.5: **3SLS-IV: first and second stage** - *Growth rate between 1990-2012*

	Stage 1 eq. (2.3)	Stage 2 eq. (2.4)
Dependent variable:	$\Delta y_{n,0}$	Δg_n
Constant	0.0207 (0.0026)***	0.0010 (0.0003)***
Religious adherents (percentage)	0.0006 (0.00005)***	
Population density (rate per m^2)	0.1114 (0.3633)	
Predicted log of initial per capita income (US$)		-0.0333 (0.0049)***

Notes: *p<0.05; **p<0.01; ***p<0.001, Standard errors in brackets

Table A.6: ***SAR model*** (2.9) - *Growth rate between 1990-2012*

	3SLS-IV (2.6)	**SAR** (2.9)
Constant	0.3476 (0.0017)***	0.1849 (0.0074)***
Log of initial per capita income (US$)	−0.0333 (0.0049)***	−0.0333 (0.0049)***
Sea level rise (m/year)	0.9467 (0.2768) ***	0.5943 (0.2524)*
Sea level rise (m/year) - squared	−0.0592 (0.0370)	−0.0444 (0.0337)
Coast distance (thousands km)	−0.0072 (0.0013)***	−0.0045 (0.0012)***
Coast distance (thousands km) - squared	0.0083 (0.0007)***	0.0045 (0.0007)***
Gov. expenditures per capita (billion US$)	−0.7102 (0.4515)	−0.5957 (0.4106)
Tax income per capita (billion US$)	4.1710 (0.3993)***	3.3698 (0.3681)***
ρ (SAR)	—	0.4583 (0.0206)***
Measures of agglomeration		
Population density (rate per m^2)	0.0976 (0.0552)	−0.0082 (0.0503)
Urban (dummy)	0.0012 (0.0003)***	0.0009 (0.0003)**
Rural (dummy)	0.00004 (0.0003)	0.0003 (0.0003)
Measures of religious adherence		
Catholics (percentage)	0.0001 (0.00001)***	0.0001 (0.00001)***
Evangelical Protestants (percentage)	0.0001 (0.00001)***	0.0001 (0.00001)***
Mainline Protestants (percentage)	0.0001 (0.00002)***	0.0001 (0.00001)***
Religious diversity (Formula (A.1))	0.0057 (0.0013)***	0.0039 (0.0012)***
Other socioeconomic and environmental indicators		
Education (percentage)	0.0004 (0.00002)***	0.0003 (0.00002)***
Highway (dummy)	−0.0002 (0.0003)	−0.0001 (0.0002)
Right to work laws (state level dummy)	0.0018 (0.0003)***	0.0010 (0.0003)***
Nonwhites (percentage)	−0.0001 (0.00001)***	−0.0001 (0.00001)***
Amenities (scale McGranahan (1999))	−0.0003 (0.0001)***	−0.0002 (0.0001)*
Regional dummy variables		
New England (dummy)	−0.0018 (0.0010)	−0.0025 (0.0010)**
Mideast (dummy)	−0.0030 (0.0008)***	−0.0023 (0.0008)**
Great Lakes (dummy)	−0.0063 (0.0009)***	−0.0031 (0.0008)***
Plains (dummy)	−0.0054 (0.0010)***	−0.0028 (0.0009)**
Southeast (dummy)	−0.0061 (0.0008)***	−0.0026 (0.0007)***
Southwest (dummy)	−0.0031 (0.0008)***	−0.0017 (0.0007)*
Rocky Mountain (dummy)	−0.0032 (0.0008)***	−0.0020 (0.0008)**

Notes: *p<0.05; **p<0.01; ***p<0.001, Standard errors in brackets

Table A.7: **SAR model** (2.9) - Impact measures, *1990-2012*

	Direct	**Indirect**	**Total**
Sea level rise (m/year)	0.6218	0.4753	1.0971
Sea level rise (m/year) - squared	−0.0465	−0.0355	−0.0820
Coast distance (thousands km)	−0.0048	−0.0036	−0.0084
Coast distance (thousands km) - squared	0.0047	0.0036	0.0084
Gov. expenditures per capita (billion US$)	−0.6232	−0.4764	−1.0996
Tax income per capita (billion US$)	3.5257	2.6948	6.2205
Measures of agglomeration			
Population density (rate per m^2)	−0.0086	−0.0066	−0.0152
Urban (dummy)	0.0009	0.0007	0.0016
Rural (dummy)	0.0003	0.0003	0.0006
Measures of religious adherence			
Catholics (percentage)	0.0001	0.0001	0.0001
Evangelical Protestants (percentage)	0.0001	0.0001	0.0001
Mainline Protestants (percentage)	0.0001	0.0001	0.0001
Religious diversity (Formula (A.1))	0.0041	0.0031	0.0072
Other socioeconomic and environmental indicators			
Education (percentage)	0.0003	0.0003	0.0006
Highway (dummy)	−0.0001	−0.0001	−0.0002
Right to work laws (state level dummy)	0.0011	0.0008	0.0019
Nonwhites (percentage)	−0.0001	−0.0001	−0.0001
Amenities (scale McGranahan (1999))	−0.0002	−0.0001	−0.0003
Regional dummy variables			
New England (dummy)	−0.0026	−0.0020	−0.0047
Mideast (dummy)	−0.0024	−0.0018	−0.0042
Great Lakes (dummy)	−0.0032	−0.0025	−0.0057
Plains (dummy)	−0.0030	−0.0023	−0.0052
Southeast (dummy)	−0.0028	−0.0021	−0.0049
Southwest (dummy)	−0.0018	−0.0014	−0.0032
Rocky Mountain (dummy)	−0.0021	−0.0016	−0.0037

Table A.8: *Comparison of SAR model (2.7) and SAR model with White errors (2.11)*

	Spatial model (2.7)	**SAR White errors (2.11)**
Constant	0.174 (0.019)***	0.177 (0.019)***
Log of initial per capita income (US$)	−0.033 (0.005)***	−0.033 (0.005)***
Sea level rise (m/year)	0.568 (0.235)*	0.577 (0.244)*
Sea level rise (m/year) - squared	−0.042 (0.030)	−0.044 (0.032)
Coast distance (thousands km)	−0.004 (0.001)***	−0.004 (0.001)***
Coast distance (thousands km) - sq.	0.004 (0.001)***	0.004 (0.001)***
Gov. expenditures per capita (bn. US$)	−0.589 (0.572)	−0.590 (0.570)
Tax income per capita (bn. US$)	3.219 (0.536)***	3.330 (0.544)***
ρ (SAR)	0.491 (0.053)***	0.481 (0.054)***
λ (SEM)	−0.114 (0.078)	—
Measures of agglomeration		
Population density (rate per m^2)	−0.012 (0.045)	−0.013 (0.046)
Urban (dummy)	0.001 (0.0003)**	0.001 (0.0003)**
Rural (dummy)	0.0004 (0.0002)	0.0003 (0.0003)
Measures of religious adherence		
Catholics (percentage)	0.0001 (0.00001)***	0.0001 (0.00001)***
Evangelical Protestants (percentage)	0.0001 (0.00001)***	0.0001 (0.00001)***
Mainline Protestants (percentage)	0.0001 (0.00002)***	0.0001 (0.00002)***
Religious diversity (Formula (A.1))	0.004 (0.001)**	0.004 (0.001)**
Other socioeconomic and environmental indicators		
Education (percentage)	0.0003 (0.00003)***	0.0003 (0.00003)***
Highway (dummy)	−0.0001 (0.0002)	−0.0001 (0.0002)
Right to work laws (state level dummy)	0.001 (0.0003)***	0.0010 (0.0003)***
Nonwhites (percentage)	−0.0001 (0.00001)***	−0.0001 (0.00001)***
Amenities (scale McGranahan (1999))	−0.0002 (0.0001)	−0.0001 (0.0001)
Regional dummy variables		
New England (dummy)	−0.003 (0.001)***	−0.003 (0.001)***
Mideast (dummy)	−0.002 (0.001)**	−0.002 (0.001)**
Great Lakes (dummy)	−0.003 (0.001)**	−0.003 (0.001)**
Plains (dummy)	−0.003 (0.001)**	−0.003 (0.001)**
Southeast (dummy)	−0.003 (0.001)**	−0.003 (0.001)**
Southwest (dummy)	−0.002 (0.001)*	−0.002 (0.001)*
Rocky Mountain (dummy)	−0.002 (0.001)*	−0.002 (0.001)*

Notes: *p<0.05; **p<0.01; ***p<0.001, Standard errors in brackets

Table A.9: **SAR White errors** (2.11) - Impact measures, *1990-2012*

	Direct	**Indirect**	**Total**
Sea level rise (m/year)	0.6069	0.5045	1.1115
Sea level rise (m/year) - squared	−0.0459	−0.0382	−0.0841
Coast distance (thousands km)	−0.0046	−0.0039	−0.0085
Coast distance (thousands km) - squared	0.0046	0.0038	0.0084
Gov. expenditures per capita (billion US$)	−0.6207	−0.5160	−1.1367
Tax income per capita (billion US$)	3.5033	2.9124	6.4157
Measures of agglomeration			
Population density (rate per m^2)	−0.0142	−0.0118	−0.0259
Urban (dummy)	0.0009	0.0008	0.0017
Rural (dummy)	0.0004	0.0003	0.0006
Measures of religious adherence			
Catholics (percentage)	0.0001	0.0001	0.0001
Evangelical Protestants (percentage)	0.0001	0.0001	0.0001
Mainline Protestants (percentage)	0.0001	0.0001	0.0001
Religious diversity (Formula (A.1))	0.0040	0.0034	0.0074
Other socioeconomic and environmental indicators			
Education (percentage)	0.0003	0.0003	0.0006
Highway (dummy)	−0.0001	−0.0001	−0.0002
Right to work laws (state level dummy)	0.0010	0.0008	0.0019
Nonwhites (percentage)	−0.0001	−0.0001	−0.0002
Amenities (scale McGranahan (1999))	−0.0002	−0.0001	−0.0003
Regional dummy variables			
New England (dummy)	−0.0027	−0.0022	−0.0049
Mideast (dummy)	−0.0024	−0.0020	−0.0043
Great Lakes (dummy)	−0.0031	−0.0026	−0.0057
Plains (dummy)	−0.0028	−0.0024	−0.0052
Southeast (dummy)	−0.0026	−0.0022	−0.0048
Southwest (dummy)	−0.0017	−0.0015	−0.0032
Rocky Mountain (dummy)	−0.0020	−0.0017	−0.0037

Table A.10: ***Spatial autoregressive model*** (2.9), *Growth rate between 1990-2012*

	Whole periods of available data	**SLR between 1979 – 2007**
Constant	0.1849 (0.0074)***	0.1842 (0.0074)***
Log of initial per capita income (US$)	−0.0333 (0.0049)***	−0.0333 (0.0049)***
Sea level rise (m/year)	0.5943 (0.2524)*	0.5750 (0.3208)•
Sea level rise (m/year) - squared	−0.0444 (0.0337)	−0.0693 (0.0583)
Coast distance (thousands km)	−0.0045 (0.0012)***	−0.0052 (0.0011)***
Coast distance (thousands km) - sq.	0.0045 (0.0007)***	0.0048 (0.0007)***
Gov. expenditures per capita (bn. US$)	−0.5957 (0.4106)	−0.6337 (0.4106)
Tax income per capita (bn. US$)	3.3698 (0.3681)***	3.3988 (0.3687)***
ρ (SAR)	0.4583 (0.0206)***	0.4610 (0.0205)***
Measures of agglomeration		
Population density (rate per m^2)	−0.0082 (0.0503)	−0.0013 (0.0501)
Urban (dummy)	0.0009 (0.0003)**	0.0009 (0.0003)**
Rural (dummy)	0.0003 (0.0003)	0.0003 (0.0003)
Measures of religious adherence		
Catholics (percentage)	0.0001 (0.00001)***	0.0001 (0.00001)***
Evangelical Protestants (percentage)	0.0001 (0.00001)***	0.0001 (0.00001)***
Mainline Protestants (percentage)	0.0001 (0.00001)***	0.0001 (0.00001)***
Religious diversity (Formula (A.1))	0.0039 (0.0012)***	0.0039 (0.0012)***
Other socioeconomic and environmental indicators		
Education (percentage)	0.0003 (0.00002)***	0.0003 (0.00002)***
Highway (dummy)	−0.0001 (0.0002)	−0.0001 (0.0002)
Right to work laws (state level dummy)	0.0010 (0.0003)***	0.0010 (0.0003)***
Nonwhites (percentage)	−0.0001 (0.00001)***	−0.0001 (0.00001)***
Amenities (scale McGranahan (1999))	−0.0002 (0.0001)*	−0.0001 (0.0001)•
Regional dummy variables		
New England (dummy)	−0.0025 (0.0010)**	−0.0027 (0.0010)**
Mideast (dummy)	−0.0023 (0.0008)**	−0.0024 (0.0008)**
Great Lakes (dummy)	−0.0031 (0.0008)***	−0.0030 (0.0008)***
Plains (dummy)	−0.0028 (0.0009)**	−0.0028 (0.0009)**
Southeast (dummy)	−0.0026 (0.0007)***	−0.0027 (0.0007)***
Southwest (dummy)	−0.0017 (0.0007)*	−0.0017 (0.0007)*
Rocky Mountain (dummy)	−0.0020 (0.0008)**	−0.0020 (0.0008)*

Notes: •p< 0.1; *p<0.05; **p<0.01; ***p<0.001, Standard errors in brackets

Table A.11: ***SAR model*** (2.9) *without government finances variables, 1990-2012*

Constant	0.1775 (0.0074)***
Log of initial per capita income (US$)	−0.0333 (0.0049)***
Sea level rise (m/year)	0.7199 (0.2564)**
Sea level rise (m/year) - squared	−0.0513 (0.0343)
Coast distance (thousands km)	−0.0046 (0.0012)***
Coast distance (thousands km) - squared	0.0045 (0.0007)***
ρ (SAR)	0.4775 (0.0206)***
Measures of agglomeration	
Population density (rate per m^2)	0.0621 (0.0504)
Urban (dummy)	0.0008 (0.0003)*
Rural (dummy)	0.0005 (0.0003) •
Measures of religious adherence	
Catholics (percentage)	0.0001 (0.00001)***
Evangelical Protestants (percentage)	0.0001 (0.00001)***
Mainline Protestants (percentage)	0.0001 (0.00001)***
Religious diversity (Formula (A.1))	0.0045 (0.0012)***
Other socioeconomic and environmental indicators	
Education (percentage)	0.0004 (0.00002)***
Highway (dummy)	−0.0002 (0.0002)
Right to work laws (state level dummy)	0.0015 (0.0003)***
Nonwhites (percentage)	−0.0001 (0.00001)***
Amenities (scale McGranahan (1999))	−0.0001 (0.0001)
Regional dummy variables	
New England (dummy)	−0.0019 (0.0009)*
Mideast (dummy)	−0.0016 (0.0008)*
Great Lakes (dummy)	−0.0029 (0.0008)***
Plains (dummy)	−0.0029 (0.0009)**
Southeast (dummy)	−0.0031 (0.0007)***
Southwest (dummy)	−0.0016 (0.0007)*
Rocky Mountain (dummy)	−0.0014 (0.0008)•

Notes: •p¡0.1; *p<0.05; **p<0.01; ***p<0.001, Standard errors in brackets

Appendix B

Appendix to Chapter 3

B.1 Soil Characteristics

The soil characteristics used in this study are described below. The description is a quotation from the data appendix of Massetti and Mendelsohn (2011) as I use the same dataset for the soil characteristics.

- ***Salinity*** - Percentage of agricultural land that has salinity-sodium problems.
- ***Flooding*** - Percentage of agricultural land occasionally or frequently prone to flooding.
- ***Wet factor*** - Percentage of agricultural land that has very low drainage (poor and very poor).
- ***K-factor*** - Average soil erodibility factor. It is the average soil loss, measured in tons/hectare. The k-factor is a measure of the susceptibility of soil particles to detachment and transport by rainfall and runoff.
- ***Slope length*** - Average slope length factor, measured in meters. Slope length is the distance from the point of origin of overland flow to the point where either the slope gradient decreases enough that deposition begins, or the runoff water enters a well-defined channel that may be part of a drainage network or a constructed channel. For the NRI, length of slope is taken through the sample point.
- ***Sand*** - Percentage of agricultural land classified as sand or coarse-textured soils.
- ***Clay*** - Percentage of agricultural land that is classified as clay.

- ***Moisture level*** - Minimum value for the range of available water capacity for the soil layer or horizon. Available water capacity is the volume of water retained in 1 cm^3 of whole soil between 1/3-bar and 15-bar tension. It is reported as centimetres of water per centimetres of soil.

- ***Permeability*** - The minimum value for the range in permeability rate for the soil layer or horizon, expressed as centimetres per hour.

B.2 Tables

Table B.1: ***Descriptive statistics***, *Soil characteristics, year* 2002

Number of observations: 2830

Variable:	**Units**	$\bar{x}$[a]	$\hat{s}(x)$[b]	**Min**	**Max**
Salinity problems	% of farmland	0.103	0.168	0.000	1.000
Prone to flooding	% of farmland	0.109	0.172	0.000	1.000
Wet factor (low drainage)	% of farmland	0.107	0.185	0.000	1.000
K-factor (erodibility-soil loss)	tons/hectare	0.304	0.072	0.100	0.550
Average slope length factor	meters	210.600	159.646	15.000	1631.200
Sand or coarse-textured soils	% of farmland	0.104	0.237	0.000	1.000
Clay	% of farmland	0.056	0.154	0.000	1.000
Moisture level	cm/cm^3	0.148	0.042	0.030	0.273
Permeability	cm/hour	1.265	1.402	0.000	20.000

[a] $\bar{x}$ indicates the sample mean

[b] $\hat{s}(x)$ indicates the sample standard deviation

Table B.2: ***OLS and SAR specification*** (3.14)

Loglinear functional form, year 2007

	OLS coefficient estimate[a]	OLS coefficient - exponent	SAR coefficient estimate[b]
ρ (SAR)	—	—	0.062 (0.011)***
Constant	0.214 (0.452)	1.238	0.085 (0.703)
Sea level rise (mm/yr)	**0.057 (0.029)***	**1.058**	**0.081 (0.049)**$^{\bullet}$
Sea level rise (mm/yr) - squared	**−0.015 (0.004)*****	**0.985**	**−0.017 (0.006)****
Lake level rise (mm/yr) - Great Lakes	**0.018 (0.007)***	**1.018**	**0.017 (0.008)***
	Geoeconomic characteristics		
Per capita income (dollars/yr, log)	0.849 (0.043)***	2.337	0.805 (0.068)***
X coordinate	0.005 (0.001)***	1.005	0.004 (0.002)$^{\bullet}$
Y coordinate	−0.004 (0.002)$^{\bullet}$	0.996	−0.004 (0.005)
Coast distance (thousands km)	−1.205 (0.038)***	0.300	−1.117 (0.082)***
Length of coast (thousands km)	−0.287 (0.557)	0.751	0.021 (0.876)
Brackish or tidal (dummy)	0.227 (0.063)***	1.255	0.161 (0.104)
Groundwater withdrawals (l/ha/day)	0.079 (0.008)***	1.082	0.075 (0.012)***
Land in farms (millions acres)	−0.672 (0.028)***	0.512	−0.671 (0.071)***
	Soil characteristics		
Salinity problems (% of farmland)	−0.033 (0.061)	0.968	−0.028 (0.095)
Prone to flooding (% of farmland)	0.139 (0.053)**	1.150	0.120 (0.072)$^{\bullet}$
Wet factor (% of farmland)	0.030 (0.053)	1.030	0.047 (0.072)
K-factor - average erodability	−0.176 (0.199)	0.839	−0.187 (0.295)
Slope length (km)	0.037 (0.061)	1.038	0.052 (0.084)
Sand (% of farmland)	−0.622 (0.080)***	0.537	−0.619 (0.108)***
Clay (% of farmland)	−0.374 (0.063)***	0.688	−0.375 (0.087)***
Moisture level (cm/cm^3)	0.496 (0.356)	1.642	0.220 (0.530)
Permeability (cm/hour)	0.077 (0.015)***	1.080	0.076 (0.018)***

Notes: $^{\bullet}$p<0.1; *p<0.05; **p<0.01; ***p<0.001, [a] Standard errors in brackets

[b] Spatial HAC standard errors in brackets

Table B.3: ***Spatial autoregressive model*** (3.14)

Loglinear functional form, year 2007

	Coefficient estimate	Coefficient - exponent	Direct[a] impacts	Total[a] impacts
ρ (SAR)	0.062 (0.011)***	1.064	—	—
Constant	0.085 (0.703)	1.089	—	—
Sea level rise (mm/year)	**0.081 (0.049)•**	**1.085**	**1.085**	**1.091**
Sea level rise (mm/yr) - squared	**−0.017 (0.006)****	**0.983**	**0.983**	**0.982**
Lake level rise (mm/yr) - Great Lakes	**0.017 (0.008)***	**1.017**	**1.017**	**1.018**
	Geoeconomic characteristics			
Per capita income (dollars/yr, log)	0.805 (0.068)***	2.237	2.238	2.359
X coordinate	0.004 (0.002)•	1.004	1.004	1.004
Y coordinate	−0.004 (0.005)	0.996	0.996	0.996
Coast distance (thousands km)	−1.117 (0.082)***	0.327	0.327	0.304
Length of coast (thousands km)	0.021 (0.876)	1.022	1.022	1.023
Brackish or tidal (dummy)	0.161 (0.104)	1.174	1.174	1.187
Groundwater withdrawals (l/ha/day)	0.075 (0.012)***	1.078	1.078	1.083
Land in farms (millions acres)	−0.671 (0.071)***	0.511	0.511	0.489
	Soil characteristics			
Salinity problems (% of farmland)	−0.028 (0.095)	0.972	0.972	0.970
Prone to flooding (% of farmland)	0.120 (0.072)•	1.128	1.128	1.137
Wet factor (% of farmland)	0.047 (0.072)	1.048	1.048	1.051
K-factor - average erodability (soil loss, tons/hectare)	−0.187 (0.295)	0.829	0.829	0.819
Slope length (km)	0.052 (0.084)	1.054	1.054	1.057
Sand (% of farmland)	−0.619 (0.108)***	0.538	0.538	0.517
Clay (% of farmland)	−0.375 (0.087)***	0.688	0.687	0.670
Moisture level (cm/cm^3)	0.220 (0.530)	1.246	1.246	1.264
Permeability (cm/hour)	0.076 (0.018)***	1.079	1.079	1.084

Notes: •p<0.1; *p<0.05; **p<0.01; ***p<0.001, Spatial HAC standard errors in brackets

[a] e to the power of the impact measures

Table B.4: ***SAR model*** (3.14) *without immediate confounders*

Loglinear functional form, year 2007

	Coefficient estimate	**Coefficient - exponent**	**Direct[a] impacts**	**Total[a] impacts**
ρ (SAR)	0.119 (0.013)***	1.126	—	—
Constant	0.346 (0.824)	1.413	—	—
Sea level rise (mm/yr)	**0.144 (0.056)***	**1.154**	**1.155**	**1.177**
Sea level rise (mm/yr) - squared	**−0.022 (0.007)****	**0.978**	**0.978**	**0.975**
Lake level rise (mm/yr) - Great Lakes	**−0.001 (0.009)**	**0.999**	**0.999**	**0.999**
	Geoeconomic characteristics			
Per capita income (dollars/yr, log)	0.746 (0.078)***	2.108	2.113	2.333
X coordinate	0.012 (0.003)***	1.012	1.012	1.013
Y coordinate	−0.0001 (0.005)	1.000	1.000	1.000
Length of coast (thousands km)	2.497 (1.262)*	12.151	12.234	17.047
Brackish or tidal (dummy)	0.143 (0.137)	1.154	1.154	1.176
Land in farms (millions acres)	−0.923 (0.100)***	0.397	0.396	0.351
	Soil characteristics			
Salinity problems (% of farmland)	0.118 (0.113)	1.125	1.125	1.143
Prone to flooding (% of farmland)	−0.049 (0.077)	0.952	0.952	0.946
Wet factor (% of farmland)	0.391 (0.079)***	1.478	1.480	1.559
K-factor - average erodability	0.102 (0.317)	1.107	1.108	1.123
Slope length (km)	0.374 (0.121)**	1.454	1.455	1.529
Sand (% of farmland)	−0.533 (0.118)***	0.587	0.586	0.546
Clay (% of farmland)	−0.115 (0.092)	0.892	0.891	0.878
Moisture level (cm/cm^3)	−0.768 (0.662)	0.464	0.463	0.418
Permeability (cm/hour)	0.094 (0.020)***	1.099	1.099	1.113

Notes: $^{\bullet}$p<0.1; *p<0.05; **p<0.01; ***p<0.001, Spatial HAC standard errors in brackets

[a] e to the power of the impact measures

Table B.5: ***SAR model*** - *Linear functional form, year* 2007

	Coefficient estimate	**Direct impacts**	**Total impacts**
ρ (SAR)	0.571 (0.061)***	—	—
Constant	−25334.000 (3924.400)***	—	—
Sea level rise (mm/yr)	**767.890 (267.000)****	**834.745**	**1830.259**
Sea level rise (mm/yr) - squared	**−103.620 (31.170)*****	**−112.643**	**−246.981**
Lake level rise (mm/yr) - Gr. Lakes	**39.487 (36.722)**	**42.926**	**94.118**
	Geoeconomic characteristics		
Per capita income (dollars/yr, log)	2638.300 (415.240)***	2868.002	6288.373
X coordinate	1.814 (10.123)	1.972	4.323
Y coordinate	6.425 (12.378)	6.985	15.315
Coast distance (km)	−1.276 (0.303)***	−1.387	−3.041
Length of coast (km)	3.955 (5.738)	4.300	9.427
Brackish or tidal (dummy)	103.750 (789.950)	112.788	247.299
Groundwater withdrawals (l/ha/day)	260.470 (74.865)***	283.146	620.826
Land in farms (thousands acres)	−0.715 (0.134)***	−0.777	−1.704
	Soil characteristics		
Salinity problems (% of farmland)	13.086 (297.650)	14.225	31.190
Prone to flooding (% of farmland)	293.620 (158.230)•	319.188	699.850
Wet factor (% of farmland)	−288.470 (259.550)	−313.585	−687.566
K-factor - average erodability (soil loss, tons/hectare)	976.500 (909.350)	1061.524	2327.495
Slope length (m)	−0.219 (0.444)	−0.238	−0.521
Sand (% of farmland)	−1654.600 (664.210)*	−1798.678	−3943.775
Clay (% of farmland)	−696.520 (243.470)**	−757.168	−1660.164
Moisture level (cm/cm^3)	−3531.500 (1966.000)•	−3838.996	−8417.372
Permeability (cm/hour)	286.050 (148.020)•	310.952	681.792

Notes: •p<0.1; *p<0.05; **p<0.01; ***p<0.001, Spatial HAC standard errors in brackets

Table B.6: ***SAR model*** (3.14) *with population growth*

Loglinear functional form, year 2007

	Coefficient estimate	Coefficient - exponent	Direct[a] impacts	Total[a] impacts
ρ (SAR)	0.073 (0.010)***	1.076	—	—
Constant	2.071 (0.737)**	7.934	—	—
Sea level rise (mm/yr)	**0.069 (0.048)**	**1.072**	**1.072**	**1.078**
Sea level rise (mm/yr) - squared	**−0.015 (0.005)****	**0.985**	**0.985**	**0.984**
Lake level rise (mm/yr) - Great Lakes	**0.019 (0.007)****	**1.020**	**1.020**	**1.021**
Geoeconomic characteristics				
Population growth rate (% - yearly average)	0.141 (0.010)***	1.151	1.151	1.164
Per capita income (dollars/yr, log)	0.590 (0.072)***	1.804	1.805	1.891
X coordinate	0.008 (0.002)***	1.008	1.008	1.009
Y coordinate	0.004 (0.004)	1.004	1.004	1.004
Coast distance (thousands km)	−1.003 (0.071)***	0.367	0.366	0.339
Length of coast (thousands km)	0.451 (0.919)	1.570	1.571	1.627
Brackish or tidal (dummy)	0.152 (0.103)	1.164	1.164	1.178
Groundwater withdrawals (l/ha/day)	0.082 (0.012)***	1.086	1.086	1.093
Land in farms (millions acres)	−0.606 (0.060)***	0.546	0.545	0.520
Soil characteristics				
Salinity problems (% of farmland)	−0.085 (0.089)	0.919	0.918	0.912
Prone to flooding (% of farmland)	0.028 (0.062)	1.028	1.028	1.031
Wet factor (% of farmland)	0.030 (0.070)	1.030	1.030	1.033
K-factor - average erodability	−0.527 (0.280)•	0.591	0.590	0.566
Slope length (km)	−0.021 (0.081)	0.980	0.980	0.978
Sand (% of farmland)	−0.482 (0.094)***	0.618	0.618	0.595
Clay (% of farmland)	−0.319 (0.071)***	0.727	0.727	0.709
Moisture level (cm/cm^3)	1.306 (0.506)**	3.690	3.695	4.091
Permeability (cm/hour)	0.042 (0.016)**	1.043	1.043	1.046

Notes: •p<0.1; *p<0.05; **p<0.01; ***p<0.001, Spatial HAC standard errors in brackets

[a] e to the power of the impact measures

Table B.7: ***SAR model*** (3.14) *with state fixed effects*

Loglinear functional form, year 2007

	Coefficient estimate	**Coefficient - exponent**	**Direct[a] impacts**	**Total[a] impacts**
ρ (SAR)	0.048 (0.008)***	1.049	—	—
Constant	1.484 (0.871)•	4.411	—	—
Sea level rise (mm/yr)	**−0.034 (0.014)***	**0.967**	**0.967**	**0.965**
Lake level rise (mm/yr) - Great Lakes	**−0.001 (0.006)**	**0.999**	**0.999**	**0.999**
Geoeconomic characteristics				
Per capita income (dollars/yr, log)	0.796 (0.057)***	2.217	2.218	2.307
X coordinate	0.015 (0.008)*	1.015	1.015	1.016
Y coordinate	−0.020 (0.009)*	0.980	0.980	0.979
Coast distance (thousands km)	−0.335 (0.213)	0.716	0.715	0.704
Coast distance - squared (thousands km)	−0.590 (0.180)**	0.554	0.554	0.538
Length of coast (thousands km)	0.370 (0.702)	1.448	1.448	1.475
Brackish or tidal (dummy)	0.187 (0.101)•	1.205	1.205	1.217
Groundwater withdrawals (l/ha/day)	0.059 (0.012)***	1.061	1.061	1.064
Land in farms (millions acres)	−0.519 (0.056)***	0.595	0.595	0.589
Soil characteristics				
Salinity problems (% of farmland)	−0.030 (0.072)	0.971	0.971	0.969
Prone to flooding (% of farmland)	0.026 (0.059)	1.026	1.026	1.028
Wet factor (% of farmland)	−0.175 (0.060)**	0.839	0.839	0.832
K-factor - average erodability	−0.821 (0.255)**	0.440	0.440	0.422
Slope length (km)	−0.069 (0.080)	0.933	0.933	0.930
Sand (% of farmland)	−0.502 (0.082)***	0.606	0.605	0.591
Clay (% of farmland)	−0.018 (0.069)	0.982	0.982	0.981
Moisture level (cm/cm^3)	1.082 (0.558)•	2.951	2.952	3.115
Permeability (cm/hour)	0.021 (0.012)•	1.022	1.022	1.023
State fixed effects				
Arizona (dummy)	0.380 (0.264)	1.462	1.463	1.491
Arkansas (dummy)	0.426 (0.101)***	1.531	1.532	1.564
California (dummy)	1.304 (0.311)***	3.685	3.687	3.934
Colorado (dummy)	0.855 (0.153)***	2.352	2.353	2.455
Connecticut (dummy)	0.979 (0.163)***	2.662	2.663	2.796
Delaware (dummy)	1.146 (0.170)***	3.145	3.146	3.330
Florida (dummy)	0.878 (0.103)***	2.405	2.406	2.514
Georgia (dummy)	0.475 (0.083)***	1.609	1.609	1.647
Idaho (dummy)	0.938 (0.24)***	2.555	2.556	2.678

Table B.7: ***SAR model*** (3.14) *with state fixed effects*

Loglinear functional form, year 2007

	Coefficient estimate	**Coefficient - exponent**	**Direct[a] impacts**	**Total[a] impacts**
Illinois (dummy)	0.611 (0.094)***	1.842	1.842	1.899
Indiana(dummy)	0.487 (0.090)***	1.627	1.628	1.667
Iowa (dummy)	0.681 (0.112)***	1.976	1.977	2.045
Kansas (dummy)	0.071 (0.103)	1.074	1.074	1.077
Kentucky (dummy)	0.340 (0.086)***	1.404	1.405	1.429
Louisiana (dummy)	0.098 (0.090)	1.102	1.102	1.108
Maine (dummy)	−0.084 (0.208)	0.920	0.919	0.916
Maryland (dummy)	0.675 (0.127)***	1.965	1.965	2.032
Massachusetts (dummy)	1.351 (0.226)***	3.860	3.862	4.130
Michigan (dummy)	0.492 (0.121)***	1.635	1.636	1.676
Minnesota (dummy)	0.481 (0.140)***	1.618	1.618	1.657
Mississippi (dummy)	−0.002 (0.067)	0.998	0.998	0.998
Missouri (dummy)	0.466 (0.091)***	1.594	1.594	1.631
Montana (dummy)	0.864 (0.211)***	2.373	2.374	2.478
Nebraska (dummy)	0.299 (0.124)*	1.348	1.348	1.369
Nevada (dummy)	−0.043 (0.273)	0.958	0.958	0.955
New Hampshire (dummy)	0.340 (0.172)*	1.404	1.405	1.428
New Jersey (dummy)	1.413 (0.136)***	4.110	4.112	4.411
New Mexico (dummy)	−0.063 (0.165)	0.938	0.938	0.936
New York (dummy)	−0.010 (0.163)	0.990	0.990	0.990
North Carolina (dummy)	0.511 (0.100)***	1.667	1.668	1.711
North Dakota (dummy)	−0.152 (0.162)	0.859	0.859	0.852
Ohio (dummy)	0.425 (0.100)***	1.530	1.530	1.563
Oklahoma (dummy)	0.232 (0.096)*	1.260	1.261	1.275
Oregon (dummy)	0.943 (0.368)*	2.568	2.567	2.691
Pennsylvania (dummy)	0.451 (0.119)***	1.569	1.570	1.605
Rhode Island (dummy)	1.390 (0.161)***	4.015	4.018	4.305
South Carolina (dummy)	0.288 (0.091)**	1.334	1.334	1.353
South Dakota (dummy)	0.007 (0.150)	1.007	1.007	1.007
Tennessee (dummy)	0.679 (0.074)***	1.973	1.973	2.041
Texas (dummy)	0.061 (0.110)	1.063	1.063	1.067
Utah (dummy)	0.940 (0.239)***	2.560	2.561	2.683
Vermont (dummy)	0.073 (0.155)	1.076	1.076	1.080
Virginia (dummy)	0.428 (0.102)***	1.534	1.535	1.568

Table B.7: ***SAR model*** (3.14) *with state fixed effects*

Loglinear functional form, year 2007

	Coefficient estimate	**Coefficient - exponent**	**Direct[a] impacts**	**Total[a] impacts**
Washington (dummy)	1.126 (0.359)**	3.084	3.086	3.263
West Virginia (dummy)	0.045 (0.105)	1.046	1.046	1.048
Wisconsin (dummy)	0.420 (0.124)***	1.522	1.522	1.554
Wyoming (dummy)	0.438 (0.179)*	1.550	1.550	1.584

Notes: •p<0.1; *p<0.05; **p<0.01; ***p<0.001, Spatial HAC standard errors in brackets,
The base category of the state level dummy variables is Alabama
[a] e to the power of the impact measures

Table B.8: ***Descriptive statistics***, *Geoeconomic variables, year* 1900

Number of observations: 2600

Variable:	**Units**	$\bar{x}$[a]	$\hat{s}(x)$[b]	**Min**	**Max**
Sea level rise - coastal[c]	mm/year	1.567	2.008	−1.625	8.675
Lake level rise - Great Lakes[d]	mm/year	−12.470	9.456	−19.310	4.979
Agricultural land value	dollars per acre	20.960	19.698	1.000	221.000
Agricultural land value	log, dollars per acre	2.636	0.951	0.000	5.398
Monthly wages to a farm hand	log, dollars	2.673	0.237	2.273	3.761
X centroid coordinate	decimal degrees	−90.860	10.978	−124.160	−67.640
Y centroid coordinate	decimal degrees	38.430	4.634	26.340	48.830
Coast distance	km	372.800	293.150	0.892	1309.000
Length of coast[c]	km	286.350	374.258	0.000[e]	2471.100
Brackish or tidal (dummy)[c]	0/1	0.327	—	—	—
Groundwater depletion[f]	l/ha/day	1.822	10.614	0.000	91.260
Land in farms	thousands of acres	295.067	184.609	1.900	2158.547

[a] $\bar{x}$ indicates the sample mean
[b] $\hat{s}(x)$ indicates the sample standard deviation
[c] Descriptive statistics of the subsample of 254 coastal counties as the value is zero for the all inland counties
[d] Descriptive statistics of the subsample of 90 counties on the coast of the Great Lakes as the value of this variable is zero for the other counties
[e] The subsample of the coastal counties includes two counties which are not directly on coast but they are very close to it and they are located on shore of a brackish lake or river. The length of coast of these two counties is therefore zero
[f] To the best of our knowledge, estimates of groundwater depletion or groundwater withdrawals for year 1900 or before are not available. Nevertheless, Konikow (2013) provides estimates of the groundwater depletion rate for some more recent historical periods, thus I use the Konikow (2013) estimates for the period 1900-1950.

Table B.9: ***Descriptive statistics***, *Soil characteristics, year* 1978

Number of observations: 2600

Variable:	**Units**	$\bar{x}$[a]	$\hat{s}(x)$[b]	**Min**	**Max**
Salinity problems	% of farmland	0.098	0.167	0.000	1.000
Prone to flooding	% of farmland	0.110	0.173	0.000	1.000
Wet factor (low drainage)	% of farmland	0.108	0.178	0.000	1.000
K-factor (erodibility-soil loss)	tons/hectare	0.305	0.069	0.100	0.550
Average slope length factor	meters	205.500	153.903	15.000	1620.200
Sand or coarse-textured soils	% of farmland	0.095	0.223	0.000	1.000
Clay	% of farmland	0.057	0.156	0.000	1.000
Moisture level	cm/cm^3	0.150	0.042	0.030	0.273
Permeability	cm/hour	1.215	1.275	0.000	20.000

[a] $\bar{x}$ indicates the sample mean
[b] $\hat{s}(x)$ indicates the sample standard deviation

Table B.10: ***SAR model*** (3.14) - *Loglinear functional form, year* 1900

	Coefficient estimate	Coefficient - exponent	Direct[a] impacts	Total[a] impacts
ρ (SAR)	0.447 (0.031)***	1.563	—	—
Constant	0.597 (0.298) *	1.817	—	—
Sea level rise (mm/year)	**0.053 (0.051)**	**1.055**	**1.057**	**1.102**
Sea level rise (mm/year) - squared	**−0.011 (0.006)•**	**0.989**	**0.989**	**0.981**
Lake level rise (mm/year) - Great Lakes	**−0.015 (0.004)*** **	**0.985**	**0.984**	**0.972**
	Geoeconomic characteristics			
Wages to a farm hand (dollars, log)	0.042 (0.130)	1.043	1.045	1.079
X coordinate	0.010 (0.004)**	1.010	1.011	1.018
Y coordinate	0.031 (0.005)***	1.031	1.033	1.058
Coast distance (thousands km)	−0.583 (0.088)***	0.558	0.543	0.344
Length of coast (thousands km)	0.341 (0.148)*	1.406	1.429	1.865
Brackish or tidal (dummy)	0.020 (0.087)	1.020	1.021	1.038
Groundwater depletion (l/ha/day)	0.004 (0.002)**	1.004	1.005	1.008
Land in farms (millions acres)	−0.418 (0.084)***	0.658	0.645	0.465
	Soil characteristics			
Salinity problems (% of farmland)	−0.055 (0.098)	0.946	0.944	0.904
Prone to flooding (% of farmland)	−0.235 (0.071)***	0.790	0.782	0.650
Wet factor (% of farmland)	0.151 (0.097)	1.163	1.171	1.318
K-factor - average erodability (soil loss, tons/hectare)	−0.601 (0.350)•	0.548	0.533	0.333
Slope length (km)	0.293 (0.104)**	1.340	1.359	1.709
Sand (% of farmland)	−0.119 (0.118)	0.888	0.883	0.804
Clay (% of farmland)	0.392 (0.112)***	1.481	1.508	2.050
Moisture level (cm/cm^3)	6.012 (0.709)***	408.243	542.791	59,648.293
Permeability (cm/hour)	0.013 (0.028)	1.013	1.014	1.024

Notes: •p<0.1; *p<0.05; **p<0.01; ***p<0.001, Spatial HAC standard errors in brackets
[a] e to the power of the impact measures

Table B.11: ***SAR model*** (3.14) - *Subsample of coastal counties*

Loglinear functional form, year 2007

	Coefficient estimate	**Coefficient - exponent**	**Direct[a] impacts**	**Total[a] impacts**
ρ (SAR)	0.032 (0.026)	1.032	—	—
Constant	−8.395 (1.781)***	0.0002	—	—
Sea level rise (mm/yr)	**0.154 (0.067)***	**1.166**	**1.166**	**1.172**
Sea level rise (mm/yr) - squared	**−0.016 (0.006)****	**0.984**	**0.984**	**0.983**
Lake level rise (mm/yr) - Great Lakes	**0.013 (0.017)**	**1.013**	**1.013**	**1.013**
	Geoeconomic characteristics			
Per capita income (dollars/yr, log)	1.405 (0.165)***	4.076	4.078	4.267
X coordinate	−0.005 (0.003)	0.995	0.995	0.995
Y coordinate	0.032 (0.012)**	1.033	1.033	1.034
Length of coast (thousands km)	−2.384 (0.841)**	0.092	0.092	0.085
Brackish or tidal (dummy)	−0.020 (0.092)	0.980	0.980	0.980
Groundwater withdrawals (l/ha/day)	0.155 (0.029)***	1.168	1.168	1.174
Land in farms (millions acres)	−0.461 (0.213)*	0.631	0.631	0.621
	Soil characteristics			
Salinity problems (% of farmland)	0.339 (0.251)	1.403	1.403	1.418
Prone to flooding (% of farmland)	0.088 (0.331)	1.092	1.092	1.095
Wet factor (% of farmland)	0.061 (0.132)	1.063	1.063	1.065
K-factor - average erodability (soil loss, tons/hectare)	1.824 (0.848)*	6.197	6.201	6.577
Slope length (km)	−0.079 (0.216)	0.924	0.924	0.921
Sand (% of farmland)	−0.079 (0.231)	0.924	0.924	0.921
Clay (% of farmland)	−1.138 (0.246)***	0.320	0.320	0.309
Moisture level (cm/cm^3)	−2.685 (1.314)*	0.068	0.068	0.062
Permeability (cm/hour)	0.016 (0.026)	1.017	1.017	1.017

Notes: •p<0.1; *p<0.05; **p<0.01; ***p<0.001, Spatial HAC standard errors in brackets

[a] e to the power of the impact measures

Table B.12: ***SAR model*** (3.14) - *Comparison of Triangular and Epanechnikov kernel*

Loglinear functional form, year 2007

		SHAC[a] Standard errors	
	Coefficient estimate	**Triangular Kernel**	**Epanechnikov Kernel**
ρ (SAR)	0.062	0.011^{***}	0.011^{***}
Constant	0.085	0.703	0.780
Sea level rise (mm/year)	**0.081**	**0.049**$^{\bullet}$	**0.054**
Sea level rise (mm/yr) - squared	**−0.017**	**0.006****	**0.006****
Lake level rise (mm/yr) - Great Lakes	**0.017**	**0.008***	**0.008***
Geoeconomic characteristics			
Per capita income (dollars/yr, log)	0.805	0.068^{***}	0.075^{***}
X coordinate	0.004	$0.002^{\bullet}$	0.003
Y coordinate	−0.004	0.005	0.005
Coast distance (thousands km)	−1.117	0.082^{***}	0.094^{***}
Length of coast (thousands km)	0.021	0.876	0.938
Brackish or tidal (dummy)	0.161	0.104	0.112
Groundwater withdrawals (l/ha/day)	0.075	0.012^{***}	0.014^{***}
Land in farms (millions acres)	−0.671	0.071^{***}	0.078^{***}
Soil characteristics			
Salinity problems (% of farmland)	−0.028	0.095	0.105
Prone to flooding (% of farmland)	0.120	$0.072^{\bullet}$	0.080
Wet factor (% of farmland)	0.047	0.072	0.081
K-factor - average erodability (soil loss, tons/hectare)	−0.187	0.295	0.332
Slope length (km)	0.052	0.084	0.086
Sand (% of farmland)	−0.619	0.108^{***}	0.120^{***}
Clay (% of farmland)	−0.375	0.087^{***}	0.099^{***}
Moisture level (cm/cm^3)	0.220	0.530	0.601
Permeability (cm/hour)	0.076	0.018^{***}	0.019^{***}

Notes: $^{\bullet}p<0.1$; $^{*}p<0.05$; $^{**}p<0.01$; $^{***}p<0.001$
[a]Spatial heteroscedasticity and autocorrelation consistent standard errors

Table B.13: ***SAR model*** (3.14) - *Globally standardised contiguity matrix*

Loglinear functional form, year 2007

	Coefficient estimate	**Coefficient - exponent**	**Direct[a] impacts**	**Total[a] impacts**
ρ (SAR)	0.021 (0.006)***	1.022	—	—
Constant	0.205 (0.724)	1.228	—	—
Sea level rise (mm/yr)	**0.073 (0.050)**	**1.076**	**1.076**	**1.077**
Sea level rise (mm/yr)- squared	**−0.017 (0.006)****	**0.983**	**0.983**	**0.983**
Lake level rise (mm/yr) - Great Lakes	**0.018 (0.008)***	**1.018**	**1.018**	**1.018**
	Geoeconomic characteristics			
Per capita income (dollars/yr, log)	0.829 (0.070)***	2.292	2.292	2.334
X coordinate	0.005 (0.002)$^{\bullet}$	1.005	1.005	1.005
Y coordinate	−0.004 (0.005)	0.996	0.996	0.996
Coast distance (thousands km)	−1.171 (0.084)***	0.310	0.310	0.302
Length of coast (thousands km)	−0.097 (0.906)	0.908	0.907	0.905
Brackish or tidal (dummy)	0.191 (0.106)$^{\bullet}$	1.210	1.210	1.215
Groundwater withdrawals (l/ha/day)	0.077 (0.013)***	1.080	1.080	1.082
Land in farms (millions acres)	−0.682 (0.073)***	0.505	0.505	0.498
	Soil characteristics			
Salinity problems (% of farmland)	−0.030 (0.098)	0.970	0.970	0.969
Prone to flooding (% of farmland)	0.130 (0.074)$^{\bullet}$	1.139	1.139	1.142
Wet factor (% of farmland)	0.042 (0.075)	1.043	1.043	1.044
K-factor - average erodability (soil loss, tons/hectare)	−0.188 (0.306)	0.829	0.829	0.825
Slope length (km)	0.046 (0.087)	1.048	1.048	1.049
Sand (% of farmland)	−0.631 (0.112)***	0.532	0.532	0.525
Clay (% of farmland)	−0.381 (0.091)***	0.683	0.683	0.677
Moisture level (cm/cm^3)	0.334 (0.548)	1.396	1.396	1.406
Permeability (cm/hour)	0.078 (0.019)***	1.081	1.081	1.083

Notes: $^{\bullet}$p<0.1; *p<0.05; **p<0.01; ***p<0.001, Spatial HAC standard errors in brackets

[a] e to the power of the impact measures

Appendix C

Appendix to Chapter 4

C.1 Climate knowledge - OCSI instrument

Below are the questions of the Ordinary Climate-Science Intelligence Assessment (OCSI) developed by Kahan (2015) which we use as a measure of climate knowledge. The questions are true or false statements. The correct answers are in bold.

1. Climate scientists believe that if the North Pole icecap melted as a result of human-caused global warming, global sea levels would rise. **FALSE**

2. Climate scientists have concluded that globally averaged surface air temperatures were higher for the first decade of the twenty-first century (2000-2009) than for the last decade of the twentieth century (1990-1999). **TRUE**

3. Climate scientists believe that human-caused global warming will result in flooding of many coastal regions. **TRUE**

4. Climate scientists believe that human-caused global warming has increased the number and severity of hurricanes around the world in recent decades. **FALSE**

5. Climate scientists believe that nuclear power generation contributes to global warming. **FALSE**

6. Climate scientists believe that human-caused global warming will increase the risk of skin cancer in human beings. **FALSE**

7. Climate scientists and economists predict there will be positive as well as negative effects from human-caused global warming. **TRUE**

8. Climate scientists believe that the increase of atmospheric carbon dioxide associated with the burning of fossil fuels will reduce photosynthesis by plants. **FALSE**

C.2 Climate knowledge and gender

As discussed in Section 4.4.1, we detect a strong evidence that our measure of climate knowledge is significantly higher for men than for women. We find this outcome merits further investigation.

We hypothesise that less educated men can have higher drop out rates from the survey than more educated men or less educated women. In other words, we believe that it can be more likely for men to abandon the whole survey if they find a series of questions to be too difficult to respond while women answer giving their best guess even if they are uncertain and continue with the survey. This could be caused by different opportunity costs, effect of pride or by males perceiving higher pressure to answer scientific questions correctly. If this is the case, our sample of complete cases will exhibit a selection bias as the ratio of less educated women will be bigger for the subsample of complete cases.

To test for presence of the selection bias, we perform a series of following proportion tests. For each category of education (and also for the whole sample) we test whether the proportion of males in the subsamle of complete observations (used observations) is approximately equal to the proportion of males in the subsample of dropped observations. The p-values of the corresponding Pearson's chi-square test statistics of the null hypothesis that the proportions are equal are summarised in Table C.1.

If the selection bias occurs, we would expect for the lower education categories the proportion of males to be significantly higher among the dropped observations than among the used observations. For the higher categories of education, on the other hand, we would expect the proportion of males to be significantly smaller among the dropped observation than among the used observations. However, this is not what we can see in Table C.1. Although the proportion tests are significant for some GCSE, GCSE and professional, the differences in proportions are opposite to what we would expect. For the lower categories of education (Some GCSE and GCSE) the proportion of males is smaller among the dropped observations than among the used observations while it is the other way around for the category of professionals. Hence, based on the proportion tests, we do not see any evidence of the selection bias.[1]

Table C.1: ***Proportion tests - no selection bias:***

Differences between ratio of males in the group of used observations and in the group of dropped observations. The tests were conducted separately for each category of education.

Education category	**Proportion of males** Used observations	Dropped observations	$\tilde{\chi}^2$ p-value	
Total	0.4858	0.4538	0.0058	**
Craft	0.6173	0.6620	0.4671	
Some GCSE	0.4957	0.4105	0.0022	**
GCSE	0.4861	0.3792	0.0066	**
A levels	0.4859	0.4671	0.5383	
Diploma	0.4609	0.4172	0.2306	
Bachelors	0.4662	0.4294	0.2470	
Professional	0.4269	0.5391	0.0474	*
Masters	0.4829	0.4000	0.1240	
PhD	0.6522	0.5625	0.4889	
No answer	0.5435	0.4920	0.3355	

Notes: $^{\bullet}$ $p < 0.1$; * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$

[1] We performed analogous series of tests to compare proportions of males among the dropped observations with the proportions of males in the whole sample. Also these tests were performed separately for each category of education. The results are qualitatively equivalent to those of the tests in Table C.1. The only difference is that the test became marginally insignificant for the category professional but this has no effect on the conclusion.

To further eliminate occurrence of the selection bias, we include interactions of gender and the education categories for which the proportion tests are significant as explanatory variables (besides the predictors selected by the lasso) and we test their significance. For the sake of clearer interpretation, we also include the main effects of the education categories. The estimates of the model with the interactions are summarised in Table C.2. None of the interactions or education categories are significant and the signs and significance levels of male and gender are the same as without the interactions.[2]

Table C.2: ***Climate change knowledge:*** *Jackknife OLS With interactions of gender and education*

Variable	**Jackknife OLS** Aggregated coefficient	**Jackknife OLS** Aggregated adjusted p-value	
Gender = male	0.3379	$< 2.00 \times 10^{-8}$	***
Cognitive reflection = 0.5	1.1967	1.0000	
Cognitive reflection = 1	0.1195	0.4384	
Cognitive reflection = 1.5	0.6160	1.0000	
Cognitive reflection = 2	0.2664	0.0001	***
Cognitive reflection = 2.5	0.4405	1.0000	
Cognitive reflection = 3	0.4551	2.31×10^{-8}	***
Education - some GCSE	−0.0890	1.0000	
Education - GCSE	0.0033	1.0000	
Education - professional	−0.0219	1.0000	
Male × education - some GCSE	−0.0494	1.0000	
Male × education - GCSE	−0.0888	1.0000	
Male × education - professional	0.2377	1.0000	
Observations:	5749		

As an additional verification that our results can not be attributed to a selection we estimate a Heckman correction models for climate knowledge. In particular, we estimate models which are referred to as Tobit-2 in Toomet and Henningsen (2008). The exclusion restriction is count of not responded questions out of those which were prior to climate

[2]We also estimated a version of this model which includes a dummy variable for each education category. Adding these dummy variables does not chance signs or significance levels of gender, cognitive reflection or interactions between gender and education categories.

questions in the survey questionnaire.[3] The estimates are summarized in Tables C.3 and C.4. The model in Table C.3 has only one explanatory variable in the selection equation, namely count of non-responded questions. The variety in Table C.4 includes also gender, education categories for which the proportion test in Section 4.4.1 (Table C.1) is significant and their interactions. The outcome equations include the predictors which were selected by the multisplit lasso (see Section 4.4.1). We can see, that the male dummy variable is still positive and strongly significant in the outcome equations even if we correct for possible selection bias (see Tables C.3 and C.4). Parameter ρ is insignificant in the models in Tables C.3 and C.4. This means that the data are consistent with no correlation of the selection and outcome equation.

We can further see in Tables C.3 and C.4 that achieving score 2 or 3 in the cognitive reflection test has positive and significant impact on climate knowledge which is consistent with the model presented in Table 4.4 in Section 4.4.1 and with the specification in Table C.2. In addition, achieving score 1 is significant in the Heckman models and score of

[3] Count of previously not responded questions is not expected to affect climate knowledge. In spite of this, we estimated a variant of multisplit lasso with the count of previously not responded questions as a potential predictor to verify whether or not it should be in the climate knowledge equation according to our estimation method. As we expected, count of previously not responded questions was not selected.

0.5 is close to significant.[4]

Table C.3: ***Climate change knowledge:*** *Heckman selection model*

Variable	**Estimate**	***p*-value**	
Probit selection equation:			
Not responded questions (count)	−0.1972 (0.0083)	$< 2.00 \times 10^{-8}$	***
Outcome equation			
Gender = male	0.3304 (0.0304)	$< 2.00 \times 10^{-8}$	***
Cognitive reflection = 0.5	1.2188 (0.7202)	0.0906	•
Cognitive reflection = 1	0.1472 (0.0387)	0.0001	***
Cognitive reflection = 1.5	0.6092 (0.8821)	0.4898	
Cognitive reflection = 2	0.3026 (0.0448)	$< 2.00 \times 10^{-8}$	***
Cognitive reflection = 2.5	0.5158 (0.4163)	0.2153	
Cognitive reflection = 3	0.4790 (0.0559)	$< 2.00 \times 10^{-8}$	***
Error terms			
Sigma σ	1.2469 (0.0107)	$< 2.00 \times 10^{-8}$	***
Rho ρ	0.0611 (0.0659)	0.3540	
Observations:	7244		

Notes: • $p < 0.1$; * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$
Standard errors in brackets

[4] Besides the Heckman selection models presented in Tables C.3 and C.4, we also estimated a version which includes all education categories and their interactions with gender as explanatory variables in the selection equation. However, the estimation algorithm was unable to estimate the coefficients with reasonable standard errors.

Table C.4: ***Climate change knowledge:*** *Heckman selection model*
With interactions of gender and education

Variable	**Estimate**	***p*-value**	
Probit selection equation:[a]			
Gender = male	−0.0163 (0.0954)	0.8642	
Not responded questions (count)	−0.1983 (0.0084)	$< 2.00 \times 10^{-8}$	***
Education - some GCSE	−0.2250 (0.1213)	0.0637	•
Education - GCSE	0.0783 (0.1658)	0.6369	
Education - professional	−0.2696 (0.2379)	0.2570	
Male × education - some GCSE	0.2926 (0.1934)	0.1303	
Male × education - GCSE	−0.3454 (0.2571)	0.1790	
Male × education - professional	0.3659 (0.3468)	0.2914	
Outcome equation			
Gender = male	0.3307 (0.0304)	$< 2.00 \times 10^{-8}$	***
Cognitive reflection = 0.5	1.2199 (0.7202)	0.0903	•
Cognitive reflection = 1	0.1476 (0.0387)	0.0001	***
Cognitive reflection = 1.5	0.6102 (0.8821)	0.4891	
Cognitive reflection = 2	0.3032 (0.0448)	$< 2.00 \times 10^{-8}$	***
Cognitive reflection = 2.5	0.5168 (0.4163)	0.2144	
Cognitive reflection = 3	0.4796 (0.0559)	$< 2.00 \times 10^{-8}$	***
Error terms			
Sigma σ	1.2469 (0.0107)	$< 2.00 \times 10^{-8}$	***
Rho ρ	0.0737 (0.0661)	0.2640	
Observations:	7244		

Notes: • $p < 0.1$; * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$
Standard errors in brackets

a We also estimated a variety of this model which includes dummy variables for all education categories in the selection equation. They are all insignificant and the signs and significance levels of the other variables are the same.

In our effort to explain the significant effect of gender, we investigate the gender balance of a set of other variables. We apply the proportion tests described above for all response categories of the following variables: occupation, sector, time spent in the UK, age (which is only available as a categorical variable), social value orientation, number of children, number of grandchildren, handedness and operating system. For most of the response categories, the proportion of males and females is about the same in the group of dropped observations as the proportion of males and females in the group of used observations; the differences in proportions are mostly insignificant. The categories that are not balanced on gender are transport sector, age categories $55-64$ and $65-74$, operating system Windows, individualist and competitive social value orientation, having one or two children, not having any grandchildren and being left-handed. For each of these 'gender-unbalanced' categories we estimate a variant of the climate knowledge model that includes the interaction of gender and the unbalanced variable in question as an additional explanatory variable. In all these models, the estimates of the dummy variable for males and the cognitive reflection test are qualitatively the same as their estimates in the main specification presented in Table 4.4. In particular, the dummy variable for males is positive and significant in all these models.

Additionally, we estimate a group of models that, besides gender and cognitive reflection, also include the interaction of gender and one of the following continuous measures among the predictors: population density, discount rate, income and net assets. The estimates are not significantly different from those obtained from the main specification (see Table 4.4). The dummy variable for males is always positive and significant. We can conclude that we do not find any evidence of selection bias. We do not present the estimates of all models discussed here to keep the length of this thesis within reasonable limits.

We take one additional step to verify whether a selection bias occurs. This step involves estimation of a battery of Heckman selection models that are analogous to the model presented in Table C.3. Besides the explanatory variables listed in Table C.3, each of the newly estimated Heckman models includes one of the variables listed in Table C.5 as a predictor in the selection equation. If the significant effect of gender is a result of a selection on one of these variables, we would expect that the significance level of gender would change. However, the significance level of the dummy variable for males does not change in any of the Heckman correction models; its sign is always the same too. The estimates of the dummy variable for males from these models are summarized in Table C.5.

Table C.5: **Heckman selection models**

Testing for possible selection on various predictors

Model	Selection variable	**Estimate of gender, 1 = male** (output eq.)
1.	Occupation	0.3305 (0.0304)***
2.	Sector	0.3307 (0.0304)***
3.	Time in UK[a]	0.3306 (0.0304)***
5.	People per mill. km^2	0.3306 (0.0304)***
6.	Income - predicted	0.3306 (0.0304)***
7.	Social value orientation	0.3307 (0.0304)***
8.	Inequity aversion	0.3301 (0.0304)***
9.	Number of children	0.3305 (0.0304)***
10.	Number of grandchildren	0.3306 (0.0304)***
11.	Discount rate yr. from now	0.3305 (0.0304)***
12.	Prime - image shown[b]	0.3306 (0.0304)***
13.	Handedness	0.3306 (0.0304)***
14.	Operating system	0.3306 (0.0304)***
15.	Age × Number of children	0.3306 (0.0304)***

Notes: $^{\bullet}$ $p < 0.1$; * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$
Standard errors in brackets
[a] For how long had the respondent been living in the UK
[b] 0= shown picture of polar bear (negative), 1=shown picture of beach (positive)

We can conclude that we did not find any evidence suggesting that the significant effect of the dummy variable for males is due to a selection bias or due to confounding with other factors. There are some previous studies that suggest that women and men can have different approaches towards climate science or science in general. According to Arcury et al. (1986, 1987), Gendall et al. (1995) and Tikka et al. (2000), men demonstrate significantly higher level of environmental knowledge than women. Hayes (2001) find that men show higher level of scientific knowledge than women based on nationally representative survey data from the United States, Great Britain, Norway, the Netherlands, Germany and Japan. Mostafa (2007) argues that women appear to be less aware about environmental issues than men. Other studies have focused on gender differences in knowledge acquisition and interest in science among high-school students. For example, Evans et al. (2002) find that boys are likely to score higher on general information and math tests than girls and Miller et al. (2006) suggest that girls are significantly less interested in science than boys.

C.3 Tables

Table C.6: *List of considered (but not selected) predictors in multisplit lasso*

Variable	**Description**
Religion	11 categories including atheist, no religion and prefer not to say
Race	8 categories including prefer not to answer
Length in UK	Question: *How long have you been living in the UK?* Response = 5 categories: All life ,more than 10 years, $5-10$ years, $1-5$ years, less than 1 year
Occupation	14 categories
Sector	18 categories
Operating system	7 categories
Social value orientation	Response = 4 categories: altruist, prosocial, individualist, competitive
Discount rate 0 vs. 5	Annual, %, invest now for five years from now
Discount rate 1 vs. 2	Annual, %, invest a year from now for two years from now
Discount rate 1 vs. 6	Annual, %, invest a year from now for six years from now
Degree of present bias	Continuous, preferences on time
Degree of hyperbolicity	Continuous, preferences on time
Annual discount rate	Continuous, preferences on time
Subsistence income (reserve)	Continuous, Bergson (1954, 1938); Samuelson (1956)
Altruist	Dummy (0/1)
Prosocial	Dummy (0/1)
Individualist	Dummy (0/1)
Competitive	Dummy (0/1)
Egalitarian	Dummy (0/1)
Ineqaverse	Dummy (0/1)
Longitude	Longitude of survey response. Degrees
Latitude	Latitude of survey response. Degrees
Letter	First letter of surname, A=1,B=2,...
Siblings	Number of siblings
Older	Number of older siblings
Children	Number of children
Grandchildren	Number of grandchildren

Notes: Variables in this table were not selected by multisplit lasso into any model

(*continued*)

Table C.7: *List of considered (but not selected) predictors in multisplit lasso*

Variable	**Description**
Handedness	0=right, 1=left
Time	Time taken to complete survey, in minutes
Hour	Hour of survey, 24 categories
Day of week	7 categories
Day of the month	Day of survey, $1-31$
Fair share	*Ordinary working people do not get their fair share of the nation's wealth.* Degree of agreement with the statement above, 5 categories
Hard work	Question: *How important is hard work for getting ahead in life?* Response = 5 categories, degree of agreement
Better off parents	Question: *Compared with your parents when they were about your age, are you better or worse in your income and standard of living generally?* Response = 5 categories (degree of agreement) and *Don't know*
Better off children	Q: *Compared with you, do you think that your children, when they reach your age, will be better or worse in their income and standard of living generally?* Answer =5 categories (degree of agreement) and *Don't know*
Always up	Dummy (0/1), Children better off me and me better off parents
Always down	Dummy (0/1), Parents better off me and me better off children
Up then down	Dummy (0/1), Me better off parents and me better off children
Down then up	Dummy (0/1), Parents better off me and children better off me
Financial literacy	3 financial problems, no. of correct answers, Lusardi and Mitchell (2014)
Understands portfolio	Dummy (0/1), 1 = understands
Incoherent dr.	Dummy (0/1), Incoherent answers between investments (0 = coherent)
Primed attitudes	1 = priming questions about time, risk, social were asked, 0 = not
Prime climate	0 = shown picture of polar bear on melting ice (negative), 1 = shown picture of people enjoying beach (positive)
Prime pension	0 = picture of troubled old man, 1 = picture of happy old man
Prime school	0 = picture of unruly kids, 1 = picture of well-behaved kids
Prime nhs	0 = picture NHS in crisis, 1 = picture love NHS
Female × handed	Interaction female and handedness
Female × children	Interaction female and number of children
Age × children	Interaction age and number of children

Notes:

c Degree of agreement with the following statement: 'Government should redistribute income from the better off to those who are less well off.' The base category is Neutral = 0.

Table C.8: ***Descriptive statistics:*** *Continuous variables*

Variable:	**Mean**	**St. dev.**	**Min**	**Max**
Income - predicted (£ per year)	27729	11719.89	3611	58326
Net assets - total assets minus total debts (£)	152542	223612.90	−400000	2500000
Population (per Km^2, LSOA[a] level)	3336	2975.38	7	25280
Population (per Km^2, LAD[b] level)	3193	3164.75	10	13870
How much is tax gas and electricity (£/yr.)	144.90	111.94	−50	500
How much is duty transport fuel (pence/yr.)	25.18	13.68	0	60
Behavioural variables				
Social value orientation (ring measure)	26.28	15.52	−16.26	83.93
Annual discount rate,%, invest now for a year from now[c]	148.7	181.81	1	500
Risk aversion - estimated median of quadratic utility function	0.33	0.01	0.29	0.38
Risk aversion - estimated median of log utility function	1.81	1.08	0.67	4.33
Risk aversion - estimated median of power utility function	0.42	0.07	0.33	0.57
Risk aversion - estimated mean of power utility function	0.74	0.26	0.33	1.07

Notes: Total number of observations: 8541

a Lower Layer Super Output Area

b Local Authority District

c This variable is called *Discount rate year from now* in the tables with regression estimates

Table C.9: ***Frequency tables:*** *Categorical variables*

Variable	**Category**	**Frequency**	**Ratio**
Education	Craft	338	0.040
	Some GCSE	1452	0.170
	GCSE A*-C grades	814	0.095
	A Level	1579	0.185
	Diploma	979	0.115
	Bachelor's degree	1523	0.178
	Professional qualifications	457	0.054
	Master's degree	564	0.066
	PhD, DPhil	124	0.015
	Prefer not to say	434	0.051
	NA	277	0.032
Household income	< 11000	919	0.158
pounds per year	$11000 - 16000$	675	0.116
before tax	$16000 - 20000$	539	0.093
self reported	$20000 - 26000$	757	0.130
	$26000 - 32000$	610	0.105
	$32000 - 39000$	666	0.115
	$39000 - 48000$	522	0.090
	$48000 - 60000$	544	0.094
	$60000 - 81000$	324	0.056
	$81000 - 100000$	119	0.021
	> 100000	128	0.022

Notes: Total number of observations: 8541

(*continued*)

Table C.10: ***Frequency tables:*** *Categorical variables*

Variable	**Category**	**Frequency**	**Ratio**
Inequity aversion	0.520	1557	0.182
(rate)	0.950	55	0.006
Bergson (1954, 1938),	1.000	652	0.076
Samuelson (1956)	1.135	127	0.015
	1.160	364	0.043
	1.255	202	0.024
	1.290	130	0.015
	1.485	385	0.045
	1.490	288	0.034
	1.500	96	0.011
	1.510	86	0.010
	1.685	202	0.024
	1.765	93	0.011
	2.120	226	0.026
	3.640	59	0.007
	3.710	2551	0.299
	NA	1468	0.172
Degree of agreement	Strongly disagree	555	0.065
with the statement:	Disagree	1121	0.131
Government should redistribute	Neutral	1952	0.229
income from the better off	Agree	2256	0.264
to those who are less well off.	Strongly agree	1206	0.141
	NA	1451	0.170
Cognitive reflection test[a]	0.0	4145	0.485
= numeracy, Frederick (2005)	0.5	3	0.0004
3 numerical problems	1.0	1519	0.178
no. of correct answers	1.5	2	0.0002
	2.0	1017	0.119
	2.5	9	0.001
	3.0	614	0.072
	NA	1232	0.144
Understands compound interest	0.0	291	0.034
1 = Understands	0.5	718	0.084
(treated as categorical)	1.0	5713	0.669
	NA	1819	0.213
Understands inflation	0.0	941	0.110
1 = Understands	0.5	953	0.112
(treated as categorical)	1.0	4206	0.492
	NA	2441	0.286

Notes: **a** This variable is called *Cognitive reflection* in the tables with regression estimates and it is treated as categorical 8541 observations

Table C.11: ***Frequency tables:*** *Binary variables*

Variable	**Frequency = 1**	**Ratio = 1**	**NA's**
Gender = male	4060	0.475	0
Equal intergenerational allocation of resources (agree = 1)[a]	793	0.110	1339
Consistent answers to risk questions (consistent = 1)	7153	0.837	0
Consist. answers within investment (consistent = 1)	981	0.115	0

Notes: Total number of observations: 8541

a This variable is equal to 1 for those respondents who believe that their income and standard of living generally is about equal to the income and standard of living of their parents (when they were about the respondent's age) and it is also equal to the income and standard of living of their children (when they will reach the respondent's age). The variable is equal to 0 for all other respondents.

Table C.12: ***Climate knowledge:*** *Jackknife OLS with total score on financial literacy*

Variable	**Aggregated coefficient**	**Aggregated adj. *p*-value**		**Aggregated VIF**
Gender = male	1.580	$< 2 \times 10^{-8}$	***	1.030
Cognitive reflection = 0.5	4.611	1.000		1.002
Cognitive reflection = 1	0.431	1.000		1.156
Cognitive reflection = 1.5	1.681	1.000		1.002
Cognitive reflection = 2	1.074	0.006	**	1.212
Cognitive reflection = 2.5	1.881	1.000		1.006
Cognitive reflection = 3	1.999	9×10^{-7}	***	1.171
Financial literacy - total score = 0.5	1.173	1.000		1.504
Financial literacy - total score = 1	0.456	1.000		3.972
Financial literacy - total score = 1.5	0.527	1.000		2.586
Financial literacy - total score = 2	0.454	1.000		5.644
Financial literacy - total score = 2.5	0.802	1.000		2.435
Financial literacy - total score = 3	1.433	0.150		6.925
Observations:		5749		

Notes: • $p < 0.1$; * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$

For the significant predictors, the signs of the coefficients of the multisplit lasso are the same as those of the jackknife OLS and also size of most of the coefficients is very comparable for these two models.

Table C.13: *Climate seriousness and climate versus policy effects perception: Jackknife OLS without climate knowledge*

	Seriousness		**Climate vs. policy**	
Variable	**Aggreg. coef.**	**Aggreg. adjusted *p*-value**	**Aggreg. coef.**	**Aggreg. adjusted *p*-value**
Gender = male	−0.481	$< 2 \times 10^{-8}$ ***	*Not included*	
Redistribution of income: disagree[a]	0.201	1.000	*Not included*	
Redistribution of inc.: neutral[a]	0.331	0.265	*Not included*	
Redistribution of income: agree[a]	0.891	$< 2 \times 10^{-8}$ ***	*Not included*	
Redistribution of income: strongly agree[a]	1.172	$< 2 \times 10^{-8}$ ***	*Not included*	
Understands inflation = 0.5	*Not included*		−0.049	1.000
Understands inflation = 1	*Not included*		−0.643	2×10^{-7} ***
Consistent answers to risk questions (0/1)	*Not included*		−0.592	$< 2 \times 10^{-8}$ ***
Observations:	5749		5749	

Notes: • $p < 0.1$; * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$

a Degree of agreement with the following statement: 'Government should redistribute income from the better off to those who are less well off.' The base category is 'Strongly disagree'.

Table C.14: ***WTP climate:*** *interaction of cultural world-view and financial literacy*

	Jackknife OLS		
Dependent variable: WTP - gas and electricity tax (£ per year)	**Aggregated coefficient**	**Aggregated adj. *p*-value**	
Age[a] 25 – 34	−11.3886	1.0000	
Age 35 – 44	−27.1860	4×10^{-5}	***
Age 45 – 54	−34.3795	2×10^{-8}	***
Age 55 – 64	−37.5114	$< 2 \times 10^{-8}$	***
Age 65 – 74	−45.2613	$< 2 \times 10^{-8}$	***
Age 74 or older	−28.8122	1.0000	
Climate versus policy effects perception	10.2983	$< 2 \times 10^{-8}$	***
Inequity aversion (categorical)[b]	*negative correlation*		**
Equal intergenerational allocation of resources (0/1)[c]	21.8916	0.0034	*
Understands compound interest = 0.5	−4.3717	1.0000	
Understands compound interest = 1	−41.6926	5×10^{-5}	***
Understands inflation = 0.5	−17.6328	0.1616	
Understands inflation = 1	−46.0609	$< 2 \times 10^{-8}$	***
Consistent answers to risk questions (0/1)	−35.4773	$< 2 \times 10^{-8}$	***
Redistribution of income (degree of agreement)[d, e]	−9.6596	0.0670	•
Redistribution of income[d] × Understands inflation	13.7064	0.0043	**
Observations:	5749		

Notes: • $p < 0.1$; * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$; mean adj. R^2: 0.279

a Age is only available as categorical. The base category is '24 or younger'.

b Inequity aversion treated as categorical (see Section 4.3.2).

c This variable is equal to 1 for those respondents who believe that their income and standard of living generally is about equal to the income and standard of living of their parents (when they were about the respondent's age) and it is also equal to the income and standard of living of their children (when they will reach the respondent's age). The variable is equal to 0 for all other respondents.

d Degree of agreement with the following statement: 'Government should redistribute income from the better off to those who are less well off.' −2 = Strongly disagree, 2 = Strongly agree.

e For the sake of simplicity we also included the main effect.

Table C.15: ***Climate vs. policy perception:*** *Jackknife OLS - robustness without WTP*

Variable	**Model 1** Aggreg. coef.	**Model 1** Aggreg. adjusted p-value	**Model 2** Aggreg. coef.	**Model 2** Aggreg. adjusted p-value
Climate knowledge[a]	-0.130	9×10^{-5} ***	-0.131	0.0002 ***
Understands inflation = 0.5	0.043	1.000	0.021	1.000
Understands inflation = 1	-0.450	0.001 **	-0.455	0.001 **
Consistent answers to risk questions (0/1)	-0.496	3×10^{-7} ***	-0.482	1×10^{-6} ***
Income- predicted (mill. £ /yr.)	3.347	1.000	*Not included*	
Income- reported (mill. £ /yr.)[b]	*Not included*		*varies*	1.000
Net assets (million £)	-0.014	1.000	0.076	1.000
People per mill. km^2-LSOA level	-15.303	1.000	*Not included*	
People per mill. km^2-LAD level	*Not included*		20.682	1.000
Climate seriousness perception	0.427	$<2 \times 10^{-8}$ ***	0.432	$<2 \times 10^{-8}$ ***
Social value orientation (ring measure)	0.006	0.250	0.006	0.555
Inequity aversion (categorical)	*varies*	1.000	*varies*	1.000
Discount rate yr. from now	-0.002	1.000	-0.001	1.000
Discount rate yr. from now - sq.	3×10^{-6}	1.000	3×10^{-6}	1.000
Risk aversion coefficient[c]	*Not included*		-0.569	1.000
Redistribution of income (categ.)[d]	+,*varies*	1.000	+,*varies*	1.000
Mean adjusted R^2:	0.226		0.230	
Observations:	5749		5659	

Notes: $^{\bullet}$ $p < 0.1$; * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$

a Squared term of climate knowledge is insignificant in this version, hence it is not included.

b Self reported income is only available as categorical.

c The risk aversion coefficient is an estimated parameter of a utility function. In this model, the mean of power function is used. We also estimated varieties of this model with different risk aversion coefficients, particularly means or medians of various utility functions. These are power, log, exponential and quadratic. The risk aversion parameter is always insignificant and whether it is included or not (or which one) does not affect sign or significance level of any other parameter.

d A degree of agreement with the statement: 'Government should redistribute income from the better off to those who are less well off.' Included to test for significance of political opinions.

C.4 Survey

Sussex survey on attitudes and government policy

Introduction
In this survey, we will ask some questions about you, and how you view things. We will also ask you what you think about UK policies on health, education, pensions, or climate.

By answering these questions, you will help researchers at the University of Sussex to understand what people know and think about public policy and its various domains.

This survey will take 25-30 minutes.

Sensitive questions have “prefer not to answer” option. By clicking “next”, you assent to taking this survey. Your responses will be kept confidential.

About you: sex and age
*Q1 Are you**
( ) male

( ) female

( ) other

( ) prefer not to say

Hidden Value: school

Value: populates with a randomly generated number between 0 and 1

Validation: Must be numeric

Logic: Show/hide trigger exists.

*Q2 How old are you?**
( ) 24 or younger

( ) 25-34

( ) 35-44

( ) 45-54

( ) 55-64

( ) 65-74

( ) 75 or older

Hidden Value: svo

Value: populates with a randomly generated number between 1 and 8

*Q3 Are you**
( ) left-handed

( ) right-handed

Hidden Value: domain

Value: populates with a randomly generated number between 1 and 6

*Q4 What is the first letter of your surname?**

( ) A

( ) B

( ) C

( ) D

( ) E

( ) F

( ) G

( ) H

( ) I

( ) J

( ) K

( ) L

( ) M

( ) N

( ) O

( ) P

( ) Q

( ) R

( ) S

( ) T

( ) U

( ) V

( ) W

( ) X

( ) Y

( ) Z

Hidden Value: s-age

Value: Populates with the **length of time** since the survey taker started the current page

---

About you: birthday and family when growing up

*Q5 In what month were you born?**

( ) January

( ) February

( ) March

( ) April

( ) May

( ) June

( ) July

( ) August

( ) September

( ) October

( ) November

( ) December

Hidden Value: env

Value: populates with a randomly generated number between 0 and 1

*Q6 On what day in the month were you born?**

( ) 1

( ) 2

( ) 3

( ) 4

( ) 5

( ) 6

( ) 7

( ) 8

( ) 9

( ) 10

( ) 11

( ) 12

( ) 13

( ) 14

( ) 15

( ) 16

( ) 17

( ) 18

( ) 19

( ) 20

( ) 21

( ) 22

( ) 23

( ) 24

( ) 25

( ) 26

( ) 27

( ) 28

( ) 29

( ) 30

( ) 31

Hidden Value: nhs

Value: populates with a randomly generated number between 0 and 1

Validation: Min = 0 Max = 10 Must be numeric

*Q7 How many other children were there in the household you grew up in?**
Children older than me: ____

Children younger than me: ____

Hidden Value: s-siblings

Value: Populates with the **length of time** since the survey taker started the current page

---

About you: ethnicity and religion

Logic: Show/hide trigger exists.

*Q8 What race/ethnicity are you?**
( ) White British / Irish

( ) White other

( ) Asian or Asian-British

( ) Black or Black-British

( ) Na'vi

( ) Mixed

( ) Other

( ) Prefer not to answer

Logic: Hidden unless: Question "What race/ethnicity are you?" is one of the following answers ("White other","Asian or Asian-British","Black or Black-British","Mixed")

Q9 How long have you been living in the UK?
( ) All my life

( ) More than 10 years (but not all my life)

( ) Between 5 and 10 years

( ) Between 1 and 5 years

( ) Less than 1 year

Hidden Value: pension

Value: populates with a randomly generated number between 0 and 1

*Q10 What religion are you?**
( ) Christian

( ) Muslim

( ) Hindu

( ) Sikh

( ) Buddist

( ) Jewish

( ) Jedi

( ) Other

( ) Agnostic / Atheist

( ) None

( ) Prefer not to answer

Hidden Value: s-ethnic

Value: Populates with the **length of time** since the survey taker started the current page

---

About you: family

Validation: Must be numeric

Logic: Show/hide trigger exists.

*Q11 How many children do you have?**
Please include step- and adoptive children.

( ) 0

( ) 1

( ) 2

( ) 3

( ) 4

( ) 5 or more

Hidden Value: prime

Value: populates with a randomly generated number between 0 and 1

Logic: Hidden unless: Question "How many children do you have?" is one of the following answers ("1")

*Q12 How old is (s)he?**

( ) 0 ( ) 1 ( ) 2 ( ) 3 ( ) 4 ( ) 5 ( ) 6 ( ) 7 ( ) 8 ( ) 9 ( ) 10 ( ) 11 ( ) 12 ( ) 13 ( ) 14 ( ) 15 ( ) 16 ( ) 17 ( ) 18 ( ) 19 ( ) 20 ( ) 21 ( ) 22 ( ) 23 ( ) 24 ( ) 25 ( ) 26 or older

Logic: Hidden unless: Question "How many children do you have?" is one of the following answers ("2")

*Q12 How old are they?**
Oldest / Youngest

( ) 0 ( ) 1 ( ) 2 ( ) 3 ( ) 4 ( ) 5 ( ) 6 ( ) 7 ( ) 8 ( ) 9 ( ) 10 ( ) 11 ( ) 12 ( ) 13 ( ) 14 ( ) 15 ( ) 16 ( ) 17 ( ) 18 ( ) 19 ( ) 20 ( ) 21 ( ) 22 ( ) 23 ( ) 24 ( ) 25 ( ) 26 or older

Logic: Hidden unless: Question "How many children do you have?" is one of the following answers ("3")

*Q12 How old are they?**
Oldest / Middle/ Youngest

( ) 0 ( ) 1 ( ) 2 ( ) 3 ( ) 4 ( ) 5 ( ) 6 ( ) 7 ( ) 8 ( ) 9 ( ) 10 ( ) 11 ( ) 12 ( ) 13 ( ) 14 ( ) 15 ( ) 16 ( ) 17 ( ) 18 ( ) 19 ( ) 20 ( ) 21 ( ) 22 ( ) 23 ( ) 24 ( ) 25 ( ) 26 or older

Logic: Hidden unless: Question "How many children do you have?" is one of the following answers ("4","5 or more")

*Q12 How old are they?**
Oldest / Youngest

( ) 0 ( ) 1 ( ) 2 ( ) 3 ( ) 4 ( ) 5 ( ) 6 ( ) 7 ( ) 8 ( ) 9 ( ) 10 ( ) 11 ( ) 12 ( ) 13 ( ) 14 ( ) 15 ( ) 16 ( ) 17 ( ) 18 ( ) 19 ( ) 20 ( ) 21 ( ) 22 ( ) 23 ( ) 24 ( ) 25 ( ) 26 or older

Validation: Min = 0 Max = 50 Must be numeric

Logic: Hidden unless: Question "How many children do you have?" is one of the following answers ("1","2","3","4","5 or more")

*Q13 How many grandchildren do you have?**

____

Hidden Value: s-children

Value: Populates with the **length of time** since the survey taker started the current page

---

About you: Education and work

*Q13 What is the highest degree you obtained?**

( ) Craft or occupational certificate

( ) Some GCSEs (or O level, CSE equivalent)

( ) Five or more GCSE A*-C grades (or O level, CSE equivalent)

( ) A Level

( ) Diploma, Certificate of Higher Education

( ) Bachelor's degree

( ) Professional qualifications, e.g., accountancy, law, medical

( ) Master's degree, Post-graduate Diploma

( ) PhD, DPhil

( ) Prefer not to say

Logic: Show/hide trigger exists.

*Q14 What is your occupation?**

( ) Manager, Director, Senior Official

( ) Professional

( ) Technical

( ) Administrative, Secretarial

( ) Skilled trade

( ) Carer

( ) Sales, Customer services

( ) Machine operator

( ) Other

( ) Student

( ) Homemaker

( ) Unemployed

( ) Retired

Logic: Hidden unless: Question "What is your occupation?" is one of the following answers ("Manager, Director, Senior

Official","Professional","Technical","Administrative, Secretarial","Skilled trade","Carer","Sales, Customer services","Machine operator","Other")

*Q15 In which sector do you work?**
( ) Agriculture, forestry, fishing

( ) Mining, quarrying

( ) Manufacturing

( ) Energy

( ) Water

( ) Wholesale and retail trade, repair

( ) Accommodation, restaurant, catering

( ) Transport, storage

( ) Financial and insurance services

( ) Information and communication technology

( ) Real estate

( ) Professional, scientific and technical services

( ) Administrative and support services

( ) Public administration and defense

( ) Education

( ) Health and social work

( ) Arts, entertainment, recreation

( ) Other

Hidden Value: s-degree

Value: Populates with the **length of time** since the survey taker started the current page

---

Attitudes
We will now some ask some questions about you view things.

Page entry logic: This page will show when: prime is exactly equal to "1"

Values
Q16 Patience is a virtue.
( ) strongly disagree ( ) moderately disagree ( ) slightly disagree ( ) neutral ( ) slightly agree ( ) moderately agree ( ) strongly agree ( ) don't know

Q17 Gambling is bad.
( ) strongly disagree ( ) moderately disagree ( ) slightly disagree ( ) neutral ( ) slightly agree ( ) moderately agree ( ) strongly agree ( ) don't know

Q18 We should help people who are worse off than us.
( ) strongly disagree ( ) moderately disagree ( ) slightly disagree ( ) neutral ( ) slightly agree ( ) moderately agree ( ) strongly agree ( ) don't know

Hidden Value: s-prime

Value: Populates with the **length of time** since the survey taker started the current page

---

An investment
After Tanaka et al. AER 2010 and Voors et al., AER 2012. Note that three questions allows us to estimate a three-parameter discount function, with a discount rate, present bias, and a degree of hyperbolicity.

*Q19 Would you rather have**

	today	£1000 in a year's time
£250 today	( )	( )
£500 today	( )	( )
£750 today	( )	( )
£850 today	( )	( )
£900 today	( )	( )
£950 today	( )	( )
£975 today	( )	( )
£990 today	( )	( )

*Q20 Would you rather have**

	today	£1000 in five years' time
£10 today	( )	( )

£30 today	( )	( )
£250 today	( )	( )
£450 today	( )	( )
£600 today	( )	( )
£750 today	( )	( )
£875 today	( )	( )
£950 today	( )	( )

Hidden Value: s-time0

Value: Populates with the **length of time** since the survey taker started the current page

---

Prospects
after Cornea and Gruener, 2002, JPubE

Q21 Compared with your parents when they were about your age, are you better or worse in your income and standard of living generally?
( ) much better off ( ) better off ( ) about equal ( ) worse off ( ) much worse off ( ) don't know

Q22 Compared with you, do you think that your children, when they reach your age, will be better or worse in their income and standard of living generally?
( ) much better off ( ) better off ( ) about equal ( ) worse off ( ) much worse off ( ) don't know

Hidden Value: s-cornea

Value: Populates with the **length of time** since the survey taker started the current page

---

Another investment

*Q23 Would you rather have**

	in a year from now	£1000 in a two years' time

£250 in a year from now	( )	( )
£500 in a year from now	( )	( )
£750 in a year from now	( )	( )
£850 in a year from now	( )	( )
£900 in a year from now	( )	( )
£950 in a year from now	( )	( )
£975 in a year from now	( )	( )
£990 in a year from now	( )	( )

*Q24 Would you rather have**

	in a year from now	£1000 in six years' time
£5 in a year from now	( )	( )
£30 in a year from now	( )	( )
£250 in a year from now	( )	( )

£450 in a year from now	( )	( )
£600 in a year from now	( )	( )
£750 in a year from now	( )	( )
£875 in a year from now	( )	( )
£950 in a year from now	( )	( )

Hidden Value: s-time

Value: Populates with the **length of time** since the survey taker started the current page

---

A quiz
Frederick, JEP, 2005
Validation: Must be numeric

*Q25 A bat and a ball cost £5.50 in total. The bat costs £5.00 more than the ball. How much does the ball cost?**

____

Validation: Must be numeric

*Q26 If it takes 5 machines 5 minutes to make 5 widgets, how long would it take 100 machines to make 100 widgets?**

____

Validation: Must be numeric

*Q27 In a lake, there is a patch of lily pads. Every day, the patch doubles in size. If it takes 48 days for the patch to cover the entire lake, how long would it take for the patch to cover half of the lake?**

____

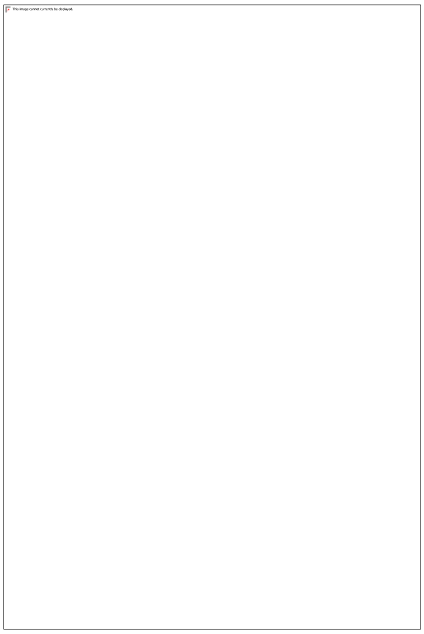
Hidden Value: s-numeracy

Value: Populates with the **length of time** since the survey taker started the current page

---

A prize draw

Page entry logic: This page will show when: svo is exactly equal to "1"



Page entry logic: This page will show when: svo is exactly equal to "2"

Page entry logic: This page will show when: svo is exactly equal to "3"

Page entry logic: This page will show when: svo is exactly equal to "4"

Page entry logic: This page will show when: svo is exactly equal to "5"

Page entry logic: This page will show when: svo is exactly equal to "6"

Page entry logic: This page will show when: svo is exactly equal to "7"

Page entry logic: This page will show when: svo is exactly equal to "8"

Page entry logic: This page will show when: svo is less than "5"

*Q28 Which prizes do you prefer?**
Your prize is on top, Anne's at the bottom.

( ) £50 £100 ( ) £55 £98 ( ) £60 £96 ( ) £65 £94 ( ) £70 £92 ( ) £75 £89 ( ) £80 £87 ( ) £85 £85

*Q28 Which prizes do you prefer?**
Your prize is on top, Anne's at the bottom.

( ) £50 £100 ( ) £55 £88 ( ) £60 £76 ( ) £65 £64 ( ) £70 £52 ( ) £75 £39 ( ) £80 £27 ( ) £85 £15

*Q28 Which prizes do you prefer?**
Your prize is on top, Anne's at the bottom.

( ) £100 £50 ( ) £98 £55 ( ) £96 £60 ( ) £93 £65 ( ) £91 £70 ( ) £89 £75 ( ) £87 £80 ( ) £85 £85

*Q28 Which prizes do you prefer?**
Your prize is on top, Anne's at the bottom.

( ) £85 £15 ( ) £85 £25 ( ) £85 £35 ( ) £85 £45 ( ) £85 £55 ( ) £85 £65 ( ) £85 £75 ( ) £85 £85

*Q28 Which prizes do you prefer?**
Your prize is on top, Anne's at the bottom.

( ) £50 £100 ( ) £60 £90 ( ) £70 £80 ( ) £80 £70 ( ) £90 £60 ( ) £100 £50

*Q28 Which prizes do you prefer?**
Your prize is on top, Anne's at the bottom.

( ) £85 £15 ( ) £88 £22 ( ) £91 £29 ( ) £94 £36 ( ) £97 £43 ( ) £100 £50

Hidden Value: s-svofem

Value: Populates with the **length of time** since the survey taker started the current page

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Page entry logic: This page will show when: svo is greater than "4"

Replace “Anne” with “John”.

Hidden Value: s-svomale

Value: Populates with the **length of time** since the survey taker started the current page

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Another quiz
Lusardi and Mitchell, JEL, 2014

Quiz score action:

Quiz Type: Tally

*Q29 Suppose you had £100 in a savings account and the interest rate was 2 percent per year. After 5 years, how much do you think you would have in the account if you left the money to grow:**

( ) more than £102 ( ) exactly £102 ( ) less than £102 ( ) do not know

*Q30 Imagine that the interest rate on your savings account was 1 percent per year and inflation was 2 percent per year. After 1 year, would you be able to buy:**

( ) more than today with the money in this account ( ) exactly the same as today with the money in this account ( ) less than today with the money in this account ( ) do not know

*Q31 Do you think that the following statement is true or false? "Buying a single company share usually provides a safer return than a mix of shares."**

( ) true ( ) false ( ) do not know

Hidden Value: s-finlit

Value: Populates with the **length of time** since the survey taker started the current page

---

Page entry logic: This page will show when: (svo is less than "5" AND Question "" is greater than "4.3")

Another prize draw

*Q32 Which prizes do you prefer?**

Your prize is on top, Anne's at the bottom.

( ) £50 £100 ( ) £60 £94 ( ) £70 £88 ( ) £80 £82 ( ) £90 £76 ( ) £100 £70

*Q32 Which prizes do you prefer?**

Your prize is on top, Anne's at the bottom.

( ) £90 £100 ( ) £92 £98 ( ) £94 £96 ( ) £96 £94 ( ) £98 £92 ( ) £100 £90

*Q32 Which prizes do you prefer?**

Your prize is on top, Anne's at the bottom.

( ) £70 £100 ( ) £76 £90 ( ) £82 £80 ( ) £88 £70 ( ) £94 £60 ( ) £100 £50

*Q32 Which prizes do you prefer?**

Your prize is on top, Anne's at the bottom.

( ) £70 £100 ( ) £76 £98 ( ) £82 £96 ( ) £88 £94 ( ) £94 £92 ( ) £100 £90

*Q32 Which prizes do you prefer?**

Your prize is on top, Anne's at the bottom.

( ) £70 £100 ( ) £76 £94 ( ) £82 £88 ( ) £88 £82 ( ) £94 £76 ( ) £100 £70

*Q32 Which prizes do you prefer?**

Your prize is on top, Anne's at the bottom.

( ) £50 £100 ( ) £60 £98 ( ) £70 £96 ( ) £80 £94 ( ) £90 £92 ( ) £100 £90

*Q32 Which prizes do you prefer?**

Your prize is on top, Anne's at the bottom.

( ) £90 £100 ( ) £92 £94 ( ) £94 £88 ( ) £96 £82 ( ) £98 £76 ( ) £100 £70

*Q32 Which prizes do you prefer?**
Your prize is on top, Anne's at the bottom.

( ) £90 £100 ( ) £92 £90 ( ) £94 £80 ( ) £96 £70 ( ) £98 £60 ( ) £100 £50

Hidden Value: s-svofem2

Value: Populates with the **length of time** since the survey taker started the current page

---

Page entry logic: This page will show when: (svo is greater than "4" AND Question "" is greater than "4.3")

Replace "Anne" with "John"

Hidden Value: s-svomal2

Value: Populates with the **length of time** since the survey taker started the current page

---

An allocation
after Fehr, Naef & Schmidt, AER, 2006, although in their case the respondent is one of the three subjects. Second question was added to distinguish between Creedy and Bergson-Samuelson preferences.

*Q33 [1/2] Consider the yearly income of Mary, Beth and Cathy in three alternative situations. Which situation do you think is best?**
( ) Mary earns £60,000, Beth £44,000 and Cathy £33,000

( ) Mary earns £58,000, Beth £44,000 and Cathy £34,000

( ) Mary earns £56,000, Beth £44,000 and Cathy £35,000

( ) Mary earns £54,000, Beth £44,000 and Cathy £36,000

( ) Mary earns £52,000, Beth £44,000 and Cathy £37,000

*Q33 [2/2] Consider the yearly income of Mark, Ben and Charles in three alternative situations. Which situation do you think is best?**
( ) Mark earns £60,000, Ben £44,000 and Charles £33,000

( ) Mark earns £58,000, Ben £44,000 and Charles £34,000

( ) Mark earns £56,000, Ben £44,000 and Charles £35,000

( ) Mark earns £54,000, Ben £44,000 and Charles £36,000

( ) Mark earns £52,000, Ben £44,000 and Charles £37,000

Hidden Value: s-alloc

Value: Populates with the **length of time** since the survey taker started the current page

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Political orientation
British Social Attitudes, 2013

*Q34 Government should redistribute income from the better off to those who are less well off.**
( ) strongly disagree ( ) disagree ( ) neutral ( ) agree ( ) strongly agree

*Q35 Ordinary working people do not get their fair share of the nation's wealth.**
( ) strongly disagree ( ) disagree ( ) neutral ( ) agree ( ) strongly agree

Q36 How important is hard work for getting ahead in life?
( ) essential ( ) very important ( ) fairly important ( ) not very important ( ) not important at all

Hidden Value: s-polorient

Value: Populates with the **length of time** since the survey taker started the current page

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Another allocation

*Q37 [1/2] Consider the yearly income of Joan, Janet and Jane in three alternative situations. Which situation do you think is best?**
( ) Joan earns £33,000, Janet £23,000 and Jane £16,000

( ) Joan earns £31,000, Janet £23,000 and Jane £17,000

( ) Joan earns £29,000, Janet £23,000 and Jane £18,000

( ) Joan earns £27,000, Janet £23,000 and Jane £19,000

( ) Joan earns £25,000, Janet £23,000 and Jane £20,000

*Q37 [2/2] Consider the yearly income of Jack, Jon and James in three alternative situations. Which situation do you think is best?**
( ) Jack earns £33,000, Jon £23,000 and James £16,000

( ) Jack earns £31,000, Jon £23,000 and James £17,000

( ) Jack earns £29,000, Jon £23,000 and James £18,000

( ) Jack earns £27,000, Jon £23,000 and James £19,000

( ) Jack earns £25,000, Jon £23,000 and James £20,000

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Value: Populates with the **length of time** since the survey taker started the current page

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Page entry logic: This page will show when: ((domain is exactly equal to "1" OR domain is exactly equal to "2") OR domain is exactly equal to "3")

Health

Logic: Hidden unless: nhs is exactly equal to "1"

Logic: Hidden unless: env is exactly equal to "1"

We will now ask you some questions about the environment and climate change.

Page entry logic: This page will show when: ((domain is exactly equal to "3" OR domain is exactly equal to "5") OR domain is exactly equal to "6")

Climate change
Kahan, 2015

*Q71. Climate scientists believe that the increase of atmospheric carbon dioxide associated with the burning of fossil fuels will reduce photosynthesis by plants.**
( ) false ( ) true

*Q72. Climate scientists believe that human-caused global warming will increase the risk of skin cancer in human beings.**
( ) false ( ) true

*Q73. Climate scientists believe that human-caused global warming will results in flooding of many coastal regions.**
( ) false ( ) true

*Q74. Climate scientists believe that if the North Pole icecap melted as a result of human-caused global warming, global sea levels would rise.**
( ) false ( ) true

*Q75. Climate scientists believe that human-caused global warming has increased the number and severity of hurricanes around the world.**
( ) false ( ) true

*Q76. Climate scientists believe that nuclear power generation contributes to global warming.**
( ) false ( ) true

*Q77. Climate scientists believe that there will be positive as well as negative effects from human-caused global warming.**
( ) false ( ) true

*Q78. Climate scientists believe that globally average surface air temperatures were higher for the first decade of the twenty-first century (2000-2009) than for the last decade of the twentieth century (1990-1999).**
( ) false ( ) true

Hidden Value: s-climknow

Value: Populates with the **length of time** since the survey taker started the current page

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Page entry logic: This page will show when: ((domain is exactly equal to "3" OR domain is exactly equal to "5") OR domain is exactly equal to "6")

Climate impacts

Validation: Min = 0 Max = 10

*Q79. How serious a problem do you think climate change is at this moment?**
0 ________________________[__]_____________________________ 10

Validation: Min = 0 Max = 10

*Q80. How serious a problem do you think climate change will be in 10 years' time?**
0 ________________________[__]_____________________________ 10

Validation: Min = 0 Max = 10

*Q81. How serious a problem do you think climate change will be in 100 years' time?**
0 ________________________[__]_____________________________ 10

Hidden Value: s-climcare

Value: Populates with the **length of time** since the survey taker started the current page

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Page entry logic: This page will show when: ((domain is exactly equal to "3" OR domain is exactly equal to "5") OR domain is exactly equal to "6")

Climate change and policy

Validation: Min = 0 Max = 10

Q82. Which affects you and your way of life more, climate change *or* policies to reduce greenhouse gas emissions*?**

0 ________________________[__]_____________________________ 10

Validation: Min = 0 Max = 10

Q83. Which will affect your children and their way of life more, climate change *or* policies to reduced greenhouse gas emissions*?**

0 ________________________[__]_____________________________ 10

Validation: Min = 0 Max = 10

Q84. Which will affect your grandchildren and their way of life more, climate change *or* policies to reduce greenhouse gas emissions*?**

0 ________________________[__]_____________________________ 10

Hidden Value: s-climpol

Value: Populates with the **length of time** since the survey taker started the current page

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Page entry logic: This page will show when: ((domain is exactly equal to "3" OR domain is exactly equal to "5") OR domain is exactly equal to "6")

UK climate policy

Validation: Min = -50 Max = 500

*Q85. The average household pays £1,369 per year for gas and electricity. Government intervention has raised the price to encourage people to use less and so reduce greenhouse house gas emissions. How much of that £1,369 is for climate policy?**

-50 ________________________[__]_____________________________ 500

Validation: Min = 0 Max = 60

*Q86. On every litre of petrol, there is a duty of 61 pence. The duty for diesel is 71 pence per litre. The duty is partly a fuel duty for financing road building and maintenance, and partly a carbon duty for encouraging people to drive less so that less carbon dioxide is emitted. The carbon duty is the same for petrol and diesel. How big do you think it is?**

0 ________________________[__]_____________________________ 60

Hidden Value: s-climspend

Value: Populates with the **length of time** since the survey taker started the current page

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Page entry logic: This page will show when: ((domain is exactly equal to "3" OR domain is exactly equal to "5") OR domain is exactly equal to "6")

Climate policy

Validation: Min = 0 Max = 500

*Q87. Actually, climate policy adds about £89 per year to the gas and electricity bill of the average household. How much do you think climate policy should add to this bill?**
0 _________________________[__]______________________________ 500

Validation: Min = 0 Max = 100

*Q88. Actually, the carbon duty is 3 pence per litre. How high do you think it should be?**
0 _________________________[__]______________________________ 100

Hidden Value: s-climbudget

Value: Populates with the **length of time** since the survey taker started the current page

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Government spending
We will now ask some questions about government spending.

Government expenditures

Validation: Min = 0 Max = 100 Must be numeric

*Q89. The government spends about £686 billion per year. How do you think this is spend? Please answer in percent - that is, pence in the pound - of total government spending.**
________Debt interest payments

________National Health Service

________Education

________Environmental protection (e.g., waste, nature)

________Pensions

________Defence

________Unemployment and social security (e.g., disability, family benefits)

________Foreign aid

________EU transfers (net)

________Other (e.g., transport, police, housing)

Hidden Value: s-govspend

Value: Populates with the **length of time** since the survey taker started the current page

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Government expenditures

Validation: Min = 0 Max = 100 Must be numeric

Q90. In fact, current government spending is as shown below. How much do you think we should spend? Please answer in percent - that is, pence in the pound - of total government spending.
Note that if you spend more than 7% on interest payments and debt reduction, the national debt will fall; and if you spend less than 7%, the national debt will rise.

________Unemployment and social security (e.g., disability, family benefits)

________National Health Service

________Pensions

________Other (e.g., transport, police, housing)

________Education

________Debt interest payments and debt reduction

________Defence

________Environmental protection (e.g., waste, nature)

________Foreign aid

________EU transfers

Hidden Value: s-govbudget

Value: Populates with the **length of time** since the survey taker started the current page

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About you
Finally, we will ask some more questions about you. Recall that all your answers will be kept strictly confidential.

About you: income
*Q91. What is your household income (before tax)?**
( ) Less than £11,000

( ) £11,000 to £16,000

( ) £16,000 to £20,000

( ) £20,000 to £26,000

( ) £26,000 to £32,000

( ) £32,000 to £39,000

( ) £39,000 to £48,000

( ) £48,000 to £60,000

( ) £60,000 to £81,000

( ) £81,000 to £100,000

( ) £100,000 or more

( ) prefer not to say

Hidden Value: s-income

Value: Populates with the **length of time** since the survey taker started the current page

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Page entry logic: This page will show when: Question "What is your household income (before tax)?" is one of the following answers ("£26,000 to £32,000","£32,000 to £39,000","£39,000 to £48,000","prefer not to say")

A lottery
After Tanaka, Camerer & Nguyen, AER, 2010. Note that with one lottery question, we can only estimate risk aversion. If we also want to estimate ambiguity aversion, a bias towards certain outcomes, and risk amplification, we should add more questions.

There are two lotteries, decided by the throw of a dice.

[1/2] In Lottery 1, you'll either win £1,000 or £2,000. You'll win £1,000 if the dice falls on 1, 2, or 3. You'll win £2,000 if the dice falls on 4, 5, or 6.
[2/2] In Lottery 1, you'll either win £1,000 or £2,000. You'll win £1,000 if the dice falls on 1, 3, or 5. You'll win £2,000 if the dice falls on 2, 4, or 6.

In Lottery 2, you'll either win £600 or a larger amount, given below. You'll win £600 if the dice falls on 1, 2, 3, 4, or 5. You'll win the larger amount if the dice falls on 6.

*Q92. Which lottery do you prefer?**

	Lottery 1: £1,000 or £2,000	Lottery 2: £600 or larger amount
Larger amount: £6,000	( )	( )
Larger amount: £6,600	( )	( )
Larger amount: £7,200	( )	( )
Larger amount: £7,800	( )	( )
Larger amount: £8,400	( )	( )
Larger amount: £9,000	( )	( )

Larger amount: £9,600	( )	( )
Larger amount: £10,200	( )	( )
Larger amount: £10,800	( )	( )
Larger amount: £11,400	( )	( )
Larger amount: £12,000	( )	( )

Hidden Value: s-risk

Value: Populates with the **length of time** since the survey taker started the current page

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Page entry logic: This page will show when: Question "What is your household income (before tax)?" is one of the following answers ("£48,000 to £60,000","£60,000 to £81,000","£81,000 to £100,000","£100,000 or more")

A lottery
After Tanaka, Camerer & Nguyen, AER, 2010. Note that with one lottery question, we can only estimate risk aversion. If we also want to estimate ambiguity aversion, a bias towards certain outcomes, and risk amplification, we should add more questions.

There are two lotteries, decided by the throw of a dice.

[1/2] In Lottery 1, you'll either win £2,000 or £4,000. You'll win £2,000 if the dice falls on 1, 2, or 3. You'll win £4,000 if the dice falls on 4, 5, or 6.
[2/2] In Lottery 1, you'll either win £2,000 or £4,000. You'll win £2,000 if the dice falls on 1, 3, or 5. You'll win £4,000 if the dice falls on 2, 4, or 6.

In Lottery 2, you'll either win £1,200 or a larger amount, given below. You'll win £1,200 if the dice falls on 1, 2, 3, 4, or 5. You'll win the larger amount if the dice falls on 6.

*Q92. Which lottery do you prefer?**

	Lottery 1: £2,000 or £4,000	Lottery 2: £1,200 or larger amount
Larger amount: £12,000	( )	( )
Larger amount: £13,200	( )	( )

Larger amount: £14,400	( )	( )
Larger amount: £15,600	( )	( )
Larger amount: £16,800	( )	( )
Larger amount: £18,000	( )	( )
Larger amount: £19,200	( )	( )
Larger amount: £20,400	( )	( )
Larger amount: £21,600	( )	( )
Larger amount: £22,800	( )	( )
Larger amount: £24,000	( )	( )

Hidden Value: s-risk

Value: Populates with the **length of time** since the survey taker started the current page

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Page entry logic: This page will show when: Question "What is your household income (before tax)?" is one of the following answers ("Less than £11,000","£11,000 to £16,000","£16,000 to £20,000","£20,000 to £26,000")

A lottery

After Tanaka, Camerer & Nguyen, AER, 2010. Note that with one lottery question, we can only estimate risk aversion. If we also want to estimate ambiguity aversion, a bias towards certain outcomes, and risk amplification, we should add more questions.

There are two lotteries, decided by the throw of a dice.

[1/2] In Lottery 1, you'll either win £500 or £1,000. You'll win £500 if the dice falls on 1, 2, or 3. You'll win £1,000 if the dice falls on 4, 5, or 6.

[2/2] In Lottery 1, you'll either win £500 or £1,000. You'll win £500 if the dice falls on 1, 3, or 5. You'll win £1,000 if the dice falls on 2, 4, or 6.

In Lottery 2, you'll either win £300 or a larger amount, given below. You'll win £300 if the dice falls on 1, 2, 3, 4, or 5. You'll win the larger amount if the dice falls on 6.

*Q92. Which lottery do you prefer?**

	Lottery 1: £500 or £1,000	Lottery 2: £300 or larger amount
Larger amount: £3,000	( )	( )
Larger amount: £3,300	( )	( )
Larger amount: £3,600	( )	( )
Larger amount: £3,900	( )	( )
Larger amount: £4,200	( )	( )
Larger amount: £4,500	( )	( )
Larger amount: £4,800	( )	( )
Larger amount: £5,100	( )	( )
Larger amount: £5,400	( )	( )
Larger amount: £5,700	( )	( )
Larger amount: £6,000	( )	( )

Hidden Value: s-risk

Value: Populates with the **length of time** since the survey taker started the current page

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Your house

*Q93. How much would you get for your house if you would sell it now?**

( ) I don't own a house ( ) less than £100,000 ( ) between £100,000 and £200,000 ( ) between £200,000 and £300,000 ( ) between £300,000 and £400,000 ( ) between £400,000 and £500,000 ( ) between £500,000 and £750,000 ( ) between £750,000 and £1,000,000 ( ) more than £1,000,000 ( ) prefer not to answer

*Q94. How high is your mortgage?**
( ) I don't have a mortgage ( ) less than £50,000 ( ) between £50,000 and £100,000 ( ) between £100,000 and £150,000 ( ) between £150,000 and £200,000 ( ) between £200,000 and £250,000 ( ) between £250,000 and £350,000 ( ) between £350,000 and £500,000 ( ) more than £500,000 ( ) prefer not to answer

Hidden Value: s-house

Value: Populates with the **length of time** since the survey taker started the current page

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Assets and loans

*Q95. What is the value of your assets?**
Savings ( ) I don't have any ( ) less than £5,000 ( ) between £5,000 and £10,000 ( ) between £20,000 and £50,000 ( ) between £50,000 and £100,000 ( ) between £100,000 and £500,000 ( ) more than £500,000 ( ) prefer not to answer

Stocks, shares and bonds ( ) I don't have any ( ) less than £5,000 ( ) between £5,000 and £10,000 ( ) between £20,000 and £50,000 ( ) between £50,000 and £100,000 ( ) between £100,000 and £500,000 ( ) more than £500,000 ( ) prefer not to answer

Other (excluding house) ( ) I don't have any ( ) less than £5,000 ( ) between £5,000 and £10,000 ( ) between £20,000 and £50,000 ( ) between £50,000 and £100,000 ( ) between £100,000 and £500,000 ( ) more than £500,000 ( ) prefer not to answer

*Q96. How much debt do you have?**
Student loans ( ) I don't have any ( ) less than £1,000 ( ) between £1,000 and £5,000 ( ) between £5,000 and £10,000 ( ) between £10,000 and £25,000 ( ) between £50,000 and £100,000 ( ) more than £100,000 ( ) prefer not to answer

Credit card arrears ( ) I don't have any ( ) less than £1,000 ( ) between £1,000 and £5,000 ( ) between £5,000 and £10,000 ( ) between £10,000 and £25,000 ( ) between £50,000 and £100,000 ( ) more than £100,000 ( ) prefer not to answer

Personal loans ( ) I don't have any ( ) less than £1,000 ( ) between £1,000 and £5,000 ( ) between £5,000 and £10,000 ( ) between £10,000 and £25,000 ( ) between £50,000 and £100,000 ( ) more than £100,000 ( ) prefer not to answer

Other (excluding mortgage) ( ) I don't have any ( ) less than £1,000 ( ) between £1,000 and £5,000 ( ) between £5,000 and £10,000 ( ) between £10,000 and £25,000 ( ) between £50,000 and £100,000 ( ) more than £100,000 ( ) prefer not to answer

Hidden Value: s-asset

Value: Populates with the **length of time** since the survey taker started the current page

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Thank you!

Validation: %s format expected

That was the final question. Please press "submit" to finish the survey.

If you want to see the results, please leave your email.

____

Thank You!
Thank you for taking our survey. Your response is very important to us.

You can click here to see the answers so far.

This survey was designed by Peter Dolton and Richard Tol of the University of Sussex.

Help a poor kid study economics.
