Climate change through a poverty lens

Stephane Hallegatte, Global Facility for Disaster Reduction and Recovery, the World Bank
Julie Rozenberg, Office of the Chief Economist, Sustainable Development Practice Group, the World Bank

Corresponding author: Julie Rozenberg (jrozenberg@worldbank.org)

Climate change impacts will depend on socioeconomic trends and development, for instance regarding demography and poverty (Hallegatte, Przyluski, and Vogt-Schilb 2011; Kriegler et al., n.d.; Wilbanks and Ebi 2013). To investigate the impacts of climate change on poverty, we therefore need to consider the range of possible socioeconomic development, i.e. a range of possible baseline (no-climate-change) scenarios.

It is impossible to forecast future socio-economic development, and future poverty levels. Past experience suggests we are simply not able to anticipate structural shifts, economic crises, technical breakthroughs, and geopolitical changes. So instead of trying to predict future socioeconomic development, we create a large set of possible baseline scenarios in which we investigate climate change impacts in each of these baselines. Our objective is to consider a range of possible futures that is large enough so that looking at climate change impacts in these futures provides insights on the possible impacts of climate change on poverty in the future.

1. Methodology

Our methodology involves two steps.

The first stage is to build, for each country, many scenarios for possible future socio-economic change, in the absence of climate change. To do so, we explore a wide range of uncertainties on future structural change, productivity growth, demographic changes, and policies, to create in each country several hundred scenarios for future income growth and income distribution. Some of these scenarios are optimistic – with rapid growth and decrease in poverty – while others are more pessimistic, with stagnating development and poverty levels. But the scenarios also differ in terms of population (age, education), economic structure (some have a quick transition away from agriculture in developing countries, other less so), and inequalities.

The second stage is to add climate change impacts in each scenario in each country. Since climate change impacts are uncertain, we consider two climate impacts scenarios, one being optimistic and the other much more pessimistic. Combining our hundreds of baseline scenarios with two climate change impact scenarios, we create a large database of scenarios in which we can examine the poverty impacts of climate change and – more importantly – the drivers of these impacts.

1.1. Micro-simulation model

We use a micro-simulation model based on household surveys and, for each country, project the pathway of individuals in the economy (the Appendix gives all details of the model). Micro-simulation models represent dozens of thousands of individuals or households per country, which...
are all assigned a weight so that the weighted sample is representative of the entire population. Here, we consider a set of households comprising individuals that are each characterized by age, sex, level of education, employment, and income.

First, we assign a category to each individual in the model, based on his/her age, skill level and sector of activity (or his/her inactivity):  1  (1) unskilled services worker; (2) skilled service worker; (3) unskilled agriculture worker; (4) skilled agriculture worker; (5) unskilled manufacture worker; (6) skilled manufacture worker; (7) adult not in the labor force; (8) elderly (above 65 years-old); (9) child (under 15 years-old).  2

Second, we “project” households into the future, in 2030. To do so, we first create hundreds of scenarios regarding how macro-level characteristics (demographic structure, economic structure, productivity in various sectors, etc.) will change in the future. These macro-level characteristics include 12 uncertain parameters reflecting:

- demographic changes, including population growth, age and skills (represented by 1 unique parameter, to keep the consistency in demographic assumption);
- structural transformations, reflected by the change in the share of labor force in each sector (2 parameters) and participation in the labor force (1 parameter);
- income changes based on productivity growth in each sector (3 parameters), skill premiums in each sector (3 parameters), pensions and social transfers (2 parameters).

Due to the uncertainty inherent in projecting these drivers, we work with a range of values for each of these parameters. These ranges are based on historical data and trends and on previous work on socio-economic scenarios such as the development of the SSPs.

**Demography.** For demographic changes, two scenarios were chosen based on population data (total population by age, sex, education) developed by IIASA for the SSP4 and SSP5 (Samir and Lutz 2014).

**Structural change.** The plausible ranges are based on the initial economic structure of each country and projected pathways, using the minimum and maximum change observed in historical data over the last 20 years to estimate the boundaries of possible future structural change.

**Participation** (i.e. the share of 15-64 years who have a job). To define a plausible range of uncertainty for this variable, we look at available historical data for all countries and all periods of time and choose boundaries slightly larger than the lowest and highest rates of change over 20 years in employment (see Appendix).

**Productivity growth.** We use a different productivity growth rate for each the tree main sectors of the economy (agriculture, industry and services). This growth rate is applied to the income of unskilled workers. The income of skilled workers will then increase with regards to the income of unskilled workers with a skill premium (here again, different a priori for each sector). For unskilled workers productivity growth rate, we calculate a range based on GDP growth in the SSPs (Chateau et al. 2012) and on the working age population growth, to make sure the range of total income growth resulting from our micro-simulation is centered around (but larger than) the SSP range. For the skill premium we use a range of 1 to 5 (this is the current range across countries). The total productivity

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1 Since the database reports only one sector of activity per individual, we are not able to account for the fact that many poor people may have multiple jobs and income sources.

2 As per WB definition, a worker is defined as skilled if he has more than nine years of education.
growth is an output of the model, as it depends on productivity growth for unskilled workers, on the skill premium and on the share of skilled workers in each sector (Rodrik 2011).

**Pensions and social transfers.** We model two types of redistribution. The first one is a universal cash transfer (or basic income, distributed to each individual aged more than 15), financed by a flat consumption tax. The second transfer represents the pensions: we model a flat tax on workers’ income and use it for cash transfers to individuals older than 65 years. The amount of the cash transfers distributed to each individual therefore depends on the level of the two taxes and on total consumption (or income) in the economy. We use a range of 0-20% for each tax.

To generate the scenarios, we use a latin hypercube sampling algorithm\(^3\) that selects 600 combinations of parameters within the chosen ranges (except for population), so that the space of possible future is homogeneously covered. To maintain the consistency of the demographic scenarios we use only the two SSP alternatives (SSP4 and SSP5, nothing “in-between”), and we duplicate the 600 scenarios using SSP4 and SSP5 for population.

Then, for each of the 1200 scenarios – i.e. for each combination of different macro-level parameter values – we change the income and weight of each household in the model to reflect macro-level changes:

- Households weights are adjusted so that the total population matches different age and skills compositions of the population, participation in the labor force, and the labor share of each sector. This reweighting process models demographic changes (e.g. older people or more skilled people) and structural transformations (e.g. less people in unskilled agriculture).

- Incomes of each individual are then changed, based on the productivity growth and skill premiums for the sector the individual belongs to, and on income redistribution. The existing variance in income in each household category is assumed unchanged (if we have 500 individuals that are skilled farmers, for instance, they have different income levels and this variance is assumed unchanged by 2030, which means that all individuals in one category see their income multiplied by the same amount). The inequality and poverty we have in our scenario is a combination of within category variance (assumed unchanged) and across-category variance (which changes with structural and productivity changes).

This process results in a database of 1200 scenarios of future poverty and distribution outcomes per country, and these 1200 scenarios cover the full space of uncertainty on the macro-level parameters.

1.2. Limits of the approach

This approach has of course many limitations that need to be taken into account in the interpretation of the results.

First, this approach can provide estimates of income distribution and poverty at different points of time, but it does not represent the full dynamics of poverty or the distinction between chronic and temporary poverty – an important limitation considering the large and frequent movements in and

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\(^3\) The latin hypercube sampling algorithm maps the n-dimension space of uncertainty so that a minimum number of scenarios cover as densely as possible the full space.
out of poverty observed in developing countries (Lanjouw, McKenzie, and Luoto 2011; Krishna 2006; Baulch 2011; Dang, Lanjouw, and Swinkels 2014; Beegle, De Weerdt, and Dercon 2006).

Second, since we combine many different possible values for all drivers, which we treat as independent, we disregard macro-economic coherence a priori. For instance, nothing prevents us from running a scenario with very high productivity growth in agriculture and no growth in the other sectors of the economy, or a scenario with a skill premium of 1 in services and 5 in industry. Other methodologies combine a macroeconomic model with micro-simulation to ensure consistency across sectors (Boccanfuso, Decaluwé, and Savard 2008; Ahmed et al. 2014; Bussolo, De Hoyos, et al. 2008). In this analysis, the lack of international consistency is not an issue as we are not trying to predict the future but we are rather looking for the necessary conditions (on those drivers) to reduce poverty. The plausibility and coherence of these conditions will be investigated ex-post. Also, there is a well-established trade-off between the internal consistency of scenarios and the risk of being too conservative – for instance by assuming that the relationship between two variables will remain unchanged over time. After all, scenarios with very high productivity growth in agriculture and no growth in the other sectors of the economy are not impossible – even though they may be less likely than other scenarios. Here, we favor the exploration of a large set of possible futures, and consider consistency only in the second phase, when representative scenarios are selected.

Finally, we do not attribute probabilities or likelihood to our scenarios – we build scenarios that represent possible evolutions of the world, irrespective of their likelihood. These scenarios thus cannot be used as forecasts or predictions of the future of poverty or as inputs in a probabilistic cost-benefit analysis. That said, they can still be an important input into decision-making.

It is fairly common in situations of deep uncertainty not to be able to attribute probabilities to possible outcomes (Kalra, Hallegatte, et al. 2014). For example, we know that conflicts, such as those in the Middle-East, could continue over decades, preventing growth and poverty reduction. But they also could subside, allowing for rapid progress. While these two scenarios are obviously possible, it is impossible to attribute probabilities to them in any reliable way. The same deep uncertainty surrounds the future of technologies and most political and socio-economic trends. In such a context, exploring scenarios without attributing probabilities to them is commonplace. The IPCC and climate community have used such long-term socio-economic scenarios (the SRES and now the SSPs) since the 1990’s, to link policy decisions to their possible outcomes (Edenhofer and Minx 2014). Similarly, the UK government performs national risk assessments using “reasonable worst case scenarios” (for example, regarding pandemics, natural disasters, technological accidents or terrorism), which are considered plausible enough to deserve attention, even though their probability is unknown (World Bank 2013, chapter 2).

While these scenarios cannot be used to perform a full cost-benefit analysis, they make it possible to elicit trade-offs and to support decision-making. For instance, they help identify dangerous vulnerabilities that can be removed through short-term interventions (Kalra, Hallegatte, et al. 2014). In our case here, our scenarios help us explore and quantify how poverty reduction can reduce the vulnerability to climate change.

1.3. Results and scenarios

Figure 1 shows an example of our baseline no-climate-change scenarios, here for Vietnam. Similar sets of baseline scenarios are produced in every country.

Each dot in Figure 1 represents one scenario, plotted as a function of the average economic growth in Vietnam (X-axis) and the income of the bottom 20 percent in the country, as a measure of how
poverty changes over time (Y-axis). Consistently with our goal of exploring the largest possible uncertainty, the range of income growth in our scenarios is much larger than the one explored in other scenario exercises, such as the SSPs.

Since, all the hypotheses that were made on the input parameters appear however possible (or at least, non-impossible) and based on historical data, these scenarios cannot be disregarded a priori. However, some of these scenarios are very pessimistic, as they combine the most pessimistic assumptions for each of the parameters, while others combine all the most optimistic assumptions.

![Figure 1 Uncertainty range on total income growth coming out of the experiment, and SSP growth for Ethiopia in SSP4 and SSP5, represented by the two vertical lines](image)

For each of the baseline scenarios presented in Figure 1, for 2030, we have a synthetic household survey, i.e. an ensemble of households with their composition (size of the household, age, education), their occupation (i.e. the sector in which they work), and their income. (Combined with weights, these households provide a representative sample of the full population.) From these ensemble, we can calculate multiple economic indicators, including the average income, the income of the bottom 20 percent or the number of people under a given poverty line, or the Gini or any other measure of inequality.

To understand what input parameters drive the dispersion of poverty across scenarios, we perform a simple analysis of variance on the income of the bottom 20% in our baseline scenarios. The analysis of variance partitions the observed variance of a variable into components attributable to different sources of variation. In other words, we are explaining the variance of the outputs of our micro-simulation (number of people in extreme poverty) model by the variance of the inputs (the twelve sources of uncertainty identified previously). Doing so tells us about the drivers that are the most important to reduce poverty over time, in various countries and at the global scale.

Figure 2 shows that the contribution of each driver to the income of the bottom 20% varies greatly across countries. In some countries demographics explain 50% of the variance while in others it do not matter much. Redistribution matters everywhere but in some countries it explains 35% of the variance of the income of the poorest while in others only 5%. Some parameters like pensions or the share of workers in the manufacture sector have a very minor role in the income of the bottom 20% in all countries.
With these baseline scenarios, we can now explore the impact of climate change on poverty, taking into account how socioeconomic development affects vulnerability to climate change.

1.4. Climate change impacts on poverty

The second step of the analysis starts from our baseline synthetic household surveys for 2030, which represent possible socioeconomic conditions in each country in 2030, at the household level. Then, for each country and each baseline scenario, we introduce the impacts of climate change impacts on each household independently (i.e. in each of the 1.4 million households explicitly modeled in our scenarios). In each country and for each baseline scenario we add climate change impacts on households’ income and ability to consume through three sectors: (1) food price and production, (2) health and labor productivity, and (3) natural disasters.

Climate change impacts are not “new” impacts: they mostly correspond to the worsening of existing issues, such as more (or less) frequent disasters or more (or less) malaria cases. In this analysis, we assume that the impacts due to the current climate are already included in our baseline scenarios. (This assumption is justified by the fact that historical data used to define the boundaries of possible values of macro-level parameters include impacts of climate variability.)

We add to these scenarios the additional impact of climate change. For malaria for instance, the current extent and impacts of the disease are assumed already included in the scenarios and we add the costs and lost income from the cases that would not have occurred in the absence of climate change. (And we remove costs and increase income where malaria is expected to decrease.)

With a 2030 horizon, impacts barely depend on emissions between 2015 and 2030 because these affect the magnitude of climate change only over the longer term, beyond 2050. Regardless of socioeconomic trends and climate policies, the mean temperature increase between 2015 and 2035 is between 0.5 and 1.2°C—the magnitude depends on the response of the climate system (Alexander et al. 2013). The impacts of such a change in climate are highly uncertain and depend on how global climate change translates into local changes, on the ability of ecosystems to adapt, on...
the responsiveness of physical systems such as glaciers and coastal zones, and on spontaneous adaptation in various sectors (such as adoption of new agricultural practices or improved hygiene habits).

To account for this uncertainty, we define a low-impact and a high-impact scenario that represent the uncertainty on the magnitude of the physical and biological impacts of climate change. For agriculture, for instance, the difference between the low-impact and the high-impact scenario comes from the uncertainty in the global climate system, crop responses, and trade models that are used. For health, one difference across low-impact and high-impact scenarios comes from the uncertainty on the additional number of cases of dengue and malaria due to climate change and on the cost of treatment.

We also add a voice and governance variable that describes how society provides services to the poor to deal with weather shocks and climate changes - through non income instruments - for instance by improving access to water and sanitation in poor neighborhoods or rural areas. This variable also affects how changes in agriculture revenues are shared across landowners and laborer. This variable is considered independent of the other drivers.

Our approach is completely from the bottom up: we change the characteristics of every households, and then we can aggregate to estimate the impact at the macroeconomic level. Our approach is complementary to top-down approaches that start by an assessment of the macroeconomic impacts of climate change and investigate the implications at the household level. This approach has its own limits, especially considering the evidence that aggregate growth is a major driver of poverty reduction (Dollar and Kraay 2002; Dollar, Kleineberg, and Kraay 2013). But our approach is more appropriate if the main impacts of climate change by 2030 will not be a reduction of aggregate growth and GDP – as suggested by the existing literature (Arent et al. 2014; Stern 2006) – and if the main channel from climate change impact to poverty will be a change in the relationship between aggregate growth and poverty (Hallegatte et al. 2014).

It remains also out of reach to include all possible impacts in such an analysis, so we considered only the channels through which climate change is most likely to affect poverty reduction. And in each channel, we focus on specific issues that have the potential to affect poverty reduction in a significant manner, and for which quantified sectoral studies have been published—for instance, we do not include the loss of ecosystem services and the nutritional quality of food. Also, we assume that sectoral impacts do not interact, which is not always valid (for instance, undernutrition increases the likelihood of disease, an interaction that has not been considered in published estimates).

It is also important to note that we cannot assess the poverty impact everywhere. Our household database represents only 83 percent of the population in the developing world. Some highly vulnerable countries (such as small islands) cannot be included in the analysis because of data limitations, in spite of the large effects that climate change could have on their poverty rates.

The following subsections describe how sectoral impacts have been introduced.

**Food prices and food production**

The vulnerability of poverty reduction to food price hikes have already been demonstrated, for instance in (Ivanic and Martin 2008; Ivanic, Martin, and Zaman 2012; Hertel, Burke, and Lobell 2010; Devarajan et al. 2013). Impacts of climate change on agriculture affect poverty in two ways (Porter et al. 2014).
First, an increase in food prices reduces households’ available income, but especially consumption of the poor who spend a large share of their income on food products. The impact in our scenarios depend on the fraction of food expenditure in total expenditure, which decreases with the income level of the household (Figure 3).

Second, food price changes affect farmers’ income. However, this channel is complex since lower yields mean that higher food prices do not necessarily translate into more farmers’ revenues: the net effect depends on the balance between changes in prices and quantities produced, and on how changes in revenues are distribution among landowners and laborers.

Figure 3 Share of food in total consumption, for each World Bank region and different income categories. Source: The World Bank Global Consumption Database.

In our assessment, food prices and production come from a global agricultural model (Havlík et al. 2015). They are different for each climate model considered, region, and global socio-economic
scenario. We assume that food prices and productions follow the SSP5 path in our *prosperity* scenario and the SSP4 path in our *poverty* scenario. Then, for each region and in each scenario, we take the minimum and maximum price increase across all climate models (Global Climate Models or GCMs) and use them as boundaries to create an ensemble of scenarios (Table 1). We use the corresponding production variations to calculate the impact on farmers’ income (ensuring that our price and production inputs are fully consistent).

Whether higher agriculture revenues (if the increase in price dominates the decrease in yield) are transmitted to poor farmers depends on how the benefits are distributed between farm laborers and landowners (see an example on Bangladesh in Jacoby, Rabassa, and Skoufias 2014). To account for these effects, we use the *voice and governance* variable: in the best governance assumption the increase in agriculture revenues is entirely transmitted to agriculture workers (due to favorable balance of power in labor markets and good governance). But only 50% is transmitted in the worst governance scenario, the rest being captured by land owners and intermediaries in the food supply chain (who are assumed rich enough not to affect our poverty estimates).

In practice, we change the income of all workers in the agricultural sector, according the “revenue difference” column in Table 1. We also rescale the (real) income of all households according to the change in food prices (“price difference” column in Table 1), accounting for the share of food in household budget (which decreases with income, see Figure 3). The impact of the agriculture channel on poverty depends on the number of farmers in each country, the income of these farmers, and the income of the entire population (which affects the share of food in consumption).
Table 1 Low-impact and high-impact changes in the agriculture sector due to climate change (RCP8.5) in 2030. Source: GLOBIOM model (IIASA). Bold numbers are positive ones.

(a) Low-impact climate change (minimum price change across GCMs)

<table>
<thead>
<tr>
<th>World Bank region</th>
<th>SSP</th>
<th>Socio-economic scenario</th>
<th>Price difference</th>
<th>Corresponding production difference</th>
<th>Corresponding revenue difference</th>
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(b) High-impact climate change (maximum price change across GCMs)

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<th>Socio-economic scenario</th>
<th>Price difference</th>
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**Health and labor productivity**

We include a set of additional impacts of climate change on health (stunting, malaria, and diarrhea).

**Stunting**

Stunting is linked to malnutrition and therefore to food price, but acts through a different channel than the direct impact on food prices on the ability to consume. It is also driven by more than access to and affordability of food (Lloyd, Kovats, and Chalabi 2011; Hales et al. 2014). Socio-economic characteristics such as parents’ education and access to basic services (especially improved drinking water and sanitation) also play a key role.

Stunting has short- and long-term impacts particularly for children younger than two. For instance, households reducing nutrition after droughts permanently lowered children stature by 2.3 to 3 cm (Dercon and Porter 2014; Alderman, Hoddinott, and Kinsey 2006). Hoddinott (2006) also observes the body mass index (BMI) of women reduced 3%; while this recovered the following year, impacts on children are long-lasting. Stunting is also linked to delayed motor development, lower IQ, more behavioral problems, lower educational achievement (less years of schooling), and reduced economic activity (Martorell 1999; Victoria *et al.* 2008; Currie 2009; Caruso 2015). These consequences have impacts on lifelong earning capacity and ability to escape poverty. In Ethiopia income were reduced by 3% for individuals who were younger than 3 year old during droughts. In Zimbabwe, children affected by droughts had 14% lower lifetime earnings (Alderman *et al.*, 2006).

Lloyds *et al* (2011) suggest that climate change could have a large impact on stunting, and even that climate change could dominate the positive effect of development in some regions, leading to an absolute increase in stunting over time. In our model, we use the ranges given in (Hales *et al.* 2014, Table 7.4) for the additional share of children estimated to be stunted because of climate change in 2030. To account for the effect of development on stunting, we investigate the distribution of stunting today using household surveys from the Demographic and Health Surveys household surveys. We find that prevalence of stunting drops for families whose income is above $8000 per year (Figure 4).

In our simulations, we randomly select a fraction of the households in the household survey with income below $8000, so that stunting prevalence is consistent with data for the current situation. Then, we increase this fraction by the fraction given in (Hales *et al.* 2014, Table 7.4) in our synthetic surveys for 2030, to account for climate change. We assume that stunted individuals have lifelong earning reduced by 5 and 15% in the low-impact and high-impact scenarios, respectively (regardless of their employment sector and skill level).

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4 The DHS surveys do not include income data so we use asset data to link the DHS surveys with income or consumption surveys from the I2D2 database. We do so by ranking households in both surveys by assets and income (assuming that the household ranking in terms of assets and income is the same). This way of coupling surveys is very simplistic and could not be applied to estimate income or asset at the household level, but it is considered sufficient to determine a threshold beyond which health issues decrease.
Malaria

Climate change threatens to reverse the progress that has been made to date in the fight against malaria. It is difficult to identify what portion of malaria incidence can be attributed today to climate change but the World Health Report estimated climatic factors to be responsible for 6 percent of malaria cases (WHO 2002). Further, even small temperature increases could have a great effect on transmission of malaria. At the global level, increases of 2 or 3 degrees centigrade could increase the number of people at risk for malaria by up to 5 percent – representing several million. Malaria could increase by 5-7 percent in populations at risk in higher altitudes in Africa, leading to an increase in the number of cases by up to 28 percent (Small et al 2003; Tanger et al 2003).

In our scenarios, we use results from (Caminade et al. 2014), which give the percentage increase in malaria cases in 2030, in each country, due to climate change. To account for uncertainty in prevalence, we assume that the number of occurrence per year for the people affected by malaria will be between 0.1 and 2 (in reality, this number will depend on the places that are affected, the type of malaria, the health condition of the population, and the available treatments and health care).

Even when not deadly, malaria is a debilitating disease that often results in recurring bouts of illness (Cole and Neumayer 2006). In this analysis, it is assumed that malaria has impacts through the cost of treatment (between $0.7 and $6 per occurrence) and lost days of work (directly or to care for someone else). We use the ranges in Table 2 extracted from (Attanasio and Székely 1999; Konradsen et al. 1997; Ettling et al. 1994; Louis et al. 1992; Desfontaine et al. 1989; Desfontaine et al. 1990; Guiguemde et al. 1994).

Like for stunting, we randomly select individuals that are affected by malaria in the current household survey and in each country, based on current prevalence. Then, we increase this fraction in the synthetic survey for 2030, using estimates of future changes due to climate change in various world regions from (Caminade et al. 2014). Then, we assume that these people affected by malaria are affected between 0.1 and 2 times per year, and lose for each occurrence of the disease a fraction of income, as presented in Table 2.
Table 2 Malaria impacts on households in our model

<table>
<thead>
<tr>
<th></th>
<th>Min impact</th>
<th>Max impact</th>
</tr>
</thead>
<tbody>
<tr>
<td>Cost of treatment</td>
<td>$0.7</td>
<td>$6</td>
</tr>
<tr>
<td>Number of days out of work</td>
<td>1</td>
<td>5</td>
</tr>
<tr>
<td>Number of occurrences per year</td>
<td>0.1</td>
<td>2</td>
</tr>
</tbody>
</table>

Diarrhea

As the third leading cause of death among low-income countries, diarrhea is an important risk for poor households due to easy contamination pathways resulting from unsatisfactory hygiene conditions and high exposure (WHO 2008). Reduction in diarrhea incidence may be undermined by climate impacts that damage urban infrastructure and reduce the overall availability of water through water resource depletion.

Here we use data by (Hutton, Haller, and others 2004) for the number of cases per country today and the cost of treatment (Table 3). According to (Kolstad and Johansson 2010) the prevalence of diarrhea could increase by 10% by 2030 because of climate change (in all regions), and we use this assessment in our scenarios.

Table 3 Diarrhea impacts on households in our model

<table>
<thead>
<tr>
<th></th>
<th>Low-impact scenario</th>
<th>High-impact scenario</th>
</tr>
</thead>
<tbody>
<tr>
<td>Cost of treatment</td>
<td>$2</td>
<td>$4</td>
</tr>
<tr>
<td>Days out of work (for the sick or the caregiver)</td>
<td>3</td>
<td>7</td>
</tr>
<tr>
<td>Number of occurrences per year</td>
<td>1</td>
<td>8</td>
</tr>
</tbody>
</table>

To account for development, as for stunting, we use DHS data to explore the relationship between the income of the households and its exposure to diarrhea (Figure 5).\(^5\) These data do not show a dramatic decrease with income and diarrhea persists at high income levels. In practice, we use a 10 percent prevalence as a reference level, beyond which diarrhea has economic impacts, and we use a linear regression to estimate the income level at which prevalence decreases below 10 percent. We find a threshold at $15,600 per year, and we assume that only households with income below this level are affected by the climate change effect on diarrhea.

Further, we assume that progress in access to water and sanitation is proportional to the voice and governance variable. In the optimistic scenario with good voice and governance, universal access to improved drinking water and sanitation is achieved in 2030, and it reduces by half the number of cases of diarrhea, consistently with the assessment in India by (Andres et al. 2014).

Of course, this assumes that the new water and sanitation infrastructure are adapted to changing future climate conditions and can continue to perform well in 2030 and beyond. This would require to account for the uncertain in climate projections in the design phase, and to invest in the

---

\(^5\) Here again we couple the DHS surveys with income and consumption surveys from the I2D2 database by ranking households.
additional cost of more resilient infrastructure, possibly factoring in safety margins and retrofit options (Kalra, Gill, et al. 2014).

Figure 5 Prevalence of diarrhea in the past 2 weeks (DHS data)

Like for stunting or malaria, we select randomly individuals in households with income below $15,600 so that the number of case match data for the current situation. Then, we change the fraction of affected people to account for climate change using (Kolstad and Johansson 2010). For the affected people because of climate change, we reduce their income using estimates of the cost of treatment and lost income.

Temperature and labor productivity.
Recent studies suggest that there is a significant impact of temperature stress on labor productivity, which may be exacerbated by global climate change (Dell, Jones, Olken, 2014). In particular, there are direct physiological effects of thermal stress on the human body, which may affect productivity and labor supply, especially in developing countries (Heal and Park, 2015). Using variations in weather, several studies identified a relationship between extreme temperature – for instance, hotter-than-average years or extremely hot days – and economic outcomes such as labor productivity (Hsiang, 2011; Sudarshan et al, 2014; Dell, Jones, Olken, 2014).

For instance, Niemelä et al. (2002) find that, above 22 degrees C, each additional degree C is associated with a reduction of 1.8 percent in labor productivity for call center workers. Adhvaryu et al (2013) and Sudarshan et al (2014) find similar results in the manufacturing sector, with worker efficiency at the plant level declining on hotter days, even after controlling for absenteeism. In Sudarshan et al (2014), days above 25 degrees C reduce productivity in manufacturing plants by about 2.8% per degree C. Reviewing experimental studies, Seppanen, Fisk et al. (2006) find that the average productivity loss from temperatures above 25°C is on the order of 2% per degree C.

Today, temperatures are about 1C higher than they would be in the absence of climate change. In 2030, the difference will be around 1.2 or 1.4C. In our analysis, we assume that that people working outside or without air conditioning will lose between 1 and 3% in labor productivity due to this change of climate, compared with a baseline with no climate change. To assess the number of people affected, we use the shares of people working outside or without air conditioning in Table 4. We select randomly a number of workers who are supposed to work outside or without air conditioning according to the fraction in Table 4, and we reduce their income by 1 to 3%.
Table 4 Share of people working outside or without air conditioning

<table>
<thead>
<tr>
<th>Share of people working outside or without air conditioning</th>
<th>National income below $10,000 per capita</th>
<th>National income above $10,000 per capita</th>
</tr>
</thead>
<tbody>
<tr>
<td>Agriculture</td>
<td>0.8</td>
<td>0.8</td>
</tr>
<tr>
<td>Manufacture</td>
<td>0.5</td>
<td>0.1</td>
</tr>
<tr>
<td>Services</td>
<td>0.3</td>
<td>0.05</td>
</tr>
</tbody>
</table>

Natural disasters

For natural disasters, we focus on direct economic losses, disregarding human losses and indirect and second-order losses (Hallegatte 2014; Hallegatte 2012).

We model the impact of the following four natural hazards on people’s income: cyclones, storm surges, floods, and droughts. For each of these hazards, we estimate the fraction of the population affected at different return period (i.e. with different probability of occurrence), and the fraction of income and consumption lost by the affected people. We proceed differently for cyclones and storm surges on the one hand, and droughts and floods on the other hand.

- The share of people affected by cyclones and storm surges is calculated based on data from the United Nations Global Assessment Report on Disaster Risk Reduction, otherwise known as GAR (UNISDR 2015). This report provides estimates for the value of asset losses associated with different hazards and return periods. Then, we use estimates of the vulnerability of people’s asset (i.e., how much is lost by each affected household) from (Hallegatte, Bangalore, and Vogt-Schilb 2016) to estimate the number of people affected by different hazards and return periods. For instance, if the 100-year storm in a country produces $10 million in asset losses, and if the average loss per affected person is $1000, then we estimate that the 100-yr storm affects on average 10,000 persons.

- For flood and drought, we follow the methodology applied in (Hallegatte et al. 2016) and we estimate the affected population by overlaying population data with hazard data taken from a global model (GLOFRIS) that produces gridded indicators of inundation depth (for flood, 1-kilometer resolution) and water scarcity (for drought, 5-kilometer resolution), for return periods from 5 to 1000 years.

Then, for all four types of hazard, we aggregated events with different return periods into an annual average number of people affected. In this study, we do not take into account differences in the exposure for people with different income levels (Hallegatte et al. 2016). However, we take into account the difference in vulnerability, i.e. we account for the fact that poor people are losing a larger fraction of their wealth, when they are affected by a natural hazards. Again, vulnerability estimates are based on (Hallegatte, Bangalore, and Vogt-Schilb 2016).

We assume that the disasters in the no climate change scenarios are already included in the baseline socio-economic scenarios, and we add in our synthetic household surveys the impact of the additional disaster losses due to climate change.

We make crude assumptions on how climate change will affect disaster losses, reflecting the large uncertainty on the effect of climate change on extreme events and the fact that losses will be highly dependent on how protections and other adaptation measures change over time. Indeed, the
change in hazard (i.e. the intensity and frequency of various event) is only one determinant of the change in disaster (i.e. the change in the impact of hazards). Risk management also plays a key role: many case studies suggest that if risk management became optimal, disaster losses could decrease over time in spite of climate change (see an example on Mumbai in (Ranger et al. 2011)). If risk management is unchanged, then disaster losses could increase exponentially with the change in hazards (see an illustration in 136 cities in (Hallegatte et al. 2013).

Here, we start from the country-specific exposure today to various hazards, and we assume that the fraction of the population that will be affected annually by different hazards increase uniformly. Population affected by flood or drought is assumed to increase by 20% to 40%; the fraction of the population affected annually by a storm surge or a cyclone is assumed to increase by 10% to 50%.

These numbers will depend on how effective and timely adaptation to new climate conditions is, so that these two assumptions can be considered as two assumption on adaptation performance. These numbers are also consistent with existing estimates, see for instance the review of 19 papers in Bouwer (2013). Further research will be needed to refine these numbers and link them to explicit assumptions regarding the adaptation process. Practically, it would require to include explicitly adaptation decision-making and investments in the model.

Here, we assume that disasters affect income only for the year when they occur. It means that we disregard the possible long-term impact of disasters at the micro- and macro-level. This is an important limitation since long-term impacts have been detected at the macro-economic scale (Hsiang and Jina 2014; Loayza et al. 2012; Strobl 2010; Coffman and Noy 2011). Long-term impacts at the individual levels are also widely reported (Carter et al. 2007; Carter and Barrett 2006; Dercon 2004; Dercon and Christiaensen 2011; Baez et al. 2014). As a result, our estimates for the impact of disaster need to be considered as underestimates, but going further would require to model explicitly the dynamics of poverty, including asset accumulation and the shock that bring back people in poverty (Beegle, De Weerdt, and Dercon 2006; Krishna 2006; Lanjouw, McKenzie, and Luoto 2011; Skoufias 2003).

2. Results

In every countries in our dataset, we now have 1,200 baseline scenarios without climate change; 1,200 scenarios with low climate change impacts; and 1,200 scenarios with high climate change impacts. For each scenario, we have the full distribution of income in the country, making it possible to assess changes in absolute or relative poverty, inequality, or aggregate income.

2.1. Results at the country level

Figure 7 shows results in terms of the impact of climate change on poverty, in four countries. These figures are histograms – not probability distribution functions – since no probability is attributed to the scenarios.

Figure 7 shows that the impacts of climate change on poverty in 2030 highly depend on baseline assumptions: for the low or the high impact scenario, estimates have very large ranges, which correspond to differences in vulnerability in different baselines. In Afghanistan, for instance, between zero and 5 percent of the population could live in extreme poverty because of climate change in 2030 in the high impact scenario. In the low impact scenario, this range is between around 0 percent and 2 percent.

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6 Some of these impacts – through stunting – are however accounted for in the health channel.
It is also interesting to note that uncertainty is much larger for the high impact scenario than for the low impact scenario. In some countries, the worst case scenario is really worrisome: in Niger and Bangladesh, for instance, climate change could push more than 6 percent of the population in poverty by 2030.

In many cases, the distribution of possible impacts is bimodal. This shape arises from the use of two demographic scenarios (SSP4 and SSP5). This is because demography is the most important driver of poverty reduction and development in the baseline scenario (see Figure 2): scenarios with low population growth (and high education) lead to faster economic development and lower poverty, and therefore lower vulnerability to climate change, and less impact of climate change on poverty.

Figure 6 Climate change impacts on the number of people living in extreme poverty in selected countries

We also look at how climate change impacts inequality, and we find that climate change increases inequality (for instance measured with the Gini index) in most scenarios in all countries (Figure 7).
This is due to multiple factors, including the larger share of expenditures dedicated to food by poor people, and their larger exposure to the health impacts described earlier.

Figure 7 Climate change impacts on the Gini coefficient in selected countries across all scenarios

And this effect is confirmed in Figure 8 Income losses for the bottom 40 percent, compared with the average in the population Figure 8, which shows income loss of the bottom 40 percent in each country (i.e. people whose income is among the 40 percent lowest in the country), compared with the average income loss in the country. The income loss of the bottom 40 percent is a relevant metric as it is used by the World Bank to define its goal to “boost shared prosperity” in the world.

Figure 8 shows that the people in the bottom 40 percent lose systematically more than the average people. On average (using a regression weighted by population), an individual in the bottom 40 percent loses 70 percent more than the average person in his or her country.
Like for the baseline scenarios, we perform an analysis of variance on the number of people who live in extreme poverty because of climate change in each country. We find that the magnitude of climate change impacts matter the most in some countries, but in other countries baseline conditions are the most important in explaining climate change impacts on the poor (Figure 9, Figure 10). In most of Asia and Latin America, the baseline is more important than the magnitude of climate impacts to assess poverty impacts.

Assuming that predicting future socioeconomic evolutions will remain impossible – due to the deep uncertainty linked to political and technological factors – then future impacts of climate change on poverty will remain unpredictable: a better understanding of physical impacts would not be enough to really improve our prediction of future impacts on poverty. It means in particular that decision-making regarding optimal mitigation targets (for instance between 1.5 and 2C) will have to be done in a context of deep uncertainty, regardless of progress on climate and climate impact sciences.

Figure 10 also has policy implications on how best to reduce future impacts of climate change on poverty. In particular, the three main determinants of future impacts on poverty suggest domains for interventions:

- The climate impact scenario matters most, suggesting that targeted adaptation policies have a key role to play. For instance, for the malaria impacts, the difference between the low impact and the high impact scenarios include the cost of treatment. Reducing the cost of treatment is an obvious way to mitigating the impacts of climate change on poverty through malaria.
- The second largest determinant is voice and governance, which include mostly (1) power relationship in the labor market in agriculture (and therefore the distribution of income
between workers and landowners) and (2) access to infrastructure services and especially improved drinking water and sanitation. These two domains are critical to mitigate the impact of climate change on poverty.

- The third driver is economic growth in the service sector. This is because a lot of poor people are working in services in the baseline scenarios, and rapid growth in service productivity would make this extremely large population less vulnerable to climate change impacts.

We can also assess aggregated impacts by summing up the individual-household impacts – resulting in what we call private household income loss (although some high income households may be missing from the surveys so we not capture 100% of the private household income). This calculation only accounts for a subsets of all impacts, since it focuses on households, and provides an estimate that is largely independent from existing assessments based on economy-wide data and focused on macroeconomic impacts. We confirm the finding that private household income losses are decreasing with the current income level (Figure 11) – as already flagged in the literature (Tol 2002;
Nordhaus 2014; Hope 2006; Hahn and Ulph 2012). This is especially the case of countries below $10,000 of GDP per capita (in PPP USD).

![Figure 11 Loss in GNI, as a function of 2015 GNI](image)

*Figure 11 Loss in GNI, as a function of 2015 GNI*
Finally, we find that the speed of development between now and 2030 matters for the impact of climate change on poor people (Figure 12). Of course, as we’ve seen in Figure 9, economic growth (or lack of economic growth) is not the main driver of climate change impacts on poverty. However, Figure 12 shows that higher income for the bottom 20% (thanks to growth and redistribution) can significantly reduce the impact of climate change on poverty. In fact, most of the impact (in relative terms) is concentrated in countries and scenarios where the income of the bottom 20 percent is below $1000 (in USD 2005PPP). Ensuring that nobody lives with less than $1000 per year in 2030 is therefore a priority to mitigate the impacts of climate change.

2.2. Impacts on the global poverty headcount

How do these country-level results affect global poverty and the objective of eradicating extreme poverty by 2030? Here, we build global scenarios to explore this question.

Global results in two representative baselines

In the Shockwaves report, to simplify the presentation, we built two contrasted global scenarios, one optimistic and one pessimistic in terms of development, to assess the total impact of climate change. These global scenarios were built by aggregating optimistic and pessimistic scenarios in each country.

In each country, we selected a box of “optimistic” scenarios (in green in Figure 13 in the case of Vietnam) and a box of “pessimistic” scenarios (in purple in Figure 13). The scenarios were selected in terms of poverty and inequality only: optimistic scenarios are the ones above the median for both the average income of the bottom 20% and for difference in growth rates between the income of the bottom 40% and average income. Similarly, pessimistic scenarios are the ones below the median for both indicators.
We then used a scenario discovery algorithm\(^7\) (Bryant and Lempert 2010) to identify a combination of input drivers that is most likely to put the scenario in the optimistic or pessimistic box. In other words, we identified the range of parameter values that are found in this subset of scenarios (we may find that the scenarios with lower poverty and lower inequality are typically those with low population: it means that most scenarios with lower poverty and lower inequality have also low population, and that most scenario with low population have also lower poverty and lower inequality). For instance, optimistic scenarios in Vietnam are mostly scenarios with high redistribution level, relatively high pension levels, low population growth and high education (SSP5 demography), and relatively high productivity growth for unskilled agricultural workers. Pessimistic scenarios are characterized by relatively low redistribution level, high population growth and low education (SSP4 demography), and low productivity growth for unskilled agricultural workers. The details are in Table 5. The other parameters (e.g., structural change or change in productivity in service or manufacturing) play only a secondary role.

Table 5: sets of conditions that characterize the scenarios in the optimistic box (defined as in Figure 13) for Vietnam. Density is the probability of a scenario which matches the set of conditions to be in the optimistic box. Coverage is the probability of a scenario which is in the optimistic box to match the set of conditions.

<table>
<thead>
<tr>
<th>Optimistic set of conditions</th>
<th>78% density</th>
<th>40% coverage</th>
</tr>
</thead>
<tbody>
<tr>
<td>High redistribution (tax for cash transfers &gt;8% of total consumption)</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>Relatively high pensions (tax &gt;5% of total consumption)</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>Low population growth, high education (SSP5)</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>Productivity growth for unskilled agriculture workers &gt;2% per year</td>
<td>-</td>
<td>-</td>
</tr>
</tbody>
</table>

\(^7\) Here we use the EMA work bench developed at Delft University: http://simulation.tbm.tudelft.nl/ema-workbench/contents.html
Table 6: drivers for the scenarios in the pessimistic box (defined as in Figure 13) for Vietnam. Density is the probability of a scenario which matches the set of conditions to be in the optimistic box. Coverage is the probability of a scenario which is in the optimistic box to match the set of conditions.

<table>
<thead>
<tr>
<th>Pessimistic set of conditions</th>
<th>- Relatively low redistribution tax for cash transfers &lt;15% of total consumption)</th>
</tr>
</thead>
<tbody>
<tr>
<td>47% density</td>
<td>- High population growth, low education (SSP4)</td>
</tr>
<tr>
<td>59% coverage</td>
<td>- Productivity growth for unskilled agriculture workers &lt;5% per year</td>
</tr>
</tbody>
</table>

To select one representative scenario in each box, we selected only scenarios that corresponded to the main set of drivers and applied the following additional criteria. For the pessimistic scenario we selected a scenario with a total income growth that is close to GDP growth in the SSP4 (the SSP scenario in which poverty and inequality remain high) and minimized structure change (to represent stagnation). For the optimistic scenario, we selected a scenario with a total income growth that is close to GDP growth in the SSP5 (the SSP scenario with the largest GDP growth), while minimizing the share of workers in agriculture, maximizing the share of workers in industry, and making sure that skill premiums are not too different between sectors.

We then aggregated all optimistic country-level scenarios into a global optimistic scenario, labelled the prosperity scenario. This scenario is consistent with the World Bank twin goals of eradicating extreme poverty and promoting share prosperity: (1) the number of people living below the extreme poverty line is less than 3% of the global population; and (2) consumption growth for the bottom 40% in countries is high. We also assumed that the world described in our prosperity scenario provides basic services (electricity, water and sanitation), basic social protection, and health care and coverage to the entire population. Since each country-level scenario is chosen so that GDP growth is close to the GDP values from the SSP5 and that most countries optimistic scenario have the demographics from the SSP5, our prosperity scenario can be considered as a quantified pathway for poverty in the SSP5. But our prosperity scenario is not the SSP5, and it does not follow the narrative from the SSP5, especially concerning the energy mix and use of fossil fuels.

Similarly, we aggregated all pessimistic country-level scenarios into a global pessimistic scenario, labelled the poverty scenario. In this scenario, extreme poverty decreases much less, to reach 11% of the global population in 2030, inequality is much larger across and within countries. In this scenario, we also assumed that access to basic services, social protection, and health care improves only marginally. This scenario is consistent with the narrative from the SSP4, and our poverty scenario can therefore be considered a quantification of poverty in SSP4.

Figure 14 shows the poverty rate (left panel) and income growth of the bottom 40 percent (right panel) in all countries, in 2007 and in 2030 in the poverty and prosperity scenarios. These two scenarios are representative of successful futures and more pessimistic ones, and can be used to assess the consequence of various shocks and stresses, accounting for the different in vulnerability due to future socioeconomic trends.
Figure 14 Poverty rates (left) and income growth of the bottom 40% (right) in the optimistic (prosperity) and pessimistic (poverty) scenarios.
We then used these two global scenarios to assess the impacts of climate change on poverty:

- In the poverty scenario, the total number of people living below the extreme poverty line in 2030 is 1.02 billion people in the high-impact scenario; this represents an increase of 122 million people compared to a scenario with no climate change. For the low-impact scenario, the additional number of poor people is 35 million people.

- In the prosperity scenario, the increase in poverty due to a high-impact climate change scenario is “only” 16 million people, suggesting that development and access to basic services (like water and sanitation) is effective in reducing poor people’s vulnerability to climate change. For the low-impact scenario, the additional number of poor people is 3 million people.

The impact on the number of people in extreme poverty assessed with this methodology suggests the potential for a large impact of climate change on poverty, with the dominant factor linked to agricultural impacts and effects on food prices, as shown in Figure 15. More precisely, the effect of increased food prices on consumer is the main determinant in these results.

These results also emphasize how “good” and inclusive development – as represented by our prosperity scenario – can prevent most of the impacts of climate change on poverty. These results also provide a first-cut assessment of countries’ vulnerabilities, and can guide further research toward the channels that are most likely to affect the poorest. They can therefore help design climate change adaptation policies that are targeted toward the poor and contribute to poverty reduction.

It is important to note that these scenarios are somewhat extreme scenarios because they are optimistic for all countries or pessimistic for all countries. However they do not provide a range of what is considered possible or plausible because they are not taken in the extremes for each country: instead, they represent typical scenarios for two possible future, one optimistic and one pessimistic. It is possible to find in our scenario set some scenarios that are better than the prosperity scenario or worse than the poverty scenario. If we simply add the worst-case scenario in every country, then the maximum number of people in poverty due to climate change in 2030 reaches 263 million people.
Global results with all baselines

Here, we look at the full range of impacts in each country, looking at all baselines. Since combining all baselines would be impossible (the total number is 1,200^92), we sample climate change impacts on poverty in each country, based on the distribution of impacts illustrated in Figure 6. Practically, we create 10,000 global baselines by selecting randomly baselines in each of the country. With these 10,000 baselines, we create 10,000 climate change scenarios with low impacts and 10,000 climate change scenarios with high impacts.

The resulting histograms are displayed in Figure 16.

Figure 16 Global impact of climate change on poverty, resulting from a sampling of the country impacts (assuming baselines are independent from one country to another).

Note that the sampling assumes that baselines are independent from one country to the other and that all baselines have the same probability in each country. Therefore, the resulting global results should not be interpreted as a probability distribution of potential global impacts, since we are not able to attribute accurate probabilities to the baseline scenarios. Instead, this distribution should be seen as a range of possible impacts depending on baseline assumptions.

For instance, both the poverty and the prosperity scenarios chosen in the Shockwaves report are in the tail of the distribution (Figure 16). This does not mean that they are less probable than scenarios which are closer to the mean. The reason why they are in the tail is because they were chosen as optimistic or pessimistic for all countries simultaneously while in Figure 16 individual country impacts are treated as independent.
Finally, we repeat this exercise by running each climate change impact one by one, in all 1200 baseline scenarios in each country. The resulting histograms for sampled global distributions (obtained as described previously) are displayed in Figure 17.

![Histograms showing the impact of climate change on poverty](image)

*Figure 17 Global impact of climate change impacts (one by one) on poverty, resulting from a sampling of the country impacts (assuming baselines are independent from one country to another).*

Like for the two Shockwaves scenarios, the biggest impacts happen through health and through food prices. But here we see that in the high impact climate change scenario, the impacts through food prices are much more dependent on the baseline than other impacts – because they depend directly on people’s income. The poorer the people, the higher share of consumption they lose if food prices increase.

This result explains and qualifies our finding that rapid development and poverty reduction makes people more resilience of climate change impacts: the main channel through which people are made more resilient is the food price channel – richer people spend a smaller share of their income for food and are less vulnerable to shocks on food prices.

This result also shows the importance of health impacts: in 2030, health impacts due to climate change keep more than 20 million in extreme poverty in almost all of our scenarios. It shows the importance of learning more about these impacts and about the policies and measures able to reduce this impact. For instance, universal health coverage – an objective of the international community – could avoid that health care expenditure bring people back in poverty and would reduce the impact of climate change on poverty.

**References**


3. Appendix: model and baselines calibration

We build a micro-simulation model that projects national household surveys into the future. It uses the I2D2 household surveys database, formatted for the GIDD model.

The model first attributes one of the following mutually exclusive categories to each person in the survey: (1) unskilled services worker; (2) skilled service worker; (3) unskilled agriculture worker; (4) skilled agriculture worker; (5) unskilled manufacture worker; (6) skilled manufacture worker; (7) adult not in the labor force; (8) elderly (above 65 years-old); (9) child (under 15 years-old). A worker is defined as skilled if he has more than nine years of education.

These categories are of course adaptable depending on the information available in the survey. For instance men and women could be separated, as well as different categories of adults that are not in the labor force (housewives, unemployed, self-employed or informal workers).

It is however important to note that these categories are chosen because they will be used to drive income growth in the scenarios, and not necessarily because they explain current income well.

For each household, we calculate the number of people belonging to each of these categories \(c_{ati}\) and we estimate current households’ revenue using these categorical predictors (with weighted linear least squares). Note that we exclude children \(\alpha_9 = 0\) as they should not contribute to the family income, and that there is no intercept in the formula:

\[
Y_{calc} = \sum_{i=1}^{8} \alpha_i c_{ati}
\]

For most countries the \(\alpha_i\) are all positive (see Table 1) and – since there is no intercept – they can be interpreted as the average per capita income brought to the household by each category of people, except children \(\alpha_9 = 0\). Importantly, these coefficients will not be used to predict income using the regression. Instead, they will be used as a basis for applying different productivity growth rates to different categories of workers. In other words, in our scenarios the households will remain the same (only their weights in the economy will change) but the \(\alpha_i\) and the error terms will grow.

In some countries \(\alpha_7 < 0\) or \(\alpha_8 < 0\) in the regression. In that case we force \(\alpha_7 = 0\) or \(\alpha_8 = 0\) and we re-estimate the other \(\alpha_i\).

Table A1. Estimated per capita income per category of people in Vietnam in the 2012 LSMS household survey.

<table>
<thead>
<tr>
<th>Category</th>
<th>Vietnam yearly per capita income (USD)</th>
</tr>
</thead>
<tbody>
<tr>
<td>(1) Unskilled workers in services</td>
<td>2547</td>
</tr>
<tr>
<td>(2) Skilled workers in services</td>
<td>5590</td>
</tr>
<tr>
<td>(3) Unskilled workers in agriculture</td>
<td>1391</td>
</tr>
<tr>
<td>(4) Skilled workers in agriculture</td>
<td>2294</td>
</tr>
<tr>
<td>(5) Unskilled workers in manufacture</td>
<td>1930</td>
</tr>
<tr>
<td>(6) Skilled workers in manufacture</td>
<td>4201</td>
</tr>
</tbody>
</table>
The initial per-capita revenue in each household $h$ can therefore be expressed as:

$$Y_{pc}(h, t_0) = \frac{\sum_{i=1}^{8} \alpha_i(t_0) \cdot cat_i(h)}{\sum_{i=1}^{9} cat_i(h)} + e(h, t_0)$$

Where $e(h)$ is an error term that depends on the household.

To build the scenarios, we proceed in three steps:

- Reweighting of the households, to model structural changes in the population (age, education) and in the economy (share of adults in the labor force, share of working population in agriculture, manufacture and services).
- Productivity growth for each category of worker, applied to the $\alpha_i$. The error term also grows like the calculated income for each household.
- Income redistribution (optional)

a. Reweighting

We re-weights households to change the demographic structure of the country (number of people by age slice and skill) as well as its economic structure (number of adults in the labor force, number of workers in each economic sector).

As there is an infinite number of solutions for the re-weighting process, we minimize the distance between current and future weights using a quadratic solver.

We exclude children from the re-weighting (we keep the number of children constant) and instead we rescale the number of children afterwards so that the total number of children in the economy matches the new demographic structure. This allows, especially in Africa, creating new categories of households with the same adults but fewer children.

The composition of households therefore do not change – except for the number of children – but their weights in the population do. For instance, in order to increase overall education levels, the algorithm gives more weights to households with educated adults and less to households with uneducated adults.

This re-weighting process already modifies income distribution (Fig. A1). It is then completed by productivity growth for each category of workers.
Figure A1: Modifications of income distribution in 2030 with the re-weighting process. Example with a random scenario in Vietnam.

b. Productivity growth

We apply productivity growth rates to the $\alpha_i$ of unskilled workers. Future workers’ incomes (before redistribution) are thus equal to $\alpha_i(t_n) = \alpha_i(t_0) \times (1 + g_{ri})^n$.

For skilled workers, we apply a skill premium to the income of the unskilled workers: $\alpha_i,skilled(t_n) = \alpha_i,unskilled(t_n) \times skill\_premium_i$

The $g_{ri}$ and $skill\_premium_i$ are input parameters of the scenario and they are treated – a priori – as independent.

Each household’s new “calculated income” is therefore equal to $Y_{calc}(t_n) = \sum_{i=1}^n \alpha_i(t_n) \times cat_i$. We call “pure productivity growth” the growth rate between $Y_{calc}(t_o)$ and $Y_{calc}(t_n)$, and we apply this growth rate to the error term.

$$e(h, t_n) = e(h, t_o) \times \frac{Y_{calc}(t_n)}{Y_{calc}(t_o)}$$

We also model a pension system by collecting a tax on working people’s income (and on error terms, but only for families with at least one member in a working category) and redistributing it to the elderlies. This represents the return on the elderlies’ savings and thus depends on the overall growth rate in the economy.

Figure A2 shows how productivity growth changes the income distribution after the re-weighting.

Accordingly, the income of households composed only of unemployed adults do not grow through productivity growth. We therefore model redistribution.

c. Redistribution

To model redistribution, we apply to flat tax to all consumptions and redistribute it as a basic income to each adult and elderly people in the population. Figure A2 illustrates the effect of redistribution on the income distribution.
Figure A2: Modifications of the income distribution in 2030 when adding productivity growth and redistribution. Example with a random scenario in Vietnam.

Accordingly, all the assumptions on demographic change, structural change, productivity growth for each category of worker, pensions and redistribution are highly uncertain. We therefore explore a large number of scenarios without selecting a priori a best guess for each of these parameters.

For demography, we use two contrasted SSPs (Shared Socio-Economic Pathways) that were built by the IIASA. For the other parameters, scenarios are constructed with plausible – yet large – ranges for each parameter, and a Latin hypercube sampling algorithm that selects a few hundreds combinations of all parameters inside those ranges.

For structural change, the plausible ranges are based on the initial economic structure of each country and historical data: we use all data available on the share of agriculture and industry in employment and on the employment rate at a given date compared to 20 years earlier (Figure A3). We select, for each initial share, the maximum and minimum share reached 20 years later and use this to define a range of uncertainty. As a result, the uncertainty on structural change will depend on the initial shares for each country. Table A2 gives an example of structure ranges used for Vietnam.

For productivity growth, ranges are chosen so that, given population growth and the changes in population structure, total GDP growth is a priori coherent with the SSP scenarios that were constructed by the OECD: we use the GDP growth rate in OECD scenarios (SSP4 and SSP5, depending on population assumptions) to find a “middle” per capita growth rate and then add + or – 5% for the range.

For skill premium, we choose a range between 1 and 5, which represents the dispersion in skill premiums for all countries in the initial year.

For pensions and for the tax used for redistribution, we take a range of [0, 20%].
Figure A3: range of uncertainty around future shares of agriculture and industry among workers and around future employment rates. Blue and green dots correspond to historical data: for each initial share (any country, any date before 1993) on the x-axis, they represent the minimum (blue) and maximum (green) share 20 year later on the y-axis (historical data has been filtered to remove outliers). Solid lines represent the range of uncertainty chosen in the model, and based on this historical data. The red line is the y=x function.

Table A2: Initial shares and scenario ranges for economic structure, and growth rates, in Vietnam.

<table>
<thead>
<tr>
<th>Vietnam</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Share of adults in the labor force (%)</strong></td>
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<tr>
<td>Initially: 81</td>
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<tr>
<td>Min 2030: 68</td>
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<tr>
<td>Max 2030: 91</td>
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<tr>
<td><strong>Share of workers in the agriculture sector (%)</strong></td>
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<tr>
<td>Initially: 45</td>
</tr>
<tr>
<td>Min 2030: 15</td>
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<tr>
<td>Max 2030: 48</td>
</tr>
<tr>
<td><strong>Share of workers in the manufacture sector (%)</strong></td>
</tr>
<tr>
<td>Initially: 24</td>
</tr>
<tr>
<td>Min 2030: 12</td>
</tr>
<tr>
<td>Max 2030: 34</td>
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</tbody>
</table>
To create scenarios, we use an optimal latin hypercube sampling algorithm to generate 600 combinations of structural change, productivity growth and redistribution and combine them with the 2 population scenarios, so that we can run 1200 scenarios per country.