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Climate change, mitigation policy, and poverty in developing countries

(Preliminary Draft)

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1 Introduction

A recent World Bank study shows that global poverty has declined from 52 percent of the developing worlds population in 1981 to 25 percent in 2005 and this change lifted about 500 million people out of the \$1.25 dollar a day poverty line (Chen and Ravallion, 2010). This is a remarkable achievement and raises expectations that it might be possible to totally eliminate extreme poverty in the near future. It is argued that sustained economic growth is a necessary condition to the reduction and eventual elimination of poverty across developing countries (World Bank, 2010). However, as we peer into the future two rising forces make the challenge of poverty reduction difficult and present major challenges to policy makers across the world.

Scientific evidence indicates that the global mean surface temperature of the planet has been rapidly rising due to increased greenhouse gas emissions (IPCC, 2007). A number of studies have documented that the ensuing climate change is likely to have negative impact on agricultural productivity in the tropic regions (Jones and Thornton, 2003). Hertel, Burke, and Lobell (2010) showed that climate change will have a significant impact on poor households in developing countries. There are also increasing concerns regarding the change in the patterns of climatic variability, which is likely to add to the already high vulnerability of poor households exacerbating the incidence, severity, and persistence of poverty in developing countries (Ahmed, Diffenbaugh, and Hertel, 2009).

Another force that might have a big say on poverty outcomes is the attempt to reduce greenhouse gases (GHGs) and their effect on developing countries. Climate change mitigation policies can affect poverty in developing countries either directly or indirectly. A good example of the direct channel is when farmers get paid for avoided deforestation. Other things remaining the same, one would expect that such payments for environmental services should help reduce poverty. The indirect channel operates through markets via changes in world prices, domestic prices and factor earnings. The fact that there are differing channels of influence suggests that the poverty impacts of climate change mitigation policy are likely to vary by region and by household type. Hussein, Hertel, and Golub (2013) provide the

first systematic analysis of the impact of a global carbon policy on poverty outcome of 14 developing countries. The authors consider a policy scenario whereby a carbon price of $\$27/tCO_2eq$ is applied to all sectors in all Annex I regions along with a global forest carbon sequestration subsidy. They find that such a policy scenario increases poverty in 11 out of the 14 countries in their sample.

The foregoing discussion raises the interesting possibility, noted by (Hertel and Rosch, 2010), that the poverty impacts of climate change mitigation policy may be more significant than the poverty impacts of climate change itself over the near term. In this paper, we bring together a novel climate-socio-economic model to test this hypothesis. We believe that this is an important question to investigate and our result will help in prioritizing future policy discussion of climate change mitigation policies and poverty in developing countries.

This paper is organized as follows. Section two discusses the source of uncertainty in the assessment of the impact of climate change and climate change mitigation policies Section three outlines the method we use to test the hypothesis. That will be followed by discussion of results in Section four. Section five concludes with brief remarks.

2 Sources of Uncertainty

Substantial uncertainties surround projections of climate change, its consequences, future path of emission, and the effect of policies aimed at mitigating the effect of climate change (Quiggin, 2008). For example, the extent and effect of the increase in GHG concentration on temperature is very uncertain. IPCC's central estimates of emissions suggest a doubling of current CO_2 concentrations by the mid-21st century, leading to projected warming of more than 1 degree Celsius to nearly 6 degrees (IPCC, 2007). How we handle future emissions of greenhouse gas emissions depend crucially on climate sensitivity. For example, stabilizing the climate below 2 degrees Celsius requires substantial decrease in emissions if we believe that the climate sensitivity is low, but it will require a complete halt of all human based emissions within the next 50 years if climate sensitivity is believed to be high (Cao and Caldeira, 2008).

The agricultural sector is expected to bear much of the economic consequences of rises in surface temperature (Jones and Thornton, 2003). But the impact is expected to differ depending on both location and type of agricultural crop. On the one hand, rise in surface temperature lead to decline in agricultural productivity in much of the tropics. Given that much of the world poor lives in that area, the implication for food security and stability of the region is dire (Hertel and Rosch, 2010). The poor will suffer both from the income side and the expenditure side of the poverty distribution. Hertel, Burke, and Lobell (2010), for example, show that over the next 20 years , the average price of cereals is likely to increase by about 30% due to climate change over this near term projection. On the other hand, it is anticipated that there are some potential near term benefits to agricultural productivity due to warming in the higher latitudes, the potential for increased precipitation, and the benefits of CO_2 fertilization(IPCC, 2007).

Climate change mitigation presents policymakers with a challenge to make decisions that have important and sometimes permanent effects on both environment and society with sparse information(Quiggin, 2008). Furthermore, the relationship between climate change and future emissions is complicated by the fact that the policy choices that will help to determine future growth in emissions are themselves a response to projections of future climate change (Quiggin, 2008). Not surprisingly, very few countries have made inroads in terms of policy design and implementation of climate change mitigation policy. The uncertainty in policy choices affects the decision making of all economic agents.

Yet another source of uncertainty comes in the form of economic response of economic agents to both climate change and the associated mitigation policies. For example, how do firms in the developed world respond to mitigation policies? How do farmers in developing countries respond to both policies and rising temperatures? In our model, economic parameters govern the response of agents to changes in exogenous variables (Hertel and Marinós, 1997). The responsiveness of agents to shocks is captured by the elasticities describing the percentage change in economically optimal quantities in response to a change in relative prices. In this study, we follow Hertel, Lobell, and Verma (2011) and focus on the elasticities

which are central to determine the poverty impacts of both shocks: the elasticity of land supply, the elasticity of labor and capital supply to agriculture, the elasticity of consumer demand for food, and the elasticity of product substitution in international trade. Distributions for each of these parameters are established based on prior econometric work, as well as theoretical restrictions and previous studies (Hertel, Lobell, and Verma, 2011) .

To recap, there are many different sources of uncertainty relevant to the assessment of poverty impacts of climate change and climate change mitigation policies. Previous authors have explored, in the context of other policy issues, the impact of such uncertainty on agricultural markets, land use and poverty (Hertel, Lobell, and Verma, 2011) and we draw here on their insights and methodology. In this paper we exploit these uncertainties to help us compare the impacts of climate change and that of mitigation policy and formally test our hypothesis. We bring together a socio-economic-environment model to help us test the hypothesis.

3 Methods

A formal test of the hypothesis requires a three stage approach. In the first stage, we formally establish the links among climate change, agricultural productivity and poverty as well as the link between climate change mitigation policy and poverty. The second stage generates distributions around these estimates using a systematic sensitivity analysis. The final stage compares the poverty outcomes from these two scenarios. The following section elaborates on each of the above stages.

3.1 Model and Data

The first stage of our study analysis establishes the is to establish the link among climate change, climate change mitigation policy, and poverty across a set sample of developing countries drawn from Latin America, Asia and Africa. We use a framework that traces how the impact of the shocks climate change affect domestic and international commodity

prices and also takes these effects to changes in wages and other factor returns in developing countries. In this paper, we combine a modified version of the standard GTAP model, GTAP-AEZ-GHG (Golub et al., 2010), with the recently developed poverty module, GTAP-POV (Hertel et al., 2011) The new model, GTAP-AEZ-GHG-POV, incorporates detailed non- CO_2 GHG (Rose and Lee, 2008) and CO_2 emissions mapped to specific countries and economic sectors.

Climate change impacts are modeled through changes in agricultural productivity. It is this agricultural productivity parameter that will be shocked based on values derived from the literature. Hertel, Burke, and Lobell (2010) collected data that shows the agricultural yield impact of climate change by the year 2030 for agricultural crop-country pairings. They summarized the 2030 impact of climate change into three yield scenarios: a most-likely or medium-productivity, a low-productivity and high-productivity. Hertel, Burke, and Lobell (2010) define the low-productivity yield scenarios as a world with rapid temperature change, in which CO_2 fertilization is expected to be low and where crops are highly sensitive to this warmer climate. The high-productivity scenario presents a slower warming, high CO_2 fertilization, and low crop-sensitivity to warming. The yield shocks for each country, crop and scenario are provided in the Appendix (Tables 3, 4, and 5). Each yield shock represents the projected percentage change in crop yield from 2001 to 2030. These tables show that the magnitude and direction of each yield shock differs by country-crop pair. For example, yields in East Asia are predicted to increase for both rice and wheat under the low-productivity scenario, while they tend to decrease for most other countries under the same scenario.

To make comparisons possible, we will focus on agriculture based mitigation policies. The policy we consider is a carbon tax imposed on CO_2 and non- CO_2 emissions from agricultural activity in Annex I along with a global forest carbon sequestration subsidy. Most of the taxed emissions are non- CO_2 emissions from livestock enteric fermentation and manure management, and emissions from fertilizer application. Admittedly, such policy scenario does not cover the range of climate change mitigation policies that are either in policy circles or that are desirable. This is a caveat of our study but we believe that the agricultural

sector is an important sector in developing countries and both climate change and the associated mitigation policies will undoubtedly focus on the sector and the economic and poverty impacts will not be small (Hertel and Rosch (2010); Hussein, Hertel, and Golub (2013)).

We use the World Banks \$1/day Purchasing Power Parity definition of poverty to ensure comparability across countries (Chen and Ravallion, 2000). We have a non-random sample of 14 countries from Africa, Asia and Latin America. These countries were selected based on availability both household survey and GTAP database (Hertel et al., 2011). Within each country, poverty within each country is broken down into seven socio-economic strata based on a households primary source of income (95 percent or more of income from the following sources): Agricultural self-employed (farm income), Non-Agricultural (non-agricultural self-employment earnings), Urban Labor (urban household, wage labor income), Rural Labor (rural household, wage labor income), Transfer payment dependent, Urban Diverse, and Rural Diverse.

In our framework, the poverty impacts of any shock is transmitted through three channels: changes in earnings, changes in taxes, and changes in the real cost of living at the poverty line (Hertel et al., 2011). Equation 1, from (Hertel et al., 2011), details the relationship between these three components and the poverty headcount in each country (r), \widehat{H}_r where the “hat” denotes percentage change in the underlying variable:

$$\widehat{H}_r = - \sum_s \beta_{rs} \cdot \varepsilon_{rs} \cdot \sum_j \alpha_{rsj}^p (\widehat{W}_{rj} - \widehat{T}_r - \widehat{C}_r^p) \quad (1)$$

The parameter α_{rsj} is the share of income obtained from factor j in that particular stratum, for households in the neighborhood of the poverty line, while β_{rs} represents the share of a given stratum, s , in national poverty in country r . The parameter ε_{rs} is the stratum-specific poverty elasticity with respect to real, after-tax income. These three parameters have been pre-estimated from household survey data for each country in our sample. \widehat{W}_{rj} is the percentage change in income from factor endowment j in region r . The second term \widehat{T}_r is the tax effect which could arise if one wants to run a policy change which is fiscally neutral. The third term within the brackets captures the spending effect. The whole term

within the brackets in equation 1 represents the percentage change in real, after-tax earnings from the different sources of income.

3.2 Systematic Sensitivity Analysis

The next stage of our analysis will make use of a systematic sensitivity analysis (SSA) to generate the poverty distributions associated with both climate change and climate change mitigation policies. The SSA solves the CGE model with respect to a symmetric triangular distribution of the shocks in order to derive the means and standard deviation of the endogenous variables. A general equilibrium model can be defined in a general form as follows (Arndt, 1996):

$$G(x, a) = 0 \tag{2}$$

Where x represents endogenous variables and a is an exogenous variable. Let $x^*(a)$ be the solution to equation 2 and $x^*(a) = H(a)$ as a vector of results. In our framework, x is either the productivity from climate change or the climate policy shock. The mean (equation 3) and variance (equation 4) of the endogenous variables is defined as follows (Arndt, 1996):

$$E[H(a)] = \int_{\Omega} H(a)g(a)da \tag{3}$$

$$E[H(a)] - E[H(a)]^2 = \int_{\Omega} (H(a) - E[H(a)])^2 g(a)da \tag{4}$$

Where $g(a)$ is the multivariate density function and Ω is the interval of integration (Arndt, 1996) demonstrates that approaching the solution to a CGE as a numerical integration problem is both accurate and easy to obtain standard deviations. Monte Carlo presents a rather simple approach to SSA but becomes computationally taxing for large. Arndt (1996) demonstrates that the Gaussian Quadrature (GQ) numerical integration technique provides robust results with fewer draws from the distribution of random variables as compared with Monte Carlo simulations. Pearson and Arndt (2000) further develop automated the procedure for the GTAP model.

3.2.1 Selecting end points for climate policy for sensitivity analysis

Our mitigation policy is based a particular value of a carbon tax of \$27/*tonCO₂eq* . While this price falls within the generally accepted price that is under discussion, it is by no means a universally accepted price of carbon. Figure 2 show the daily price of European Union allowances during the 2008-2011 period.

We will use the carbon price data to characterize the uncertainty associated with mitigation policy. We will assume that the time period we selected adequately captures the historic variation in the price of carbon and proceed to employ an Autoregressive Moving Average (ARMA) model to characterize the systematic changes in that variable. This is a popular time series tool used mostly for forecasting purposes (Hamilton, 1994) . The specification of the ARMA model takes the form:

$$Z_t = \sum_{i=t-p}^{t-1} \alpha_i Z_i + \sum_{j=t-q}^{t-1} \varphi_j \varepsilon_j \quad (5)$$

Where t is the time period, α and φ are the parameters to be estimated, Z is the price of carbon and ε_j is the error term. The autoregressive term (p) and the moving average (q) are selected using the Box and Jenkins approach (Hamilton, 1994).

The first step in fitting a time-series model is to check for stationarity. Figure 2 reveals a clear trend and we need to use unit root test to determine the presence of either a deterministic or stochastic trend. The Augmented Dickey-Fuller (ADF) test is one of the most commonly use tests for stationarity and works with a null hypothesis is that the series has a unit root. Our ADF test result shows that the carbon price data has a unit root. The ADF test statistics indicate a stochastic trend and that differencing the data is necessary to make it stationary (see Figure 3).

The key main result of interest from the above ARMA regressions is the normalized standard deviation of the estimated residuals. This is calculated as \sqrt{V} divided by the carbon price mean and multiplied by 100, where V is the variance of the estimated residuals (Valenzuela et al., 2007). It summarizes provides information on the variability of the non-

systematic aspect of the carbon price. The next step is to translate this information to a form useful for stochastic simulation of the CGE model. Following the approach of (Arndt, 1996) and Pearson and Arndt (2000), we use a symmetric triangular distribution as to approximate the distribution of residuals from our single region the estimate. The endpoints of the symmetric triangular distribution are recovered calculated using the mean and variance of the estimated residuals according to the formula: $c = \mu + \sqrt{6V}$, where c is an endpoint of the distribution, μ is the mean of the residuals and V is the variance of residuals. This method of stochastic simulation requires solving the CGE model with respect to this approximating distribution of productivity shocks such that means and standard deviations can be recovered for the endogenous variables (Valenzuela et al., 2007).

4 Results

Table 1 shows the distribution of poverty changes induced by the variability in climate change and the specific climate change mitigation policy that was introduced. The second column shows the mean of the changes in poverty headcount in percentage terms that is coming from impacts of climate change on crop yields. The mean results indicate that the overall impact of climate change is to increase poverty in 11 out of the 14 countries in our sample. From Table 1 we see that these poverty increases directly follow from the negative impact of climate change on yield. Countries from East Asia and Latin America see the highest increase (in absolute terms, see the AAV) in poverty due to climate change. These results match the medium climate scenario result reported in Hertel, Burke, and Lobell (2010).

Column 5 reports the mean impacts of mitigation policy on poverty. The results indicate that mitigation policy under consideration help to reduce poverty in 5 of the 14 countries in our sample. Based on the relative magnitude of the poverty impacts of mitigation policy, one could rank the sample countries in tiers of high, medium and low impact. Countries from Latin America generally see higher impact of the mitigation policy. All countries in this region, with the exception of Chile, see substantial increase in poverty. Asian countries belong to the third group. With the exception of Malawi, African countries experience

moderate poverty declines from the mitigation policy. In general, what we have observed is that, for the mitigation policy to reduce national poverty, and have greater impact, the rural poverty share must be high and earnings from land in the poor agricultural households must be non-trivial. Chile, Vietnam and Thailand present cases where gains from the mitigation policy are large enough to dominate the climate change impacts (Hussein, Hertel, and Golub, 2013)

The fourth and seventh columns of Table 1 display the coefficient of variation (CV) of poverty distributions from the two shocks. In general, the CV values (in absolute terms) for climate change are higher than the absolute CV values of column. This suggests that we are more uncertain about the impact of climate change on yields than we are about the future path of carbon price. This is not that surprising given that our proxy for mitigation policy is carbon price data from just one market while the climate shocks are collected from a large number of studies covering the entire planet. Figure 5 reports the 95 percent confidence intervals for the change in headcount poverty following the two shocks. Generally, the confidence intervals are a lot tighter for the mitigation policy shock, while the intervals for climate change are wider for places like Chile, Indonesia, and Vietnam.

We are now in a position to formally test our hypothesis and Table 2 shows the result of a formal statistical comparison of the two distributions of poverty changes. The evaluation of the significant mean differences between climate change effects and that of climate change mitigation policy is based on the standard t-test. To reiterate, the test compare the poverty distribution created by the variability in climate change (along with economic response) and mitigation policy (along with economic response). We make the following general observations. First, it is apparent that climate change and climate change mitigation policies create two distinct poverty distributions i.e. the p-values for the t-test are small (less than 0.05 for all countries except Bangladesh) meaning that null hypothesis of the equality of the magnitudes of the impacts of climate change and climate change mitigation on poverty is rejected. Second, there is substantial regional variation on how the policy shocks affect poverty outcome. For countries in Africa and Asia (except Indonesia), the increase in poverty due to

mitigation policy is smaller than the increase due to climate change. In Latin America, with the exception of Chile, climate change mitigation policy leads to worse poverty outcome than climate change.

Figure 6 through Figure 9 plot the distributions of poverty changes in Mozambique, Brazil, Thailand, and Indonesia. These countries are chosen to illustrate cases where the effects of climate change are discernible and greater than the effects of mitigation policy (Brazil and Indonesia), while the opposite is true for Mozambique and Thailand.

5 Remarks

This paper tries to compare the relative poverty impacts of climate change and climate change mitigation policy. We exploited three main sources of uncertainty to help us test the hypothesis that, in the near term, the poverty impacts of climate change mitigation policy is more significant than the poverty impacts of climate change itself. We model climate change uncertainty by sampling from a distribution of productivity shocks reflecting the impacts of climate on agricultural yields in 2030. We took the volatility in EU carbon market as a proxy for uncertainty in climate change mitigation policy. We also took into consideration that both the climate change and climate policy shocks affect economic agents whose response to the shocks is uncertain. We find that the poverty impact of climate change mitigation is higher than the poverty impact of climate change in 6 out of the 14 countries in our sample. That is, we find support for our claim i.e. the poverty consequence of the mitigation policy outweighs the impact of climate change, in Brazil, Mexico, Colombia, Peru, Venezuela, and Indonesia. For African countries in our sample, poverty impact of climate change consistently outweighs the impact of mitigation policy. This regional disparity of results calls for a climate policy prescription that is tailored to regional concerns.

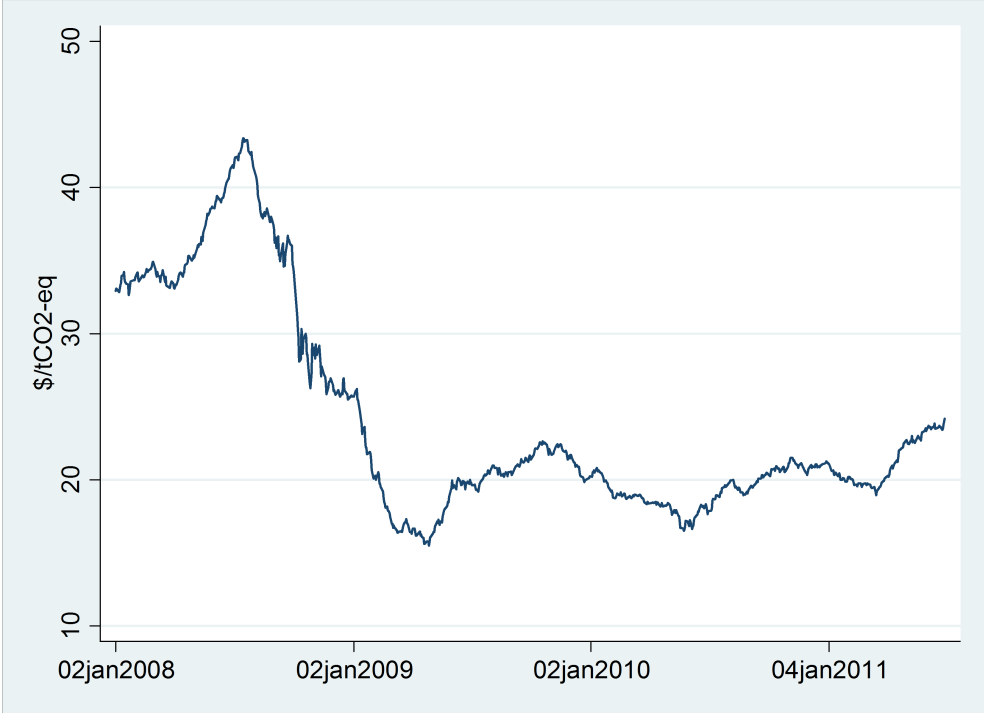
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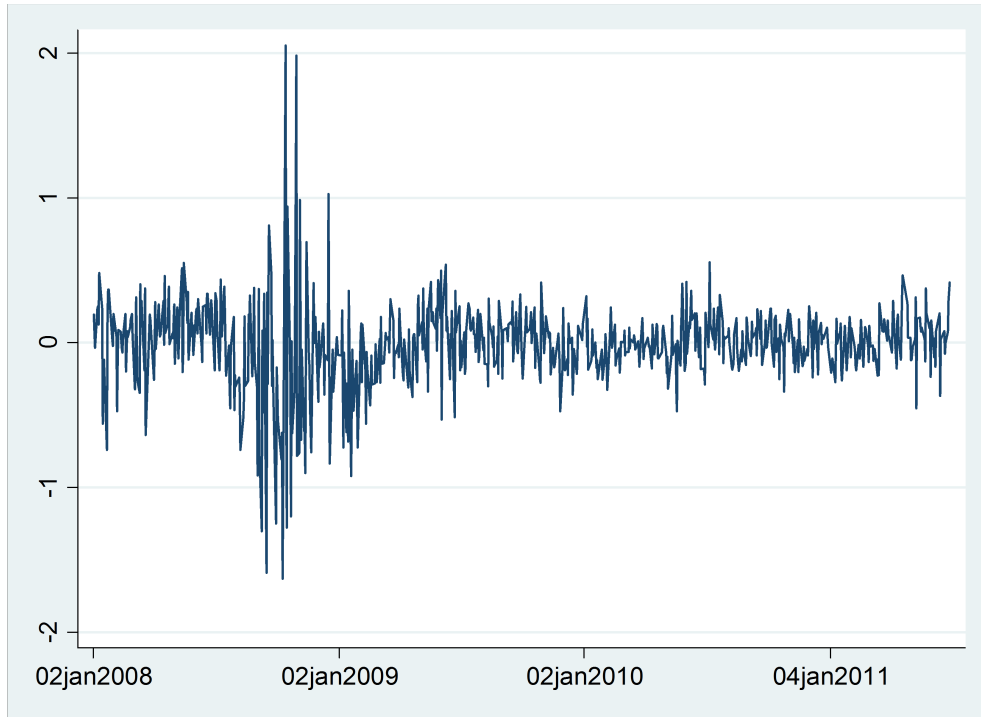
6 Appendix

Figure 1: Price of Carbon¹



Source: Reserve Bank of Australia and IMF

Figure 2: Price of Carbon(first difference)



Source: Authors' computations, Reserve Bank of Australia

Figure 3: National poverty headcount impacts, 95% confidence interval

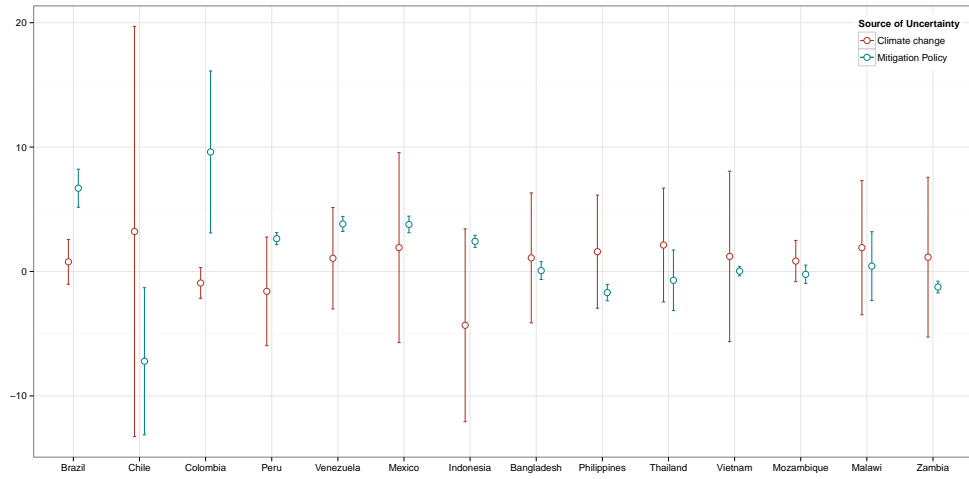


Figure 4: Poverty distribution in Mozambique

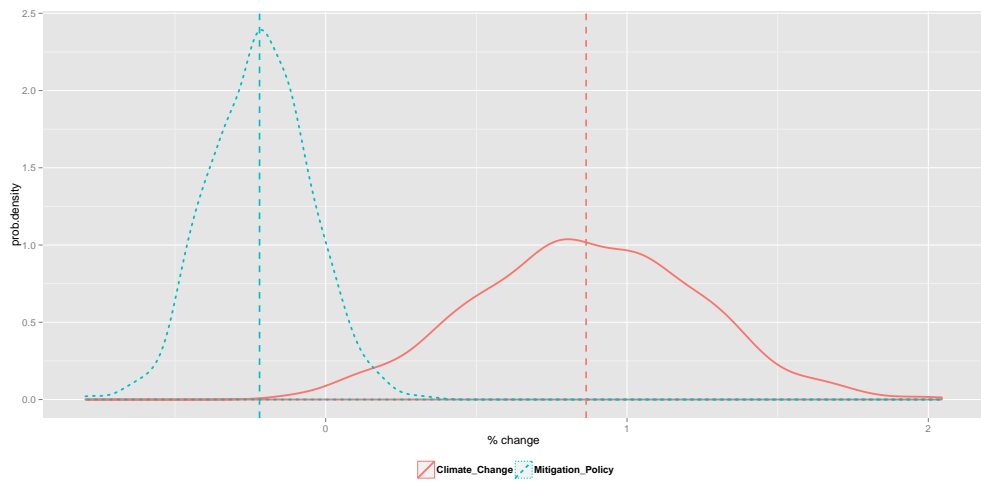


Figure 5: Poverty distribution in Brazil

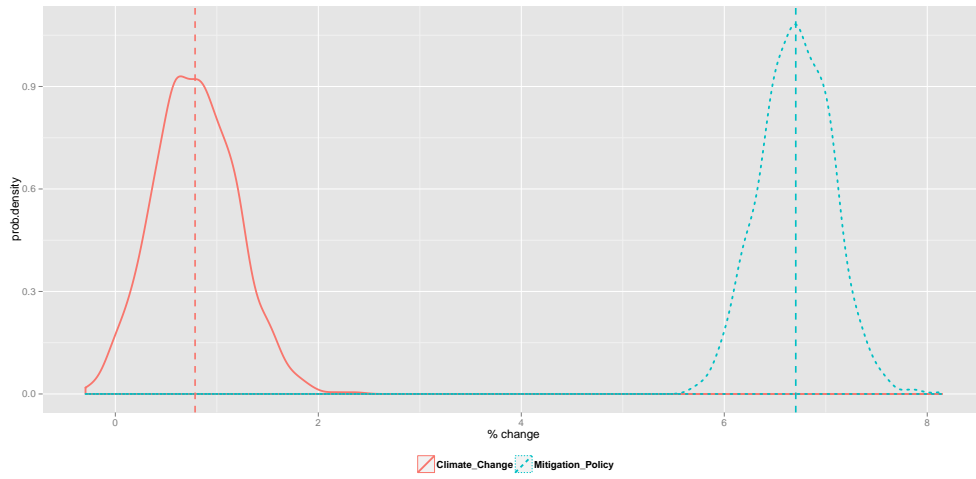


Figure 6: Poverty distribution in Thailand

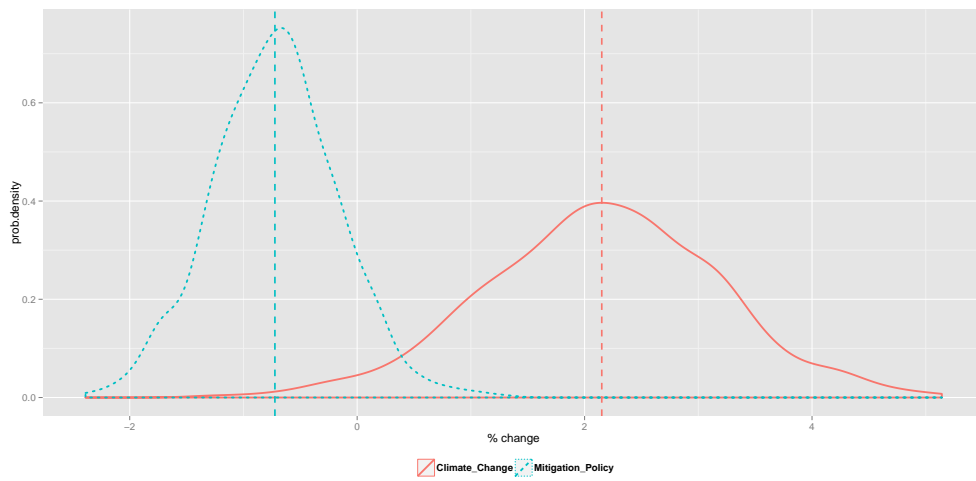


Figure 7: Poverty distribution in Indonesia

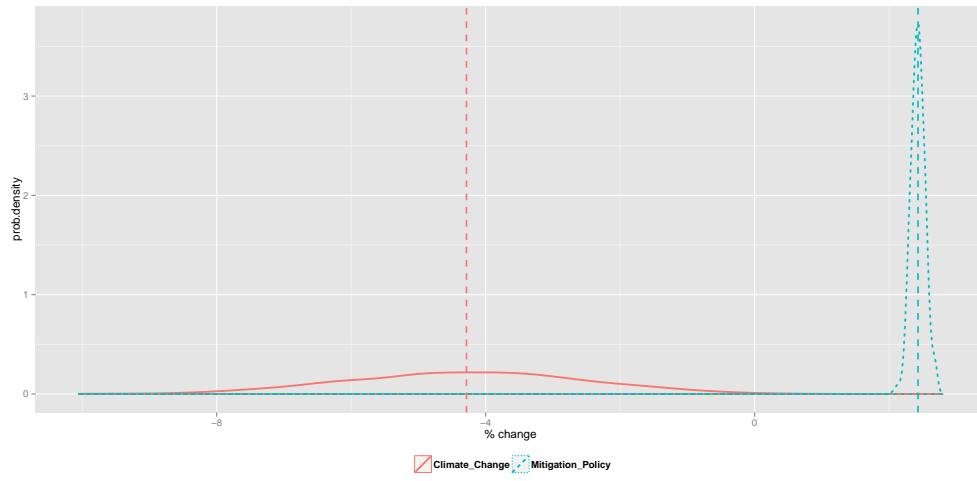


Table 1: Mean and Standard deviations of poverty changes

(1)	Climate Change			Climate Change Mitigation Policy		
	Mean	Standard Deviation	CV	Mean	Standard Deviation	CV
(1)	(2)	(3)	(4)	(5)	(6)	(7)
South America						
Brazil	0.78	0.40	51.8	6.69	0.34	5.1
Chile	3.21	3.69	114.8	-7.22	1.32	-18.3
Colombia	-0.92	0.28	-29.9	9.61	1.46	15.1
Mexico	1.92	1.71	88.8	3.78	0.15	4
Peru	-1.59	0.98	-61.2	2.64	0.11	4.1
Venezuela	1.07	0.91	85.8	3.82	0.14	3.5
<i>Average</i>	0.75	-	-	3.22	-	-
<i>AAV</i>	1.58	-	-	5.67	-	-
Asia						
Bangladesh	1.09	1.17	106.8	0.07	0.16	221.5
Indonesia	-4.32	1.73	-401	2.43	0.11	4.4
Philippines	1.59	1.02	63.8	-1.69	0.15	-8.7
Thailand	2.13	1.02	48.1	-0.71	0.54	-77
Vietnam	1.21	1.53	126.3	0.03	0.08	247
<i>Average</i>	0.34	-	-	0.03	-	-
<i>AAV</i>	2.07	-	-	0.99	-	-
Africa						
Malawi	1.92	1.21	62.9	0.43	0.62	142.8
Mozambique	0.84	0.37	44	-0.23	0.16	-72.8
Zambia	1.15	1.44	124.7	-1.25	0.11	-8.4
<i>Average</i>	1.3	-	-	-0.35	-	-
<i>AAV</i>	1.3	-	-	0.64	-	-

Source: Authors' computations. CV=Coefficient of Variation. AAV=Absolute Average: it is the average of the absolute values.

Table 2: Comparison of Poverty Impacts

Countries	<i>t</i> -Statistic	<i>p</i> -value
Brazil	38.11	0.000
Chile	-8.24	0.000
Colombia	30.4	0.000
Mexico	3.26	0.010
Peru	14.29	0.000
Venezuela	9.03	0.000
Bangladesh	-2.62	0.140
Indonesia	11.67	0.000
Philippines	-9.64	0.000
Thailand	-7.81	0.000
Vietnam	-2.31	0.050
Malawi	-3.48	0.000
Mozambique	-8.24	0.000
Zambia	-5.01	0.000

Source: Authors' computations

Table 3: Productivity shock: Low scenario

Regions	Paddy_rice	Wheat	CrGrains	OthAgr	Oilseeds
USA	-10	2	-32	-10	-10
EU27	-5	7	-17	-5	-5
BRAZIL	-10	-3	-17	-10	-5
CAN	-10	7	-17	-10	0
JAPAN	2	4	-7	-3	2
CHIHKG	-12	2	-22	-15	-12
INDIA	-15	-3	-17	-10	-10
C_C_Amer	-15	-3	-12	-15	-15
MEX	-15	-3	-12	-15	-15
S_o_Amer	-10	-3	-17	-10	-10
COL	0	7	-10	0	0
PER	0	7	-7	0	0
VEN	-10	-3	-17	-10	-10
CHL	-10	-3	-2	-10	-10
E_Asia	5	12	-2	5	5
IDN	0	7	-7	0	0
MYS	0	7	-7	0	0
R_SE_Asia	-15	-3	-17	-10	-10
PHL	-10	-3	-17	-10	-10
THA	-10	-3	-17	-10	-10
VNM	-10	-3	-17	-10	-10
R_S_Asia	-15	-3	-17	-10	-10
BGD	-10	-3	-17	-10	-10
Russia	-5	7	-17	-5	-5
Oth_CEE_CIS	-5	7	-17	-5	-5
Oth_Europe	-5	7	-17	-5	-5
MEAS_NAfr	-5	2	-12	-5	-5
S_S_AFR	-15	-3	-22	-15	-15
MWI	-15	-3	-22	-15	-15
MOZ	-15	-3	-22	-15	-15
ZMB	-15	-3	-22	-15	-15
UGA	-15	-3	-22	-15	-15
Oceania	-5	-5	-17	-5	-10

Source: Hertel et al (2010)

Table 4: Productivity shock: Medium scenario

Regions	Paddy_rice	Wheat	CrGrains	OthAgr	Oilseeds
USA	-3	2	-15	2	2
EU27	7	7	-5	7	7
BRAZIL	-3	-3	-10	-3	2
CAN	-3	7	-10	2	12
JAPAN	9	4	0	4	9
CHIHKG	0	2	-10	-8	0
INDIA	-5	-3	-10	-3	-3
C_C_Amer	-3	-3	-5	-3	-3
MEX	-3	-3	-5	-3	-3
S_o_Amer	-3	-3	-10	-3	-3
COL	7	7	-3	7	7
PER	7	7	0	7	7
VEN	-3	-3	-10	-3	-3
CHL	-3	-3	10	-3	-3
E_Asia	12	12	5	12	12
IDN	7	7	0	7	7
MYS	7	7	0	7	7
R_SE_Asia	-5	-3	-10	-3	-3
PHL	-3	-3	-10	-3	-3
THA	-3	-3	-10	-3	-3
VNM	-3	-3	-10	-3	-3
R_S_Asia	-5	-3	-10	-3	-3
BGD	-3	-3	-10	-3	-3
Russia	7	7	-5	7	7
Oth_CEE_CIS	7	7	-5	7	7
Oth_Europe	7	7	-5	7	7
MEAS_NAfr	2	2	-5	2	2
S_S_AFR	-3	-3	-10	-3	-3
MWI	-3	-3	-10	-3	-3
MOZ	-3	-3	-10	-3	-3
ZMB	-3	-3	-10	-3	-3
UGA	-3	-3	-10	-3	-3
Oceania	7	7	-5	7	2

Source: Hertel et al (2010)

Table 5: Productivity shock: High scenario

Regions	Paddy_rice	Wheat	CrGrains	OthAgr	Oilseeds
USA	4	14	-3	14	14
EU27	19	19	7	19	19
BRAZIL	4	4	-3	4	9
CAN	4	19	-3	14	24
JAPAN	16	11	7	11	16
CHIHKG	12	14	12	-1	12
INDIA	4	4	-3	4	4
C_C_Amer	9	9	2	9	9
MEX	9	9	2	9	9
S_o_Amer	4	4	-3	4	4
COL	14	14	4	14	14
PER	14	14	7	14	14
VEN	4	4	-3	4	4
CHL	4	4	22	4	4
E_Asia	19	19	7	19	19
IDN	14	14	7	14	14
MYS	14	14	7	14	14
R_SE_Asia	4	4	-3	4	4
PHL	4	4	-3	4	4
THA	4	4	-3	4	4
VNM	4	4	-3	4	4
R_S_Asia	4	4	-3	4	4
BGD	4	4	-3	4	4
Russia	19	19	7	19	19
Oth_CEE_CIS	19	19	7	19	19
Oth_Europe	19	19	7	19	19
MEAS_NAfr	9	9	2	9	9
S_S_AFR	9	9	2	9	9
MWI	9	9	2	9	9
MOZ	9	9	2	9	9
ZMB	9	9	2	9	9
UGA	9	9	2	9	9
Oceania	19	19	7	19	14

Source: Hertel et al (2010)