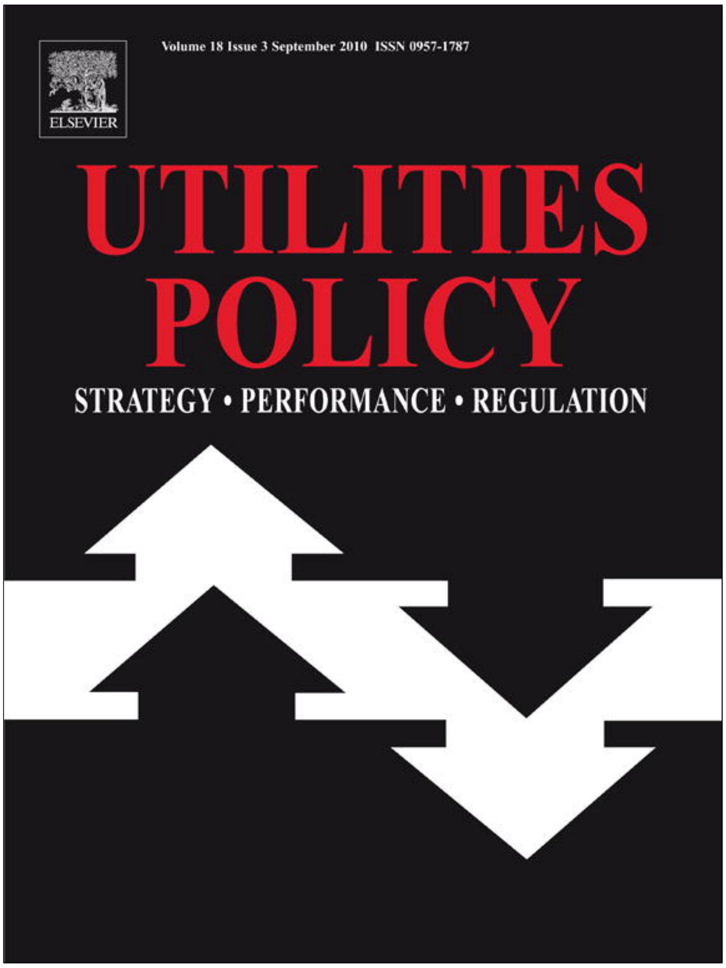
Volume 18 Issue 3 September 2010 ISSN 0957-1787
ELSEVIER
UTILITIES
POLICY
STRATEGY • PERFORMANCE • REGULATION

Utilities Policy 18 (2010) 142–153

Contents lists available at ScienceDirect

Utilities Policy

journal homepage: www.elsevier.com/locate/jup

The costs of adaptation to climate change for water infrastructure in OECD countries☆

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ARTICLE INFO

Article history:
Received 29 October 2009
Received in revised form
7 March 2010
Accepted 20 March 2010

JEL classification:
H23
L95
Q25
Q54

Keywords:
Climate change
Adaptation
Infrastructure
Water supply
Wastewater

ABSTRACT

There is concern that climate change may greatly increase the costs of providing water infrastructure in rich countries, but the estimates available cannot be compared across countries. This paper develops and applies a top-down approach to estimate the costs of adapting to climate change on a consistent basis for different climate scenarios. The analysis separates (a) the costs of maintaining service standards for a baseline projection of demand, and (b) the costs of changes in water use and infrastructure as a consequence of changes in climate patterns. The engineering estimates focus on the direct capital and operating costs of adaptation without relying upon economic incentives to affect patterns of water use. On this assumption, the costs of adaptation are 1–2% of baseline costs for all OECD countries with the main element being the extra cost of water resources to meet higher level of municipal water demand. There are large differences in the cost of adaptation across countries and regions. Adopting an economic approach under which water levies are used to cap total water abstractions leads to a large reduction in the burden of adaptation and generates savings of $6–12 billion per year under different climate scenarios.

1. Introduction

No matter what measures are adopted to mitigate climate change, some degree of climate change seems to be unavoidable by the middle or end of the current century. Various studies have asserted that the challenge of adapting water infrastructure in particular countries to take account of the impacts of climate change may be large – see, for example, EEA (2007), Ludwig et al. (2009), UNECE (2008). These results are mostly based upon micro-level studies for individual utilities or localities which are then scaled up to yield national estimates. Such studies underpin a belief that the costs of adapting to climate change for the water sector in rich countries may be substantial.

The difficulty in assessing such evidence is that studies do not adopt a consistent baseline or sector coverage, either in estimating the costs of adaptation or in considering how significant any increase in costs may be. There is also a tendency to talk about "the" costs of adaptation, even though there are likely to be large differences between the costs associated with different climate scenarios. Since the various climate models generate very different climate projections for specific countries or region – even for 2050 – it is misleading to combine results derived from different climate scenarios.

For these reasons this paper presents the results of an alternative "top-down" approach that is applied in a consistent manner to all OECD countries. We have attempted to estimate the efficient costs of adaptation, assuming that costs are incurred when and as needed up to 2050 but taking account of prospective climate change up to 2100 when constructing new infrastructure or replacing existing infrastructure. In OECD countries most discussion of climate change focuses on extreme weather events – droughts, storms, etc. Unfortunately, global climate models (GCMs)

☆ Note: This paper was presented at the CCRP Workshop on Water Regulation and Competition Policy held at the Aston Business School in July 2009. It is based upon work that was commissioned by the World Bank for the Economics of Adaptation to Climate Change study with funds provided by the Governments of the Netherlands, Switzerland and the United Kingdom. The analysis, results and views expressed in the paper are those of the authors alone and do not represent the position of the World Bank or any of its member countries. We are grateful to Urvashi Narain, Jim Neumann and Jason Price, and a referee for comments on earlier versions of this work. They are not responsible for any errors or opinions in this paper.

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doi:10.1016/j.jup.2010.03.002

are not capable of generating detailed projections of weather variability. Our estimates rely upon an engineering-economic approach to setting design standards based on relationships between the probability of extreme weather events and the distributions of weather outcomes given climate variables.

Another important issue concerns the balance between the supply of and demand for water resources. Agriculture accounts for more than 80% of water abstractions in OECD countries and the marginal value of water in agriculture is much lower than its marginal value for other uses. We have assumed that the amount of water abstracted for municipal and industrial use is held constant at the base level, so that the impact of changes in reliable water availability falls on the agricultural sector. On the other hand, any increase in water demand due to climate change is assumed to involve a fixed marginal cost reflecting the cost of either water recycling or (in some places) desalination.

2. Measuring the costs of adaptation

The work presented in this paper is an extension of work undertaken as part of a World Bank study of the costs of adapting to climate change for infrastructure over the period from 2010 to 2050 – the Economics of Adaptation to Climate Change (EACC) – see World Bank (2009). The basic approach is conceptually simple. For any country j and date t ($t = 2010, 2015, \ldots, 2050$) we start from the assumption that there is some "efficient" level of provision of infrastructure of type i, which will be denoted by Q_{ijt}. The efficient level of infrastructure is that which would be reached if the country had invested up to the point at which the marginal benefits of additional infrastructure just cover the marginal costs – both capital and maintenance – of increasing the stock of infrastructure – see, example, AICD (2009), Estache et al. (2005), and Fay and Yepes (2003).

In the period from t to $t+1$, for example from 2010 to 2015, the country will have to invest in order to meet the efficient level of infrastructure in $t+1$ and to replace infrastructure in situ at date t which reaches the end of its useful life during the period. Thus, the total value of investment in infrastructure of type i in country j and period t is

$$I_{ijt} = C_{ijt}\left[Q_{ijt+1} - Q_{ijt} + R_{ijt}\right] \tag{1}$$

where C_{ijt} is the unit cost of investment and R_{ijt} is the quantity of existing infrastructure of type i that has to be replaced during the period. The change in the total cost of infrastructure investment may be expressed in terms of the total differential of (1) with respect to the relevant climate variables that affect either unit costs or efficient levels of provision for infrastructure of type i:

$$\Delta I_{ijt} = \Delta C_{ijt}\left[Q_{ijt+1} - Q_{ijt} + R_{ijt}\right] + \left(C_{ijt} + \Delta C_{ijt}\right)\left[\Delta Q_{ijt+1} - \Delta Q_{ijt} + \Delta R_{ijt}\right] \tag{2}$$

An equivalent equation may be derived for the costs of operating and maintaining infrastructure. In the discussion that follows, the first part of the right hand side of equation (2) is referred to as the Delta-C component of the cost of adaptation – this represents the impact of changes in the unit cost of physical infrastructure given the baseline investment program. The second part is referred as the Delta-V component – this is the cost of changes in the physical amount of infrastructure due to the impact of climate change.

2.1. Delta-C

At the simplest level, changes in temperature, precipitation or other climate variables may alter the direct cost of constructing infrastructure to provide a fixed level of service. Changes in the frequency and/or the severity of storms, flooding and other extreme weather events may compromise the performance of infrastructure designed to existing standards. Our analysis assumes that design standards should be adjusted so as to deliver the same level of performance as would have applied if climate change had not occurred – see Canadian Standards Association (2006). Thus, if roads or buildings are currently constructed to withstand a 1 in 50 or 1 in 100-year flood or wind storm, then the same design standard should apply but under the circumstances of a changed frequency or severity of those events.

The changes in the unit costs – ΔC_{ijt} – represent the additional costs of building infrastructure that delivers the original level of performance in the face of different climatic stresses[1]. The derivation of the cost changes, expressed as marginal dose-response relationships for different climate stressors, are detailed in Chinowsky et al. (2009). These relationships are applied to changes in climate variables by country and time period for each climate scenario.[2] This gives a series of cost increases – at constant 2005 prices – by type of infrastructure, country, time period, and climate scenario. When applied to the baseline projection of physical infrastructure, we obtain the Delta-C cost of adaptation – i.e. the difference between the cost of the baseline investment program for a stable climate and for a changing climate. A similar exercise may be carried out for operating, maintenance and replacement costs in order to calculate the increment in annualised infrastructure costs as a consequence of climate change. An example of the Delta-C approach is a study of the costs of adaptation to climate change in Alaska – Larsen et al. (2008) – which looks at the costs of maintaining and replacing a fixed stock of physical infrastructure. However, this study relied upon a very detailed inventory of infrastructure assets and took no account of changes in the amounts of infrastructure over the time horizon.

2.2. Delta-V

The quantities of infrastructure assets required (holding income constant) may change as a consequence of different climatic conditions. Climate change may change the level or composition of demand for water services at given levels of income, so we need to calculate the net impact of these changes in terms of capital and operating costs.

To approach this issue we have to consider the mechanisms by which changes in climate may affect the demand for infrastructure and how we might identify these consequences. For example, it is generally accepted that demand for electricity depends upon climate in general, but it is not so easy to identify the key climate parameters when estimating the demand for electricity generating capacity. The same issue arises when considering how changes in climate may affect the demand for water infrastructure. It is likely that climate variables affect economic activity holding other factors constant – for example, through the level and composition of agricultural output – and this will influence the nature of investment in water supply. There are more complex but potentially large effects operating through the economic geography of urban life, industry and commerce.

[1] One can adopt different terminologies to describe the impact of climate change on costs. We have focused on changes in the unit cost of infrastructure designed to meet a constant standard of performance in a context of changing climate stresses. A referee has pointed out that this can equally be viewed as a change in the quality-adjusted quantity of infrastructure. Our approach is one possible description that follows the way in which engineers tend to think about the cost of physical infrastructure.

[2] Most climate models generate projections for 2° grid squares. For this study, these projections have been downscaled to 0.5° grid squares and variously weighted averages of the grid square values have been computed for each country. Unless stated otherwise, references to climate variables should be construed as referring to the population-weighted averages of the variables across the grid squares that cover the country.

The difficulty in identifying the Delta-V component of adaptation costs follows from two more or less intractable aspects of the empirical work.

(a) Many of the impacts of climate on demand for infrastructure are long term in nature. This may not be true for all types of infrastructure, but some of the influence of climate on the demand for water infrastructure may operate over a period of one, two or many decades. There are two consequences. First, one should not think of the Delta-V component of the costs of adaptation as arising on a regular schedule every decade. The calculation merely identifies additions to and subtractions from a liability (or asset) that will materialise in future as economic activity adjusts to the changes in climate that are taking place. Second, in planning for future infrastructure development governments need to consider how climate change may affect the amount and type of infrastructure that is required.
(b) In practice, there is no way of examining the empirical impact of climate on the demand for infrastructure other than through some form of panel data analysis – pooling data for countries, regions, states or other geographical units over time. Inevitably, climate is a cross-sectional variable which may easily be confounded with other cross-section fixed effects – e.g. institutions. Some economists draw the conclusion that climate variables should not be used in this way. We do not accept this view, since it closes off any possibility of estimating the impact of climate change on overall demand for infrastructure. Instead, we have carried out an extensive econometric analysis of the role of climate variables in modelling the demand for infrastructure.

Climate change may also shorten the lifespan of existing infrastructure, perhaps because it has the wrong characteristics or is located in the wrong place. This implies a change in the level of replacement investment – ΔR_{ijt} in equation (2) – that should be taken into account. It is difficult to estimate the appropriate adjustment in a top-down model, so we have made a broad allowance by reducing the lifespan of all assets in situ in 2005.

3. Economic and climate data

The core data used in this study is the World Development Indicators (WDI) database published annually by the World Bank which provides panel data for more than 200 countries and for the period 1960–2006. The year 2005 is treated as the base year for all of our estimation. Our work relies upon the 2009 version of the database. The WDI data has been supplemented with data on infrastructure availability from a wide variety of sources including other international organisations, official country data, and various systematic surveys such as the Demographic and Health Surveys that are broadly consistent across countries. Even so, the final dataset is very patchy in terms of coverage, especially for earlier periods. The country panels are unbalanced and there are many missing values for intermediate years. Thus, it is generally impossible to make use of econometric specifications involving autoregressive or similar errors over time.

Describing the historic climate in a manner that is compatible with macroeconomic data is far from straightforward without any of the complications of projecting climate change into the second half of the 21st century. We have used a dataset of historic weather data compiled by the Climate Research Unit at the University of East Anglia for 0.5° grid squares for land areas of the globe – roughly 50 km square. Summary statistics have been computed for each grid cell for monthly average, maximum and minimum temperatures (in degrees C) and precipitation (in mm) for the period 1901–2002. The distribution of temperatures over years is generally accepted as being well-approximated by the normal distribution, so we have used the mean and standard deviation for each grid cell. For precipitation the distribution is closer to log-normal so the mean and standard deviation of ln(precipitation + 1 mm) were calculated in addition to the mean of precipitation[3].

Extreme weather conditions pose both practical and conceptual difficulties. Historical weather data is not sufficiently detailed to estimate, for example, the 99th percentiles of daily maximum and minimum temperatures, 24 h precipitation or wind speed for all grid cells. Hence, it is necessary to rely upon estimated or assumed relationships between monthly averages or variances and extreme weather conditions when deriving and applying the dose-response relationships to estimate changes in the unit cost of infrastructure required to maintain design standards. The conceptual problem concerns the definition of an appropriate description of extreme, rather than average, weather conditions in equations for the quantity of physical infrastructure that is required. The variance of climate variables for a single grid cell may provide a guide to extreme weather conditions in that cell, but defining equivalent measures for a country is more complicated because it requires very detailed information on spatial correlations that cannot be projected into the future.

To make progress we have focused on two separate issues. The first is the extent to which extreme weather conditions are a significant factor influencing the quantity of infrastructure that countries choose to provide. This will affect the Delta-V component of the cost of adaptation. The second is the impact of future changes in the frequency and/or severity of extreme weather on the design standards adopted for infrastructure and, through this route, on the cost of building or maintaining infrastructure in future.

The data does not allow us to address the first issue in more than an approximate way. In addition to average annual temperature and total precipitation, the effect of seasonal variability is captured by (a) the temperature range defined as the difference between the average maximum temperature in the hottest month and the average minimum temperatures in the coldest month, and (b) the precipitation range defined as the difference between maximum monthly precipitation and minimum monthly precipitation. We have also included the 99th percentiles of monthly maximum temperature and maximum monthly precipitation by grid – derived in the manner described below – averaged over grid cells in our econometric models as the best available proxies for extremes of temperature and precipitation. In addition, we have included measures of the within-country variation in climate conditions – described below – in our analysis.

The second issue is one aspect of the larger question of how climate projections to 2050 and beyond should be incorporated in the analysis. Global climate models (GCMs) are programmed to produce projections of different variables for different time periods. At a micro scale there are large differences between the results generated by the various models, so that it is necessary to very careful about relying upon a single model. The standard deviation of projections for any one grid cell is typically large relative to the mean value of the projected change up to 2050 or even 2100. Further, our econometric models suggest that the ranges between maximum and minimum monthly temperatures and precipitation are often important drivers of infrastructure demand. The projections used to calculate the Delta-V costs must be based upon climate scenarios that generate monthly maximum and minimum temperatures as well as average temperatures, which restricts the set of GCMs that can be used.

[3] The shift of +1 mm is required because precipitation is zero for many months at some grid squares, which would generate missing values without the shift. The standard deviations are required because some of our dose-response relationship depend upon extreme rather than central values of the distributions.

For the main scenario analysis in this study we have used results from the NCAR CCSM-3 and CSIRO-3 models (abbreviated to NCAR and CSIRO). These differ significantly in their patterns of climate change at regional and country level. The models are part of a larger set of 26 GCMs which have been examined in detail by the MIT Joint Program on the Science and Policy of Global Change – see, for example, Sokolov et al. (2009). As part of their analysis, the MIT group have downscaled the climate projections to match the 0.5° grid cells used for the historic climate data, so population- and area-weighted means were constructed for the countries covered by our study for the NCAR and CSIRO scenarios.

These projections are not sufficient for the Delta-C analysis, because design standards for certain types of infrastructure are driven by extreme values rather than monthly average values. As in the case of historical climate data, we have dealt with the need for measures of extreme weather conditions in an indirect manner. Most statements about the severity or frequency of extreme weather conditions in future rely on existing relationships between the average values of climate variables – e.g. air or sea temperatures, monthly precipitation – and the number or severity of hurricanes, typhoons, rainstorms, etc. Our analysis of the Delta-C cost of adaptation follows the same approach. We have proceeded as follows:

(a) Use the normal or log-normal distributions of monthly averages of maximum/minimum temperature and monthly precipitation to estimate the 99th percentile of monthly maximum temperature, the 1st percentile of monthly minimum temperature and the 99th percentile of maximum monthly precipitation[4].
(b) Express these percentiles as a ratio of the maximum/minimum of monthly average maximum/minimum temperatures and the maximum monthly precipitation and assume that these ratios will remain broadly constant in future.
(c) Apply the ratios of the 99th/1st percentiles to the associated monthly extremes for 2050 in order to compute the change from extreme values for the historic climate to extreme values for the climate scenario in absolute units – degrees C or mm of rainfall.
(d) In the case of wind speed, we have assumed a unit elasticity of the 99th percentile of wind speed with respect to the 99th percentile of precipitation.

Country estimates of the climate variables were constructed using grid cell means for monthly temperatures and precipitation. The primary variables are population-weighted averages using the population in each country in each grid cell to weight the grid cell means, thus reflecting the average exposure for the population of each country[5]. Alternative sets of country means weighted by (a) the land areas in each cell, and (b) the inverse of population in each cell were also constructed[6].

The primary climate variables used in the econometric analyses are population-weighted averages. We have tested whether using either the inverse-population-weighted and area-weighted means instead of or in addition to the population weighted means improves the performance of our equations. In all of the cases that we have examined the area-weighted climate variables are dominated by the inverse population-weighted (ipop) climate variables which reflect climate conditions in thinly populated areas of each country. Thus, we focus on identifying whether the ipop variables should be added to the equations used for projecting infrastructure demand[7].

The climate variables allow for seasonal and extreme weather variability. It is more difficult to investigate the role of within-country differences in climate, since the non-climate variables refer to country averages or aggregates. Where there are significant differences between the population-weighted and inverse population-weighted variables, including both will capture the influence of climate in densely and thinly populated areas. To supplement this we have used the population-weighted standard deviations of the grid cell values of the climate variables. These standard deviations tend to be larger for countries spanning many climatic zones, provided that the zones are not too thinly populated.

4. Econometric specification

In considering the specification of the econometric analysis it has to be remembered that the goal is to generate projections of the average demand for infrastructure up to 2050, whether or not these are affected by climate. The key implication is that it is not appropriate to include, for example, indicators of governance or institutional development in the analysis. To the extent that (a) institutional factors influence the current level of infrastructure provision, and (b) there is a correlation between institutional development and GDP per person or urbanisation, then the impact of institutional development will be (partly) captured by the coefficients on GDP per person or urbanisation in the reduced form discussed below.

There are, in fact, a very limited number of variables for which independent projections extending to 2050 have been constructed and can be used. In addition to the climate variables discussed above, these are total population, the age structure of the population, urbanisation, and growth in income (GDP per capita measured at purchasing power parity) plus a number of geographical features which act as country fixed effects[8].

The basic approach for the econometric analysis is to develop a reduced form specification of the efficient demand for the services provided by each type of infrastructure. We assume that the structural equation defining the efficient demand for infrastructure type i in country j in period t may be written as:

$$Q_{ijt} = f_i\{P_{jt}, Y_{jt}, C_{ijt}, X_{jt}, Z_{ijt}, V_{jt}, t\} \quad (3)$$

The variables are defined as follows:P_{jt} is the population of country j in period t;

[4] The 1st percentile of minimum monthly precipitation is zero for practically all grid cells, so that there is little point in including this in the analysis.

[5] There is one complication. Just over 10% of grid cells cover more than one country, but the data only provides the land area of each country in each grid cell plus total population in the grid cell. It is, therefore, necessary to assume that population density is uniform over these grid cells so that population is split between countries in the same proportion as land area.

[6] Horowitz (2008) discusses the possible consequences of the endogeneity of population-weighted average temperature and income arising if people tend to locate in areas with the most favourable climate. However, this argument has less weight for a group of climate variables, especially when population-weighted and inverse population-weighted climate variables are included.

[7] One point to note is that annual average temperature is negative or very small in a number of countries, especially for the inverse population-weighted means – e.g. Canada. The transformation adopted was to add 40 °C to all temperatures. This value reflects the range from the minimum value of the monthly minimum temperature (−29.1 °C) and the maximum value of the monthly maximum temperature (+46.9 °C). Average annual precipitation is positive for all countries, so that no shift is required before taking logs.

[8] The demographic projections are based on the Medium Fertility projection in UN Population Division's 2006 Revision which is linked to the urbanisation projections. The central scenario for growth rates for GDP per person at purchasing power is computed by taking the average of 5 economic integrated assessment models -Hope (2003), Nordhaus (1999), Tol (2007), IEA (2008) and DOE-EIA (2008). The average growth rate for world GDP in real terms is very close to the IPCC A2 SRES scenario, but the country growth rates are not based upon the downscaled versions of that scenario since those were constructed with a base date of 1990 and the relative country weights are very out of date.

Y_{jt} is average income per head for country j in period t;
C_{ijt} is the unit cost of infrastructure type i for country j in period t;
X_{jt} is a vector of country characteristics for country j in period t;
Z_{ijt} is a vector of economic or other variables that affect the demand for infrastructure type i for country j in period t; and
V_{jt} is a vector of climate variables for country j in period t.

We can observe or project values for some of these variables – notably P, Y, X, and V (dropping subscripts). For the other variables we assume that:

$$C_{ijt} = c_i\{Y_{jt}, X_j, Z_{ijt}, V_{jt}, t\} \tag{4}$$

and

$$Z_{ijt} = g_i\{Y_{jt}, X_{jt}, V_{jt}, t\} \tag{5}$$

Solving for Z_{ijt} and C_{ijt} allows us to write the reduced form as

$$Q_{ijt} = h_i\{P_{jt}, Y_{jt}, X_{jt}, V_{jt}, t\} \tag{6}$$

Since there are no strong priors on the appropriate functional forms for $f_i\{\ \}$, $c_i\{\ \}$, and $g_i\{\ \}$ we can use a standard flexible functional form to represent the demand equation $h_i\{\ \}$ in terms of the explanatory variables. For this purpose we have adopted a restricted version of the translog specification. Using the notation $x_j = \ln(X_j)$, the general translog function for infrastructure services may be written as:

$$\begin{aligned} d_{ijt} = {} & \alpha_i + \beta_{pi}p_{jt} + \beta_{yi}y_{jt} + \sum \beta_{xim}x_{mjt} + \sum \beta_{vir}v_{rjt} + \gamma_{yi}y_{jt}^2 \\ & + \sum \gamma_{xim}x_{mjt}^2 + \sum \gamma_{ril}v_{rjt}^2 + \sum \rho_{im}y_{jt}x_{mjt} + \sum \varphi_{ir}y_{jt}v_{rjt} \\ & + \sum \sigma_{imn}x_{mjt}x_{njt} + \sum \phi_{imr}x_{mjt}v_{rjt} + \sum \theta_{irs}v_{rjt}v_{sjt} \end{aligned} \tag{7}$$

In practice, it is often difficult to estimate the full translog specification using the more complex econometric models, so the approach adopted was to start with the log-linear specification and then test whether the coefficients on the quadratic and cross-product terms are significant. Because this involves repeated testing of overlapping specifications, we have followed the spirit of the Bonferroni adjustment to test statistics by using a significance level of 1% in deciding whether to include climate and other variables in the models[9].

Including average temperature in the demand models raises a concern that it may serve as a proxy for institutional and other factors that determine actual outcomes, perhaps as a consequence of historical patterns of development. Various models appear to show that a higher average temperature (usually for the capital city of the country) is associated with lower average income per person. Going further, the arguments developed by Acemoglu et al. (2001) (AJR) and Horowitz (2008) suggest that temperature may serve as an instrument for variables such as institutional development, disease, worker productivity or some combination of such factors. We have considered various ways of dealing with this problem.

(a) The AJR and Horowitz studies use colonial (mostly 18th century) mortality as an instrument for institutional development and found that this had a very significant coefficient in their equations for recent economic growth and GDP per person[10]. Since estimates of colonial mortality are not available for more than one-half of the countries in our sample, we have used an alternative set of instrumental variables. Demographic variables for the early 1950s taken from UN data provide good instruments because they are closely correlated with the historical endowment of both institutions and infrastructure, but demographic changes over the past 50 years mean that they are less associated with current patterns[11]. Two instruments – the crude birth rate and infant mortality, both for 1950–1954 – have been used because they capture the highest proportion of the cross-country variation of the demographic variables examined. Consistently, one or both of the variables have coefficients that are significantly different from zero at the 95% or 99% level.
(b) The role of climate as an instrument for institutional development is a geographical argument – i.e. it is about the geography of economic development – as much as it is about climate per se. Unfortunately, the data on water infrastructure – large N but small T – does not permit the use of standard spatial panel models as in Kapoor et al (2007). Instead, we have estimated models using robust standard errors that allow for a general pattern of spatial dependence between countries – see Driscoll and Kraay (1998), Hoechle (2007).[12]
(c) The arguments have focused on the role of temperature as a proxy for institutional development. It is much harder to understand how either temperature range or precipitation range could serve as good proxies for institutional development. Introducing inverse population-weighted climate variables alters the situation even further, since by definition these reflect climate patterns in areas where people do not live and have not lived in large numbers[13].

After extensive and careful investigation of potential instruments, the evidence strongly points to the conclusion that climate does and will have a significant influence on demand for water infrastructure. The primary investigation of alternative specifications is carried out using pooled OLS with Driscoll-Kraay standard errors[14]. In the case of the proportions of the population covered by water and sewer networks, the dependent variable is the logit of

[9] This rule is not applied rigidly. For example, consistent sequential testing for the inclusion of climate variables is not possible if the p-values for one or more non-climate variables would warrant their exclusion from some combinations of climate variables but not for others.

[10] It would be straightforward to develop similar arguments for the impact of disease and worker productivity as influences on economic growth. In each case our demographic instruments are likely to be better instruments than settler mortality. However, the AJR argument about institutional development seems more plausible when considering demand for infrastructure.

[11] The actual variable used in the AJR study is ln(settler mortality). For 63 countries in their samples (excluding The Bahamas) the correlations between ln(settler mortality) and our historic demographic variables are 0.46 for ln(crude birth rate), 0.67 for ln(infant mortality), and −0.69 for ln(life expectancy). The correlations with AJR's proximate indicator of institutions (average protection against expropriation risk 1985–1995) are −0.58 for ln(settler mortality), −0.57 for ln(crude birth rate), −0.69 for ln(infant mortality), and 0.65 for ln(life expectancy). Hence, our historic demographic indicators should provide better instruments for institutional influences than AJR's use of settler mortality.

[12] Driscoll-Kraay standard errors are robust to panel heteroscedasticity and temporal autocorrelation as well as spatial interdependence. The estimation is carried out using Hoechle's xtscc procedure in Stata, which generalises the Driscoll-Kraay estimator to allow for unbalanced panels.

[13] The absolute values of the correlation coefficients between the logs of similarly weighted climate variables are less than 0.7 across our sample of countries with the sole exception of total precipitation and precipitation range. Both temperature and precipitation are negatively correlated with temperature range. The correlation coefficients between population-weighted and inverse population-weighted variables range from 0.78 to 0.84 with the exception of temperature range for which the correlation is 0.95. As a consequence we have only used the population-weighted temperature range in our analysis.

[14] There is an important feature of the Driscoll-Kraay/Hoechle procedure that needs to be kept in mind. The method relies upon the derivation of a robust covariance matrix for a sequence of cross-sectional averages. The panels used for our analysis are very unbalanced and do not span continuous periods of time. Nonetheless, cross-sectional averages can be calculated for more than 25 years. The sample of countries in each cross-sectional average differs, but this is consistent with the way in which the covariance estimator is specified. Thus, even though the Driscoll-Kraay analysis relies upon asymptotics as $T \to \infty$, the nature of our data is consistent with its basic requirements.

the relevant shares in order to translate values between 0 and 1 to the entire real line with shares censored at 0.001 and 0.999. A panel tobit model has been used to estimate the demand equations for coverage rates for which a significant fraction of observations are censored from above with the upper limit equal to logit(0.999).

In addition to climate variables, the explanatory variables in the base models are:

- Log of population.
- Logs of GDP per person at 2005 PPP, country size, and urban population as % of total population plus quadratic terms in these variables.
- Log of a cross-country building cost index with the US = 1.0.
- Logs of the proportions of land area that are desert, arid, semi-arid, steep, very steep and have no soil constraints for agriculture – obtained from FAO's Terrastat database.
- Logs of the crude birth rate and infant mortality for 1950–1954.
- Dummy variables for World Bank regions.

Tests for the inclusion of non-climate and climate variables are performed separately. First, the non-climate variables are examined in a model including the main climate variables. Second, the population-weighted (pop) and inverse population-weight climate (ipop) variables are tested and variables with insignificant coefficients are dropped. Third, the variables for extreme values and intra-country variability are tested. Finally, interactions with GDP and urbanisation are tested for the climate variables which have been retained. The equations for water use per person are estimated using total population weights, while the equations for coverage rates are estimated using weights for urban or rural populations as appropriate. In all cases the weights are normalised to sum to the number of observations used for the analysis.

5. The effects of climate on demand for water infrastructure

5.1. Water use

The dependent variables for water use are the logs of water abstractions per person for municipal and industrial use – derived from FAO data. This includes water that is lost in treatment and in water supply networks. Models (1)–(3) in Table 1 summarise the results of the econometric analysis for municipal water use per person. The best specification includes population-weighted precipitation, precipitation range and extreme temperatures. Another point to note is the quadratic in GDP per person[15]. The results seem to be intuitively reasonable, reflecting rainfall patterns where people live and the effect of changes in GDP on water use. The quadratic terms in GDP per person imply that water consumption per person reaches a peak at an income of about $15,000 per capita in 2005 PPP and falls gradually as countries get richer beyond this point.

Models (4)–(6) in Table 1 summarise the results for industrial water use per person. In this case, the tests reject the hypotheses that the population-weighted and/or inverse population-weighted climate variables have zero coefficients. The detailed investigation identifies population-weighted temperature range and precipitation range plus inverse population-weighted precipitation and precipitation range as having significant coefficients. In addition, greater within-country variation in temperature range is associated with higher industrial water use. The quadratic in GDP per person implies that industrial water per person declines with income for middle and high income countries.

There are significant interactions between the inverse-population-weighted climate variables and GDP per person. These interactions mean that the effect of climate differs for high and low income countries. For high income countries, greater precipitation – holding precipitation range constant – is associated with higher industrial water use, whereas for low income countries it is associated with lower industrial water use. Use of water in industry is a derived demand, so climate variability within countries affects the scale and location of food processing and similar resource-based industries as well as the balance between inter-regional and international trade. This is why climate conditions in both densely and thinly populated areas all have an influence on this derived demand.

5.2. Water and sewer connections

Table 2 summarises the results for coverage rates of piped water supply and sewer network in urban and rural areas. Models (1)–(6) are based upon panel tobit estimation, allowing for the upper censoring of countries with reported coverage of 99.9% or higher, whereas there is no censoring for rural sewer coverage. For urban water coverage, temperature and precipitation range are significant variables on their own, but they are displaced by the extreme weather variables when tested jointly. Within-country variability in precipitation affects rural water coverage, presumably through the cost or availability of alternative water sources. Since coverage rates for urban networks are close to or equal to 99.9% in OECD countries, changes in climate variables have no effect on urban network coverage. However, changes in average temperature and precipitation may affect the numbers of households connected to public water and sewer systems in rural areas[16].

For the purpose of costing wastewater treatment we have assumed that the BOD/COD concentration and other characteristics of sewage handled by wastewater treatment plants correspond to typical values for municipal wastewater. This implies that industries will be expected to process wastewater with high concentrations of industrial pollutants. Further, it is assumed that wastewater treatment plants are scaled to process 80% of the volume of water treated by water treatment plants, allowing for network losses and wastewater that is not discharged to sewers.

6. Calculating the costs of adaptation

The calculation of the cost of adaptation involves a number of steps. The description that follows focuses on capital costs. A similar process is required to estimate changes in the costs of operation and maintenance, both for the baseline level of infrastructure and for changes in infrastructure resulting from changes in climate conditions[17]. Full details of the calculations are given in the appendices to World Bank (2009).

[15] This is an example of a variable that is significant at the 1% level in some specifications but only at the 5% level in others. The variable has been retained here because the inverted U-shaped relationship between water use per person and GDP per person is well-documented for rich countries with good data – e.g. the US.

[16] It should be emphasised that this is not a matter of whether households have access to some form of adequate water supply or sanitation. The dependent variable is the proportion of households that are connected to public networks, rather than relying upon equivalent individual arrangements.

[17] The analysis is formulated in terms of periods that are referred to by the first year in the period – i.e. 2010–2014 is shortened to 2010. No attempt is made to allow for within-period changes in variables. Some of the demographic variables (urbanisation and population age structure) used in the projection equations are based on period averages. For other variables, such as income and total population, the added complexity of using period averages outweighs the potential benefits.

Table 1
Equations for water use per person.

	Ln(Municipal water use per person)			Ln(Industrial water use per person)		
	(1)	(2)	(3)	(4)	(5)	(6)
Ln(Population)				0.258***	0.263***	0.146*
				(0.062)	(0.053)	(0.058)
Ln(GDP per person)	2.004**	1.848**	1.836*	2.983**	2.699**	2.867**
	(0.735)	(0.697)	(0.707)	(1.063)	(0.959)	(1.094)
Ln(Country size)				−0.229***	−0.146**	−0.207***
				(0.037)	(0.052)	(0.051)
Ln(% urban)	0.567***	0.597***	0.557***			
	(0.074)	(0.070)	(0.070)			
Ln(GDP per person) squared	−0.106*	−0.0965*	−0.0952*	−0.161*	−0.143*	−0.201**
	(0.042)	(0.040)	(0.040)	(0.064)	(0.057)	(0.061)
Ln(Temperature − pop)	1.066**			0.692		
	(0.343)			(1.398)		
Ln(Precipitation − pop)	−0.178	−0.336***	−0.217*	0.320		
	(0.180)	(0.094)	(0.083)	(0.421)		
Ln(Temp range − pop)	0.475**			1.754***	1.773***	1.382***
	(0.158)			(0.404)	(0.214)	(0.252)
Ln(Precip range − pop)	0.236	0.403***	0.294**	−0.824*	−0.626***	−0.662***
	(0.182)	(0.112)	(0.097)	(0.322)	(0.133)	(0.082)
Ln(Temperature − ipop)	0.019			−1.306*		
	(0.229)			(0.595)		
Ln(Precipitation − ipop)	0.111			−0.566*	−0.611**	−3.578***
	(0.083)			(0.229)	(0.192)	(0.886)
Ln(Precip range − ipop)	−0.058			0.895***	0.947***	3.798***
	(0.107)			(0.254)	(0.232)	(1.049)
Ln(Temp max 99th pctile − pop)			0.703***			
			(0.167)			
Ln(SD of Temperature range − pop)						0.600***
						(0.106)
Ln(Precipitation − ipop) *						0.385***
Ln(GDP per person)						(0.099)
Ln(Precip range − ipop) *						−0.372**
Ln(GDP per person)						(0.115)
Observations	366	366	366	335	335	334
Number of countries	159	159	159	156	156	155
R-squared	0.981	0.979	0.980	0.956	0.953	0.960
DF	19	14	15	21	18	21
P-value for all climate variables = 0	0.000			0.000		
P-value for pop climate variables = 0	0.000			0.000		
P-value for ipop climate variables = 0	0.313			0.000		

Note: Standard errors are shown in brackets underneath the relevant coefficients – $^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$. In addition to the variables shown, the equations include ln(Building cost) [municipal water use], ln(% steep land), ln(% verys steep land) [industrial water use], ln(% land with no soil constraint) [industrial use], ln(Birth rate 1950), ln (Infant mortality 1950), dummy variables for World Bank regions, and a constant. Source: Authors' estimates.

6.1. *Step 1 – construct baseline projections of infrastructure investment*

The equations discussed in the previous section are used to construct baseline projections of the efficient stock of infrastructure assets for 5-year periods from 2010 to 2050 under the assumption of no climate change[18]. The value of new investment required for infrastructure type *i* for country *j* in period *t* is obtained by multiplying $\Delta Q_{ijt} = Q_{ijt+1} - Q_{ijt}$ by C_{ij}, the unit cost of infrastructure type *i* in country *j* at 2005 prices. In addition to new investment, we have estimated the amount of investment that would be required to replace infrastructure assets that reach the end of their economic life using a continuous depreciation assumption – i.e. in period *t* the required replacement investment is $(5/L_i)^* Q_{ijt}$ where L_i is the typical economic life of infrastructure of type *i*.

[18] The projections rely upon the best linear unbiased predictor for the models as discussed in Baltagi et al. (2009). This is equivalent to Xβ from the estimated equation plus a fraction of the mean of the country residuals for the relevant country. The fraction depends upon the variance components of the model.

6.2. *Step 2 – add alternative climate scenarios*

The data used for the baseline projections is supplemented with projections of the climate variables for the NCAR and CSIRO scenarios. These are constructed as deltas at different dates with respect to the no climate change baseline derived from calculations of monthly average, maximum and minimum temperatures and precipitation.

6.3. *Step 3 – project infrastructure quantities under the alternative climate scenarios*

This is similar to the projection of baseline infrastructure quantities in Step 1 but using the climate variables for the alternative climate scenarios.

6.4. *Step 4 – Apply the dose-response relationship to estimate changes in unit costs for alternative climate scenarios*

We calculate the changes in unit costs for infrastructure type *i* in country *j* for period *t*, ΔC_{ijt}, using the climate change deltas for the alternative climate scenarios and the dose-response relationships. There is a complication that has to be considered. Normal

Table 2
Equations for water and sewer coverage.

	Logit(Urban water coverage)		Logit(Rural water coverage)		Logit(Urban sewer coverage)		Logit(Rural water coverage)	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Ln(Population)	0.438***	0.413***	0.490***	0.365***	0.377**	0.309**	0.846***	0.820***
	(0.117)	(0.109)	(0.112)	(0.110)	(0.121)	(0.115)	(0.143)	(0.211)
Ln(GDP per person)	0.895***	0.835***	2.818***	2.913***	2.850***	3.012***	2.985***	1.811***
	(0.151)	(0.150)	(0.306)	(0.299)	(0.333)	(0.321)	(0.791)	(0.520)
Ln(Country size)	−0.674***	−0.473***	1.439***	1.502***	2.323***	2.575***	0.840	0.491
	(0.119)	(0.094)	(0.309)	(0.305)	(0.393)	(0.372)	(0.549)	(0.381)
Ln(% urban)	−3.777***	−3.514***	1.346***	1.308***			1.078**	1.056**
	(1.001)	(0.997)	(0.233)	(0.233)			(0.388)	(0.337)
Ln(GDP per person)* Ln(Country size)			−0.280***	−0.288***	−0.306***	−0.324***	−0.190**	−0.140**
			(0.034)	(0.034)	(0.040)	(0.039)	(0.062)	(0.044)
Ln(GDP per person)* Ln(% urban)	0.452***	0.444***						
	(0.132)	(0.131)						
Ln(Temperature − pop)	−8.541***		−0.849		−6.082**	−6.115***	0.113	
	(2.333)		(2.365)		(2.152)	(1.398)	(2.612)	
Ln(Precipitation − pop)	−0.753		−1.537**	−1.407***	−0.220		0.251	
	(0.535)		(0.552)	(0.225)	(0.516)		(0.537)	
Ln(Temp range − pop)	−1.325		−1.250		−0.654		−1.145**	
	(0.694)		(0.727)		(0.756)		(0.353)	
Ln(Precip range − pop)	−0.299		0.868		0.155		−0.799	
	(0.531)		(0.580)		(0.535)		(0.720)	
Ln(Temperature − ipop)	−2.628*		−6.593***	−5.849***	−1.207		−5.031***	−4.323***
	(1.044)		(0.915)	(0.672)	(0.898)		(0.646)	(0.579)
Ln(Precipitation − ipop)	0.389		0.178		−0.493	−0.691***	−1.292***	−1.673***
	(0.394)		(0.373)		(0.355)	(0.119)	(0.124)	(0.299)
Ln(Precip range − ipop)	−0.362		−0.585		−0.260		0.799*	
	(0.438)		(0.413)		(0.433)		(0.317)	
Ln(Temp max 99th pctile − pop)		−6.232***						
		(1.116)						
Ln(Precip max 99th pctile − pop)		−1.851***						
		(0.258)						
Ln(SD of Precipitation − pop)				0.739**				
				−0.274				
Ln(GDP per person) * Ln(Precipitation − ipop)								0.122**
								−0.0413
Model	Tobit	Tobit	Tobit	Tobit	Tobit	Tobit	POLS	POLS
Observations	579	579	544	544	316	316	269	269
Number of countries	156	156	154	154	139	139	123	123
DF	20	14	19	15	20	15	22	18
No of censored obs	94	94	36	36	10	10	0	0
P-value for all climate variables = 0	0.000		0.000		0.000		0.000	
P-value for pop climate variables = 0	0.000		0.008		0.059		0.000	
P-value for ipop climate variables = 0	0.090		0.000		0.000		0.000	

Note: Standard errors are shown in brackets underneath the relevant coefficients – $^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$. In addition to the variables shown, the equations include ln(Building cost) [rural sewers], ln(% desert) [rural sewers], ln(% arid land) [all sewers], ln(% semi-arid land) [urban sewers], ln(Birth rate 1950), ln(Infant mortality 1950), dummy variables for World Bank regions, and a constant. POLS = pooled OLS with Driscoll-Kraay standard errors. Source: Authors' estimates.

engineering practice does not take account of changes in underlying climate conditions. Thus, in designing for a 100-year storm the engineer looks at the characteristics of the 100-year storm on the basis of evidence of storms up to the current date. Clearly, this does not allow for changes in the severity of the 100-year storm that might be expected to occur over the life of the asset.

Instead, we have assumed that the asset is designed to withstand the worst weather conditions that it might be exposed to over its life – i.e.

$$\Delta C_{ijt} = d\left[\max\left(V_{jt}, \ldots, V_{j,t+L_i}\right)\right] C_{ij} \tag{8}$$

If climate change leads to a monotonic change in the relevant weather variables, this implies that the asset is significantly over-designed for most of its working life, because it will only be exposed to the most severe weather conditions at the very end of its life. Designing for the worst outcome over the life of the infrastructure will tend to overstate the costs of adaptation.

The calculations may be illustrated by considering the impact of annual precipitation on commercial and similar buildings that form part of a water or sewage treatment plant. Assume that a new treatment plant is to be built in 2030 at a location that has a base (NoCC) precipitation of 100 cm per year. It is projected that over the life of the plant the country will experience an increase of 25 cm in average annual precipitation as a consequence of climate change. Our dose-response relationship postulates that the building code is updated for each 10 cm increase in precipitation, each time increasing average cost per square meter by 0.8% of the base construction cost. Thus, anticipating the change in climate means that the construction cost in 2020 will be 1.6% higher (2 building code updates @ 0.8% increase per update) than it would have been in the baseline with no climate change. Finally, we have assumed that such buildings account for 20% of the total cost of treatment plants, so this increase translates to an overall increase of 0.32% in capital spending on treatment plants built in the country in the five year period 2030–2034.

It is assumed that the building code updates ensure that maintenance costs for buildings constructed to the new standard are the same as those for buildings constructed to the original code with no climate change. On the other hand, there are additional maintenance costs for buildings constructed to the original (NoCC) building code as a consequence of climate change. So, a treatment plant built in 2000 will incur additional maintenance for buildings due to higher precipitation than originally envisaged in order to offset a reduction in expected life due to accelerated ageing.

6.5. Step 5 – estimate the change in total investment and maintenance costs for the baseline projections

This yields the Delta-C estimates of the cost of adaptation for each climate scenario with two variants corresponding to the alternatives at Step 4 above.

6.6. Step 6 – estimate the change in investment and maintenance Costs due to the difference between the baseline infrastructure quantities and the alternative climate scenario quantities

This yields the Delta-V estimates of the cost of adaptation for each climate scenario.

6.7. Step 7 – special adjustments

We have incorporated some special factors in the calculation of the costs of adapting to climate change that could not be represented by the general dose-response relationships. These are:

(a) Changes in patterns of rainfall due to climate change may reduce or increase the safe yield from reservoirs and rivers, thus altering the amount of investment in infrastructure required to meet future demand for raw water. This is a complex topic that is addressed in separate work undertaken for the EACC study – Ward et al. (2009). Agriculture is the primary user of water resources in all OECD countries and it has the lowest value-added per cubic meter of water abstracted. We assume that the adjustment to changes in water availability – holding water demand constant – will fall on the agriculture sector and does not represent a cost of adaptation for the water sector. On the other hand, if climate changes results in a higher level of demand for treated water, then the water sector has to bear the cost of meeting the extra demand for raw water resources. This will vary across river basins and countries but it should not exceed the marginal cost of water recycling or desalination. On this basis we have used a figure of US$0.30 per cubic meter at 2005 prices as the best estimate of the long run marginal cost of raw water in this study[19].
(b) The operating costs of water treatment plants may increase as a result of climate change. This is likely to be associated with changes in levels of peak flow in rivers from which water is abstracted, so the model allows for cost of chemicals to increase pro rata with maximum monthly precipitation.
(c) Changes in temperature affect the rate at which oxygen levels recover in rivers to which the effluent is discharged from wastewater treatment plants. This implies higher operating costs at treatment plants to maintain the quality of receiving waters. The increase in O&M costs is linked to the increase in average temperatures.

7. The costs of adaptation

Table 3 shows the projected changes in municipal, industrial and total water use in 2050 due to climate change by regional sub-groups of OECD countries. A broad pattern is that climate change tends to increase municipal demand for water and to reduce industrial demand with Eastern Europe as an outlier. The source of the difference is that municipal water use is driven by maximum temperature and precipitation patterns in heavily populated areas, whereas industrial water use is strongly influenced by precipitation in thinly populated areas. The climate scenarios, especially NCAR, generate important differences in the impact of climate change on rainfall patterns in more and less populated regions of OECD countries.

Table 3
Increase in water use due to climate change for OECD countries by region (Percentage increase in 2050 relative to no climate change scenario).

Region	NCAR scenario			CSIRO scenario		
	Municipal	Industrial	Total	Municipal	Industrial	Total
Western Europe	18%	−8%	−2%	7%	−10%	−6%
Eastern Europe	6%	26%	17%	4%	−3%	0%
North America	11%	−17%	−3%	9%	−10%	0%
Far East & Pacific	4%	−8%	0%	13%	−22%	1%
Total	11%	−9%	−1%	9%	−10%	−2%

Source: Authors' estimates.

Since industrial water use accounts for about 60% of total use of treated water, the overall impact is a reduction in total use. But, treating water for municipal use tends to be more costly than treatment for industrial use, so the shift in the composition of demand may, under some conditions, increase total costs. There are also significant differences between regions which may affect total costs due to different underlying growth rates. Hence, the choice of climate scenario is very important for any conclusions about both the total costs of adaptation and how these costs will be distributed.

The costs of adaptation for the full period 2010–2050 by region are shown in Tables 4 and 5 along with total baseline costs in the absence of climate change. For all water services the total cost of adaptation amounts to about 2% of the baseline cost of providing these services for the NCAR scenario and is about 1% of the baseline for the CSIRO scenario. Regional differences are large with a range from a cost of about 13% of baseline costs for Eastern Europe and a small saving (negative cost) for North America in the NCAR scenario. Under the CSIRO scenario Eastern Europe still experiences a positive cost but Western Europe has a small savings. For all regions it is the increase in municipal water demand leading to increased costs of water resources as well as water and sewage treatment that drives the results[20].

Overall, our analysis suggests that climate change will slightly reduce the total costs of installing and operating water and sewer network. There are three key reasons for this outcome:

(a) Existing water & sewer networks are designed to cope with substantial variations in water flows, while the capital costs of new or replacement assets are not sensitive to changes in the volume of water over a fairly wide range.
(b) We have assumed that storm water drainage and sanitary sewers are separated – in line with current practice. Changes in patterns of precipitation will certainly require investment in more and larger storm water drains, but this is treated as urban infrastructure rather than as a part of sewer networks.
(c) Climate change reduces coverage rates for rural water and sewer networks relative to the baseline with no climate

[19] The average cost of desalination is considerably higher than this figure, but it yields the equivalent of treated water so one must deduct the long run marginal cost of water treatment to obtain the marginal cost of raw water.

[20] Note that there is a strong upward bias to the cost of adaptation under our assumptions. We allow for the cost of obtaining additional water resources when total water demand with climate change exceeds total demand with no climate change, but this is not symmetric. If total water demand falls due to climate change, then the cost of adaptation is zero rather than negative since agriculture is assumed to take up the water resources that are freed.

Table 4
Costs of adaptation for OECD countries by region for NCAR scenario (Totals, 2010–50, US$ billion at 2005 prices, no discounting).

	Western Europe	Eastern Europe	North America	Far East & Pacific	Total
Water resources					
Total cost	109	51	101	12	272
Baseline cost	295	77	454	89	915
Water treatment					
Delta-C cost	2	0	9	1	12
Delta-V cost	7	37	(57)	1	(11)
Total cost	9	37	(48)	2	1
Baseline cost	1321	319	2018	408	4066
Water networks					
Delta-C cost	0	0	0	0	0
Delta-V cost	(2)	(2)	(7)	(2)	(14)
Total cost	(2)	(2)	(7)	(2)	(13)
Baseline cost	197	63	255	103	617
Sewer networks					
Delta-C cost	0	0	0	0	1
Delta-V cost	(8)	(6)	(21)	(5)	(40)
Total cost	(8)	(6)	(21)	(5)	(39)
Baseline cost	499	162	673	261	1595
Sewage treatment					
Delta-C cost	1	0	1	0	3
Delta-V cost	2	24	(51)	1	(25)
Total cost	3	24	(49)	1	(22)
Baseline cost	716	166	1123	222	2227
All water services					
Delta-C cost	3	1	11	1	15
Delta-V cost	108	104	(35)	7	183
Total cost	110	104	(25)	8	199
Baseline cost	3027	786	4523	1083	9419

Source: Authors' estimates.

Table 5
Costs of adaptation for OECD countries by region for CSIRO scenario (Totals, 2010–50, US$ billion at 2005 prices, no discounting).

	Western Europe	Eastern Europe	North America	Far East & Pacific	Total
Water resources					
Total cost	24	23	69	13	128
Baseline cost	295	77	454	89	915
Water treatment					
Delta-C cost	3	0	6	2	11
Delta-V cost	(28)	17	7	3	(1)
Total cost	(25)	17	13	5	10
Baseline cost	1321	319	2018	408	4066
Water networks					
Delta-C cost	0	0	0	0	0
Delta-V cost	(1)	(1)	(6)	(2)	(10)
Total cost	(1)	(1)	(6)	(2)	(10)
Baseline cost	197	63	255	103	617
Sewer networks					
Delta-C cost	0	0	0	0	1
Delta-V cost	(4)	(2)	(18)	(4)	(27)
Total cost	(4)	(2)	(17)	(3)	(27)
Baseline cost	499	162	673	261	1595
Sewage treatment					
Delta-C cost	1	0	1	0	2
Delta-V cost	(18)	11	(2)	1	(7)
Total cost	(17)	12	0	1	(5)
Baseline cost	716	166	1123	222	2227
All water services					
Delta-C cost	4	1	8	2	14
Delta-V cost	(27)	48	50	12	83
Total cost	(24)	49	58	15	98
Baseline cost	3027	786	4523	1083	9419

Source: Authors' estimates.

change, though not in absolute terms. This effect is particularly marked in North America and is a consequence of the large and highly significant negative coefficients on the inverse population-weighted temperature in models (4) and (8) of Table 2. The coefficients mean that people are more likely to rely upon individual rather than network water/sanitation systems in countries with large extents of terrain that is hot and thinly populated, because rural networks are costly to install and operate under such conditions.

Up to this point we have followed what may be described as an engineering approach to estimating the costs of adaptation. The Delta-C estimates rely on the assumption that adjustments to design standards will drive the costs of adaptation for new and existing capital assets, including the associated operating and maintenance costs. Similarly, the Delta-V estimates assume that adaptation takes the form of providing additional infrastructure to meet changes in demand caused by climate change. In economic terms this approach establishes an upper bound on the cost of adaptation, so it is worth considering how far alternative methods of adaptation might reduce the cost.

The results of our analysis offer a relatively clear alternative. The Delta-V costs of adaptation for water resources, which are determined by changes in water use, are greater than the net cost of adaptation for all water services. Thus, we consider what would happen if policies were designed to ensure that the overall level of water use does not increase as a result of climate change. This leads to a price-based or economic approach to calculating the cost of adaptation as illustrated in Fig. 1. The line NoCC shows the price-quantity demand relationship for water with no climate change. Climate change shifts the relationship upwards to the line CC leading to an increase $\Delta Q = Q_{CC} - Q_{NoCC}$ in the amount of water used if the unit stays constant at P_{NoCC}. Now, suppose that the price is increased by $\Delta P = P_{CC} - P_{NoCC}$, chosen so that the level of demand is restored to its NoCC level. In that case, the cost of adaptation may be calculated as the classic excess burden of a tax, the area ABC under the demand curve, which may be approximated by $\Delta P \Delta Q/2$. This area may be greater or less than the engineering cost of adaptation which is P_{NoCC} ΔQ, but it would only be appropriate to adopt the economic approach if the excess burden is less than the engineering cost.

The estimation of the excess burden depends upon two sets of assumptions.

(a) *Price elasticities of water demand*. We have taken these from a survey of published estimates undertaken by the World Bank as part of a study of the impact of subsidies in the electricity and water sectors – Komives et al. (2005), Table 2.2. The mean and median price elasticities are −0.38 for residential demand and −0.54 for industrial demand.
(b) *Water prices/costs without climate change*. The difficulty is that the prices/costs for water use vary within and between countries by type of user, volume of consumption, geographical area, etc. It is necessary to make some kind of simplifying assumption. For this study we have assumed that water utilities set charges to recover the full economic cost of treating water and wastewater.

For small changes in water demand due to climate change, the excess burden may be written as:

$$EB = \left(\frac{-1}{2\varepsilon}\right)\left(\frac{\Delta Q}{Q}\right)(P\Delta Q) \quad (9)$$

where ε is the appropriate elasticity and $P\Delta Q$ is the engineering cost of adaptation. Thus, the excess burden expressed as a percentage of

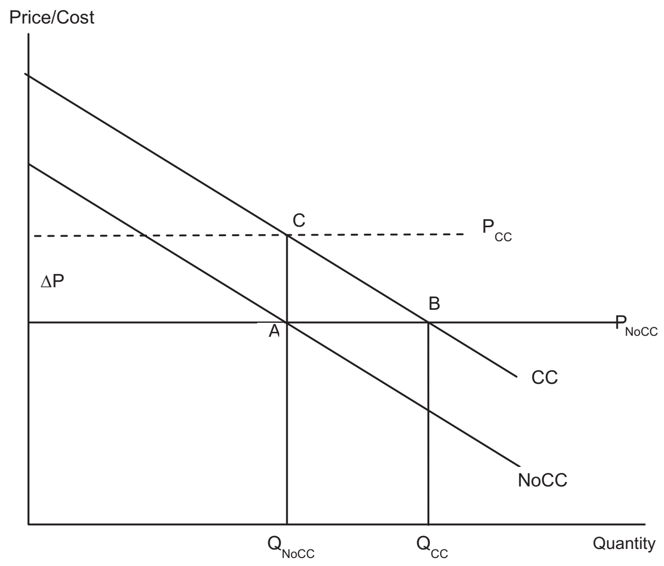

Fig. 1. Water levy to offset the impact of climate change.

Table 6
Economic and engineering costs of adaptation for OECD countries by region (Totals, 2010–50, US$ billion at 2005 prices, no discounting).

	Western Europe	Eastern Europe	North America	Far East & Pacific	Total
A. NCAR scenario					
Water resources					
Engineering cost	109	51	101	12	272
Economic cost	0	0	0	0	0
Baseline cost	295	77	454	89	915
Water treatment					
Engineering cost	9	37	(48)	2	1
Economic cost	(57)	28	(132)	(6)	(167)
Baseline cost	1321	319	2018	408	4066
Sewage treatment					
Engineering cost	3	24	(49)	1	(22)
Economic cost	(20)	18	(52)	(1)	(55)
Baseline cost	716	166	1123	222	2227
All water services					
Engineering cost	110	104	(25)	8	199
Economic cost	(87)	38	(212)	(13)	(274)
Baseline cost	3027	786	4523	1083	9419
Saving from economic adaptation	197	66	187	21	473
B. CSIRO scenario					
Water resources					
Engineering cost	24	23	69	13	128
Economic cost	0	0	0	0	0
Baseline cost	295	77	454	89	915
Water treatment					
Engineering cost	(25)	17	13	5	10
Economic cost	(45)	(2)	(44)	(5)	(96)
Baseline cost	1321	319	2018	408	4066
Sewage treatment					
Engineering cost	(17)	12	0	1	(5)
Economic cost	(21)	0	(5)	0	(26)
Baseline cost	716	166	1123	222	2227
All water services					
Engineering cost	(24)	49	58	15	98
Economic cost	(72)	(5)	(73)	(10)	(159)
Baseline cost	3027	786	4523	1083	9419
Saving from economic adaptation	48	54	131	25	257

Source: Authors' estimates.

the engineering cost will be x times the percentage change in water use, where $x \approx 1.32$ for municipal use and $x \approx 0.93$ for industrial use. The actual calculation is somewhat more complicated because we assume that the price increase is implemented through a uniform levy on water abstraction that is passed through to the bulk price of treated water, whereas water users pay prices that include distribution costs. The typical ratio of user price to bulk water price for municipal water use is substantially higher than for industrial water use, so that the following equation has to be solved for $\Delta P/P$ is

$$Q_m[CC]\left[1+\frac{1}{\sigma_m}\frac{\Delta P}{P}\right]^{\varepsilon_m}+Q_i[CC]\left[1+\frac{1}{\sigma_i}\frac{\Delta P}{P}\right]^{\varepsilon_i} = Q_m[NoCC]+Q_i[NoCC] \quad (10)$$

in which the subscripts m and i denote municipal and industrial water use and σ is the ratio of the user cost to the bulk water cost in each category of use.[21]

Table 6 compares the economic and engineering costs of adaptation for the two scenarios on the assumption that levies on water abstraction are used to ensure that the total volume of water abstracted does not rise as a result of climate change[22]. The economic approach does not alter the costs of constructing and maintaining water and sewer networks, so these are excluded from the table. The implementation of a price-based cap on total abstractions generates large savings relative to the engineering approach. The reduction in the cost of adaptation from adoption of the economic approach is $473 billion over 40 years or nearly $12 billion per year under the NCAR scenario. The reduction is smaller but still important for the CSIRO scenario. The gains arise from the asymmetry that is built into the mechanism – abstractions are capped by use of the water levy, but there is no limit on the reduction in investment and O&M costs where climate change leads to a decline rather than an increase in total water use. There is an important lesson here: intelligent policies to adapt to climate change do not have to be symmetric. Countries can benefit fully from favourable aspects of climate change and simultaneously adopt policies designed to minimise the economic burden of adjusting to its adverse effects.

8. Conclusion

The work reported in this paper represents the most extensive and careful effort that has been made to estimate the costs of adapting to climate change for infrastructure and the water sector in particular. The results for water services are not outliers – the costs of adaptation are similarly modest for other types of infrastructure.

It is striking that the overall cost of adapting to climate change, given the baseline level of infrastructure provision, is less than 2% of total cost of providing that infrastructure for OECD countries in aggregate. While there are differences across regions and sectors, the pattern is clear and unambiguous – the overall costs of

[21] Use of the excess burden triangle is an approximation that will over-estimate the welfare cost of adjustment to the water levy for non-marginal changes along a constant elasticity demand curve. However, the better approach of integrating the area under the demand curve for different categories of user requires information that we do not have when it comes to dealing with the adjustment for wastewater treatment.

[22] Note that the calculation is not symmetric. If climate change would lead to a reduction in water abstraction, we assume that the prices of raw and bulk water are held constant in real terms, so that the savings in capital and operating costs are taken in account in the same manner as for the engineering costs of adaptation.

adaptation are quite small in relation to other factors that may influence the future costs of infrastructure.

Second, our analysis shows that key components of the cost of adaptation can be reduced drastically if an economic approach to adaptation is followed rather than an engineering approach. Identifying a suitable market-based approach is straightforward in this case because it is the increase in total water use that determines the major part of the costs of adaptation. Using this approach converts an overall cost of adaptation under the NCAR from an average of about \$5 billion per year (\$199 billion over 40 years) to a net saving of more than \$7 billion per year (\$274 billion over 40 years) for all OECD countries.

Finally, even among the rich countries of the OECD the distribution of the burden of adapting to climate change is very uneven. For the NCAR scenario the relative cost of adaption is much higher for Eastern Europe than for Western Europe because climate change is predicted to increase water demand in Eastern Europe in contrast to the other regions. It is particularly beneficial to adopt an economic approach to adaptation under such circumstances.

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