TECHNICAL NOTE

Linking macro- and micro-economic models for understanding distributional impacts of low-carbon development in India

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Technical notes document the research or analytical methodology underpinning a publication, interactive application, or tool.

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ABSTRACT

India's long-term decarbonisation efforts require significant structural changes in the economy as we step up renewable energy and move to a low-carbon development pathway. The current literature discusses the macroeconomic and sectoral but not the distributional impacts of climate action. Since large disparities exist among India's socioeconomic groups, the low-carbon transition will affect income and social groups differently. To address this gap, this technical note describes a methodology for quantifying household level impacts across different income groups in India.

We have used the Global Income Distribution Dynamics (GIDD) framework in connection with the macroeconomic Green Economy Model for India (GEM-India). In its previous applications, the GIDD has been used in conjunction with computable general equilibrium (CGE) models. Here, we have replaced the use of CGE models with a system dynamics model, the GEM-India. We therefore explain how the GEM and GIDD are linked, using variables like GDP growth, wages, employment and so on, and how the household survey data form the basis for the microsimulation to help produce distributional impact outputs, which include private consumption by income groups, Gini coefficient, sectoral composition of skilled and unskilled labour and the like. The climate policies are implemented through the macro model, the GEM, and the microsimulation redistributes the effects of the changes at the macroeconomic level amongst income groups and gender in terms of wages, poverty, employment and so forth. This technical note lays out the methodology to link climate policy implementation to household-level income and employment impacts, but not its results.

INTRODUCTION

At COP26 in Glasgow, India committed to achieving net zero by 2070. In setting this long-term goal, India also announced new climate action targets for 2030:

- 50 percent power generation from non-fossil fuels supported by technology transfer and low-cost international climate finance
- Carbon intensity reduction of 45 percent over 2005 levels
- An additional carbon sink of 2.5 to 3 billion tonnes of carbon dioxide (Mitra et al. 2021; Government of India 2022)

This transition will require structural changes in the country's economy and strong climate policies. For example, to achieve the net zero 2070 target, India would need to scale up the share of non-fossil sources in electricity generation to over 75 percent (compared to around 25 percent at present) by 2050. This would require the addition of around 2,000 gigawatts of fossil-free capacity (Swamy et al. 2021). At the same time, clean electricity or green hydrogen must increasingly replace fossil fuel use in the industry and transport sectors. These transitions will in turn have an impact on gross domestic product (GDP), employment and other such indicators, which are extremely important for India as a developing nation. However, the transitions also present an opportunity to plan climate policies in a manner that lays the foundation for a more robust economy.

Only a few modelling studies have looked at the effects of climate action on economic outcomes—like GDP and employment—in India. These models find that climate action creates more GDP growth as well as employment, that is, both are positively correlated (Swamy et al. 2021). Other models, like the E3-India model, also dive into the regional impacts of climate action and reducing emissions intensity at the national and state level, where changes are driven by market and policy interventions. However, this model only considers scenarios up to 2035, incorporating how green initiatives and interventions affect different income groups but not in the long term (up to 2070) (Joshi and Mukhopadhyay 2022). While existing analyses convey the potential macroeconomic and sectoral impacts of climate action in India, no analysis currently available quantitatively estimates distributional impacts in the long term, that is, how macroeconomic effects will be distributed across social and income groups over a period of almost 50 years. The large disparities and inequalities which exist among socioeconomic groups in India (Anand and Thampi 2021) also make it important to understand how decarbonisation can affect various sections of society, thereby informing the formulation of more equitable and inclusive climate policies. A set of actions which can induce positive impacts for all would also receive more political support, making it easier to implement these actions as well.

To study the interrelationship between climate action, the economy and resource use in more detail, World Resources Institute India and KnowlEdge SRL (Switzerland) are developing the Green Economy Model for India (GEM-India). The GEM-India is a system dynamics model that represents the Indian economy at an aggregate level and allows users to create 'what-if' scenarios for different combinations of climate policies through 2070[1]. The model generates results for emissions, GDP, employment, income, resource use like land and water, and so on. However, being a simplified and high-level macroeconomic model, the GEM does not estimate these impacts of the transition on different income and social groups.

We have therefore linked the GEM to the Global Income Distribution Dynamics (GIDD) framework to offer a microeconomic perspective to macroeconomic changes caused during and by this transition. The GIDD framework was developed by the World Bank (Bussolo et al. 2008a) to estimate the impact of global trade policies and national-level policy changes on social groups within countries. It is based on previous macro-micro simulations (Bourguignon and Bussolo 2013) and follows a top-down approach that models most of the behaviour by solving a macroeconomic model. This generates a series of linking aggregate variables (LAVs)—representing aggregate macroeconomic outcomes resulting from a set of policy interventions—that become the input for a microsimulation (Bourguignon et al. 2008). The microsimulation uses these LAVs in conjunction with household survey data to estimate the distributional impacts of policy interventions. The GIDD can be connected to different kinds of macroeconomic models, most commonly a computational general equilibrium model (Ahmed et al. 2020).

While other models also look at distributional impacts, the GIDD is the first global model of microsimulation to be tested across and within countries. The GIDD microsimulation framework was first presented by the World Bank in 2008 as a part of the book *The Impact of Macroeconomic Policies on Poverty and Income Distribution: Macro-Micro Evaluation Techniques and Tools* (Bourguignon et al. 2008). The intention of the book was to explain the poverty and income distribution impacts of trade reform, financial crises and reforms, as well as economic growth. The GIDD framework has mostly been used in conjunction with computable general equilibrium (CGE) models like ENVISAGE or LINKAGE (also developed by the World Bank) that model the global economy. At the global level, the GIDD has been used to study the impact of economic growth and income distribution (Bussolo et al. 2008b). In India, in contrast, the GIDD has been used to understand modelling gaps in understanding the relationship between food demand and income distribution (Cirera and Masset 2010). In the global context, the GIDD has been used to understand the distributional impacts of carbon pricing worldwide and within countries by looking at global poverty and the impacts of mitigation policies (Chepeliev et al. 2021; De Hoyos and Medvedev 2009; González 2016). Each of these models attempts to answer specific questions about the micro-level impacts on household income and employment and their linkages with policy or economic changes. In this instance, we modify the GIDD to link with a system dynamics model (SDM), the GEM-India. This is a departure from previous iterations of the GIDD that were linked to CGE models. SDMs have greater flexibility and can capture interactions and interlinkages between sectors, while CGE models the economy and value chains in a lot more detail (Bassi 2016). However, in linking with the GIDD, the main requirement is that the model endogenously calculated the LAVs that the GEM is equipped for.

The GIDD facilitates insights about poverty, inequality, sectoral employment and wages (male and female workers), projecting how these indicators change over time. These insights can bring out the welfare-related consequences of climate policies. The subsequent sections describe the approach, methodology and limitations of the linkage of GEM-India with the GIDD framework and the steps of the microsimulation and how it might be used to uncover these policy insights.

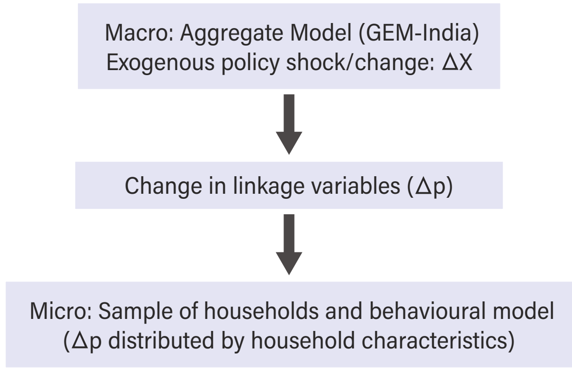
OBJECTIVE AND APPROACH

This section describes the objectives and approach of our macro-micro linkage and gives an overview of the GEM-India and the GIDD framework, along with their roles and interaction in this context[2].

Our objective in performing a macro-micro linkage is to study the potential impact of climate policies on welfare at the household-level[3]. The macro model estimates the impacts of enacted policies on outputs like economic growth and employment at an aggregate level, which serve as linking variables. The micro model helps us determine what these growth and employment trends may mean in terms of households being lifted from poverty, or for which income classes or population subgroups these changes may be most significant (Figure 1). Additionally, connecting macro and micro simulations can help in evaluating redistributive policies that affect different income groups (Bourguignon and Bussolo 2013; Zachmann et al. 2018).

The GEM-India serves as the macro model in this macro-micro simulation. It models the three major sectors of the economy—agriculture, industry and services—projecting

Figure 1 | **Top-down macro-micro model linkage**

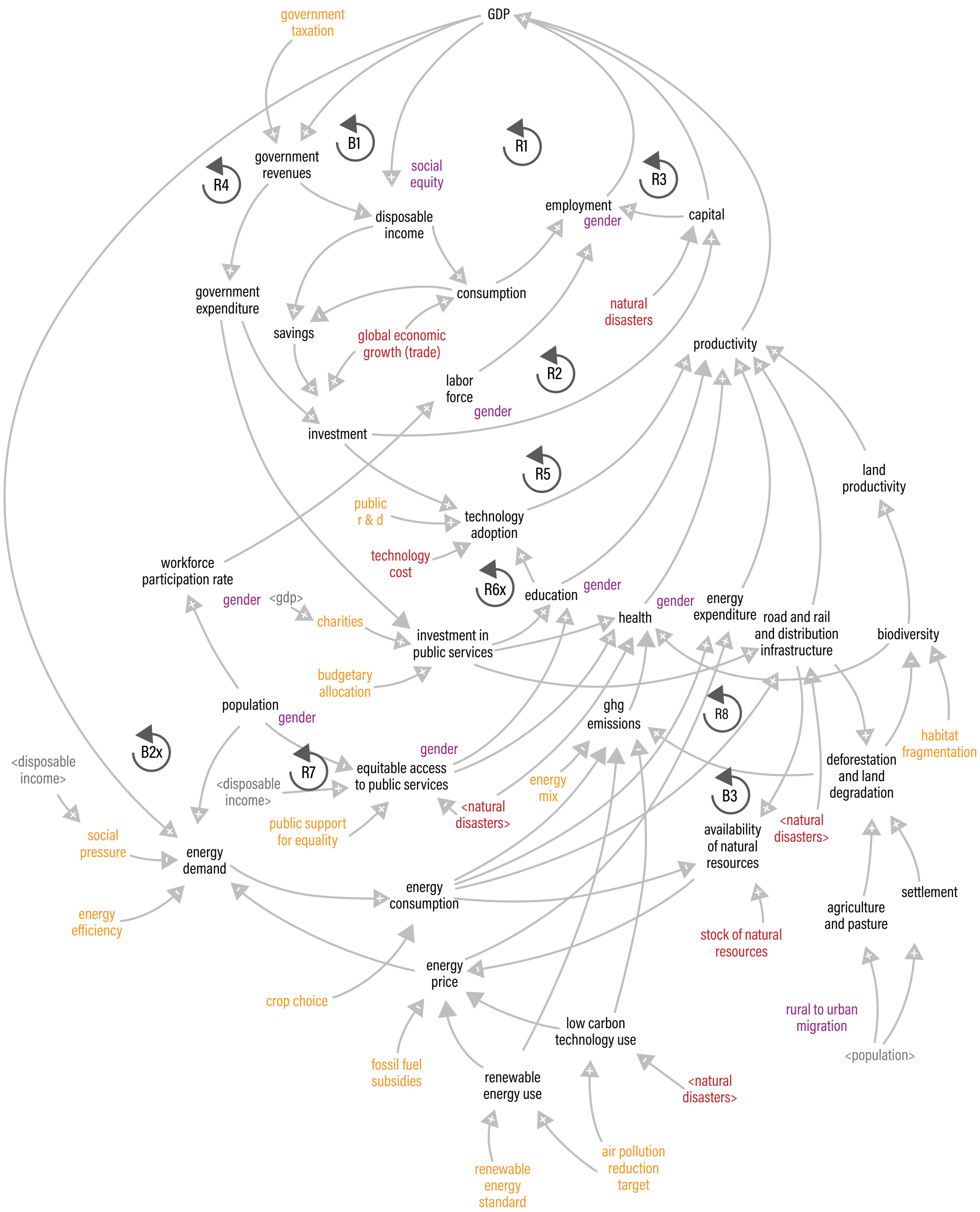


Source: Bourguignon and Bussolo 2013.

production and employment in these sectors as well as linking them to energy use, infrastructure and technology. Each of these sectors is linked to the others through balancing and reinforcing loops. The model allows users to enact climate policies and considers their potential intersectoral interactions. A combination of these climate policy interventions helps create what-if scenarios, and the values of the relevant linking variables are based on these scenarios. The structure, data sources and assumptions of the model are explained in a technical note for the GEM-India model (Golechha et al. 2022). Figure 2 is a high-level systems map of the Green Economy Model that has been expanded and customised for India.

The systems map represented in Figure 2 is a high-level causal loop diagram which incorporates the representation of the five capitals in the GEM. Human capital is represented by the labour market and employment, which are connected to social capital through education- and health-related variables. These two are, in turn, linked with economic and financial capital through economic variables of spending, consumption and investments. These, in turn, are dependent on manufactured or physical capital and infrastructure. Both economic and physical capital also represent the production in the economy and are dependent on natural capital or natural resources. A feedback loop from economic to social and human capital also exists where spending on education and health has an overall effect of increasing labour productivity and thereby GDP. A system dynamics model is characterised by such feedback loops. The ones that represent the core engines of the system are known as reinforcing loops (marked as R in Figure 2), and the ones that oppose the direction of these loops are called balancing loops (marked as B in Figure 2) (Golechha et al. 2022). The population, education and labour in the model are disaggregated by age and gender, and the GIDD incorporates the household-level data on employment and consumption, which help disaggregate the population by income groups as well.

Figure 2 | **High-level systems map for the GEM-India**



Source: Golechha et al. 2022.

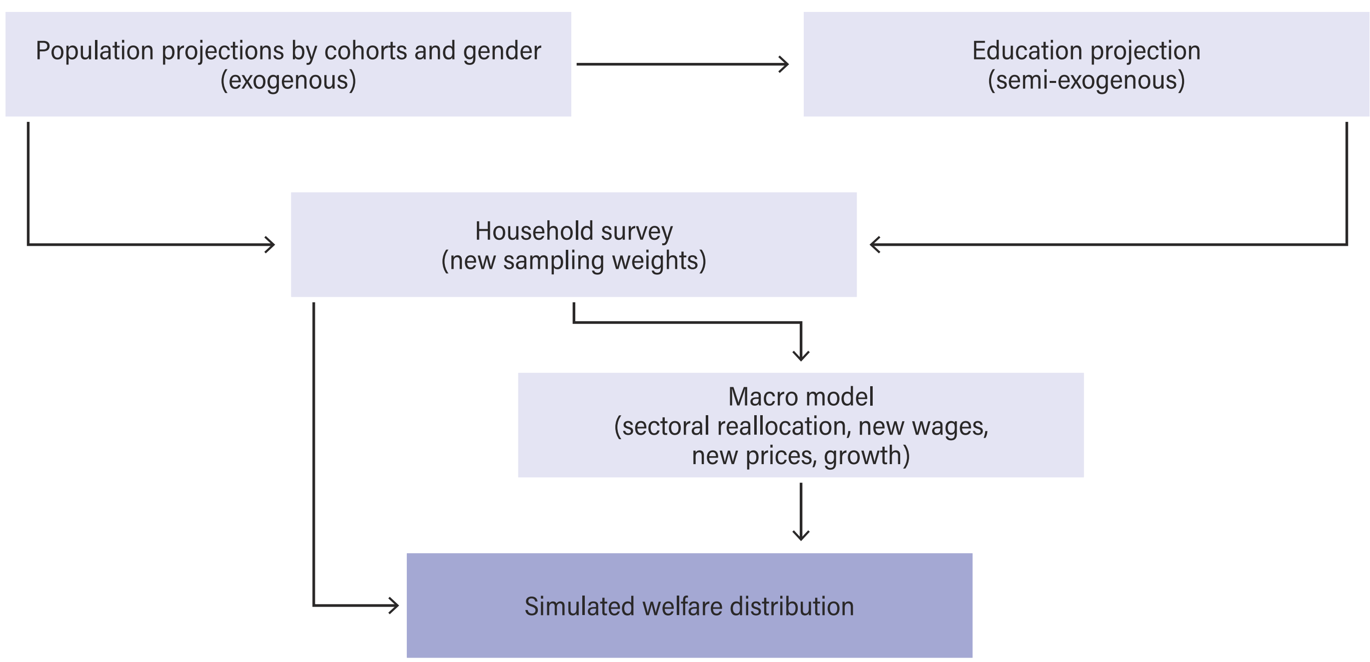
Figure 3 elaborates how the macro model links with the microsimulation, the variables it supplies and the steps involved in simulating the distributional impacts. The GIDD accounts for the changes in the size of population groups, formed based on age and education characteristics, over time. The GIDD uses an exogenous population projection, partitioned into groups—by age, education and gender—and simulates educational attainment in the population through a pipeline effect, as younger and more educated cohorts replace older cohorts over time. The resulting projection is then used to 'reweight' the historical household survey data, that is, it is used to resize each group in the historical household survey for each year of the simulation. The household data from the NSS 68th round survey include data on

- the household characteristics, including household size, assets owned, social group and so on;
- demographics, including educational attainment, age, sex and so on;
- primary and secondary economic activities (for every worker);
- nature of employment (for every worker);
- consumption expenditure (for households); and
- other expenditure (for households). (NSSO 2011a, 2011b)

This, in turn, impacts the supply of skilled and unskilled labour (determined by education) in each year, which is then input into the macro model (GEM) as represented in Figure 3[4]. This, however, is not a feedback but merely an intermediate input for the macro model. Considering the former projection, the GEM generates a set of linking aggregate variables (LAVs), including employment by sector, new relative wages and growth in private consumption, which allow the GIDD to simulate a new household-level welfare distribution for the climate scenario enacted in GEM. The calculation of these variables is given below in the subsection 'Linking aggregate variables: The macro piece of the puzzle'.

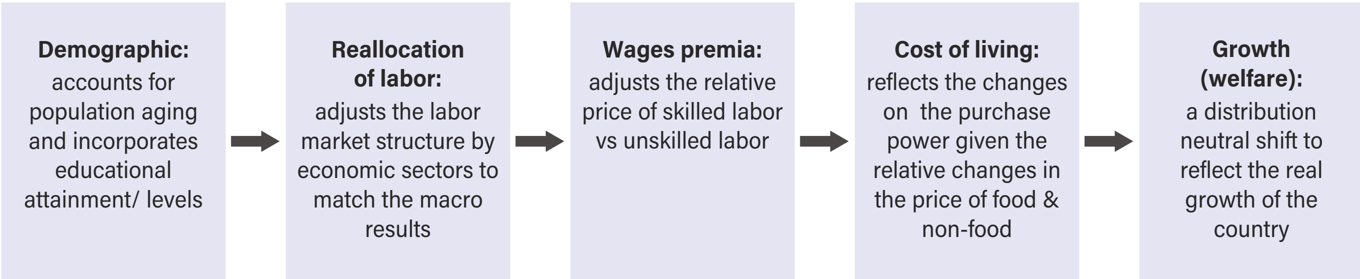
The GIDD microsimulation simulates the new welfare distribution using five modules. The first four account for growth-neutral distributional effects on household income, while the final module accounts for the effects of economic growth. The first module addresses changes in the demographic and education structure, the second allows for sectoral reallocation of labour, the third deals with relative wages for different types of workers, the fourth considers changes in relative consumption prices of food versus non-food commodities and the fifth accounts for the effect of economic growth. In this case, the consumer price module (Module 4) was not implemented due to lack of data. Each module is explained in detail in the next section. Figure 4 gives an overview of the structure and modules of the GIDD as it has been implemented in conjunction with the GEM.

Figure 3 | **GIDD methodological framework**



Source: Adapted from Bourguignon and Bussolo (2013).

Figure 4 | **Structure and modules of the GIDD**



Source: Authors.

DATA NEEDS

The GEM supplies economic growth trends, prices and wages to the microsimulation. In doing so, the GEM incorporates the effects of different climate policies, feedback loops and intersectoral interactions as well. This means that the linking aggregate variables endogenously calculated in the GEM are dynamic and dependent on the climate policy packages implemented in the GEM. The microsimulation does not incorporate policy inputs. These are only included in the macro model. The impacts of the changes projected by the GEM in these variables are then distributed amongst the households and income groups based on the household data that the microsimulations, in turn, are based on. Table 1 summarises these variables.

In terms of the data used, the microanalysis relies on the National Sample Survey (NSS) 2011–12 (IHSN 2011–12), the most recent household survey that collected data about household consumption. The survey is one of the earliest household surveys and until 2012 was the instrument used to measure poverty. The NSS 2017–18 microdata were not released by the Indian government due to concerns about data quality (Edochie et al. 2022). The sample includes 457,000 observations organised in 102,000 households and is representative at a regional level. Since the available data do not include information about the earnings of employers and the self-employed, consumption per worker is used as a proxy for household income (Srivastava and Mohanty 2010).

LIMITATIONS

There are three types of limitations: those pertaining to the macro model (the GEM), those pertaining to the data sources and those pertaining to the microsimulation.

- **Wages are not market-clearing:** In the context of developing countries, we consider wage as a market-clearing mechanism for the labour market to be unrealistic. Except in localised circumstances, there is an excess of labour supply and firms can hire the labour they need. This signifies that the wage is not a dynamic variable that determines the market-clearing labour supply and demand. The model also does not necessitate that the labour market be in equilibrium at any stage and, therefore, can give rise to cases where there are labour shortages and an excess as well. The macro model is also a disequilibrium model, and the micro model mimics its results. Therefore, if there is a certain level of employment in a particular sector, the micro model will not change the same in case of a shortage of labour in one over excess in another but will let it remain so.
- **Macro-level policies exclude certain interventions and their impacts:** The GEM helps create what-if scenarios from the extremely long time horizon of 2000–2070, and the farther away we get in the time horizon, the greater the uncertainty. The microsimulation also works with these uncertain results, and therefore both approaches require methods of addressing such uncertainties. The main sources of uncertainty in system dynamics modelling come from the inherent randomness of nature, human behaviour, and social and technological randomness. The latter being the most relevant in this case, most system dynamics models consider these factors as resulting from the system and therefore deal with them by using what-if scenarios. However, even while models like the GEM endogenously address these factors, the possibility of structural change remains. Other aspects of uncertainty

Table 1 | **List of linking aggregate variables**

VARIABLES	GENERATED BY	INPUT FOR
Population projections by five-year-cohort and gender (medium variant)	UN World Population Prospects (2019 revision)	GEM and GIDD
Population by skill level (skilled vs. unskilled) and age cohort (five-year groups)	GIDD demographic module	GEM
Number of workers by skill level and sector for each scenario	GEM	GIDD labour reallocation module
Earnings by skill level and sector for each scenario	GEM	GIDD wage premia module
Consumer prices for food and non-food for each scenario	Not yet provided	GIDD consumer prices module
Private consumption (real) for each scenario	GEM	GIDD growth module

Note: Each variable is required yearly for the full period under analysis (e.g., 2011–50). GEM = Green Economy Model; GIDD = Global Income Distribution Dynamics.
Source: Authors' own.

come from unreliability and structural uncertainty. The unreliability comes from data sources. In this case, the latest household data end in 2011–12, which might reduce their applicability for scenarios till 2070. The structural uncertainty, however, comes from factors falling beyond the boundaries of the model and data used. In this case, in the absence of income data, consumption has been used as a proxy or the GEM does not consider the use of certain technologies like storage in the energy sector, and thus the costs and impacts of these interventions are unknown (Pruyt 2007). Some uncertainties may also arise from behavioural as well as regional and spatial dynamics, but they are beyond the scope of the two models. Even though we do model consumption as well as employment, which might be affected by these factors, these dynamics are not a part of the GEM-GIDD linkage. We must look to connections with spatial models to bring about the regional dynamics that is possible to incorporate. Behavioural dynamics are much more difficult to include, so we shall refrain from expanding the model in that direction.

- **There is no feedback from micro to the macro model, only one-way linkage:** In this approach there are no feedbacks from the microanalysis to the macro results, that is, if there is a redistribution, for instance, affected in the microanalysis, such results will not be reflected in the macro results again. This approach therefore does not allow the modelling of households' responses to income and price changes (Bourguignon and Bussolo 2013). This also means that the changes affected in the microsimulation do not reflect in the macro model. In this way, we may be underestimating the impact that distributional changes, sectoral and employment composition, and the like have on the larger economy.
- **Definitions of 'skilled' and 'unskilled' do not yet consider skilling interventions or vocational trainings:** The GIDD assumes a constant rate of education attainment across age cohorts over time—it simulates educational attainment in the population through a pure 'pipeline' effect, as younger and more educated cohorts replace older cohorts over time (further details under 'Module 1' in the next section). This implies that the impact of economic growth on educational attainment is not considered, which in turn implies that the total number of skilled workers in the population over time could be underestimated[5]. Another limitation in this context is that the only determinant of skill is 'years of schooling/education'. This implies that the analysis does not capture the effect of any changes in specific skill requirements that could occur because of climate policies on employment, and that the current analysis, thereby, excludes the possibility of evaluating the impact of any skilling policies in this context.
- **Cost-of-living impacts have not been considered yet:** The consumer prices module has not been implemented in this iteration of the GIDD microsimulation due to lack of relevant data. The absence of the results of this module means that the calculated change in household consumption in the microsimulation will not capture the effect of differing consumption patterns among different households—such as changes in share of consumption expenditure on food for lower-income households.
- **Consumption is used as a proxy for income, and some data do not pertain to informality in the economy:** As mentioned in the previous section, the microsimulation is based on the household survey data collected by the NSS. Since the data do not capture income directly, we have considered consumption as a proxy for income. The

NSS also does not capture informality in employment and therefore offers only a partial picture of the employment data.

- **Some limitations are related to data:** Since the data are 10 years old, they may not accurately reflect the household behaviour given the structural changes in the economy—especially in terms of household consumption, income and employment—between 2012 and 2022 (IHSN 2011–12). Moreover, since consumption is used as a proxy for labour income, the results can only show the direct impact of climate policies on their consumption expenditure and not on household income.

DISTRIBUTIONAL ANALYSIS: MACRO-MICRO SIMULATION FRAMEWORK

This section will expand upon the linkages between the macro model (GEM) and the microsimulation, including the linking aggregate variables (LAVs) and the wage calculations.

Linking aggregate variables: The macro piece of the puzzle

To the existing structure of the GEM as described by Golechha et al. (2022), one new module was added for the purpose of linking it with GIDD. This 'micro-macro' module uses the employment and income outcomes calculated by the GEM for a climate scenario and disaggregates them further based on household survey data from the GIDD to produce the LAVs.

Employment outcomes calculated in the GEM are disaggregated into agriculture, industry and services employment. These are further disaggregated in this module into skilled and unskilled jobs for agriculture, industry, unsophisticated services, sophisticated services and public administration. The employment data capture gender in its composition and match the same with the employment data from the macro model, which incorporates male and female participation in the labour market through the labour force participation rate[6]. Table 2 lists the set of services that fall under sophisticated and unsophisticated services.

Table 2 | **Subsectors comprised in sophisticated and unsophisticated services**

CATEGORY	SERVICES
Sophisticated services	Information and communication
	Professional services
	Education and health
Unsophisticated services	Wholesale and retail trade
	Transportation and storage
	Accommodation, food services and entertainment
	Support services

Source: Authors' own.

Calculation of skilled and unskilled workers by sector

Total skilled and unskilled labour supply in the population for each year (calculated by the GIDD by reweighting household survey data based on educational attainment over time) is input into each module from the GIDD. This is allocated across sectors based on sectoral demand. To calculate skilled and unskilled labour demand by sector, the GEM assumes that the demand for skilled and unskilled labour changes over time and increases towards skilled labour, especially in the industrial and services sectors. The raw data on employment are used to estimate the share of jobs that are skilled within a specific sector. For instance, we calculate the percentage of skilled labour in the industrial sector based on data on total employment, skilled and unskilled jobs.

To capture this change, an index of 'per capita disposable income' is used together with an elasticity, indicating that the more the country develops (using disposable income as a proxy), the greater the demand for skilled jobs[7]. Equation 1 highlights how this relationship determining skilled labour in the industry sector is structured. The share of skilled labour in the services sector is calculated in a similar manner. Employment in a particular sector is determined dynamically and endogenously by the GEM, and employment multiplied by the share of skilled labour helps determine the total amount of skilled labour in a particular sector.

Equation 1. Calculation of sectoral wage indices using public administration sector as an example

share of skilled labour industry =

MIN (1, 0.142471 **relative pc real disposable income^ elasticity of skilled labour industry to pc disposable income*) *skilled labour industry* = *employment industry*share of skilled labour industry*

In the unsophisticated services and public administration sectors, the share of skilled jobs is specified as a fraction and not calculated based on the relationship with per capita disposable income. The value being multiplied by the relative per capita real disposable income, '0.142471', has been calculated using employment data from the NSS 67th round survey, giving the labour structure in the economy by sector and skill. Table 3 gives this labour structure.

Table 3 is summarises the NSS micro-level data, divides the population into skilled and unskilled workers and indicates the distribution of these workers across the five economic sectors. This is not an output of either of the models but only a snapshot of the NSS data as used by the GEM-GIDD linkage.

As indicated in Table 4, the total number of skilled and unskilled workers is estimated by multiplying employment by sector (as estimated by the GEM for agriculture, industry and services) by the percentage of skilled and unskilled labour within each sector. The GIDD gives the share of skilled and unskilled labour by sector and inputs it in the GEM as shown in Table 1. The disaggregation of services into sophisticated services, unsophisticated services and public administration is based on data from the household survey. In other words, it is assumed in the GEM that the services sector includes all sophisticated services, unsophisticated services and public administration.

Table 3 | **Labour structure by sector and skill**

SECTOR	UNSKILLED	SKILLED	TOTAL	SHARE OF UNSKILLED LABOUR	SHARE OF SKILLED LABOUR	TOTAL	FINAL RATIOS
Agriculture, forestry	18,00,16,180	1,54,80,459	19,54,96,639	52%	20%	46.2%	0.08
Manufacturing, mining	88,03,818	1,46,26,781	10,26,64,969	25%	19%	24.2%	0.14
Unsophisticated services	6,62,01,215	2,01,06,813	8,63,08,028	19%	26%	20.4%	0.23
Sophisticated services	60,71,628	2,25,55,179	2,86,26,807	2%	29%	6.8%	0.79
Public administration	47,46,976	56,88,813	1,04,35,789	1%	7%	2.5%	0.55
Total	**34,50,74,187**	**7,84,58,045**	**42,35,32,232**				**0.19**

Source: Authors' own.

Table 4 | **Assumptions related to skilled and unskilled labour across the different sectors considered in the GEM**

VARIABLE NAME	DESCRIPTION	VALUE	SOURCE
Elasticity of skilled labour industry to per capita disposable income	Per capita disposable income is a proxy for the country's growth and development; positive elasticity assumes that the increase in income will reflect an increased demand for skilled labour in the industry and services sector. The elasticity value is set at 0.2 for both sectors, indicating that a unit change in per capita disposable income will cause the share of skilled labour for industry and services to change by a factor of 0.2 or 20%.	0.2	Value set for model calibration[a]
Elasticity of skilled labour services to per capita disposable income		0.2	Value set for model calibration
Elasticity of public administration employment to public consumption	Related to relative government consumption, this elasticity is used to determine the share of employment in public administration. The GEM assumes that the employment in public administration is a subset of employment in the services sector. Here, a unit change in relative government consumption results in a 5% proportional change in the share of employment in public administration.	0.05	Value set for model calibration
Share of skilled labour in public administration	This is a simple fraction that specifies which percentage of jobs in the public administration sector is assumed to represent skilled ones.	0.55	Based on NSS 67th round household-level data

Note: a. Model calibration is a process where the values of certain parameters are calculated based on historical data. Part of the data is used to develop the trajectory and then project the values forward to match the projections with the data. These values in the table have been calculated based on historical data series for multiple variables and datasets and determined to ensure that model outcomes were accurate; hence, they are not always based on literature or have a set source. Each of these elasticities is calculated based on calibration only. The reference to historical data is only in case of the number of skilled and unskilled workers in a particular sector and their disposable income and private consumption. To calibrate these two, the elasticity values are adjusted, and a final value is arrived at by trial and error.

Source: Authors' own.

Wage calculations

The number of employed skilled and unskilled people by sector is then used to estimate wages. The wage is calculated as a multiplication of the number of people employed and the unit wage per year, based on the sector and skills (Figure 5).

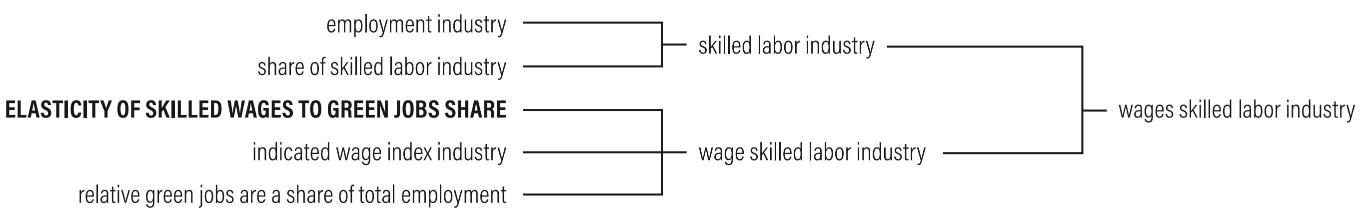
The individual wage level is estimated using the following steps:

1. Household data from the NSS 2011–12 survey are used to obtain the base wage level.
2. A salary escalation is applied in the GEM (macro model) to capture differences between wages as reported in the data (e.g., from 2011–12) and current values (e.g. based on assumptions regarding a salary escalation trend). If data are from 2020 or 2021, and inflation has been very low, this adjustment may not be required. The reasons for incorporating the salary escalation from 2011 are that it would be inconsistent to have the same wage level throughout the simulation time and that the historical data are only present till 2011.
3. An adjustment is applied to account for the balance of labour supply and demand across the economy. In other words, when labour is scarce, wages are expected to be higher. Conversely, when unemployment is high, wages are expected to be lower than in a baseline scenario. This adjustment considers wages to be proportional to labour productivity. Labour productivity is driven by the demand for labour—that is, this adjustment considers the need to increase labour productivity in the case of labour shortages, resulting in higher wages.
4. An adjustment is made to qualify whether labour shortages could emerge equally or differently in the agriculture, industry, services and government sectors. This adjustment compares the annual rate of change in employment in the different sectors, to determine if one or more of these is characterised by comparatively higher or slower growth. In essence, the factor mentioned in step 3 captures macroeconomic, national-level dynamics of the labour sector and affects wages across the board. This additional adjustment affects each of the sectors differently.

As described in Table 5, wages are based on historical data and affected by the strength of the labour market nationwide and in specific sectors. The four steps elaborated above are used to distribute the employment and income changes amongst households.

Figure 5 shows the shows the economy-wide labour market situation. The indicated wage index variable captures adjustments mentioned in points 2 and 3. The indicated

Figure 5 | **Causes tree for the estimation of wages for a single sector and skill type in the industry sector and replicated across different sectors**



Source: Authors.

Table 5 | **Assumptions related to salary escalation**

VARIABLE NAME	DESCRIPTION	VALUE	SOURCE
Change in real salary escalation from 2011	This variable captures how salaries have increased since 2011. The salary escalation variable has been represented as a stock in the GEM and captures the percentage of annual increase in salaries. This variable directly impacts this stock. The stock then goes on to affect the wage index for agriculture, industry, services and public administration.	3% or 0.03	Value set for model calibration

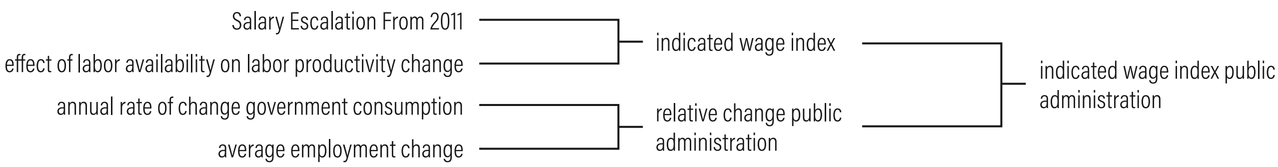
Source: Authors' own.

wage index is then used to determine wage indices for each sector that capture the adjustment mentioned in point 4 (see Figure 6).

As indicated above, in the steps used to estimate the sectoral wage level, the wage index considers two main elements: (1) upward or downward pressure at the national level to modify wages ('indicated wage index'), which takes into account historical data on wage per employee (see step 1), salary escalation over time (see step 2) and the effect of labour availability at the macro level (see step 3); and (2) the sector-specific dynamics (see step 4) that capture the specific rate of change in employment creation in one sector as opposed to other sectors.

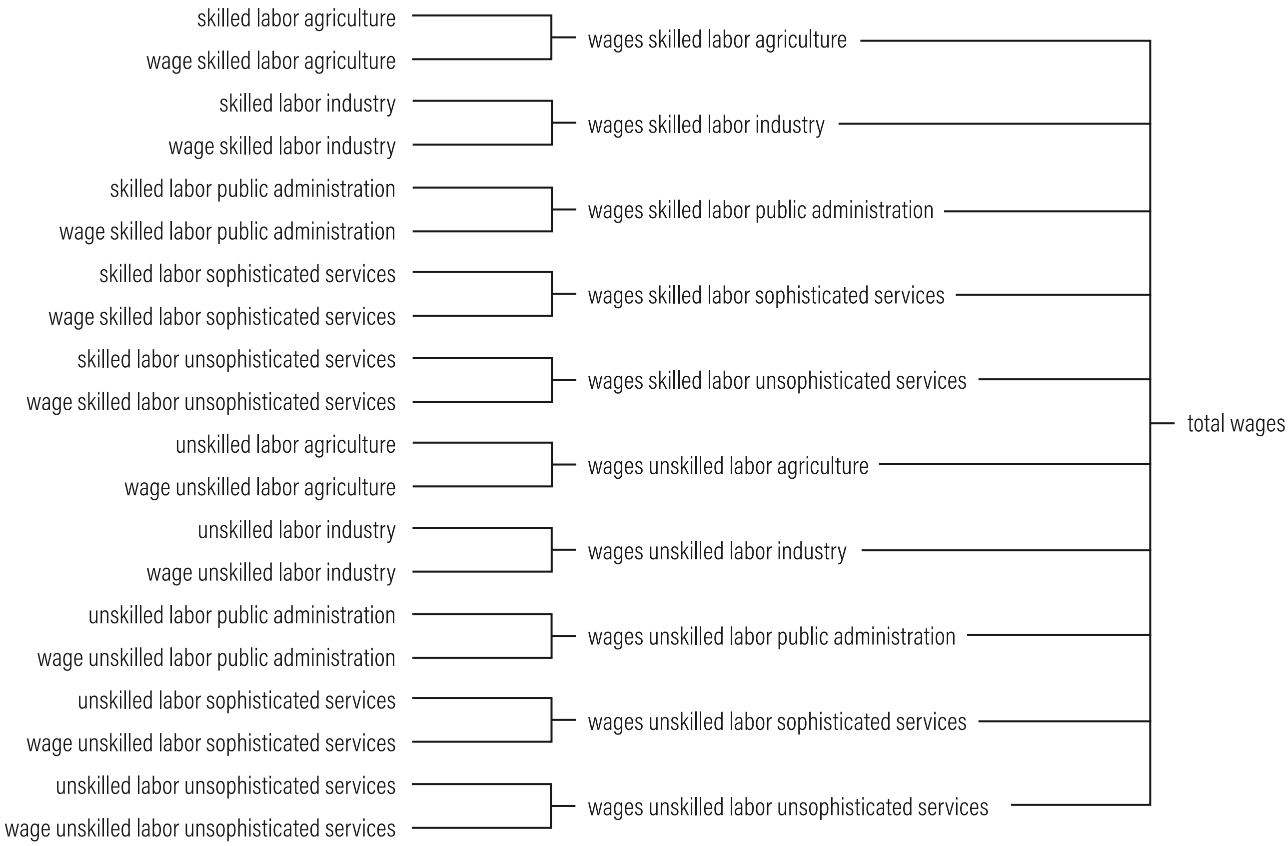
The total wages at the country level are then calculated as the sum of all annual wages (estimated as employment, multiplied by annual wage per person), for all people employed in the country across sectors and with different levels of skills (Figure 7).

Figure 6 | **Causes tree for the consideration of salary escalation and labour market dynamics in the estimation of wages for public administration jobs and replicated across the various sectors**



Source: Authors.

Figure 7 | **Causes tree for the estimation of total wages at the national level**



Source: Authors.

Calculation of private consumption

Another macroeconomic variable supplied to the microsimulation is private consumption, which is calculated in the GEM endogenously based on disposable income and propensity to consume (see Equation 2).

Equation 2. Calculation of private consumption

*private consumption = disposable income*propensity to consume*

The components resulting in this calculation include how nominal production determines disposable income and how relative per capita disposable income and initial propensity to consume determine final propensity to consume, as described in Figure 8. Equations 3 and 4 show how the model calculates disposable income and propensity to consume.

Equation 3. Calculation of private disposable income consistent with national accounts calculations

Disposable income = nominal production – 'government domestic revenue (excluding grants)' + interest on public debt

The disposable income in the economy is calculated by subtracting taxes and other payments by households to the government from nominal production (represented here as 'government domestic revenue (excluding grants)') and adding the interest on public debt that the government pays to households, as shown in Equation 3.

Equation 4. Calculation of propensity to consume

*Propensity to consume = initial propensity to consume (time)*relative per capita real disposable income^elasticity of propensity to consume to income*COVID impact on propensity to consume*

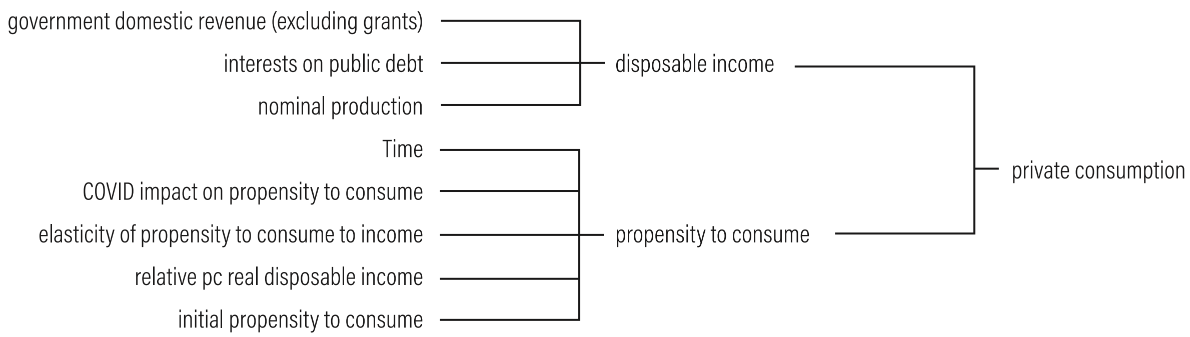
Propensity to consume is dependent on the relative per capita disposable income and the elasticity of propensity to consume to income as shown in Equation 4. Initial propensity to consume has been set to match historical data with model results, that is, to calibrate the model to historical data. It also takes into account the pandemic's impact on the propensity to consume. The values of the assumptions and component variables are given in Table 6.

These three pieces of data—skilled/unskilled workers employed by sector, wages by skill and sector, and total private consumption (real)—serve as the linking aggregate variables that are passed to the microsimulation.

Microsimulation structure

The microsimulation contains a total of five modules. Table 7 summarises these modules and their outputs, which we explain subsequently. The inputs from the macro model are mimicked by the microsimulation. The climate policies are implemented only in the GEM, and the microsimulation only reallocates the impacts amongst income groups and gender. We use different scenarios from the GEM and the respective values of the LAVs supplied for the microsimulation to compare the values from the different scenarios. This helps us understand the distributional impacts of different low-carbon pathways. Table 7 also lists inputs from the macro model and the reallocation and redistribution affected at each stage of the microsimulation.

Figure 8 | **Causes tree for the calculation of private consumption**



Source: Authors' own.

Table 6 | **Assumptions related to propensity to consume**

VARIABLE	DESCRIPTION	VALUE	SOURCE
Initial propensity to consume	The initial propensity to consume contains the values that indicate the share of disposable income which goes towards private consumption. These values have been set at 0.65 from 2000 to 2018 and 0.7 from 2018 onwards. This has been done so that the endogenous values of private consumption match the historical data from the national accounts data for India. After 2018, the model also includes the effect of changes in disposable income and assumes an elasticity of propensity to consume to income of −0.1.	2000–2018: 0.65 2018–70: 0.7	MoSPI national accounts data from 2000 to 2019
Elasticity of propensity to consume to income		−0.1	Values set for model calibration
COVID impact on propensity to consume	This variable captures the impacts of the COVID-19 pandemic on the propensity to consume. This factor is multiplied by the remaining variables in determining the propensity to consume. It considers the average impact of COVID on employment (as calculated by the model) and the elasticity of private consumption to COVID (set at 0.5) and uses that to calculate the impact on propensity to consume. This effect only occurs during 2019 and 2020.	2000–2018: 1 2019: 0.99 2020: 0.97 2021–70: 1	As determined by the model, that is, endogenously determined

Note: MoSPI = Ministry of Statistics and Programme Implementation.

Source: Authors' own.

Table 7 | **Inputs and outputs by GIDD module**

MODULE	INPUT	OUTPUT
Demographic	Initial sampling weights come from NSS 2011–12 data and UN WPP population projections	New set of sampling weights
Labour reallocation	New set of sampling weights Number of workers by skill level and sector for each scenario (GEM)	Simulated economic sector Simulated wage after labour reallocation Simulated household consumption after labour reallocation
Wage premia	New set of sampling weights Earnings by skill level and sector for each scenario (GEM) Simulated economic sector Simulated wage after labour reallocation (GIDD)	Simulated wage after wage premia Simulated household consumption after wage premia
Consumer prices	New set of sampling weights Original share of food in total household consumption (NSS 2011) Simulated wage after wage premia (GIDD) Consumer prices for food and non-food for each scenario (GIDD)	Simulated household consumption after consumer prices module (not implemented in this case due to lack of continuous data)
Growth	New set of sampling weights Private consumption (real) for each scenario Simulated household consumption after consumer prices module (GIDD)*	Simulated household consumption after the distribution neutral growth module

Notes: The consumer prices module has not been implemented for India. Therefore, the growth module takes the household consumption after wage premia as an input instead of the simulated household consumption after consumer prices. GEM = Green Economy Model; GIDD = Global Income Distribution Dynamics; NSS = National Sample Survey.

Source: Authors' own.

Module 1. Demographics and education structure

This module accounts for the change in population groups, formed based on age and education characteristics, over time. The GIDD uses an exogenous population projection corresponding to the medium variant of the UN '2019 Revision of World Population Prospects'. The population is partitioned by age group (five-year cohorts), gender and skill level (in the case of working-age population, which is defined as people ages 15–64[8]).

To model the changes in demographic structure over time, the demographic module applies the Wittenberg (2010) cross-entropy method to reweight the NSS 2011–12 (68th round)[9]. This assumes that the share of population by skill level per age cohort remains constant as the population ages. Even assuming a constant educational attainment over time implies an increase in the share of skilled working-age population through a pure 'pipeline' effect, as younger cohorts age and replace unskilled workers (Bourguignon and Bussolo 2013). This assumption is conservative, as increased economic growth could lead to higher rates of educational attainment over time for developing economies.

The cross-entropy reweighting estimates a new set of sampling weights for each year employing the *maxentropy* command (Wittenberg 2010), which uses a maximum-likelihood estimation routine to calibrate the sampling weights of the original survey so that the total population matches the UN Prospects and educational attainment. Afterwards, a constant weight within households is imposed to maintain household survey consistency. Consequently, the new set of weights produced by this method assigns a larger sampling weight than is assigned to older and more skilled individuals. This group is assumed to expand in future decades of the model timeframe. Despite only considering age, gender and education to create the constraints, this reweighting affects all other variables in the survey.

Educational attainment is used as the sole determinant of skill. Two different categories of skill levels were considered: 0–11 years of education and 12 years or more of education. Based on these categories, we have divided the workforce into skilled and unskilled labour. The latter (> 12 years of education) has been classified as skilled labour. This is a simplistic way of representing 'skills' and would not capture the actual skill gaps required because of the green transition. However, it does build a foundation from which to develop the model further. We intend to incorporate a more detailed representation of the education sector throughout the macro and micro models. The demographic module affects the distribution of welfare over time, as skilled workers are expected to earn more than unskilled workers.

Figure 9 shows the population pyramids by age cohort, gender and level of education constructed using this approach. As India's demography transitions, the pyramid base narrows and the shape of a column emerges. The increase in the share of skilled working-age cohorts is evident as the blue (for females) and yellow (for males) bars become larger relative to the size of the green bars (for females) and the red bars (for males) (UN Population Fund 2024).

Figure 10 complements the population pyramids and presents a marginal decreasing growth in the share of skilled working-age population for females and males. It also shows that the male population studied is considerably more skilled than its female counterpart.

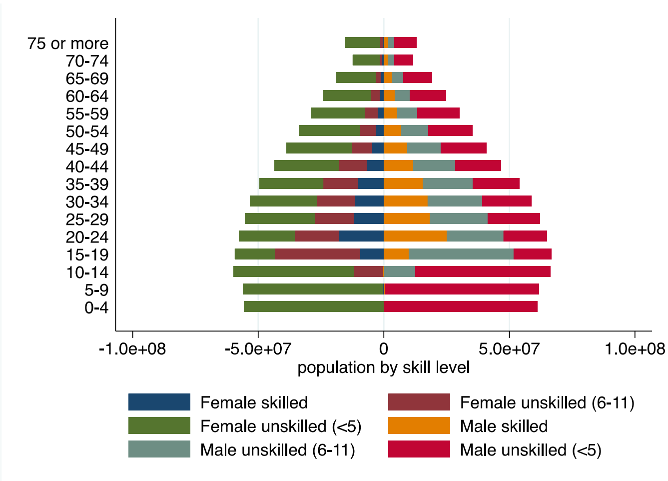
Module 2. Reallocation of labour

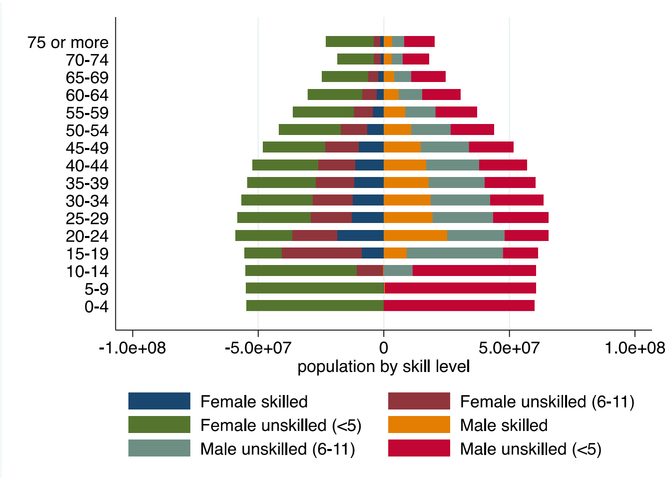
The labour reallocation module is implemented after the demographic module with the aim of transferring workers from one economic sector to another to reflect the macroeconomic shocks and changes projected by the GEM. The economic sectors considered by the GEM and the GIDD include agriculture, industry, sophisticated services, unsophisticated services and the public sector (see Table 8 for more detail). Each of these sectors is subdivided according to the skill level, and workers can only access jobs that match their skill level. For instance, a skilled manufacturing worker can only be reallocated to another skilled job position.

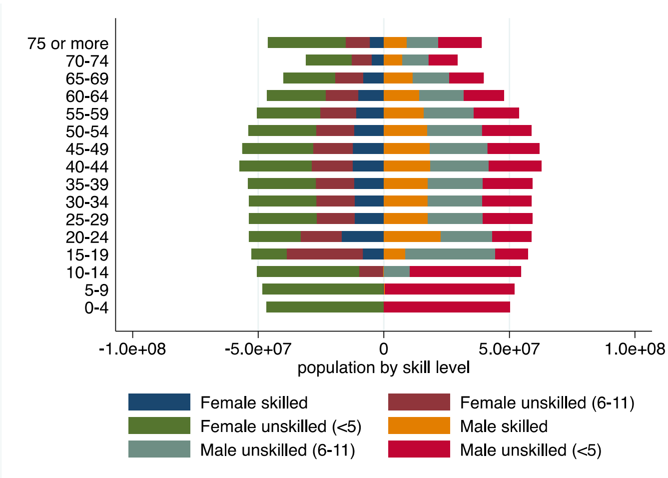
The reallocation module uses new sample weights created by the demographic module. The application of new sample weights affects the original structure of employment by economic sector. However, the reallocation module compensates such changes to mimic the employment structure as projected by the macro model (GEM) for each year of analysis for each of the five sectors into which the GEM has divided the economy. In other words, when the reweight exercise overestimates the share of workers in a particular sector compared to what is projected by the GEM, the sector is denominated as a shrinking sector. If the reweight exercise underestimates the share of workers in an economic sector (compared to the GEM), the sector is categorised as expanding (Chepeliev et al. 2021). The following paragraphs detail the criteria used to move workers from shrinking sectors to expanding ones.

A multinomial logit regression is used to estimate the likelihood of each worker's being in each of the five economic sectors given their characteristics, including years of education, gender, age, state and whether they live in an urban or a rural area (see Appendix A). Workers in shrinking sectors are sorted according to their probability of being in that sector, and those with the lowest probability are identified as migrants (to be

Figure 9 | **Population pyramids by age cohort, gender and level of education**

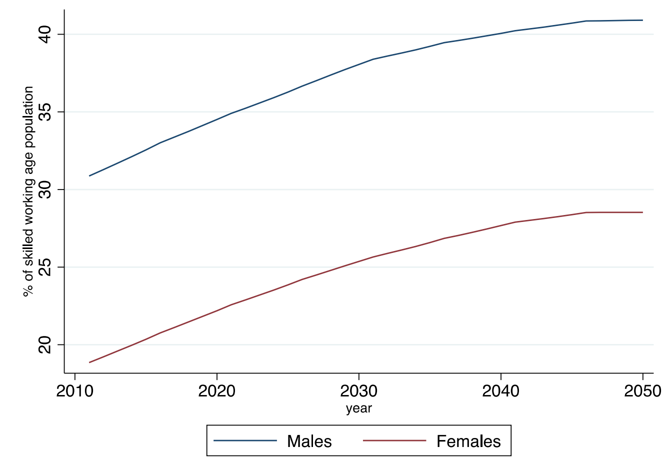






Source: Elaborated by the authors based on data from UN population projection statistics.

Figure 10 | **Working-age population by skill level as a share of total population**



Source: Elaborated by the authors based on UN population projection statistics.

reallocated to other sectors)[10]. The number of migrants per sector depends on the gap between the micro projections and the macro projections. Migrant workers are assigned to the economic sector where they are most likely to be, given the results of the multinomial logit. After the reallocation, a new wage is assigned to migrant workers using a set of Mincer equations (Akay and Uyar 2016) and adding a factor to account for the unobservable characteristics of each worker[11]. The factor is estimated considering the residual of the Mincer equation of their original sector and scaled using the ratio of the standard deviation of the new and the original sector (Chepeliev et al. 2021).

Households without members in the labour market do not receive a shock from implementing this module. At the end of this module, household consumption and per capita consumption are estimated again, and both are adjusted by a factor to restore the average per capita consumption of the original NSS survey. That the households do not receive a shock implies that implementing labour reallocation only simulates distributional effects and has a neutral effect on the welfare level of households. In other words, individuals' experiences only change their consumption in relation to other individuals because of this module's being implemented[12].

Module 3. Wage premia

In contrast with the reallocation of labour, the wage premia module operates at the level of skill (skilled versus unskilled workers) and by economic sector. In other words, the module scales the wages simulated by the reallocation of labour module of skilled workers using a factor equal to the ratio of the average wage of skilled workers and the average wage of unskilled workers by economic sector. This ratio (or the wage

Table 8 | **Activities included in each economic sector**

SECTOR	ECONOMIC ACTIVITIES INCLUDED
Agriculture	Agriculture
Manufacturing	Mining, public utilities and construction
Sophisticated services	Commerce, accommodation, transportation and communications, finance
Public administration	Public administration, education and activities of extraterritorial organisations and healthcare
Unsophisticated services	Other personal services, domestic personnel and self-production, residential care, social work, creative arts and entertainment, sports activities, activities of membership organisations

Note: The NSS survey classifies economic activities using the National Industrial Classification 2008, https://www.ncs.gov.in/Documents/NIC_Sector.pdf.

Source: Authors' own.

premia) for each sector is obtained from the GEM, based on the differential relative demands for labour (by skill) across sectors. For example, the higher the demand for skilled labour in industry, the higher the wage premia in this sector will be relative to other sectors.

The purpose of this module is to adjust the relative wage gap by skill for each sector in the microsimulation, in accordance with the results of the macro model (GEM) in achieving consistency in relative factor returns by skill and sector between the two.

Module 4. Changes in relative prices (not implemented)

Changes in consumption prices affect individuals' purchasing power. Furthermore, changes in different commodity prices affect households differently; for example, in poorer households, the consumption of food tends to make up a higher share of their total consumption. The purpose of this module is to model the impact on consumption of changes in relative prices of two baskets of goods: food and non-food. For simplicity's sake, we assume that households expend the same share of income on each basket of goods despite experiencing changes in their income over time. This assumption could be relaxed by using an Engel's curve. This module has not been implemented as the GEM does not produce a projection of commodity prices (except energy prices).

Module 5. Distributional-neutral growth

In this module, it is assumed that each household in the country experiences the private consumption growth estimated by the macro model (after having accounted for growth-neutral distributional effects in the previous modules). Consequently, consumption growth is considered neutral on the income distribution. In the previous modules, we account for the employment and income shifts based on the size of the economic sectors without considering the GDP growth for each sector. These shifts comprise the growth-neutral distribution. We undertake the growth-related adjustments in this module. Since the income and employment shifts have been affected in the previous module, we require this module to scale the results according to the GDP growth rate received from the GEM. This is what we mean by distribution-neutral growth.

A passthrough of 0.67 (Edochie et al. 2022) was used to adjust the growth rate of private consumption from the GEM to the microsimulation. This passthrough is necessary to account for the differences between the household consumption when it is measured by a top-down method like the macroeconomic model, the GEM in this case, and when it is estimated using bottom-up household surveys. In other words, the passthrough factor is used as a way of ensuring that the growth prevalent at the macro level, calculated in the GEM, is included in the changes in private consumption in the microsimulation.

Framework outputs

In this subsection, we demonstrate illustrative outputs of the GEM-GIDD linkage. Since the two models are currently being developed, the scenarios and the results that we present are liable to change. However, to understand how they might be used by policymakers, we must highlight the nature of the outputs that the models can deliver. We should also note that the outputs from the model are not predictions but projections. This means that they indicate possible outcomes of a climate policy package. This can help policymakers understand the direction of the impacts of certain climate policies and gain some idea of the impacts' magnitude. In presenting these illustrative results, we hope to showcase the former of these uses.

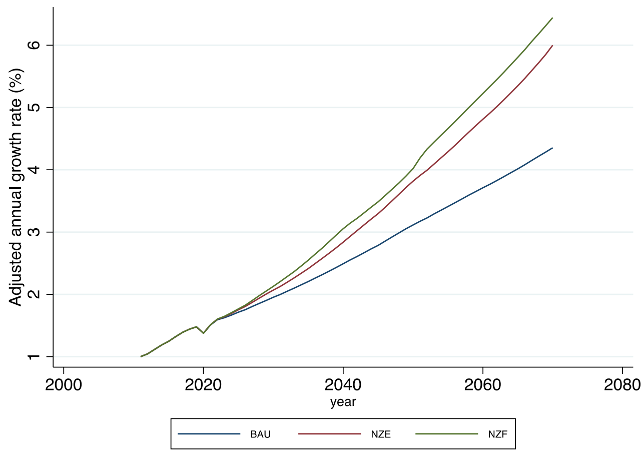
The primary output of the GIDD framework is a household consumption curve that acts as a proxy to capture the impacts of climate policies on household income. Spread across income deciles or groups, this private consumption curve can be used to calculate the Gini coefficient and poverty head count, as well as to map the distribution of per capita consumption across income groups, thereby facilitating interpretation of climate policies' impact on poorer sections of society.

We have also included the disaggregation of the population by gender in the GIDD and, therefore, also have the capability to analyse climate policy impacts on male and female workers—for example, income changes and skill levels by gender. A comparative analysis of these outputs across multiple climate scenarios constructed in the GEM can help us compare how one policy package performs over another as far as distributional impacts are concerned amongst income groups or by gender and inform more equitable and inclusive policymaking. Figures 11 and 12 give examples of the results.

Figure 11 is an illustrative representation of three scenarios—one business-as-usual scenario and two possible net zero scenarios—showing growth in private consumption from 2000 to 2070 as a result of climate policy implementation in the macro model. Figure 12 offers a snapshot of the impact on wages (per worker consumption) by income centiles and gender in 2020 and 2050. Comparing the two figures shows a rise in compensation for all workers, with upper-income centiles gaining more than lower-income centiles. Comparing the two figures also shows that female workers in lower-income centiles do not benefit from the growth as much as their counterparts in upper-income centiles. The same is true of male workers but with a slightly lower magnitude.

However, these graphs are illustrative and do not reflect the actual numbers seen in the GEM-GIDD framework of models. They do, however, indicate the kind of results we can expect from the microsimulation.

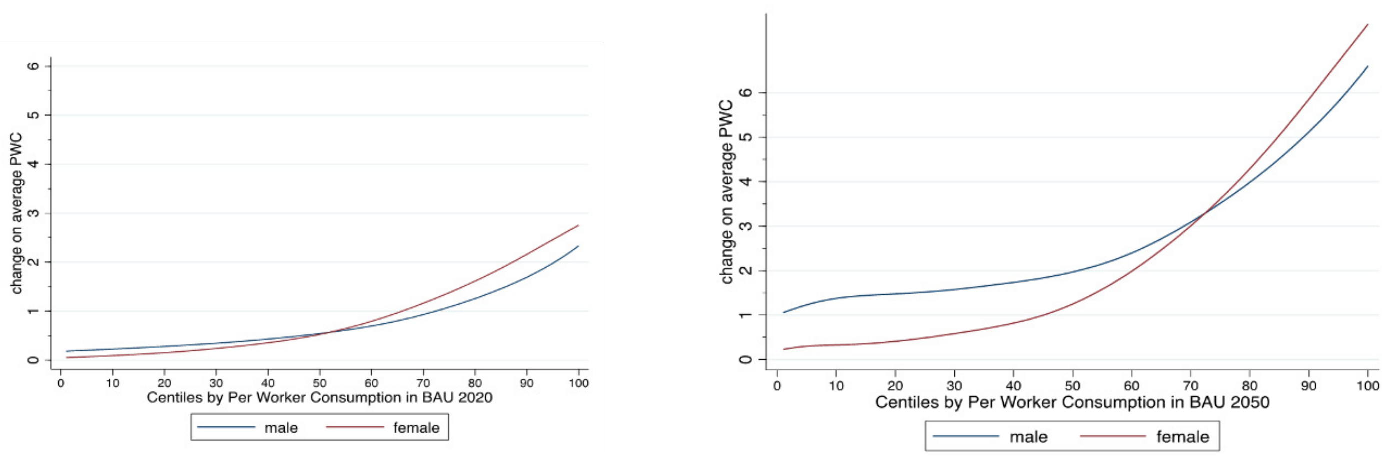
Figure 11 | **How private consumption growth would look after adjusting the passthrough factor, across three scenarios (illustrative)**



Notes: BAU = business as usual; NZE = net zero energy; NZF = net zero full.

Source: Authors.

Figure 12 | **Example of how the impact of climate policies is shown as an output for income groups, across male and female workers and across time (illustrative) (left (a) and right (b))**



Note: BAU = business as usual; PWC = per worker consumption.

Source: Authors.

Use for policymakers

We can now list some of the information that policymakers can derive and suggest the kinds of recommendations these outputs can help us present.

- The Gini coefficient and poverty headcount curves, as well as the household consumption curves, show how inequality and poverty change according to the climate policy packages being implemented in the macro model. These demonstrate the kind of effect climate policies can have on households' income and consumption. In the illustrative results, we find that climate policies can result in increased inequality, which could make a case for stronger social protection for low-income households.
- The PWC curves shown in Figure 12(b) can also help us understand the wage gap between male and female workers and how it changes over time under the influence of climate policy packages. This could indicate whether the wage gap is likely to increase in the future and as well as the need for labour and wage reform.
- Employment across sectors and the distribution of skilled and unskilled workers can help policymakers foresee demand for skilled workers and whether a skill gap is to be expected. This could help policymakers decide whether to introduce skilling programs that complement the climate policies being implemented.

CONCLUSION AND WAY FORWARD

The GIDD and GEM help us understand how different climate policy packages and low-carbon pathways affect different income groups economically and the policies' impact on income and consumption across gender. We have listed limitations we need to address over the next couple of years to make the microsimulation more robust and insightful.

These would include calculating the wage changes in each sector dynamically so we can determine wages and employment levels across sectors, which can also facilitate feedback relationships between the macro and micro models. At the current stage, we are unable to estimate the cost-of-living impacts of climate policies on different income groups due to a lack of relevant data. We have, however, collected further data on different food and non-food consumer baskets and their price indices and will be incorporating them as we develop the models further. As we complete the incorporation of these changes, we will also look at recursive feedback from the microsimulation to the macro model and vice versa to incorporate the impacts of policies such as carbon tax redistribution and subsidy reallocation on different income groups. These will then feed into income changes at the macro level. We also will have to incorporate the impacts of economic growth on educational attainment over time, which would increase the demand for skilled jobs, and thereby wages and income as well.

Another objective of the GEM and GIDD linkage is to help outline decarbonisation pathways that are just and equitable. The insights from the model include the impact of climate policies on wages of male and female workers, inequality and poverty in the economy, and employment and consumption among households. These indicators can signify how economic growth is distributed amongst households and which income groups gain the most dividend. If climate policy impacts are regressive, this could indicate the need for progressive welfare policies. The shifts in employment from one sector to another signify the need for greater skilling to enable the expansion of one sector over another in the economy—depending upon the demand for skilled and unskilled labour in each sector. Similarly, the impact of wages of male and female workers across income groups shows how the gender wage gap changes over time across income groups. These insights could help policymakers bridge such gaps through corrective measures and supporting labour laws. These insights will be valuable for policymakers as they create a just and equitable transition.

With updated datasets, as they become available, this suite of models can be updated to make it more relevant to the current state of the economy. We can also expand the use of the framework by creating feedbacks to the macro model and by incorporating redistribution policies in the microsimulation. As we further develop the model, the insights from this linkage of macro model and microsimulation can help better inform policymakers of the distributional impacts of climate action.

APPENDIX A

The multinomial (polytomous) logistic regression used to predict the probability of each worker aged 15 to 64 being in the industry where they currently work is modelled as in Equation A-1. Where is a constant and is a vector of regression coefficients, including gender, age, education level and urban or rural setting, for *j* = 1, 2, ..., *j*, where *j* is equal to five economic sectors and *i* includes the different income groups.

Equation A-1.

$$\eta_{ij} = \log\frac{\pi_{ij}}{\pi_{ij}} = \propto_j + x_i'\beta_j$$

ENDNOTES

1. What-if scenarios enable understanding of the impacts or outcomes of different policies with different levels of implementation over time.

2. In this context, macro refers to variables and quantities at the national level, while micro represents the same at a household level.

3. In this case, welfare includes indicators like income, employment and inequality.

4. In the model, we assume that any worker with 12 years or less of education will be classified as unskilled, while those with more than 12 years of education will be classified as skilled.

5. Skilled workers have been defined as members of the labour force with more than 12 years of education.

6. This is an assumption based on historical data that provide the labour force participation rate for male and female workers.

7. 'Per capita disposable income' represents the average income per person after direct taxes and is based on national income accounting.

8. This does not match the current official working ages for India and instead approximates the productive parts of the population.

9. Cross-entropy is a measure of the difference between two probability distributions for a given random variable or set of events. The cross-entropy method is a statistical method for evaluating properties of a particular probability distribution, while only having samples generated from a different distribution than the distribution of interest. This is done by drawing a sample from the probability distribution. It minimises the cross-entropy between this distribution and a target distribution to produce a better sample in the next iteration.

10. In this case, 'migrants' refers to the workers moving from one sector to another and has nothing to do with the geographic migration of labour.

11. The Mincer equation for wage determination is an econometric equation that incorporates the impact of education, experience and individual observable characteristics like gender, state and so on, as well as an error variable to account for unobservable characteristics.

12. Since the available microdata of the NSS 2011 survey do not have information about the labour incomes of self-employed people and employers, consumption per worker is used as a proxy for individual labour incomes (the terms labour income and wages are used interchangeably in this text). It is assumed that changes in consumption per worker are reflected as a 1:1 ratio on the aggregate consumption per household.

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ABOUT WRI INDIA

WRI India is a global research organization that turns big ideas into action at the nexus of environment, economic opportunity, and human well-being.

Our challenge

Natural resources are at the foundation of economic opportunity and human well-being. But today, we are depleting Earth's resources at rates that are not sustainable, endangering economies and people's lives. People depend on clean water, fertile land, healthy forests, and a stable climate. Livable cities and clean energy are essential for a sustainable planet. We must address these urgent, global challenges this decade.

Our vision

We envision an equitable and prosperous planet driven by the wise management of natural resources. We aspire to create a world where the actions of government, business, and communities combine to eliminate poverty and sustain the natural environment for all people.

Our approach

COUNT IT

We start with data. We conduct independent research and draw on the latest technology to develop new insights and recommendations. Our rigorous analysis identifies risks, unveils opportunities, and informs smart strategies. We focus our efforts on influential and emerging economies where the future of sustainability will be determined.

CHANGE IT

We use our research to influence government policies, business strategies, and civil society action. We test projects with communities, companies, and government agencies to build a strong evidence base. Then, we work with partners to deliver change on the ground that alleviates poverty and strengthens society. We hold ourselves accountable to ensure our outcomes will be bold and enduring.

SCALE IT

We don't think small. Once tested, we work with partners to adopt and expand our efforts regionally and globally. We engage with decision-makers to carry out our ideas and elevate our impact. We measure success through government and business actions that improve people's lives and sustain a healthy environment.