Global Environmental Change 27 (2014) 9–18

Contents lists available at ScienceDirect

Global Environmental Change

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

Understanding the adaptation deficit: Why are poor countries more vulnerable to climate events than rich countries?

Samuel Fankhauser *, Thomas K.J. McDermott

Grantham Research Institute on Climate Change and the Environment and Centre for Climate Change Economics and Policy (CCCEP), London School of Economics, Houghton Street, London WC2A 2AE, United Kingdom

ARTICLE INFO

Article history:
Received 26 September 2013
Received in revised form 19 March 2014
Accepted 24 April 2014
Available online 29 May 2014

JEL classification:
O11
O13
Q54
Q56

Keywords:
Climate change
Adaptation
Development
Extreme events
Disaster risk

ABSTRACT

Poor countries are more heavily affected by extreme weather events and future climate change than rich countries. One of the reasons for this is the so-called adaptation deficit, that is, limits in the ability of poorer countries to adapt. This paper analyses the link between income and adaptation to climate events theoretically and empirically. We postulate that the adaptation deficit may be due to two factors: A *demand effect*, whereby the demand for the good "climate security" increases with income, and an *efficiency effect*, which works as a spill-over externality on the supply-side: Adaptation productivity in high-income countries is enhanced because of factors like better public services and stronger institutions. Using panel data from the Munich Re natural catastrophe database we find strong evidence for a demand effect for adaptation to two climate-related extreme events, tropical cyclones and floods. Evidence on the efficiency effect is more equivocal. There are some indications that adaptation in rich countries might be more efficient, but the evidence is far from conclusive. The implication for research is that better data, in particular on adaptation effort, need to be collected to understand adaptation efficiency. In terms of policy, we conclude that inclusive growth policies (which boost adaptation demand) should be an important component of international efforts to close the adaptation deficit.

1. Introduction

There is broad agreement that low-income countries are more vulnerable to current climate variability and future climate change than rich countries (e.g. World Bank, 2013). The insight is based partly on forward looking studies that assess the likely impact of future climate change (Tol, 2002a,b; Parry et al., 2007) and partly on empirical evidence that looks at the impact of extreme climate events in the past (Kahn, 2005; Toya and Skidmore, 2007).

Various explanations have been proffered as to why this is the case. Some authors point to the higher exposure of low-income countries to climate risk, for example due to a semi-arid climate or the concentration of populations in hazard zones. Others highlight the high sensitivity of low-income countries to such risks because of their heavy reliance on agriculture. Both these factors clearly matter (Bowen et al., 2012; Schumacher and Strobl, 2011).

However, the most powerful explanation is arguably the existence of an adaptation deficit in low-income countries (the term is due to Burton, 2009). Low-income countries are less able to deal with climate events because they lack the institutional, financial or technological capacity to adapt effectively (Yohe and Tol, 2002; Tol and Yohe, 2007; Brooks et al., 2005; Barr et al., 2010).

The aim of this paper is to shed further analytical and empirical light on the nature of the adaptation deficit. In particular, we ask whether the deficit is the result of inefficiencies in the provision of adaptation services or the rational allocation of scarce resources to more pressing needs.

The answer is important because it informs the appropriate policy response to high climate vulnerability. Inefficiencies in the provision of adaptation services would call for measures to boost adaptation efficiency. If the main cause is different priorities within a tight budget, the right solution may be growth policies to loosen the budget constraint (Schelling, 1992,

* Corresponding author. Tel.: +44 20 71075427.
E-mail address: s.fankhauser@lse.ac.uk (S. Fankhauser).

http://dx.doi.org/10.1016/j.gloenvcha.2014.04.014
0959-3780/

1997)–bearing in mind that certain types of growth can increase sensitivity to climate events (Bowen et al., 2012).

Theoretically, we find that both these factors may play a role: Income can affect the level of climate security first through a *demand effect* and second through an *efficiency effect*. The demand effect is straightforward: If the good ‘‘climate security’’ – or adaptation – has a positive income elasticity, rich countries will demand more of it. The efficiency effect works through an externality on the supply-side. Rich countries have more of certain assets – such as good public services, sound institutions and the ability to process knowledge – which are welfare-enhancing in their own right, but also have spill-overs for climate security. That is, they make the production of the good ‘‘climate security’’ more efficient.

We then seek to identify the two effects empirically, using panel data on climate-related natural disasters for a large number of countries between 1980 and 2008. The idea of using natural disaster data to identify adaptive capacity goes back at least to Yohe and Tol (2002; also Tol and Yohe, 2007). However, those papers were primarily interested in the degree of substitutability between adaptation factors, and their analysis was limited, in part due to the use of cross-sectional data. Other contributions are concerned with effects of disasters on economic growth (e.g. Noy, 2009; Strobl, 2010, 2011; McDermott et al., 2013) as opposed to explaining the severity of the disaster losses. There is also a strand of literature on the welfare impacts of economic ‘‘disasters’’ (Barro, 2006; Gabaix, 2008).

Our approach and aim are similar to recent contributions by Bakkensen (2013) Hsiang and Narita (2012), and Schumacher and Strobl (2011), while also building on earlier work by Kahn (2005), Anbarci et al. (2005), Toya and Skidmore (2007), and Kellenberg and Mobarak (2008). However, we deviate from those papers in several important ways.

On the theoretical side, our main innovation is the explicit distinction between supply (production efficiency) factors and demand factors in explaining adaptation to extreme events. Most of the existing literature seeks to explain the adaptation deficit by reference to the demand side. The motivation for additional protection is derived from an increasingly valuable stock of assets, which makes further adaptation worthwhile (e.g. Schumacher and Strobl, 2011; Hallegatte, 2013; Hsiang and Narita (2012). In our framework, adaptation is determined by a desire for greater (personal) protection from environmental risks, which is compared, importantly, to the cost of providing this protection.

Hsiang and Narita (2012) model optimal adaptation as a function of initial wealth, time preferences and hazard exposure. They predict that optimal adaptation is increasing in hazard exposure and in initial wealth. However, their model ignores the relative costs of adaptation (or its efficiency) and how these might vary with different levels of adaptation effort, capital stocks and wealth. The models of Schumacher and Strobl (2011) and Hallegatte (2013) both focus on the interaction of hazard exposure and wealth. Both models also allow for decreasing effectiveness (or increasing costs) of adaptation as effort increases, but neither allows for varying levels of efficiency in the supply of adaptation.

Our empirical contribution follows from the predictions of the theoretical model. We test explicitly for evidence of both a demand and a supply (efficiency) effect in the level of adaptation to disaster risk. The empirical setup is relatively flexible on the demand side, compared to the standard in the literature, which enables us to identify distinct drivers of demand. In addition to the income-related demand effect (our primary variable of interest) we also test for a scale effect (related to the value of assets or number of people exposed) and a substitution effect, where insurance offers an alternative to adaptation. The empirical challenge on the supply side is the absence of data on adaptation effort (e.g., adaptation spending) and the correlation of efficiency factors with income. We experiment with different data sets and model structures to overcome this problem, although the identification of supply-side effects remains weak.

We also deviate from the previous literature by employing a different dataset, the natural catastrophe (NatCat) database of Munich Re. This database is arguably more comprehensive in its coverage of disaster events, compared to the standard EM-DAT database (see further discussion in Section 3). One advantage of the NatCat data is that they include damage estimates for a far greater number of events than in EM-DAT, allowing us to provide results not just for lives lost, as is customary, but also for asset damages. We study losses from floods and tropical cyclones, the two largest climate-related disaster categories in terms of damages and fatalities.

Another advantage is that Munich Re also provides estimates of insured losses, which enables us, for the first time, to identify any substitution effects between adaptation and insurance.

The data also allow us to control systematically for event magnitude. Past studies often fail to distinguish between events of different magnitude, or do so only partially. For example, Noy (2009), Kahn (2005), Keefer et al. (2011), Anbarci et al. (2005) and Schumacher and Strobl (2011) control for earthquake magnitude only, while Bakkensen (2013) and Hsiang and Narita (2012) include magnitude data for tropical cyclone events only. Nordhaus (2010), Mendelsohn et al. (2012), Hsiang (2010), and Strobl (2011) include hurricane magnitude data, but focus exclusively on the US. Neumayer et al. (2013) is one of the few papers to include global data for multiple disaster types, while controlling for magnitude in each case.

The rest of the paper is structured as follows. Section 2 contains a simple theoretical model that introduces the two channels (demand and supply-side efficiency) through which income affects climate security. Section 3 sets up our empirical model, the results of which are discussed in Section 4. Section 5 discusses potential shortcomings and methodological refinements. Section 6 concludes.

2. A simple theoretical model

We can think of adaptation to climate events as a consumption choice between two goods. The first good is climate security, A, and satisfies our desire to be safe from environmental harm. Natural disasters cause hardship well beyond the foregone value of consumption, and this creates a willingness to pay for climate security (aside from the obvious threat to human life, Norris et al., 2002 document the mental health impacts of disasters on survivors). The second good is a composite consumption good, C, which represents all other goods and services.

For simplicity we keep the level of environmental harm constant. Households choose their preferred combination of climate security and consumption in the face of a given climate hazard. Evidently, the choice will be influenced by the nature of the hazard (i.e., the intensity and probability of extreme events) and society's exposure to it (i.e., people and assets in risk zones). The relationship is often non-linear. For example, Schumacher and Strobl (2011) find that for minor hazards adaptation levels can be close to zero (see also Hsiang and Narita, 2012; Kellenberg and Mobarak, 2008). In the empirical analysis we will control for these factors, but for the purposes of the theoretical model we assume a constant hazard level.

The choice between consumption C and climate security A is then modelled as the interaction between the cost of producing A

and the utility people derive from consuming it (for a dynamic model see Hallegatte, 2011).

We start with a representative household and its utility function, $U = U(C, A; \bar{H})$. Utility is a function of the two goods consumption, C, and climate security A. The utility function has the usual properties, i.e., $U_C > 0$; $U_{CC} < 0$; $U_A > 0$; $U_{AA} < 0$; $U_{CA} > 0$. Households have an exogenous income, Y, and they maximise utility subject to the budget constraint $Y = C + \pi A$, where π is the unit price of adaptation. The exogenous parameter $\bar{H}$ is there to remind ourselves that utility also depends on the level of climate hazard, which for the time being we keep constant.

The optimisation problem $\max_A U(Y - \pi A,\ A; \bar{H})$ yields the first-order condition $U_A = \pi U_C$, which can be solved for the optimal level of adaptation. The demand function is

$$A^D = A^D(Y, \pi; \bar{H}) \tag{1}$$

Differentiating the first-order condition, and remembering the second-order condition, confirms that $A^D_Y > 0;\ \ A^D_\pi < 0$ as one would expect. We are mostly interested in the first of the two derivatives. It is a standard income elasticity, although here we label it our *demand effect*. It tells us that as long as climate security is not an inferior good the demand for adaptation should go up as income rises.

On the production side, climate security may be delivered by either public agents (governments) or private agents (firms). While they have different objective functions, their optimisation problem is structurally similar, and we can think of both as maximising the net benefit (profit) from adaptation. The optimisation problem takes the form $\max_A \pi A - c(\varphi, A)$

The cost function, c, is convex in adaptation effort, $c_A > 0$; $c_{AA} > 0$ Costs also depend on an efficiency parameter, φ, which can be thought of as reflecting total factor productivity in the implicit production function. We assume $c_\varphi < 0$; $c_{\varphi\varphi} > 0$; $c_{A\varphi} < 0$. The first-order condition $\pi = c_A$ can be solved for the supply function

$$A^S = A^S(\varphi, \pi) \tag{2}$$

where $A^S_\varphi > 0;\ A^S_\pi > 0$. The price effect is as expected. The derivative with respect to φ states that as production efficiency increases, costs come down and supply goes up. This is our *efficiency effect*.

The hypothesis is that adaptation efficiency depends on factors such as institutional quality, social capital and an effective public sector that are also correlated with income. Owing to a positive spill-over from income to production efficiency a rise in income would then be expected to increase the supply (or reduce the cost) of adaptation.

There is some evidence of such income-related spill-overs. Studies on adaptive capacity invariably highlight factors such as literacy, governance and access to credit, which are correlated with income (Barr et al., 2010; Brooks et al., 2005; Tol and Yohe, 2007). Miao and Popp (2013) find that risk-mitigating innovation increases with income. Further afield, total factor productivity in industry tends to be associated with similar factors (e.g., good institutions, Isaksson, 2007), while Greene (2004) finds the efficiency of public health provision to be correlated with income.

Despite these pointers the existence – and indeed the sign – of the efficiency effect cannot be ascertained a priori, however, and must await empirical confirmation.

We are now in a position to calculate the market equilibrium by equating adaptation supply (Eq. (2)) and demand (Eq. (1)). More specifically we equate the inverse supply and demand functions $A^S_{-1} = A^D_{-1}$ to eliminate the (unobserved) price and derive:

$$A^* = A(Y, \varphi;\ \bar{H}) \tag{3}$$

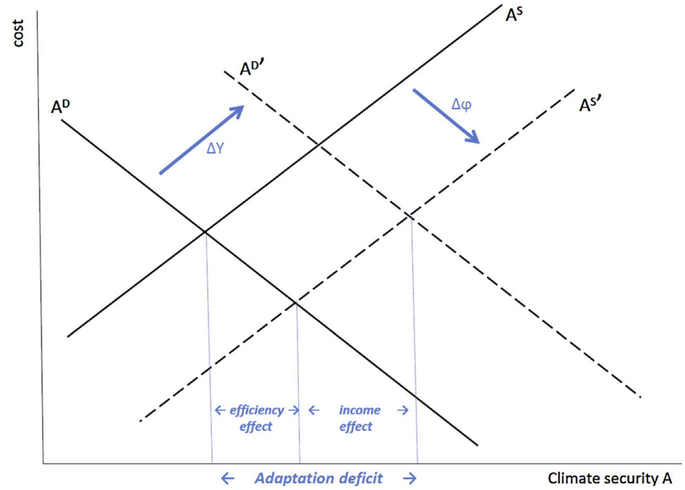

Fig. 1. The adaptation deficit as a function of income and efficiency effects.

Eq. (3) depicts the equilibrium relationship between climate security and income we wish to study – the adaptation deficit – and reintroduces the two channels through which an adaptation deficit might occur: An income effect, A_Y that is positive as long as climate security is not an inferior good, and an efficiency effect, A_φ, which we suspect may have some link to income. By differentiating the market equilibrium condition $A^S_{-1} = A^D_{-1}$ we confirm

$$A_Y > 0;\ \ A_\varphi > 0. \tag{4}$$

Fig. 1 summarises the two effects graphically, as an income-related shift in the demand for climate security and an efficiency related increase in the supply of climate security.

3. From theory to empirics

3.1. Data

We now turn to the empirical estimation of Eq. (3), using data from the Munich Re NatCat database. The Munich Re data are in many ways richer and less selective than the familiar EM-DAT data commonly used to estimate global disaster impacts (www.em-dat.be). The NatCat database records all natural hazard events worldwide that result in property damage or personal injury. In contrast, events are registered in EM-DAT only if one of the following criteria has been met: 10 or more people reported killed, a hundred or more people reported affected, a declaration of a state of emergency, or a call for international assistance.

The difference is potentially important for the study of adaptation to disaster risk. Where adaptation levels are highest, events are less likely to exceed the inclusion criteria for EM-DAT and are therefore missing from studies relying on this data set. As an illustration, the Munich Re data set contains more than 31,000 disaster entries (approximately 20,000 for the period 1980–2008), including 17,500 unique entries with positive recorded loss. In comparison, EM-DAT contains 8105 natural disaster entries for the period 1980–2009, of which just 3000 record a loss estimate (Neumayer et al., 2013). EM-DAT is also known to exhibit certain biases related to the way in which data are compiled (e.g. Gall et al., 2009).

The Munich Re data are not without gaps. In a comparison of three disaster databases (EM-DAT, NatCat and the Sigma database maintained by Swiss Re), Guha-Sapir and Below (2002) found that, across 120 events that were common to all three databases, economic damages were unreported in 58% of cases in NatCat (the equivalent figures for EM-DAT and Sigma were 62 and 66%, respectively). The number of events where fatalities were unreported was the same in each database (3%). It is also possible that the greater number of events in the NatCat database could be, at least partly, the result of the different approaches to the classification of events (as multiple versus single occurrences across different countries or over time), making comparisons across databases more difficult.

These issues notwithstanding, the Munich Re data are highly suitable to our purposes, given the greater coverage of disaster losses and the inclusion of insured losses in the data. For reasons of data quality and completeness we restrict our attention to the period 1980–2008, and we focus on the two climate-related events that account for most disaster deaths and economic damages: floods and tropical cyclones. Across the 25 event categories distinguished in the database, floods and cyclones account for 33% of deaths and 43% of economic damages.

Reducing the sample in this way still leaves us with over 5400 observations, drawn from more than 200 countries. Because our explanatory variables are only available at an annual frequency, we aggregate the events data to the country–year level. This process leaves us with 2274 country–year observations, comprised of 1779 country–years with floods and 495 country–years with tropical cyclones. In our regressions, a number of disaster observations are lost where economic data (GDP) is not available for all country–years.

Economic data (GDP, GDP per capita, and government spending) are from the World Bank's World Development Indicators. Estimates of country size (area in km^2) are from the Portland State University Country Geography data set (see http://www.pdx.edu/econ/country-geography-data).

3.2. Regression model

An immediate complication in our estimation procedure is that we do not observe adaptation effort, A, our variable of primary interest. What NatCat records instead is the actual damage of natural disasters, D. We overcome the problem by postulating the following relationship between adaptation effort and observed damages (see for example Schumacher and Strobl, 2011):

$$D = I(1 - A) \tag{5}$$

where I is a measure of the unmitigated physical impact of an event. From the disaster risk and climate change vulnerability literature (e.g., Field et al., 2012) we know that I is a function of the intensity or magnitude of an event (e.g. the wind speeds observed during a storm) and the sensitivity or exposure of society to events of given magnitude. Eq. (5) suggests that as long as we control for the factors explaining I, observed damages should be a reasonable indicator of adaptation effort.

Based on Eqs. (3) and (5) we can now formulate the basic structure of our empirical problem:

$$D_{it} = \boldsymbol{a} \cdot \boldsymbol{I_{it}} + \boldsymbol{b} \cdot \boldsymbol{Y_{it-1}} + z \cdot \varphi_{it-1} + u_{it} \tag{6}$$

where i and t denote country and time subscripts, respectively, and u_{it} is the error term. We will estimate the equation separately for each hazard type, using OLS and negative binomial regressions. Before we do so it is worth discussing the main variables.

Our dependent variable, D_{it}, is measured in two ways: either as economic damages or as lives lost. Most of the existing literature concentrates on the human costs of disaster events (e.g. Kellenberg and Mobarak, 2008; Anbarci et al., 2005; Kahn, 2005). Relatively few studies have used economic damages as the outcome of interest (exceptions include Schumacher and Strobl, 2011; Neumayer et al., 2013). This reflects, at least in part, concerns about the reliability of economic damage estimates (see discussion of data quality above).

On the right-hand side the equation includes three types of explanatory variables. We use lagged values for most of them (excluding disaster magnitude) in order to avoid any potential endogeneity bias.

The first set of controls, $\boldsymbol{I_{it}}$, is a vector of variables to normalise the intensity of events and the exposure of countries to events, as suggested by Eq. (5). The intensity of events is controlled by top wind speed in the case of tropical cyclones and by local precipitation in the case of floods. The data on top wind speeds are obtained from the Munich Re database. In aggregating events to the annual level, it is necessary to take account of the non-linear relationship between wind speed and damages. The best estimate appears to be a cubic relationship (see Emanuel, 2005; Bakkensen, 2013). We therefore take the cubed power of top wind speed prior to aggregating across multiple events.

In the case of floods, no intensity variables are included in the Munich Re database, and we use precipitation data from Neumayer et al. (2013) instead. These data represent local rainfall anomalies (deviations from long-term averages) associated with a particular flood event.

Exposure of a country is controlled by population, in the case of disaster deaths, and by GDP in the case of economic damages. GDP represents the flow of income derived from productive assets and should therefore be a reasonable proxy for the value of the capital stock. We also include land area as a measure of impact density. The intuition is that, for a given population size or GDP, a larger land area reduces the likelihood that a disaster event will strike a heavily populated or asset-rich zone. The final exposure variable is a time trend to capture changes over time in technology or disaster reporting (which are common across countries).

The second element of the equation, $\boldsymbol{Y_{it-1}}$, is a vector of variables intended to measure the drivers of adaptation demand. The vector includes income per capita, insurance coverage (insured losses as a % of total) and disaster propensity The expected effect of income per capita follows straight-forwardly from our theoretical model. The disaster propensity variable (from Neumayer et al., 2013) captures the average exposure of a country to a given disaster type over the long-term. A higher long-term exposure increases the incentive to undertake costly adaptation measures (see also Hsiang and Narita, 2012; Schumacher and Strobl, 2011; Keefer et al., 2011). Disaster propensity is therefore a relevant component of the demand effect. We also include insurance coverage as part of our demand effect. Insurance is a close substitute for adaptation, and we would expect a negative relationship between the extent of insurance cover and the demand for adaptation.

The third element of Eq. (6) is our measure of efficiency, φ_{it-1}. Our ability to identify an efficiency effect is constrained on two fronts. The first best option would be to measure adaptation effort and test directly for its efficiency. However, data on adaptation spending is patchy at best. As far as we are aware, no systematic cross-country comparisons or databases exist. Measuring adaptation efforts is clearly a priority for future research efforts.

Our efforts to measure efficiency are further complicated by the close correlation between income and the various factors associated with greater adaptive efficiency, such as literacy, governance, and public services, as highlighted in studies of adaptive capacity (see e.g. Barr et al., 2010; Brooks et al., 2005; Tol and Yohe, 2007). Indeed, our theoretical model predicts that efficiency gains occur through a positive spill-over from income to production efficiency, making the two effects difficult to distinguish empirically (see Section 2).

We have systematically tested for all the factors generally thought to be associated with adaptation efficiency – including for example literacy, life expectancy, institutional quality, income inequality, financial sector development, trade openness and macroeconomic stability – but failed to establish any consistent relationship with damages from disasters. This may have been because efficiency effects are not present in the data, or it could be that the high correlation between these variables and income prevented us from isolating efficiency effects from the demand effects.

We instead report on two further tests for the presence of efficiency effects. In the first test, we use general government spending (as a % of GDP) as a proxy for the quality of public services (such as early warning systems and evacuation procedures) and test its effect on the impact of disasters. Government spending (as a % of GDP) is positively correlated with income (the correlation coefficient is around 0.5 in our sample), but not to the same extent as other efficiency-related variables, such as political risk (a measure of institutional quality), life expectancy and financial sector development (all of which have correlation coefficients of 0.7 or above with respect to income, for our sample).

As a second test for efficiency effects we divide our sample between OECD (or more broadly high-income) countries and non-OECD (non-high income) countries. If there are income-related spillover effects, we would expect higher income countries to be more efficient in the provision of adaptation. Controlling for demand-side effects, a given event should cause lower losses in the rich (OECD) sub-sample.

4. Empirical results

4.1. Full sample results

Results for our full sample of countries are presented in Tables 1–4. Our calculations distinguish between two measures of impact (lives lost, economic damages) and two types of hazards (floods, cyclones), resulting in four sets of regressions. While our main focus is on cross-sectional results (representing comparisons of long-term adaptation across countries), we also include specifications that include country fixed effects (corresponding to short-term adaptations for a given country).

Table 1
Damages from floods, full sample.

Dep var: ln damages (millions of 1995 USD)				
Model	OLS (1)	OLS (2)	OLS (3)	OLS (4)
Ln rain	0.671***	0.602***	0.615***	0.607***
	(0.05)	(0.05)	(0.05)	(0.05)
Ln GDP	0.874***	0.845***	0.883***	1.141
	(0.12)	(0.11)	(0.11)	(1.10)
Ln GDPpc	−0.285*	−0.524***	−0.575***	−0.786
	(0.16)	(0.14)	(0.15)	(1.02)
Ln insured (% of damages)		0.962***	0.962***	0.994***
		(0.07)	(0.07)	(0.07)
Ln Gov Exp (% of GDP)			−0.021	−0.193
			(0.31)	(0.34)
Country fixed effects	N	N	N	Y
Obs.	1635	1635	1578	1578
Countries	151	151	144	144
R^2	0.3347	0.4088	0.4243	0.4098

Standard errors clustered by country, in parentheses. All models include a year trend. Models 1, 2 and 3 also control for country area (in km^2) and flood propensity.
* $p < 0.10$.
** $p < 0.05$.
*** $p < 0.01$.

Table 2
Damages from tropical cyclones, full sample.

Dep var: ln damages (millions of 1995 USD)				
Model:	OLS (1)	OLS (2)	OLS (3)	OLS (4)
Ln (top wind speed)^3	1.415***	1.103***	1.090***	1.120***
	(0.18)	(0.18)	(0.16)	(0.15)
Ln GDP	0.885***	0.681***	0.734***	−0.185
	(0.21)	(0.22)	(0.19)	(2.86)
Ln GDPpc	−0.445*	−0.827***	−1.037***	1.034
	(0.26)	(0.23)	(0.18)	(2.75)
Ln insured (% of damages)		1.057****	1.042***	1.069***
		(0.13)	(0.13)	(0.16)
Ln Gov Exp (% of GDP)			1.288**	−0.029
			(0.63)	(1.06)
Country fixed effects	N	N	N	Y
Obs.	344	344	337	337
Countries	44	44	44	44
R^2	0.3880	0.4976	0.5092	0.2836

Standard errors clustered by country, in parentheses. All models include a year trend. Models 1, 2 and 3 also control for country area (in km^2) and tropical cyclone propensity.
* $p < 0.10$.
** $p < 0.05$.
*** $p < 0.01$.

Across all four tables, the consistency of the coefficients on the magnitude variables (rain and wind) provides reassurance that these measures – albeit imperfect approximations of event severity – offer strong explanatory power in each case. We also find, as expected, that impact increases with exposure, that is, fatalities increase with population and damages with the value of assets exposed (GDP). The validity of our modelling setup is further supported by the relatively high R-squared values, with our models generally explaining between 40 and 50% of the variation in damages and fatalities across countries.

Across both asset damages and fatalities, we find strong evidence in support of the demand-side hypothesis, based on the coefficients on GDP per capita. At higher income, demand for adaptation is higher and losses for a given event (controlling for severity and exposure) will be lower. However, GDPpc is not significant in the regressions that include country fixed effects, indicating that it is differences in income levels across countries, rather than changes in income over time, that matter for disaster losses.

As expected, insurance is positively associated with damages and fatalities. Insurance acts as a substitute for adaptation and leads to moral hazard: agents with high insurance cover are less inclined to invest in adaptation. This finding is consistent across all model specifications, including those that include country fixed effects. Damages are found to increase one-for-one with the proportion of losses insured, while for fatalities the elasticities are much lower.

Turning to our attempts to identify efficiency effects, we find mixed evidence on the role of government spending – our proxy for public services like emergency services and social safety nets – in determining losses from disasters. Higher government spending is associated with fewer deaths from both floods and tropical cyclones, suggesting some relative efficiency in reducing the number of people killed by disasters for countries with higher government spending.

However, the results are not consistent across the asset-damage regressions. In one model specification, higher government spending is associated with higher damages. This might be

Table 3
Fatalities from floods, full sample.

Dep var:	Ln deaths	Ln deaths	Ln deaths	Ln deaths	Deaths	Deaths
Model:	OLS	OLS	OLS	OLS	NB	NB
	(1)	(2)	(3)	(4)	(5)	(6)
Ln rain	0.291***	0.284***	0.293***	0.296***	0.319***	0.323***
	(0.03)	(0.03)	(0.03)	(0.03)	(0.05)	(0.04)
Ln population	0.685***	0.682***	0.694***	−0.027	0.687***	0.649***
	(0.07)	(0.07)	(0.07)	(0.49)	(0.09)	(0.09)
Ln GDPpc	−0.335***	−0.361***	−0.346***	−0.102	−0.711***	−0.652***
	(0.04)	(0.05)	(0.05)	(0.14)	(0.08)	(0.07)
Ln insured (% of damages)		0.094**	0.098**	0.193***		0.177**
		(0.04)	(0.04)	(0.04)		(0.07)
Ln Gov Exp (% of GDP)			−0.355**	−0.126		−1.027***
			(0.16)	(0.21)		(0.26)
Country fixed effects	N	N	N	Y	N	N
Obs.	1635	1635	1578	1578	1635	1578
Countries	151	151	144	144	151	144
R^2	0.4577	0.4596	0.4795	0.2132		

Standard errors clustered by country, in parentheses. All models include a year trend. Models 1–3, 5 and 6 also control for country area (in km^2) and flood propensity.
*$p < 0.10$.
** $p < 0.05$.
*** $p < 0.01$.

because government spending is also associated with more infrastructure assets (controlling for GDP), and therefore higher exposure. However, the lack of consistency in the findings makes us cautious about interpreting the results in relation to government spending.

One possibility is that, rather than measuring public service quality, government spending is simply a proxy of public adaptation and therefore determined by a combination of both demand and supply effects. However, we did not find evidence to support this idea in the, admittedly sparse, data that we were able to compile on (public) adaptation spending. Looking at the cross section, there is no strong correlation between government spending and adaptation spending between countries, although for a given country public adaptation spending does appear to respond to changes in general government spending (see Committee on Climate Change, 2014 for the UK and Geloof and Kruik, 2012 for the Netherlands; also http://www.aideffectiveness.org/CPEIR for Nepal, Bangladesh, Thailand, Philippines and Cambodia).

4.2. Splitting the sample

In a further attempt to identify efficiency effects, we split our sample into rich country (OECD and other high income) and poor country (non-OECD, non-high income) sub-samples and repeat our analysis. The results are presented in Tables 5–8. Our focus here is on the elasticity of impacts (asset damages or fatalities) with respect to the magnitude of the disaster event. Controlling for demand effects (via GDPpc), and exposure (via total GDP or population), we are interested in how responsive impacts are to the severity of the event across our sub-samples. If income is associated with more efficient adaptation, then we would expect to find lower elasticities with respect to event magnitude in the rich sub-sample.

Our results show – if anything – the opposite pattern; the elasticity of asset damages with respect to event magnitude is clearly bigger in the rich sub-sample. However, this difference is attenuated when we control for insurance, indicating again that insurance acts as a substitute for adaptation (at least in our rich

Table 4
Fatalities from tropical cyclones, full sample.

Dep var:	Ln deaths	Ln deaths	Ln deaths	Ln deaths	Deaths	Deaths
Model:	OLS	OLS	OLS	OLS	NB	NB
	(1)	(2)	(3)	(4)	(5)	(6)
Ln (top wind speed)^3	0.701***	0.633***	0.655***	0.634***	1.020***	0.795***
	(0.12)	(0.12)	(0.12)	(0.11)	(0.12)	(0.12)
Ln population	0.679***	0.634***	0.630***	1.319	0.808***	0.643***
	(0.08)	(0.09)	(0.09)	(1.23)	(0.13)	(0.12)
Ln GDPpc	−0.511***	−0.639***	−0.601***	−0.302	−0.593***	−0.754***
	(0.06)	(0.07)	(0.07)	(0.30)	(0.10)	(0.08)
Ln insured (% of damages)		0.230**	0.252**	0.314***		0.516***
		(0.10)	(0.10)	(0.11)		(0.10)
Ln Gov Exp (% of GDP)			−0.232	−0.793		−1.087***
			(0.34)	(0.61)		(0.34)
Country fixed effects	N	N	N	Y	N	N
Obs.	344	344	337	337	344	337
Countries	44	44	44	44	44	44
R^2	0.5136	0.5281	0.5341	0.2929		

Standard errors clustered by country, in parentheses. All models include a year trend. Models 1, 2 and 3 also control for country area (in km^2) and tropical cyclone propensity.
*$p < 0.10$.
** $p < 0.05$.
*** $p < 0.01$.

Table 5
Damages from floods, split sample.

Dep var: ln damages (millions of 1995 USD)	OECD (and other high income)			Non-OECD (non-high income)		
Model:	OLS	OLS	OLS	OLS	OLS	OLS
	(1)	(2)	(3)	(4)	(5)	(6)
Ln rain	1.061***	0.750***	0.722***	0.593***	0.572***	0.549***
	(0.13)	(0.12)	(0.13)	(0.06)	(0.06)	(0.05)
Ln GDP	0.531***	0.511***	0.761	0.988***	0.962***	0.812
	(0.13)	(0.08)	(2.40)	(0.14)	(0.14)	(1.50)
Ln GDPpc	−0.252	−0.641***	−0.377	−0.565***	−0.588***	−0.489
	(0.24)	(0.21)	(2.08)	(0.20)	(0.20)	(1.44)
Ln insured (% of dam's)		1.033***	1.059***		0.789***	0.751***
		(0.07)	(0.08)		(0.13)	(0.16)
Country fixed effects	N	N	Y	N	N	Y
Obs.	453	453	453	1182	1182	1182
Countries	41	41	41	110	110	110
R^2	0.3207	0.5079	0.4823	0.3303	0.3476	0.3440

Standard errors clustered by country, in parentheses. All models include a year trend. Models 1–2, and 4–5 also control for country area (in km^2) and flood propensity.
* $p < 0.10$.
** $p < 0.05$.
*** $p < 0.01$.

sub-sample). For fatalities the elasticities across sub-samples are very similar.

The income elasticities are also worth comment. They appear to be larger in the rich sub-sample (this is most noticeable for tropical cyclone events). This suggests non-linearity in the income-impact relationship, but could also be evidence of relative efficiency – higher income has a bigger impact in reducing losses in rich countries than for the lower-income sample. However, it could equally be interpreted as simply different priorities, if richer countries are willing to devote a greater proportion of their incomes to adaptation efforts.

Again, we are unable to identify definitively an efficiency effect in our data and must conclude either that efficiency effects are minor, or that our data are inadequate to separate efficiency from demand effects.

5. Methodological discussion

We next explore methodological issues to ascertain the validity of our findings. A first question to ask is whether there might have been other, superior model specifications. An alternative – and subject to data availability perhaps superior – way to measure the efficiency component of the model would be stochastic frontier analysis (developed by Aigner et al., 1977, and Meeusen and van den Broeck, 1977). Stochastic frontier analysis has been used in numerous papers on the productive or cost efficiency of firms. However, the approach was primarily designed to measure production inefficiencies across firms that are relatively homogenous (e.g. a sample of firms all operating in the same sector). It is less appropriate for cross-country comparisons involving large variation in economic and social conditions although there are cross-country applications (e.g. Greene, 2004). The application of

Table 6
Damages from tropical cyclones, split sample.

Dep var: ln damages (millions of 1995 USD)	OECD (and other high income)			Non-OECD (non-high income)		
Model:	OLS	OLS	OLS	OLS	OLS	OLS
	(1)	(2)	(3)	(4)	(5)	(6)
Ln (top wind speed)[3]	1.880***	1.252***	1.289***	1.261***	1.031***	1.007***
	(0.21)	(0.17)	(0.18)	(0.23)	(0.22)	(0.20)
Ln GDP	1.392***	0.998***	0.808	0.666**	0.555*	1.803
	(0.37)	(0.27)	(4.58)	(0.29)	(0.28)	(4.66)
Ln GDPpc	−2.799**	−2.792**	−0.556	−0.286	−0.455	−0.948
	(1.23)	(1.17)	(5.30)	(0.39)	(0.39)	(4.23)
Ln insured (% of dam's)		1.267***	1.178***		0.963***	0.987***
		(0.15)	(0.19)		(0.17)	(0.26)
Country fixed effects	N	N	Y	N	N	Y
Obs.	110	110	110	234	234	234
Countries	11	11	11	33	33	33
R^2	0.4996	0.6639	0.5682	0.3181	0.3870	0.2615

Standard errors clustered by country, in parentheses. All models include a year trend. Models 1–2, and 4–5 also control for country area (in km^2) and tropical cyclone propensity.
* $p < 0.10$.
** $p < 0.05$.
*** $p < 0.01$.

Table 7
Fatalities from floods, split sample.

	OECD (and other high income)				Non-OECD (and non-high income)			
Dep var:	Ln deaths	Ln deaths	Ln deaths	Deaths	Ln deaths	Ln deaths	Ln deaths	Deaths
Model:	OLS	OLS	OLS	NB	OLS	OLS	OLS	NB
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Ln rain	0.338***	0.291***	0.265***	0.577***	0.276***	0.270***	0.290***	0.222***
	(0.05)	(0.05)	(0.05)	(0.05)	(0.04)	(0.04)	(0.04)	(0.05)
Ln population	0.451***	0.448***	−0.383	0.920***	0.812***	0.804***	−0.073	0.801***
	(0.07)	(0.08)	(0.71)	(0.11)	(0.08)	(0.08)	(0.68)	(0.09)
Ln GDPpc	−0.285	−0.347*	−0.258	−1.102***	−0.118*	−0.133*	−0.040	−0.377***
	(0.17)	(0.17)	(0.26)	(0.33)	(0.07)	(0.07)	(0.15)	(0.10)
Ln insured (% of damages)		0.157***	0.200***	0.260***		0.241**	0.188	0.838*
		(0.03)	(0.02)	(0.07)		(0.10)	(0.11)	(0.48)
Country fixed effects	N	N	Y	N	N	N	Y	N
Obs.	453	453	453	453	1182	1182	1182	1182
Countries	41	41	41	41	110	110	110	110
R^2	0.3411	0.3727	0.2274		0.4347	0.4386	0.0997	

Standard errors clustered by country, in parentheses. All models include a year trend. Models 1–2, 4–6 and 8 also control for country area (in km^2) and flood propensity.
* $p < 0.10$.
** $p < 0.05$.
*** $p < 0.01$.

stochastic frontier analysis to our natural disaster data also poses methodological/conceptual challenges, such as a lack of data on input costs (e.g. how much is spent on climate protection measures) and the large proportion of zeroes in the casualty data, which require a model capable of handling non-normally distributed outcome variables (such as the negative binomial model that we use).

A second question to ask is whether there are any issues with the specification we did choose. The regressions involving economic damages as the outcome variable are estimated by standard OLS regressions, with a log-log model specification. Results with number of deaths as the outcome of interest were also obtained by OLS with a log-log specification (taking ln(1 + number killed) as the outcome variable). This is for ease of comparison and interpretation of coefficients. However, given the distribution of disaster fatalities, with a large number of zeroes (approximately 23% of tropical cyclone country–years and 32% of flood country–years) we also provide results using the negative binomial regression. This model is preferred to a Poisson model due to the over-dispersion of the disaster fatalities data (the mean of this series is 214, with a standard deviation of 3456) and is consistent with the existing literature (e.g. Keefer et al., 2011; Kellenberg and Mobarak, 2008). We also experimented with alternative estimators to the negative binomial, notably a Poisson QMLE estimator, and the results are consistent.

Another alternative would be the zero-inflated negative binomial (ZINB) model, given the relatively large number of zeros in the data. However, the ZINB model assumes that the data are the result of two distinct underlying processes, whereby a proportion of the observed zeroes are the result of some distinct category within the data for which the probability of zero is 1 (see Keefer et al., 2011). Given that our data are drawn from a database of natural disaster events, which by their very definition pose a threat to human life, an assumption of zero probability of death, even for a subset of the data, would seem too strong.

A third concern is whether we control appropriately for the intensity of events, that is, the completeness of vector **I**. The

Table 8
Fatalities from tropical cyclones, split sample.

	OECD (and other high income)				Non-OECD (and non-high income)			
Dep var:	Ln deaths	Ln deaths	Ln deaths	Deaths	Ln deaths	Ln deaths	Ln deaths	Deaths
Model:	OLS	OLS	OLS	NB	OLS	OLS	OLS	NB
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Ln (top wind speed)[3]	0.653***	0.580**	0.624**	0.875***	0.724***	0.635***	0.593***	0.780***
	(0.19)	(0.19)	(0.21)	(0.14)	(0.14)	(0.14)	(0.13)	(0.12)
Ln population	1.060***	1.014***	7.748	1.329***	0.642***	0.599***	3.485**	0.716***
	(0.12)	(0.14)	(4.45)	(0.12)	(0.11)	(0.12)	(1.57)	(0.10)
Ln GDPpc	−1.239*	−1.285*	−0.593	−1.641***	−0.525***	−0.634***	−0.211	−0.758***
	(0.58)	(0.65)	(0.73)	(0.51)	(0.12)	(0.12)	(0.30)	(0.11)
Ln insured (% of damages)		0.148**	0.173***	0.299***		0.375*	0.498**	0.593***
		(0.06)	(0.03)	(0.09)		(0.20)	(0.20)	(0.19)
Country fixed effects	N	N	Y	N	N	N	Y	N
Obs.	110	110	110	110	234	234	234	234
Countries	11	11	11	11	33	33	33	33
R^2	0.5765	0.5891	0.2949		0.4160	0.4416	0.1851	

Standard errors clustered by country, in parentheses. All models include a year trend. Models 1–2, 4–6 and 8 also control for country area (in km^2) and tropical cyclone propensity.
* $p < 0.10$.
** $p < 0.05$.
*** $p < 0.01$.

destructiveness of storms in particular has many dimensions – including wind speed, rainfall, forward velocity and radius of maximum winds (Strobl, 2010) – which we are unable to capture fully. Similarly, the intensity of a flood event is unlikely to be fully captured by local precipitation data, as factors such as local topography are also relevant. Our disaster magnitude variables are thus, of necessity, rough proxies for the true intensity of the experienced event. However, as our magnitude variables are highly significant predictors of disaster losses they represent an improvement on omitting this factor from the analysis entirely.

The way differences in exposure are controlled for needs to strike a balance between accuracy and exogeneity. By choosing population and land mass as the main controls we opt for variables that are clearly exogenous. Other measures of people and assets at risk, e.g., those located in hazard zones, may offer a more precise description of exposure, but the decision to locate in hazard zones is arguably influenced by the desire to manage the risks involved. That is, it reflects endogenous adaptive behaviour. We have included a time trend, which captures trends in location behaviour over time that are common across countries. We also experimented with specifications that included urbanisation as an additional control, but found this variable to be insignificant. This gives us some reassurance that differences in exposure and sensitivity are adequately controlled for.

Our analysis has focused on two specific disaster categories, floods and tropical cyclones. Other important climate-related disasters are not included, notably droughts, heat waves and wind storms. There has been some work on the economic impact of heat waves (Martin et al., 2011), but the data to do so systematically is lacking. A disaster category that is amenable to systematic analysis, and in fact accounts for a large proportion of disaster losses, is earthquakes. Earthquakes are of less interest here, given our focus on climate-related adaptation, and they already feature prominently in the literature (e.g. Anbarci et al., 2005; Keefer et al., 2011).

6. Conclusions

This paper analyses the link between income and adaptation to past and future climate events. It is widely accepted that poor countries are more heavily affected by extreme weather events and hence future climate change than rich countries. The discrepancy has even been given its own name: the adaptation deficit. We argue theoretically that the adaptation deficit may be due to two factors: A *demand effect*, whereby the demand for the good ‘‘climate security’’ increases with income, and an *efficiency effect*, which works as a spill-over externality on the supply-side. Because of these spill-overs, adaptation productivity is enhanced in the socio-economic context of high-income economies.

We find empirically that there is a strong and unambiguous demand effect. An increase in per capita income reduces the impacts of extreme events in all cases and for most model specifications (except those including country fixed effects). A higher income also increases the demand for substitutes to adaptation, in particular insurance cover, but the demand effect remains strong even if we control for this factor.

There is much more ambiguity about the efficiency effect. We find some evidence of efficiency spill-overs associated with government spending (a measure of adaptation-related public goods, such as safety nets and emergency response systems), but overall the empirical evidence is patchy and weak.

We cannot conclude from this that there is no efficiency effect. Rather, we hypothesise that the efficiency effect may be masked by the demand effect and determine that the data are insufficient for its identification. A more conclusive analysis would require better data on adaptation effort – the amount of capital and resources devoted to disaster risk management and adaptation. Information about adaptation spending is limited, especially but not only in developing countries, and we see it as a research priority to close this gap.

Research on the link between economic growth and resilience to climate risk is still patchy, and there is scope for further analysis also in other areas. One important question which has not been addressed is how income changes the sensitivity of economies to climate events. We account for this crudely by controlling for either GDP or population size. However, there are much richer dynamics, which remain unexplored, of how trends like economic diversification, globalization, urbanisation and migration to coasts affect the long-term vulnerability of countries to climate risk.

While research on these questions continues, some policy implications can already been drawn. Perhaps the most powerful lesson concerns the importance of inclusive (and low-carbon) growth policies as a way to close the adaptation deficit from the demand side. We know that some development policies can increase vulnerability to climate events (Bowen et al., 2012), but climate-sensitive development is clearly an important complement to dedicated adaptation policies.

While our results are equivocal on the efficiency effect, we do not conclude that development assistance is all that is needed, as suggested by for example Schelling (1992, 1997). There is enough evidence to suspect that adaptation efficiency might be uneven and that some countries or adaptation actors might require help to put in place an effective adaptation response. And even if current response systems are efficient, most developing countries will need help to handle the step change from current climate vulnerability to future climate change.

Acknowledgments

This research is part of the green growth programme at the Grantham Research Institute, which is funded by the Global Green Growth Institute, as well as the Grantham Foundation for the Protection of the Environment, and the Economic and Social Research Council (ESRC) (Grant No. ES/K006576/1) through the Centre for Climate Change Economics and Policy. We are grateful to Munich Re for granting us access to their Natural Catastrophe database, and to Laura Bakkensen, Federico Belotti, Jonathan Colmer, Stephene Hallegatte, Cameron Hepburn, Adriana Kocornik-Mina, Stefania Lovo, Michael Mullan, Eric Neumayer, Nicola Ranger, Malcolm Smart, Swenja Surminski, the journal editors and two anonymous referees for their comments and feedback. The usual disclaimer applies.

References

Aigner, D.J., Lovell, C.A.K., Schmidt, P., 1977. Specification and estimation of frontier production, profit and cost functions. J. Econom. 25, 21–37.
Anbarci, N., Escaleras, M., Register, C.A., 2005. Earthquake fatalities: the interaction of nature and political economy. J. Public Econ. 89, 1907–1933.
Bakkensen, L., 2013. Adaptation and Natural Disasters: Evidence from Global Tropical Cyclone Damages and Fatalities, mimeo. Yale University.
Barr, R., Fankhauser, S., Hamilton, K., 2010. Adaptation investments: a resource allocation framework. Mitig. Adapt. Strateg. Global Change 15 (8), 843–858.
Barro, R.J., 2006. Rare disasters and asset markets in the twentieth century. Q. J. Econ. 121, 823–866.
Bowen, A., Cochrane, S., Fankhauser, S., 2012. Climate change, adaptation and growth. Climatic Change 113, 95–106.
Brooks, N., Adger, N., Kelly, M., 2005. The determinants of vulnerability and adaptive capacity at the national level and the implications for adaptation. Global Environ. Change 15, 151–163.
Burton, I., 2009. Climate change and the adaptation deficit. In: Schipper, E.L.F., Burton, I. (Eds.), The Earthscan Reader on Adaptation to Climate Change. Earthscan, London.

Committee on Climate Change, 2014. Flood and Coastal Erosion Risk Management Spending. Policy Note. http://www.theccc.org.uk/wp-content/uploads/2014/01/2014-01-21-ASC-Policy-Note-flood-defence-spending-FINAL.pdf.

Emanuel, K., 2005. Increasing destructiveness of tropical cyclones over the past 30 years. Nature 436 (7051), 686–688.

Field, C., et al., 2012. Managing the Risks of Extreme Events and Disasters to Advance Climate Change Adaptation. A Special Report of the Intergovernmental Panel on Climate Change. Cambridge University Press, Cambridge.

Gabaix, X., 2008. Variable rare disasters: a tractable theory of ten puzzles in macro-finance. Am. Econ. Rev. 98, 64–67.

Gall, M., Borden, K.A., Cutter, S.L., 2009. When do losses count? Six fallacies of natural hazards loss data. Bull. Am. Meteorol. Soc. 90, 799–809.

van Geloof, E.W., de Kruik, M.J., 2012. Adaptation and Mitigation Expenditures Due to Climate Change of the General Government 2007–2010. Statistics Netherlands, The Hague.

Greene, W., 2004. Distinguishing between heterogeneity and inefficiency: stochastic frontier analysis of the World Health Organization's panel data on national health care systems. Health Econ. 13, 959–980.

Guha-Sapir, D., Below, R., 2002. The Quality and Accuracy of Disaster Data: A Comparative Analysis of Three Global Data Sets. The ProVention Consortium, The Disaster Management Facility The World Bank Available:In: http://www.proventionconsortium.org/publications.htm.

Hallegatte, S., 2011. How Economic Growth and Rational Decisions Can Make Disaster Losses Grow Faster than Wealth, Policy Research Working Paper No. 5617. World Bank.

Hallegatte, S., 2013. A Normative Exploration of the Link Between Development, Economic Growth and Natural Risk, Fondazione Eni Enrico Mattei Working Papers No. 780.

Hsiang, S.M., 2010. Temperatures and cyclones strongly associated with economic production in the Caribbean and Central America. Proc. Natl. Acad. Sci. 107, 15367–15372.

Hsiang, S.M., Narita, D., 2012. Adaptation to cyclone risk: evidence from the global cross-section. Climate Change Econ. 3 (2) .

Isaksson, A., 2007. Determinants of Total Factor Productivity: A Literature Review. Research and Statistics Branch, UNIDO.

Kahn, M., 2005. The death toll from natural disasters: the role of income, geography and institutions. Rev. Econ. Stat. 87, 271–284.

Keefer, P., Neumayer, E., Plumper, T., 2011. Earthquake propensity and the politics of mortality prevention. World Dev. 39, 1530–1541.

Kellenberg, D., Mobarak, A., 2008. Does rising income increase or decrease damage risk from natural disasters? J. Urban Econ. 63, 788–802.

Martin, R., Muûls, M., Ward, A., 2011. The Sensitivity of UK Manufacturing Firms to Extreme Weather Events, Working Paper. Grantham Research Institute and Centre for Climate Change Economics and Policy, London School of Economics.

McDermott, T.K.J., Barry, F., Tol, R.S.J., 2013. Disasters and development: natural disasters, credit constraints and economic growth. Oxf. Econ. Pap., http://dx.doi.org/10.1093/oep/gpt034 (first published online November 5, 2013).

Meeusen, W., van den Broeck, J., 1977. Efficiency estimation from Cobb–Douglas production function with composed errors. Int. Econ. Rev. 18, 435–444.

Mendelsohn, R., Emanuel, K., Chonabayashi, S., Bakkensen, L., 2012. The impact of climate change on global tropical cyclone damage. Nat. Climate Change 2, 205–209.

Miao, Q., Popp, D., 2013. Necessity as the Mother of Invention: Innovative Responses to Natural Disasters, NBER Working Paper 19223. National Bureau of Economic Research, Boston, MA.

Neumayer, E., Plumper, T., Barthel, F., 2013. The political economy of natural disaster damage. Global Environ. Change, http://dx.doi.org/10.1016/j.gloenvcha.2013.03.011.

Nordhaus, W.D., 2010. The economics of hurricanes and implications of global warming. Climate Change Econ. 1, 1–20.

Norris, F.H., Friedman, M.J., Watson, P.J., Byrne, C.M., 2002. 60,000 disaster victims speak: Part I. An empirical review of the empirical literature, 1981–2001. Psychiatry 65, 207–239.

Noy, I., 2009. The macroeconomic consequences of disasters. J. Dev. Econ. 88, 221–231.

Parry, M., et al., 2007. Climate Change 2007: Impacts, Adaptation and Vulnerability. Contribution of Working Group II to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change Cambridge University Press, Cambridge, UK.

Schelling, T., 1992. Some economics of global warming. Am. Econ. Rev. 82, 1–14.

Schelling, T., 1997. The cost of combating global warming: facing the tradeoffs. Foreign Aff. 76 (6), 8–14.

Schumacher, I., Strobl, E., 2011. Economic development and losses due to natural disasters: the role of hazard exposure. Ecol. Econ. 72, 97–105.

Strobl, E., 2010. The economic growth impact of natural disasters in developing countries: evidence from hurricane strikes in the Central American and Caribbean regions. J. Dev. Econ. 97, 130–141.

Strobl, E., 2011. The economic growth impacts of hurricanes: evidence from US coastal counties. Rev. Econ. Stat. 93, 575–589.

Tol, R.S.J., 2002a. Estimates of the damage costs of climate change – Part 1: Benchmark estimates. Environ. Resour. Econ. 21 (1), 47–73.

Tol, R.S.J., 2002b. Estimates of the damage costs of climate change – Part II: Dynamic estimates. Environ. Resour. Econ. 21 (2), 135–160.

Tol, R., Yohe, G., 2007. The weakest link hypothesis for adaptive capacity: an empirical test. Global Environ. Change 17, 218–227.

Toya, H., Skidmore, M., 2007. Economic development and the impacts of natural disasters. Econ. Lett. 94 (1), 20–25.

World Bank, 2013. Turn Up the Heat. Climate Extremes, Regional Impacts, and the Case for Resilience World Bank, Washington, DC.

Yohe, G., Tol, R., 2002. Indicators for social and economic coping capacity – moving toward a working definition of adaptive capacity. Global Environ. Change 12 (1), 25–40.