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Grantham Research Institute on
Climate Change and
the Environment

Understanding the Adaptation Deficit

Why are poor countries more vulnerable to climate events than rich countries?

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September 2013

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Abstract

Poor countries are more heavily affected by extreme weather events and future climate change than rich countries. This discrepancy is sometimes known as an adaptation deficit. This paper analyses the link between income and adaptation to climate events theoretically and empirically. We postulate that the adaptation deficit is 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 infrastructure and stronger institutions. Using panel data from the Munich Re natural catastrophe database we find evidence for both effects in two climate-related extreme events: tropical cyclones and floods. The demand effect is uniformly strong, but there is considerable variation in adaptation efficiency. We identify the countries where inefficiencies are largest. Lower adaptation efficiency is associated in particular with less government spending, an uneven income distribution and bad governance. The conclusion for policy is that international efforts to close the adaptation deficit have to include both inclusive growth policies (which boost adaptation demand) and dedicated adaptation support (which enhances spill-overs), the latter targeted at the countries with the highest adaptation inefficiencies.

Keywords: climate change, adaptation, development, extreme events, disaster risk

JEL classification: O11, O13, Q54, Q56

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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, Noy 2009, 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, economic or financial capacity to adapt effectively (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 this 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, 1997) – bearing in mind that certain types of growth can increase sensitivity to climate events (Bowen et al 2012).

We argue that both these factors play a role. Income affects 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 strong social capital, sound institutions, high regulatory standards and good public services – 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 document the existence of the two effects empirically, using data on climate-related natural disasters for a large number of countries between 1980 and 2008. Our approach and aim are similar to Bakkensen (2013), Hsiang and Narita (2012), Kahn (2005) and Toya and Skidmore (2007), but we improve on those papers in several ways, including by using a superior data set.

The Munich Re natural catastrophe data we use are considerably richer and less selective than the familiar EM-DAT data commonly used to estimate global disaster impacts (www.emdat.net). The NatCat database records all natural hazard events worldwide that result in property damage or personal injury. It contains more than 31,000 disaster entries, including 17,500 unique entries with positive recorded loss. In comparison, EM-DAT contains 8,105 natural disaster entries for the period 1980 to 2009, of which just 3,000 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). Events are registered 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 superior coverage in the Munich Re data allows us to study disasters without undue concerns about potential biases in the data. It allows us to provide results not just for lives lost, as is customary, but also for asset damages, and to control systematically for disaster magnitude. Past studies in this area often fail to distinguish between climate 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. (2010), 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.

Our paper differs from others in the analytical question we answer. The idea of using data on natural disaster losses to identify adaptation capacity goes back at least to Tol and Yohe (2002; 2007). However, those papers focus on testing the degree of substitutability between adaptation factors, while their analysis of natural disaster losses was limited, in part due to the use of cross-sectional data. Other contributions are concerned with effect 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).

Papers that attempt to identify the determinants of disaster losses tend to focus narrowly on the relationship with income, along with various political economy stories (Anbarci et al. 2005, Hsiang and Narita 2012, Schumacher and Strobl, 2011, Keefer et al. 2011, and Neumayer et al. 2013). Our paper differs from these contributions by establishing a clear, if simple theoretical framework on the link between income and disaster loss. This allows us to construct country efficiency rankings and identify countries that perform particularly well or badly, given their income level, in terms of disaster management.

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. There is a significant literature on the mental health impacts of disasters, which finds conditions such as post-traumatic stress disorder (PTSD), depression and anxiety to be common amongst populations that have experienced and survived disasters (see the review by Norris et al. 2002). The second good is a composite consumption good, *C*, which represents all other goods and services.

One might then construct a production possibility frontier that charts how units of consumption can be converted into units of climate security, subject to an overall budget constraint. However, to make the internal workings of this choice more overt, we model the decision explicitly 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 $U = U(C, A)$. Utility 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 optimisation problem $max_A\ \ U(Y - \pi A,\ A)$ yields the first-order condition $U_A = \pi U_C$, which can be solved for the optimal level of adaptation. The demand function is

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

Differentiating the first-order condition, and remembering the second-order condition, confirms that $A_Y^D > 0;\ A_\pi^D < 0$ 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 will go up as income rises.

On the production side, climate security is delivered in a way that maximizes profit. 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 link to income on the supply-side is created if efficiency levels depend on variables that are also loosely correlated with income, such as institutional quality, social capital and an effective public sector. 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. The existence – and indeed the sign – of the efficiency effect cannot be determined *a priori* and must await empirical confirmation. The hypothesis is that adaptation efficiency depends on a vector of variables whose correlation with income is not perfect, so that the income and efficiency effects can be identified empirically.

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

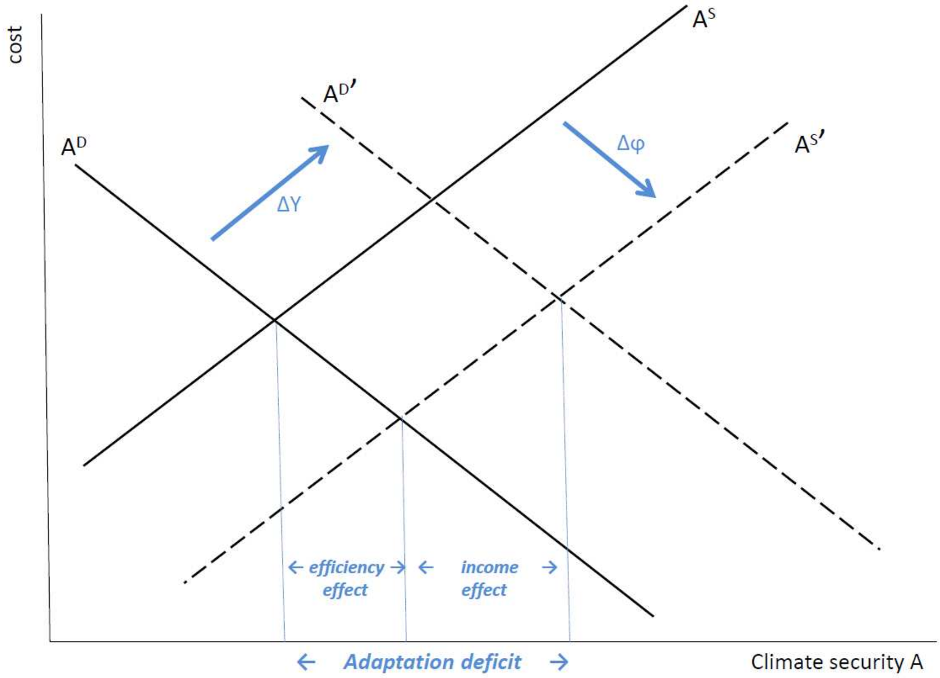
$$A^* = A(Y, \varphi) \tag{3}$$

Equation (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

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

Figure 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.

Figure 1: **The adaptation deficit as a function of income and efficiency effects**



3. From theory to empirics

We now turn to the empirical estimation of equation (3), using data from the Munich Re natural catastrophe (NatCat) database.

The NatCat database includes a total of some 31,000 individual entries. We restrict our attention to the period 1980 to 2008, for reasons of data quality and completeness, leaving us with a sample of some 20,000 observations, drawn from more than 200 countries. The database includes 25 different event categories, but we focus our analysis on the two climate-related event categories that account for most disaster deaths and economic damages: floods and tropical cyclones. These two event categories account for 33% of the deaths and 43% of the economic damages in the database, and between them comprise over 5,400 entries. 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 2,277 country-year observations, comprised of 1,779 country-years with floods and 498 country-years with tropical cyclones.

An immediate complication is that the data do not include 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:

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

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. Equation (5) implies that as long as we control for the factors explaining *I*, observed damages will be a reasonable indicator of adaptation effort.

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

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

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. However, 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, and Neumayer et al. 2013). This reflects, at least in part, concerns about the reliability of economic damage estimates in publicly available datasets like EM-DAT. The Munich Re database in contrast benefits from the unique perspective of the world's largest re-insurance company, who make it their business to obtain accurate estimates of the damages caused by natural disasters. That said, there is still likely to be greater measurement error in the damages series than for lives lost, even in our dataset.

On the right-hand side the equation includes three types of explanatory variables. The first set of controls, $\boldsymbol{I}_{it}$, is a vector of variables to normalize the intensity of events and the exposure of countries to events, as suggested by equation (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. It has been shown that losses associated with tropical cyclones generally increase with the cube of the top wind speed (Emanuel, 2005). We therefore take the cubed power of top wind speed as our measure of tropical cyclone intensity. 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.

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 in the economy and should therefore represent 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 is the income variable, Y_{it-1}, which measures the demand effect. We also include disaster propensity (from Neumayer et al., 2013) as a further determinant of demand. This variable 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. Disaster propensity is therefore a relevant component of the demand effect. Hsiang and Narita (2012), Schumacher and Strobl (2011), Keefer et al. (2011), and Neumayer et al. (2013) have all shown that disaster losses are negatively associated with hazard exposure.

The third element of equation (6) is a vector of variables associated with the efficiency effect, $\boldsymbol{\varphi}_{it-1}$. These include measures of institutional quality, income inequality (the Gini coefficient), education (primary school enrolment rates), health (life expectancy), government expenditure (as a % of GDP), openness (trade as a % of GDP), and financial sector development (private sector credit/GDP). While the choice of variables to include is in part intended to capture those most frequently included in the existing literature, we ultimately include a richer set of explanatory variables than is customary in the literature.

Most of our explanatory variables are obtained from the World Bank's World Development Indicators database, and are available at an annual frequency over our entire sample period. One exception is the Gini coefficient, which is calculated only sporadically. For this reason, we use the average of the available observations for each country, taking comfort from the fact that Gini values vary considerably more between countries than within countries over time.

Institutional quality is measured using Political Risk Services ICRG data, which offers the longest available time series; beginning in 1984 (thus the regressions that include these data start in 1985). We include both the aggregate political risk measure, and separately, its 12 constituent elements (we only report results for individual sub-components where significant). Alternative measures of institutional quality, such as the World Bank's Worldwide Governance Indicators (Kaufmann et al. 2010) and Country Policy and Institutional Assessments (CPIA) or the Polity IV measure of democracy, are not available for a sufficient number of countries or years. As a robustness check, we ran regressions including country averages of these alternative variables. They do not change the qualitative nature of the results we report below. We use lagged values for most of the explanatory variables (excluding disaster magnitude) in order to avoid any potential endogeneity bias.

4. Empirical results

Our calculations distinguish between two measures of impact (lives lost, economic damages) and two types of hazards (floods, cyclones). The outcome is four sets of regressions, the results of which we report in Tables 1-4. The layout of the tables reflects the three sets of explanatory variables identified in equation (5). That is, we have controls for intensity and exposure, variables explaining demand, and variables measuring efficiency spillovers. In each of the tables the first column reports results of regressions that include only the event normalisation and demand effects. In columns 2, 3 and 4 we include the efficiency spillover variables, initially excluding the Political Risk variable, because it restricts the sample to years since 1985 (inclusive). We then include the aggregate Political Risk variable in column 3 and, finally, replace this aggregate measure with its 12 subcomponents in the regressions reported in column 4.

A. Disaster deaths

Tables 1 and 2 are concerned with disaster deaths as the outcome of interest. The tables show that both the magnitude and population variables are highly significant predictors of disaster fatalities. The time trend for deaths from flood events is significant and negative, indicating that these have been reduced over time, holding other variables constant. The time trend is also negative for deaths from tropical cyclones (although only significant in one model specification).

The results for the demand variables are as expected, with higher GDP per capita and higher hazard exposure being associated with a lower number of deaths from disasters. This relationship is robust to the inclusion of the efficiency variables.
To give a sense of the magnitude of the observed effects, a 10% rise in GDP per capita reduces fatalities from floods by around 1.4% at the median value of loss. The coefficients in the tropical cyclones regressions are of similar magnitude (ranging between -0.56 and -0.78). However, the median number of deaths from tropical cyclones in our sample is considerably higher; a 10% rise in GDP per capita reduces median deaths from tropical cyclones by between 0.5 and 0.7%. (To derive an elasticity, we divide the coefficient by the total number of deaths, for an expression of the form (per cent change in death) / (per cent change in income). The elasticity varies depending on the point at which it is evaluated. We chose the median number of deaths).

Turning to the efficiency variables, we find that higher income inequality (as captured by a country's average Gini coefficient) is associated with more deaths from disasters. This relationship is strongest and most robust for flood events. For tropical cyclones, the Gini is only significant for the model without institutional variables. We also find that better quality political institutions (as measured by the aggregate Political Risk variable) reduce disaster deaths, although the aggregate measure is only marginally significant for floods and is not significant for tropical cyclones. (A higher score on this variable indicates lower risk).

When we include the 12 subcomponents of the Political Risk measure (column 4 of each table), one consistent finding is that disaster deaths are reduced in countries with a better Investment Profile. (We only report coefficients for subcomponents that were significant in the regressions). This variable includes assessments of factors that affect risk to investments, including contract viability, the risk of expropriation, profit repatriation and payment delays. Deaths from floods are also lower in countries with a lower risk of religious tension or religious interference in politics. For tropical cyclones, the number of deaths is lower in countries with lower risk of military influence in politics and lower risk of external conflict (including external diplomatic and political pressure, such as withholding of aid, trade restrictions and other forms of sanctions).

One other consistent result is that a higher ratio of government expenditure to GDP reduces the number of deaths from both floods and tropical cyclones. Although the variable measures government consumption (not investment), it seems to capture the relative provision of public goods, such as climate protection.

The results for the other variables that we include are somewhat inconsistent across the two disaster categories. For tropical cyclones higher primary school enrolment rates reduce disaster deaths. However, for floods, there is some evidence that higher school enrolment rates are associated with an increased number of deaths, although this is not a consistent finding across model specifications. We also experimented with a range of different measures of education participation, including secondary and tertiary enrolment rates, net (as opposed to gross) enrolment rates, and also female-only enrolment rates. None of these alternatives changed the qualitative results, nor did their inclusion produce more significant or consistent results.

Life expectancy and trade openness do not appear to matter for disaster deaths. However, higher credit-to-GDP ratios appear to be associated with an increased number of lives lost, although again for flood events this finding is not consistently significant across model specifications. This result may appear surprising at first, since previous studies (e.g. Noy 2009, McDermott et al. 2013) have found that greater financial sector development mitigates the growth impacts of disasters. It appears that access to credit primarily matters for recovery and reconstruction (as emphasised by

McDermott et al. 2013), therefore affecting the indirect impacts of disasters on economic growth. On the direct impacts of disasters it could be that two opposing effects are at work. On the one hand, higher credit availability may help finance risk reduction measures, thus reducing impact, but on the other hand, large credit-to-GDP ratios may be associated with housing developments in vulnerable locations such as on flood plains. It is also worth noting that a number of these variables (government expenditure, credit/GDP and life expectancy in particular) are highly correlated with GDP per capita, which could explain some of the variation in results.

B. Economic Damages

Turning to the results for economic damages (presented in Tables 3 and 4), we see again that the magnitude and total GDP (normalisation) variables are highly significant predictors of economic damages from both floods and tropical cyclones. Having controlled for the value of assets exposed (total GDP), higher GDP per capita is associated with lower damages from these climate-related disasters, as our model predicts. The estimated coefficients from these regressions are directly comparable as damage elasticities, given that the regressions are specified in log-log form. Thus, the coefficients on GDP per capita indicate that a 10% rise in GDP per capita reduces economic damages from flood events by between 3 and 5%, and from tropical cyclones by between 5 and 19%.

The propensity measures have the correct sign, higher propensity being associated with lower losses from a given disaster event, but are not significant in most specifications. It has been shown that people respond differently to the propensity of high versus low intensity events (e.g. Bakkensen, 2013). The insignificance of the propensity measures could therefore be the result of competing effects from past experiences of low versus high intensity events. This is something we are exploring in more detail in extensions to this research currently under way.

While we find a significant income effect in each model specification, the efficiency effect (i.e. production externalities and income spill-overs) appears to be less pronounced in the case of assets as compared with lives lost. For floods, the only consistently significant efficiency variables are the Gini and life expectancy, with both showing counter-intuitive signs.

The negative coefficient on the Gini variable indicates that higher inequality is associated with lower economic damages from floods. This change in sign for the Gini coefficient between the regressions for deaths from floods and those for economic damages from floods is an intriguing finding. The sharp contrast in the effects of inequality for lives lost as opposed to assets destroyed could be evidence of a location effect. For example, poor people tend to live in more vulnerable locations, such as on flood plains (Albala-Bertrand, 1993; Anbarci et al. 2005). This segregation effect is likely to be more pronounced in unequal societies. Thus, inequality puts a greater number of people in harm's way, but because poor households own relatively little, inequality may also be associated with a lower value of assets exposed. An alternative interpretation is that the economic losses suffered by poorer people are not counted in official figures, either because they lack formal insurance and record keeping of assets, or because (in an unequal society) economic losses suffered by the poor are simply ignored, whereas deaths are less easy to ignore (see e.g. Hallegatte et al. 2010).

For tropical cyclones, the Gini coefficient is as expected, with higher inequality increasing economic losses. The positive coefficients on the aggregate political risk measure and its 'socioeconomic conditions' and 'ethnic tensions' subcomponents, indicate that better institutions (or lower political risk) based on these measures, are associated with higher economic damages from tropical cyclones. There is also, again, some evidence that both higher credit/GDP and life expectancy are associated with higher economic losses. Greater trade openness, on the other hand, reduces losses from cyclone events.

C. Country efficiency rankings

For policy purposes it would be interesting to know more about the relative adaptation efficiency of countries, as countries with lower efficiency spillovers may require additional technical assistance.

The country efficiency rankings, presented in Tables 5 and 6, are based on the regression results discussed in the preceding section. We calculate an efficiency index for each country, based on a weighted sum of the efficiency variables found to be statistically significant predictors of the number of people killed for each disaster category. The weights are the coefficients from the regressions reported above. The rankings presented in Tables 5 and 6 represent country averages over the sample period.

The country rankings for flood events produce a recognisable pattern, with predominantly Northern European countries towards the top, while those at the lower end of the rankings include fragile states, such as Haiti and Zimbabwe. Somewhat more surprising, perhaps, is the relatively low ranking, given its wealth, of the United States, which ranks below average, alongside China, India, Cote d'Ivoire and Nicaragua. This reflects a moderately high income inequality and low government spending in that country. It is notable that a number of authors have emphasized the role of social inequalities in exacerbating the human impacts of hurricane Katrina (e.g. Atkins and Moy 2005, Elliott and Pais 2006, and Tierney 2011). Bakkensen (2013) also calls the US a "damage outlier".

Another surprising ranking is that of Bangladesh, a country which, in spite of its poverty, has put significant effort into reducing its vulnerability to disasters. This may be because our measure only captures general government expenditures, rather than dedicated disaster management spend. Harder to explain is the relatively strong performance of a number of sub-Saharan African countries, e.g. Tanzania, Burkina Faso, Ghana, Malawi and Botswana, which all feature in the rankings alongside the likes of Japan, the Netherlands, France, the UK, and New Zealand.

The country rankings for tropical cyclones are based on a much smaller sample, since cyclones only affect a relatively small number of countries. However, the pattern that emerges from the rankings based on tropical cyclones is quite similar to that from floods. For countries that feature in both rankings, those with high adaptive capacity for flood events also have relatively high adaptive capacity for tropical cyclone events. This is reflected in the high degree of rank correlation between the country efficiency rankings for the two event categories (Spearman's rho=0.7454, N=36, p-value=0.0000).

5. Methodological discussion

We next explore some methodological issues to test the validity of our findings. A first question to ask is whether there might have been a superior, alternative model specification. One potential alternative 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 (Greene, 2004), although there are cross-country applications (e.g. Greene 2005). The application of stochastic frontier analysis to our natural disaster data also poses a number of 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 zeros 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 methodological 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. For the regressions with number of deaths as the outcome of interest, estimation by OLS would not be appropriate, given the distribution of disaster fatalities. Estimation is therefore by 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 337, with a standard deviation of 4,678) and is also 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 zeros 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

Measuring production efficiency is complex and there may be omitted variables in the efficiency vector $\boldsymbol{\varphi}$. Our model includes all the standard variables offered in the literature (Noy 2009, Toya and Skidmore 2007, Tol and Yohe 2007). This gives us some comfort that there are no obvious measurable omissions, although intangible factors such as a country's "risk culture" are of necessity excluded.

We did not include country fixed effects for the simple reason that some of the differences in efficiency across countries that we are interested in are likely to evolve relatively slowly over time. Including country fixed effects would therefore not allow us to identify the efficiency effect. To understand the implications of this choice we repeated the analysis using country fixed effects. As a general pattern, we found the efficiency variables lost significance in these regressions, although there were some exceptions. For example, government spending remained significant in the regression for economic damages from flood events. The sub-components of the institutional quality index were also significant in some of the regressions, but not consistently so. These results indicate, as anticipated, that the identified efficiency effect is predominantly due to between-country (cross-sectional), rather than within-country differences. This is not surprising, given that the variation in institutional quality, for example, is much greater between countries than within countries over time. Similarly, differences in the Gini coefficient are entirely absorbed by the inclusion of the country fixed effects, since we only have sufficient data to use country averages for this variable. We note that a similar pattern was found in relation to the income effect when we included country fixed effects, with the coefficient on GDP per capita insignificant in many of the regressions or substantially smaller in magnitude where it remained significant. As an alternative, we also ran regressions including region fixed effects, based on eight distinct regions. The results from these regressions were qualitatively similar to those reported here.

Another concern is whether we control appropriately for the intensity of events, that is, the completeness of vector ***I***. The destructiveness of storms in particular has many dimensions – including wind speed, rainfall, forward velocity, radius of maximum winds etc. (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 other 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 and sensitivity, 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, and Keefer et al. 2011). Nevertheless, a cross-check may be informative. Repeating our analysis on earthquakes, we found results on the normalization and demand variables in line with the existing literature, which reports a strong demand effect. However, the analysis of adaptive efficiency to earthquake events is complicated by the fact that small-scale damages from relatively minor earthquakes appear to be essentially random (as argued by Neumayer et al. 2013). Kellenberg and Mobarak (2008) have also argued that the links between human behavioural choices and exposure to risk are not as strong for earthquakes as for floods and windstorms.

5. 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 is 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 demand effect. A 10 per cent increase in income (GDP per capita) reduces the economic damages from climate disasters by between 3% and 5%, or perhaps as much as 19% in the case of cyclones. The income elasticity on disaster-related fatalities is lower – perhaps because the protection of lives is a priority at all levels of income – but still significant.

We find considerable variation in the efficiency effect. Adaptation efficiency is not uniform, even after controlling for income. There are instances of adaptation inefficiency. In particular, the strength of efficiency spill-overs varies with government spending (a measure of investment in adaptation-related public goods), institutional quality and income distribution, although the dynamics on this last variable are quite complex.

This has important policy implications. If adaptation efficiency was perfectly correlated with income, there would be no need for special adaptation measures, only for policies that boost income. The unevenness of the efficiency effect confirms that closing the adaptation deficit in fact requires a combination of general measures aimed at promoting growth and development *and* dedicated assistance targeted at enhancing spill-over effects. The results also point to a preference for certain types of development, in particular inclusive growth that also reduces income inequalities and development models that emphasise institutional quality.

We identify the countries where the efficiency spill-overs are weakest, and where the need for adaptation assistance may therefore be the strongest. The list of priority countries includes many of the most vulnerable states, and as such is fairly intuitive. But it also contains some surprises, including countries such as Bangladesh that are often associated with good disaster risk management. However, the list should be treated with caution as methodological and data problems prevent a reliable identification.

Research on the link between economic growth and resilience to climate risk is still patchy, and there is scope for much further analysis. 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 at work of how trends like economic diversification, urbanization and migration to coasts affect the long-term vulnerability of countries to climate risk.

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Table 1: Numbers killed by flood events

Negative binomial regression	Dependent Variable: Number Killed			
	(1)	(2)	(3)	(4)
"Normalisation"				
Magnitude	0.320***	0.328***	0.436***	0.451***
	(0.04)	(0.04)	(0.04)	(0.04)
Population	0.703***	0.810***	0.790***	0.726***
	(0.08)	(0.10)	(0.09)	(0.09)
Area (Km^2)	-0.047	-0.107	-0.089	-0.130**
	(0.09)	(0.08)	(0.08)	(0.07)
Time trend	-0.043***	-0.045***	-0.034***	-0.031**
	(0.01)	(0.01)	(0.01)	(0.01)
"Demand"				
GDPpc	-0.691***	-0.684***	-0.659***	-0.683***
	(0.07)	(0.10)	(0.11)	(0.11)
Flood Propensity	-0.139*	-0.271***	-0.404***	-0.368***
	(0.07)	(0.08)	(0.08)	(0.08)
"Efficiency"				
Gini (avg.)		1.480***	1.324***	1.309***
		(0.43)	(0.43)	(0.48)
Pol. risk			-0.931*	
			(0.54)	
Gov. stability				0.543*
				(0.32)
Investment Profile				-0.962***
				(0.33)
Relig. in Politics				-0.675***
				(0.26)
School enrol. (prim.)		0.979**	0.589	0.771
		(0.45)	(0.42)	(0.54)
Credit/GDP		0.209	0.214	0.311**
		(0.16)	(0.13)	(0.12)
Life exp		0.785	2.052*	1.186
		(1.15)	(1.05)	(1.21)
Trade		-0.143	-0.160	-0.279
		(0.19)	(0.22)	(0.22)
Gov. exp.		-0.794***	-0.785***	-0.678**
		(0.27)	(0.28)	(0.28)
Constant	82.870***	74.847***	54.567**	50.709*
	(19.65)	(19.08)	(24.01)	(28.13)
Obs.	1634	1294	1038	1038
Countries	148	130	113	113

Standard errors (clustered at the country level) in parentheses. Explanatory variables entered in logs and (with the exception of *Magnitude*, *Area* and *Gini*) lagged one period. * p<0.10, ** p<0.05, *** p<0.01.

Table 2: Numbers killed by tropical cyclones

Negative binomial regression	Dependent Variable: Number Killed			
	(1)	(2)	(3)	(4)
"Normalisation"				
Magnitude	1.039***	0.984***	1.107***	1.120***
	(0.12)	(0.12)	(0.11)	(0.12)
Population	0.832***	0.793***	0.907***	1.028***
	(0.13)	(0.11)	(0.14)	(0.14)
Area (Km^2)	-0.608***	-0.617***	-0.565***	-0.515***
	(0.12)	(0.10)	(0.11)	(0.14)
Year (time trend)	-0.029	-0.029	-0.046**	-0.028
	(0.02)	(0.02)	(0.02)	(0.02)
"Demand"				
GDPpc	-0.563***	-0.783***	-0.732***	-0.570***
	(0.09)	(0.13)	(0.15)	(0.17)
Cyclone Propensity	-0.488***	-0.382***	-0.443***	-0.508***
	(0.11)	(0.09)	(0.08)	(0.09)
"Efficiency"				
Gini (avg.)		1.858**	1.446	0.528
		(0.76)	(1.04)	(1.01)
Pol. risk			-0.702	
			(0.69)	
Investment Profile				-1.405*
				(0.74)
Ext. Conflict				-1.665**
				(0.69)
Milit. in Politics				-1.366***
				(0.51)
Democracy				1.006*
				(0.59)
School enrol. (prim.)		-1.313*	-1.972**	-2.695**
		(0.73)	(0.82)	(1.31)
Credit/GDP		0.812***	0.669*	0.455*
		(0.27)	(0.37)	(0.25)
Life exp		1.534	2.971	0.522
		(2.32)	(2.90)	(3.13)
Trade		-0.323	-0.008	0.365
		(0.31)	(0.32)	(0.33)
Gov. exp.		-1.477***	-1.483***	-1.937***
		(0.38)	(0.33)	(0.64)
Constant	54.082	49.120	81.534**	58.627
	(38.90)	(36.97)	(40.95)	(47.63)
Obs.	341	287	251	251
Countries	44	38	36	36

Standard errors (clustered at the country level) in parentheses. Explanatory variables entered in logs and (with the exception of *Magnitude*, *Area* and *Gini*) lagged one period. * p<0.10, ** p<0.05, *** p<0.01.

Table 3: Economic Damages from Flood Events

	Dependent Variable: Economic Damages			
	(1)	(2)	(3)	(4)
"Normalisation"				
Magnitude	0.687***	0.733***	0.845***	0.832***
	(0.05)	(0.06)	(0.06)	(0.06)
Total GDP	0.885***	0.543***	0.703***	0.713***
	(0.12)	(0.12)	(0.12)	(0.12)
Area (Km^2)	-0.055	0.139	0.121	0.082
	(0.09)	(0.10)	(0.10)	(0.09)
Time trend	-0.023**	-0.022	-0.060***	-0.020
	(0.01)	(0.01)	(0.02)	(0.02)
"Demand"				
GDPpc	-0.317*	-0.384**	-0.498**	-0.496***
	(0.17)	(0.16)	(0.20)	(0.18)
Flood Propensity	-0.166	-0.051	-0.166	-0.140
	(0.11)	(0.12)	(0.13)	(0.12)
"Efficiency"				
Gini (avg.)		-2.202***	-2.269***	-2.073***
		(0.64)	(0.70)	(0.73)
Pol. risk			0.796	
			(0.65)	
Investment Profile				-1.349**
				(0.52)
Milit. in Politics				0.722*
				(0.37)
School enrol. (prim.)		0.107	-0.012	0.129
		(0.45)	(0.56)	(0.60)
Credit/GDP		0.016	0.006	-0.001
		(0.16)	(0.20)	(0.19)
Life exp		4.655***	4.068***	4.025***
		(1.15)	(1.41)	(1.46)
Trade		-0.179	0.014	-0.005
		(0.38)	(0.42)	(0.41)
Gov. exp.		0.037	-0.314	-0.525
		(0.33)	(0.38)	(0.41)
Constant	26.376	19.044	92.072***	16.855
	(18.13)	(26.63)	(33.99)	(39.82)
Obs.	1634	1294	1038	1038
Countries	148	130	113	113

Standard errors (clustered at the country level) in parentheses. Explanatory variables entered in logs and (with the exception of *Magnitude*, *Area* and *Gini*) lagged one period. * p<0.10, ** p<0.05, *** p<0.01.

Table 4: Economic Damages from Tropical Cyclones

	Dependent Variable: Economic Damages			
	(1)	(2)	(3)	(4)
“Normalisation”				
Magnitude	1.409***	1.481***	1.581***	1.650***
	(0.18)	(0.16)	(0.14)	(0.14)
Total GDP	0.871***	0.813***	1.104***	0.812***
	(0.21)	(0.18)	(0.13)	(0.15)
Area (Km^2)	-0.312	-0.573***	-0.711***	-0.718***
	(0.19)	(0.16)	(0.17)	(0.13)
Time trend	0.015	0.021	-0.015	0.066
	(0.02)	(0.02)	(0.03)	(0.04)
“Demand”				
GDPpc	-0.474*	-1.305***	-1.856***	-1.211***
	(0.26)	(0.25)	(0.34)	(0.30)
Cyclone Propensity	-0.115	-0.170	-0.272	-0.263*
	(0.19)	(0.18)	(0.17)	(0.15)
“Efficiency”				
Gini (avg.)		4.171**	3.558**	4.481***
		(1.68)	(1.68)	(1.54)
Pol. risk			2.874*	
			(1.42)	
Socioec. Condition				2.994***
				(0.79)
Investment Profile				-2.171*
				(1.24)
Ethnic Tensions				1.274*
				(0.70)
School enrol. (prim.)		-0.329	-2.733	-0.846
		(1.56)	(2.06)	(2.44)
Credit/GDP		1.391***	0.961**	0.398
		(0.35)	(0.42)	(0.35)
Life exp		6.574*	9.249**	4.204
		(3.43)	(3.78)	(3.36)
Trade		-1.324**	-1.274**	-1.818***
		(0.60)	(0.57)	(0.50)
Gov. exp.		0.490	0.639	0.900
		(0.83)	(0.93)	(1.07)
Constant	-59.578	-102.364**	-40.900	-176.56**
	(41.37)	(48.61)	(67.61)	(79.02)
Obs.	341	287	251	251
Countries	44	38	36	36

Standard errors (clustered at the country level) in parentheses. Explanatory variables entered in logs and (with the exception of *Magnitude*, *Area* and *Gini*) lagged one period. * p<0.10, ** p<0.05, *** p<0.01.

Table 5: Country Efficiency Rankings: Floods

Index > +1			
Czech Republic	Finland	Croatia	Austria
Denmark	Slovenia	Ukraine	Belgium
Sweden	Bulgaria	Latvia	Yemen, Rep.
Slovak Republic	Hungary	Germany	Albania
Norway	Poland	Belarus	
+0.5 < Index < +1			
Tanzania	Azerbaijan	Japan	New Zealand
Netherlands	Estonia	Armenia	Italy
France	Ghana	Malawi	United Kingdom
Mongolia	Burkina Faso	Luxembourg	
Romania	Canada	Botswana	
0 < Index < +0.5			
Moldova	Kazakhstan	Gabon	Portugal
Togo	Uganda	Ireland	Ethiopia
Greece	Congo, Dem. Rep.	Jamaica	Papua New Guinea
Australia	Spain	Congo, Rep.	
Zambia	Russian Federation	Syrian Arab Republic	
Suriname	Korea, Rep.	Angola	
0 > Index > -0.5			
Costa Rica	Morocco	Uruguay	Madagascar
Guyana	Israel	China	Switzerland
Liberia	Trinidad and Tobago	Jordan	Mozambique
Gambia, The	Kenya	United States	Nicaragua
Niger	Mexico	India	
Sri Lanka	Cote d'Ivoire	Cameroon	
-0.5 > Index > -1			
Turkey	Algeria	Argentina	Philippines
Tunisia	Guinea	Brazil	Indonesia
Senegal	Mali	Vietnam	
Namibia	Paraguay	Colombia	
Peru	Egypt, Arab Rep.	Bolivia	
Index < -1			
Zimbabwe	Ecuador	Guatemala	Haiti
Honduras	Panama	Pakistan	
Venezuela, RB	Chile	Dominican Republic	
El Salvador	South Africa	Iran, Islamic Rep.	
Bangladesh	Thailand	Malaysia	

Rankings based on results in column 4 of Table 1 (using data on numbers killed). The index has been normalised to have mean zero and standard deviation of 1. Higher index scores indicate greater efficiency in reducing disaster deaths. Table based on average values of the index over the sample period.

Table 6: Country Efficiency Rankings: Tropical Cyclones

Index > +0.5			
Brazil	Canada	New Zealand	
Russia	Portugal	Jamaica	
+0.5 > Index > 0			
Australia	Trinidad and Tobago	Mexico	Japan
Spain	Costa Rica	Morocco	China
0 > Index > -0.5			
United States	Malaysia	Iran, Islamic Rep.	Sri Lanka
Colombia	Korea, Rep.	Papua New Guinea	
-0.5 > Index > -1			
India	Vietnam	Dominican Republic	Indonesia
Philippines	El Salvador	Venezuela, RB	Mozambique
Madagascar	Honduras	Nicaragua	
Index < -1			
Thailand	Guatemala	Haiti	Bangladesh

Rankings based on results in column 4 of Table 2 (using data on numbers killed). The index has been normalised to have mean zero and standard deviation of 1. Higher index scores indicate greater efficiency in reducing disaster deaths. Table based on average values of the index over the sample period.

Annex

Summary statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
dis_deaths	3208	336.8017	4677.55	0	160105
lndis_l~1995	3208	.6663024	3.574607	-4.887403	11.77232
lngdp_u~1995	2956	24.64413	2.362038	16.12891	30.0007
lngdppc~1995	2956	7.799839	1.591082	4.485685	11.44553
lngini_avg	2900	3.663599	.2266152	3.175551	4.235772
lnpolrisk	2314	4.137009	.2676731	2.335052	4.574711
lngovexp	2872	2.598754	.4009645	.3185919	3.772283
lntrade	2937	3.965616	.6136801	-1.031157	6.063667
lnlifeexp	3172	4.196053	.1510344	3.616543	4.412884
lncredit	2815	3.4848	.9697314	-.3815606	5.766635
lnschpri	2672	4.582171	.2487458	2.623302	5.438579
lnt3_top_w~d	449	14.16641	1.220815	10.85555	16.90861
lnprop_t3_~d	468	16.85829	1.461118	11.31801	18.83224
lnsum_prec~s	3075	2.979665	2.059817	-5.703783	8.817218
lnprop_sum~s	3143	6.225331	2.035659	-3.506558	10.41865

Correlations

	lngdp_~5	lngdpp~5	lngini~g	lnpolr~k	lngovexp	lntrade	lnlife~p	lncredit	lnschpri
lngdp_u~1995	1.0000								
lngdppc~1995	0.6781	1.0000							
lngini_avg	-0.4106	-0.2876	1.0000						
lnpolrisk	0.4690	0.6979	-0.2732	1.0000					
lngovexp	0.2814	0.4957	-0.2190	0.4111	1.0000				
lntrade	-0.4357	-0.0493	0.1121	0.1720	0.0680	1.0000			
lnlifeexp	0.5989	0.7867	-0.2879	0.6156	0.2800	0.0750	1.0000		
lncredit	0.6860	0.7033	-0.2995	0.6026	0.4112	-0.0636	0.6233	1.0000	
lnschpri	0.2833	0.2602	0.1271	0.2648	0.0686	0.0528	0.4461	0.2225	1.0000