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A New Static Multi-Regional Input Output Model for Household Behavior of India

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Abstract: This paper calculates the CO_2 equivalents footprint of private consumption in the India by five groups of household income, using a fully fledged macroeconomic input-output model covering 59 industries and five groups of household income for the India. Due to macroeconomic feedback mechanisms, this methodology not only takes into account intermediate demand induced by the demand of a household group, but also: (i) private consumption induced in the other household groups, (ii) impacts on other endogenous final demand components, and (iii) negative feedback effects due to output price effects of household demand. Direct household emissions from household energy consumption are taken into account in a non-linear specification. Emissions embodied in imports are calculated using the results of a static MRIO (Multi-Regional Input-Output) model. The footprint is calculated separately for the consumption vector of each of the five income groups. The simulation results yield an income elasticity of direct and indirect emissions at each income level that takes all macroeconomic feedbacks of consumption into account and differs from the ceteris paribus emission elasticity in the literature. The results further reveal that a small structural 'Kuznet effect' exists.

Keywords: Carbon footprint, Computable General Equilibrium (CGE) modeling, Income distribution, India.

JEL codes: C67, Q52, Q54

1. Introduction

The environmental impact of inequality in the income distribution has been the object of many theoretical and empirical studies. The main question was, if reducing inequality and rising incomes along the growth process might 'automatically' decrease environmental pressure. The 'strong' version of this hypothesis where environmental pressure (emissions, energy/resource use) is even reduced when the schedule of all household incomes shifts upwards, is the

'Environmental Kuznets Curve' (EKC). The general result of empirical studies at the national level is that some decrease in environmental pressure can be identified, but that does not suffice to reduce environmental pressure. The empirical studies comprise econometric studies in the spirit of the EKC literature (Ravaillon, et al. 2020, Borghesi, 2020) as well as studies that combine input-output (IO) or life-cycle methods with others to quantify the footprint of different income groups (Weber and Matthews, 2007, and more recently Chancel and Piketty, 2015).

Since the seminal paper of Boyce (2014), most authors find a negative relationship between inequality and emissions, i.e. higher inequality leads to lower emissions. The ECK studies also include cross terms between indicators of inequality (Gini index) and aggregate income, allowing for a change in the emission elasticity of income growth in the case of changes in the income distribution. Borghesi (2020) discusses these findings in the light of the literature and concludes with mixed evidence: positive effects of inequality on emissions (poor households using less efficient equipment and more energy/resources) and negative effects (rich households consuming more aggregate energy/resources) might balance.

The studies that use input-output (IO) analysis for calculating the footprint usually calculate direct and indirect emissions of households, and often yield the result that indirect emissions have a higher share in total footprint for high income households than for low income. This is seen to be due to the fact that there is a minimum as well as a maximum need of direct energy for heating, lighting and transport, but consumption of other energy intensive goods increases with income and therefore indirect emissions. Parikh et al. (2019) as well as Weber and Matthews (2007) show that for top income households the share of indirect CO_2e (CO_2 equivalents, i.e. (GHG emissions, including CH_4 and N_2O) emissions is significantly higher than for households at the bottom of the income distribution.

One objective of the literature consists in deriving an income elasticity of carbon emissions, either from a cross section or an aggregate time series data set. Weber and Matthews (2007), who combine IO analysis with econometric estimation, find expenditure elasticity between 0.6 and 0.8 and income elasticity between 0.35 and 0.52. Lenzen et al. (2016) review this work on elasticities and derive a similar range, but conclude that the literature exhibits a large heterogeneity of estimated elasticity values. It must be noted that the methodology consists of calculating the CO_2e footprint in a first step and then applying econometric analysis on these results in a second step. The econometric analysis, which attempts to identify the households' reactions, therefore is not integrated with the IO analysis used for calculating the footprint. Another study (Duarte *et al.,* 2015) also uses a Computable General Equilibrium (*CGE*) model to calculate the full macroeconomic impact of household behaviour, but the consequences for emissions are attributed from outside from the results of an IO model (though the IO database is the same as the one for the CGE model). The recent study by Chancel and Piketty (2015) combines footprint calculations from a MRIO analysis with income distribution data via income elasticity values taken from the literature.

The existing literature has not yet used IO approaches that integrate household behavior for deriving the footprint of different income groups, from which the income elasticity can be derived directly, without any further econometric analysis. This paper attempts to fill this gap and the income elasticity derived takes into account macroeconomic (or general equilibrium) feedbacks and therefore is not limited to the ceteris paribus condition that needs to hold for the elasticity values estimated in the literature. The model used can be seen as a hybrid between an econometric IO and a CGE model and splits the consumption block into five groups of household income (quintiles). Aggregate consumption depends on income, wealth and liquidity constraints, consumption by commodity on prices as well. Production is modeled via a Translog model that is fully integrated into the IO structure. Besides that, the model also comprises a labor market block (wage curves) and a public sector block that closes the model via a fixed deficit/GDP rule. The analysis in this paper extends the existing literature by taking into account that (i) consumption of each household group induces consumption in the other groups via an income and wealth multiplier, (ii) consumption of each household group induces wage and price effects due to the demand pull, and (iii) consumption of durables reacts in a non-linear form, so that energy consumption linked to the durable stock shows non-linear reactions with respect to income as well.

These effects partly magnify the footprint compared to traditional static IO analysis ((i)) and partly diminish it ((ii)). The non-linear property ((iii)) yields a heterogenous income elasticity of the footprint across income groups. This is an ex post elasticity from model simulation results, taking into account all macroeconomic feedbacks.

The paper is organized as follows: section 2 describes the model with an emphasis on consumption, production and trade, including the derivation of direct and indirect household CO_2e footprint. Section 3 reports the results for the CO_2e footprint by quintile and calculates the model simulation income elasticity. The values of this elasticity define the reaction of the CO_2e footprint when ascending from one quintile to the next and are not constant and different from the range found in the literature. The income elasticity of the CO_2e footprint considerably decreases when moving from bottom to top income. Another interesting result is that when macroeconomic feedbacks are taken into account (additionally to pure IO linkages), indirect effects are more important for bottom income households than for top incomes. The results indicate a small 'Kuznet effect', partly due to a higher saving rate and less emission intensive consumption structures of top incomes. This effect results in a less than proportionate rise of the CO_2e footprint with a rise in income, which though does not suffice to compensate for the much higher level of consumption of top incomes. In section 4 some conclusions are drawn.

2. The model

The DYNK (DYnamic New Keynesian) model approach applied in this study is a hybrid between an econometric IO and a CGE model and is characterized by the integration of rigidities and institutional frictions. In the long run the model works similar to a CGE model, and explicitly describes an adjustment path towards a long-run equilibrium. The term 'New Keynesian' refers to the existence of a log-run full employment equilibrium, which will not be reached in the short run, due to institutional rigidities. These rigidities include liquidity constraints for consumers (deviation from the permanent income hypothesis), and wage bargaining (deviation from the competitive labour market). The model describes the inter-linkages between 59 industries as well as the consumption of five household income groups by 47 consumption categories and covers the India.

The model of households' demand comprises three nests, where in the first nest the demand for durables (owned houses, vehicles) and total nondurables is derived from a buffer-stock model of consumption. The second nest links energy demand (in monetary and physical units) to the durable stock (houses, vehicles, appliances) taking into account the energy efficiency embodied in the stocks. Direct CO_2e emissions of households are derived from the energy flows determined in this nest. In the third nest eight categories of non-energy nondurable demand are determined in a flexible demand system (The Almost Ideal Demand System (AIDS) model) and then further be split up into 47 categories via fixed shares. The model of production links the input-output structures (Leontief technologies) of 59 domestic and imported inputs to a Translog model with *K*, *L*, *E*, M^m (imports) and M^d (domestic) factors. The factor energy (*E*) is further split up into 26 types of energy, from which CO_2e emissions of production are derived, a part of which constitutes the domestic indirect CO_2e emissions of households. The imported indirect CO_2e emissions of households are taken from simulation results with a MRIO model (Arto et al., 2014). The labour market is specified via wage curves, where wage increases by industry depend on productivity, the consumer price and the distance to full employment. The model is closed by endogenizing parts of public expenditure in order to meet the midterm stability program for public finances in the India.

2.1. Household behaviour and private consumption

The consumption block differentiates between different stages and separability is assumed between these stages. The separability assumption in that context also implies that the dynamic decision process is disentangled as lined out in Attanasio and Weber (2005).

At the first stage, the demand for durables (real estate property and vehicles) is modeled in a way consistent with the version of the buffer stock model described in Luengo-Prado (2016). Further, total nondurable demand is also specified in a way consistent with the main properties of the buffer stock model (excessive smoothing, excess sensitivity). All model parameters are based on dynamic estimation of panel data for India (2005-2021).

At the second stage, energy consumption, disaggregated into: heating, electricity and fuels for transport, is modeled as a service demand in terms of utilization of the capital (durable) stock. An important variable is the average energy efficiency of the corresponding durable stocks (dwelling for heating, vehicles for fuels for transport, and appliances for electricity). The transport part allows for substitution between public transport services and private car transport. For this second stage, the model parameters are based on estimations with in India (2005 – 2021).

Finally, the third stage contains the model of non-energy nondurable consumption, modeled in a demand system. This is again split into two nests: (i) an aggregate level of eight categories, described in an The Almost Ideal

Demand System (AIDS) model, and (ii) a detailed model of 47 The *Classification* of Individual Consumption According to Purpose (*COICOP*) categories, explained by sub-shares of the aggregate categories that change over time and can be changed exogenously for model simulation purposes. The econometric estimation has been carried out for in India (2005 – 2021), as well as for data from the household survey 2020/2021 for India.

2.1.1. Durable demand and total nondurables

Starting point for determining total private consumption is the buffer-stock model, developed by Deaton (2021) and Carroll (2017). We apply a specification, where buffer-stock saving is not motivated by income uncertainty, but by down payments for purchase of durables, as laid down in Luengo-Prado (2016). Consumers maximize the present discounted value of expected utility from consumption of nondurable commodity and from the service provided by the stocks of durable commodity:

$$\max_{(C_t, K_t)} V = E_0 \left\{ \sum_{t=0}^{\infty} \beta^t U(C_t, K_t) \right\} \tag{1}$$

Specifying a The constant-relative-risk-aversion (CRRA) utility function and a budget constraint the model can be solved in terms of first order conditions, but not in terms of explicit demand functions. The budget constraint in this model without adjustment costs for the durables stock is given by the definition of assets, A_t:

$$A_t = (1+r)(1-t_r)A_{t-1} + YD_t - C_t - (K_t - (1-\delta)K_{t-1}) \tag{2}$$

In (2) the sum of C_t and $(K_t - (1-\delta)K_{t-1})$ represents total consumption, i.e. the sum of nondurable and durable expenditure (with depreciation rate of the durable stock, d). The gross profit income rA_{t-1} (with interest rate r) is taxed with tax rate t_r. Disposable household income excluding profit income, YD_t, is given as the balance of net wages $(1-t_S-t_Y)w_t H_t$ and net operating surplus accruing to households $(1-t_Y)\Pi_{h,t}$, plus transfers Tr_t:

$$YD_t = (1-t_S-t_Y)w_t H_t + (1-t_Y)\Pi_{h,t} + Tr_t \tag{3}$$

The following taxes are charged on household income: social security contributions with tax rate t_S, which can be further decomposed into an employee and an employer's tax rate (t_{WI} and t_L) and income taxes with tax rate t_Y. The wage rate w_t is the wage per hour and H_t are total hours demanded by firms. Wage bargaining between firms and unions takes place over the employee's gross wage, i.e. w_t (1 - t_L).

All the income categories are modelled at the level of quintiles q of household incomes (q = 1…5):

$$YD_t = \sum_q \left[\left(1 - t_{S,q} - t_{Y,q}\right) w_{t,q} H_{t,q} + (1 - t_{Y,q}) \Pi_{t,q} + Tr_{t,q}\right] \tag{4}$$

Financial assets of households are built up by saving after durable purchasing has been financed, and the constraint for lending is:

$$A_t + (1 - \theta) K_t \geq 0 \tag{5}$$

This term represents voluntary equity holding, as the equivalent of the other part of the durable stock (θK_t) needs to be held as equity. The consideration of the collateralized constraint is operationalized in a down payment requirement parameter θ, which represents the fraction of durables purchases that a household is not allowed to finance. One main variable in the buffer stock-model of consumption is 'cash on hand', X_t, measuring the household's total resources: $X_t = (1 + r_t)(1 - t_r)A_{t-1} + (1 - \delta)K_{t-1} + YD_t$. The model is specified here in the form of demand functions that are consistent with the model properties. These comprise non-linear consumption functions for durables, which are based on the concave shape of the policy functions for consumption in Luengo-Prado (2016), and where, with higher levels of durables per households (K_t/h_t), the marginal propensity of investment in durables, C_{Kt} with respect to X_t decreases. The down payment parameter q in Luengo-Prado (2016) represents a long-term constraint between the liabilities stock and the durable stock of households and is specified here by imposing limits to the down payment for durable purchases. Durables in this model are owned houses (dwelling investment) and vehicles. The long-run demand functions for the two durable categories ($C_{dur,t}$) is a function of 'cash on hand' (X_t), the down payment for durable purchases (θ_{Ct}), as well as static user costs of durables, $p_{dur,t}(r_t + \delta)$

$$\log C_{dur,t} = \log C_{dur,t}\left[\log X_t, \theta_{Ct}, \log\left(p_{dur,t}(r_t + \delta)\right), \log\left(K_{t-1}/h_{t-1}\right)\right] \tag{6}$$

The long-run demand function for total nondurable consumption is a function of 'cash on hand' and down payments for durable purchases ($\theta_{Ct} \log C_{dur,t}$)

$$\log C_{nondur,t} = \log C_{nondur,t}\left[\log X_t, \theta_{Ct} \log C_{dur,t}\right] \tag{7}$$

The latter takes into account that households need to finance down payments, and will not do so by savings in the same period but will smooth nondurable consumption accordingly. The estimation is carried out as error correction panel data estimation and the results are used to calibrate the model at the level of the 5 quintiles of income, which are characterized by different values for the durable stocks per household. Therefore, the model contains growth rates for $C_{dur,t}$ and $C_{nondur,t}$ for each quintile (*q*).

The data for the estimation of consumption demand functions are mainly taken from India's National Accounts. The capital stock of housing property was estimated for one year, based on the Household Financial and Consumption Survey (HFCS) of the India. A more simple procedure could be applied to vehicles, as the expenditure data are available and no revaluation of the existing stock needed to be taken into account there.

The down payment for durable purchases, θ_{Ct} is calculated by relating the change in liabilities to the durable demands. The original θ_t from Luengo-Prado (2016) is measured in this model by the relationship (1 – liabilities/durable stock) and can only be controlled by fixing certain values of θ_{Ct} and solving the model to derive the path of θ_t. In an iterative procedure dynamic convergence towards target values of θ_t can then be achieved.

Once the full model is set up with the integrated consumption block, the property of 'excess sensitivity' can be tested. Excess sensitivity describes the empirical fact that the growth rate of consumption – partly – reacts to the lagged growth rate of disposable (or labour) income. This issue has been raised by Hall (2018) and confronted the Permanent Income Hypothesis with contradicting empirical findings. The full model presented here is run until 2050, so that endogenous disposable household income is generated. Then excess sensitivity is tested by setting up the regressions that Hall (2018) proposed to test the influence of transitory income shocks on consumption. That means regressing the growth rates for $C_{dur,t}$ and $C_{nondur,t}$ for each quintile (*q*) on lagged disposable income growth (without profit income) for each quintile, generated by the full model. Profit income is not included, because it is endogenous and depends on equity built up, which in turn is a result of the inter-temporal optimization. Luengo-Prado (2016) also carries out excess sensitivity tests with her calibrated model, based on US household survey data and confronts these results with US stylized macroeconomic facts. The excess sensitivity coefficients, i.e. the marginal propensity of consumption (MPC) with respect to lagged income change, found by Luengo-Prado (2016) are 0.16 (nondurables) and 0.26 (durables). The results from the model solution until 2050 (Table 1) clearly reveal that for the 5^{th} and partly for the 4^{th} quintile durable and nondurable consumption do not statistically significantly depend on transitory income shocks. The MPC is higher in general for lower income households and for situations with higher liquidity constraints (higher θ). The 'low θ scenario' corresponds to a financial regime, where the relationship debt to durable stock does not significantly decrease, i.e. no major debt deleveraging by households occurs. The 'high θ scenario' corresponds to debt deleveraging so that the relationship debt to durable stock in the long-run decreases to its values before 2020, i.e. before the main expansion of household debt began. The multiplier of policies that influence income is therefore not constant, but depends on the situation of the economy and the income groups that are most affected.

2.1.2. Energy demand

The energy demand of households comprises fuel for transport, electricity and heating. These demands are part of total nondurable consumption and separability from non-energy nondurable consumption is assumed. According to the literature on the rebound effect (e.g.: Khazzoom, 1989), the energy demand is modeled as (nominal) service demand and the service aspect is taken into account by dealing with service prices. The durable stock of households (vehicles, houses, appliances) embodies the efficiency of converting an energy flow into a service level $S = \eta_{ES} E$, where E is the energy demand for a certain fuel and S is the demand for a service inversely linked by the efficiency parameter (η_{ES}) of converting the corresponding fuel into a certain service. For a given conversion efficiency, a service price, p_S, (marginal cost of service) can be derived, which is a function of the energy price and the efficiency parameter: $p_S = p_E / \eta_{ES}$. Any increase in efficiency leads to a decrease in the service price and thereby to an increase in service demand ('rebound effect').

For transport demand of households we take substitution between public (C_{pub}) and private transport (C_{fuel}) into account. The price for fuels, $pc_{S,fuel}$, is defined as a service price. Total transport demand of households depends on the composite price of private and public transport, as well as on total nondurable expenditure. The demand for transport fuels is linked to the vehicle stock and depends on the service price of fuels as well as on the endowment of vehicles of the population. The latter term is important because the second car of the household usually is used less in terms of miles driven than the first.

$$\log\left(\frac{C_{fuel,t}}{K_{veh,t}}\right) = \mu_{fuel} + \gamma_{fuel}\log\left(\frac{p_{fuel,t}}{\eta_{fuel,t}}\right) + \xi_{fuel}\log\left(\frac{K_{veh,t}}{h_t}\right) \tag{8}$$

In (8) m_{fuel} is a constant or a cross section fixed effect and g_{fuel} is the price elasticity under the condition that there is a unitary elasticity of fuel demand to the vehicle stock.

The equations for heating and electricity demand are analogous to equation (8) and have the following form:

$$\log\left(\frac{C_{heat,t}}{K_{hous,t}}\right) = \mu_{heat} + \gamma_{heat}\log\left(\frac{p_{heat,t}}{\eta_{heat,t}}\right) + \xi_{heat}\log(dd_{heat}) \tag{9}$$

$$\log\left(\frac{C_{el,t}}{K_{app,t}}\right) = \mu_{el} + \gamma_{el}\log\left(\frac{p_{el,t}}{\eta_{el,t}}\right) + \xi_{el}\log(dd_{heat}) \tag{10}$$

In both equations the variable heating degree days dd_{heat} is added. The durable stocks used are the total housing stock ($K_{hous,t}$) and the appliance stock ($K_{app,t}$). The latter is accumulated from consumption of appliances, C_{app}, which in turn is explained in a log linear specification like total transport demand. The energy expenditure of households is based on The Central Statistics Office (CSO), the Energy Accounts from the WIOD database, as well as IEA Energy Prices. Energy efficiency for electricity and for heating is calculated from the ODYSSEE database. Efficiency of the car fleet is taken from a revised version of the GAINS project database. The panel data set resulting from this data collection process comprises from India. All equations have been estimated in a dynamic autoregressive distributed lag (ADL) specification. The price elasticity values (Table 2) found here for heating, transport fuel and electricity (around – 0.8) are outside the range established by the existing literature for the energy price elasticity. That can be explained by two factors. First, the elasticity values presented here measure the service price elasticity and the reaction of service demand to both price changes and improvements of energy efficiency in the durable stock. Service price have been almost constant in the sample period used for estimation due to energy efficiency improvements, whereas demand has increased considerably. This is consistent with part of the literature on the (price) rebound effect that finds rebound effects of 100% in some cases. Second, the elasticity values calculated here are conditional on the stock of durables thereby implicitly assuming a unitary elasticity of energy demand to the durable stock as a strong driving force of demand (Table 2). Again, the estimation results have been taken to calibrate the model for energy demand by quintile (q). The model therefore comprises C_{fuel}, C_{heat}, and C_{el} at the level of quintiles, taking into account the endowment of each quintile with durable stocks.

2.1.3. Nondurable (non-energy) demand

The non-energy demand of nondurables is treated in a demand system. The one applied in this DYNK model is the Almost Ideal Demand System (AIDS), starting from the cost function for $C(u, p_i)$, describing the expenditure function (for C) as a function of a given level of utility u and prices of consumer goods, p_i (see: Deaton and Muellbauer, 1980) . The AIDS model is represented by the well known budget share equations for the i nondurable goods in each period:

$$w_i = \alpha_i + \sum_j \gamma_{ij} \log p_j + \beta_i \log\left(\frac{C}{P}\right) \; ; i = 1 \ldots n,\ 1 \ldots k \qquad (11)$$

with price index, P_t, defined by $\log P_t = \alpha_0 + \sum_i \alpha_i \log p_{it} + 0.5 \sum_i \sum_j \gamma_{ij} \log p_{it} \log p_{jt}$,

often approached by the Stone price index: $\log P_t^* = \sum_k w_{it} \log p_{it}$ .The expressions for expenditure (η_i) and compensated price elasticities (ε_{ij}^C) within the AIDS model for the quantity of each consumption category C_i can be written as (the details of the derivation can be found in Green, and Alston, 2020):

$$\eta_i = \frac{\partial \log C_i}{\partial \log C} = \frac{\beta_i}{w_i} + 1 \qquad (12)$$

$$\varepsilon_{ij}^C = \frac{\partial \log C_i}{\partial \log p_j} = \frac{\gamma_{ij} - \beta_i w_j}{w_i} - \delta_{ij} + \varepsilon_i w_j \qquad (13)$$

In (13) δ_{ij} is the Kronecker delta with $\delta_{ij} = 0$ for $i \neq j$ and $\delta_{ij} = 1$ for $i = j$.

The commodity classification $i = 1 \ldots n$ in this model comprises the n non-energy nondurables: (i) food, and beverages, tobacco, (ii) clothing, and footwear,

(iii) furniture and household equipment, (iv) health, (v) communication, (vi) recreation and accomodation, (vii) financial services, and (viii) other commodities and services.

The data for econometric estimation are taken from The Central Statistics Office (CSO) National Accounts (2005 – 2021) for the panel data model and from Indian household surveys 2020/2021 for the cross section model (Salotti, et al., 2015). For the cross section model no price variance across time is available and therefore the AIDS model reduces to the simple specification in that case:

$$w_i = \alpha_i + \beta_i \log\left(\frac{C}{P}\right) \; ; \; i = 1 \ldots n, \; 1 \ldots k \tag{14}$$

This model can still be used to derive expenditure elasticity according to (12).

The main results of the estimation of the demand system for non-energy nondurables are the expenditure elasticity from both models (panel and cross section) and the price elasticity from the panel data model (Table 2). The price elasticity shows considerable heterogeneity across categories. For the expenditure elasticity values the results of both models differ considerably. While the expenditure elasticity of the panel data model is mainly distributed around unity, the expenditure elasticity of the cross section model differs largely between categories.

The model has been calibrated starting with the elasticity values reported in Table 2 by combining the price elasticity with the expenditure elasticity of the cross section model. This is done by inverting equation (12) and (13) and inserting the budget shares of the India (one economy) and yields parameter values for β_i and γ_{ij}.

2.1.4. Total household demand

The household model described determines in three stages the demand for different categories of durables, energy demand and different categories of nondurables. The first stage yields (column) vectors of total nondurable consumption $(\mathbf{c}_{\text{nondur}})$ and of investment in owned houses $(\mathbf{c}_{\text{hous}})$ and in vehicles $(\mathbf{c}_{\text{veh}})$ by quintile (*q*). From the second stage one derives (column) vectors of fuel, heat, and electricity consumption, again by quintile (*q*): $\mathbf{c}_{\text{fuel}}$, $\mathbf{c}_{\text{heat}}$, and $\mathbf{c}_{\text{el}}$.

Nondurable non-energy consumption (the vector by quintiles) is then given by:

$$\mathbf{c}_{\mathrm{NE}} = \mathbf{c}_{\mathrm{nondur}} - \mathbf{c}_{\mathrm{fuel}} - \mathbf{c}_{\mathrm{heat}} - \mathbf{c}_{\mathrm{el}} \qquad (15)$$

The matrix of commodities of non-energy consumption by quintiles ($\mathbf{C}_j$) is in a next step derived from multiplying the matrix of budget shares by quintiles, W, determined in equation (11), with the vector of nondurable non-energy consumption (converted into a diagonal matrix):

$$\mathbf{C}_{\mathrm{j}} = \mathbf{W}\left[\hat{\mathbf{c}}_{\mathrm{NE}}\right] \qquad (16)$$

where j = 1…8 are the eight non-energy consumption commodities.

The final result of this procedure is a matrix of durable, energy and non-energy consumption by quintiles ($\mathbf{C}_C$):

$$\mathbf{C}_{\mathrm{C}} = \begin{bmatrix} c_{hous,1} & \cdot & \cdot & \cdot & c_{hous,5} \\ c_{veh,1} & \cdot & \cdot & \cdot & c_{veh,5} \\ c_{fuel,1} & \cdot & \cdot & \cdot & c_{fuel,5} \\ c_{heat,1} & \cdot & \cdot & \cdot & c_{heat,5} \\ c_{el,1} & \cdot & \cdot & \cdot & c_{el,5} \\ .. & .. & .. & .. & .. \\ c_{j,1} & \cdot & \cdot & \cdot & c_{j,5} \\ .. & .. & .. & .. & .. \end{bmatrix}$$

This matrix is then transformed into a consumption matrix by commodities of the input-output core in the DYNK model and quintiles in purchaser prices, C_{pp}, by applying the bridge matrix, B_C:

$$C_{pp} = B_C \, C_C \qquad (17)$$

The bridge matrix links the classification of consumption commodities (COICOP) to the industry classification of the DYK model. The consumption vector in purchaser prices and industry classification is derived by summing up over C_{pp}: $\mathbf{c}_{pp} = C_{pp}\boldsymbol{e}$ with $\boldsymbol{e}$ as the diagonal matrix (per quintiles) of the unity vector.

This vector is then split up into a domestic and imported part for each commodity (see section 2.3 on trade) and converted into producer prices by reallocating trade and transport margins to the corresponding industries and subtracting taxes less subsidies. That yields the vectors of total domestic ($\mathbf{c}^d$) and imported ($\mathbf{c}^m$) consumption, with $\mathbf{c} = \mathbf{c}^d + \mathbf{c}^m$, all valued at producer prices. For this conversion a matrix of net tax rates (with identical tax rates on domestic and imported commodities) is applied.

2.1.5. Direct CO_2e footprint of households

The two directly emission relevant energy categories (fuel and heating) of the model of energy consumption need to be directly linked to the energy accounts by user (59 industries plus households) and detailed fuel category (26) in physical units. This is done in two several steps. First, the vector $\begin{bmatrix} c_{fuel} \\ c_{heat} \end{bmatrix}$ is deflated by aggregate prices of fuels and heating, where these energy prices are not specified as deflators, but as monetary values per physical energy unit (TJ). Then the deflated categories, in energy units, are allocated to the 26 energy types (e) of the model by applying fixed sub-shares, s_{ef}. The aggregate prices used for the first step (for fuel and heating, p_f) are defined by the exogenous prices by energy type (p_e) and the corresponding sub-shares: $p_f = \sum_e s_{ef} p_e$. This gives a matrix of direct energy consumption of households by type of energy (e) and quintile (q), whose elements are defined as $c_{e,q} = s_{ef,q} \dfrac{c_{f,q}}{p_f}$:

$$\mathbf{C}_e = \begin{bmatrix} c_{e1,1} & .. & .. & .. & c_{e1,5} \\ .. & .. & .. & .. & .. \\ .. & .. & .. & .. & .. \\ c_{e26,1} & .. & .. & .. & c_{e26,5} \end{bmatrix}$$

Applying a (row) vector of fixed CO_2 emission factors per unit of energy type ($\mathbf{em}_{GHG,e}$) to the physical energy consumption by energy type and quintile finally yields the (row) vector of *direct* CO_2 emissions of household consumption by quintile $EM_{GHG,q}$:

$$\mathbf{EM}_{\mathrm{GHG,q}} = \mathbf{em}_{\mathrm{GHG,e}}[\mathbf{C}_{\mathrm{e}}] \tag{18}$$

2.2. Firm Behaviour and Production Structure

The production side in the DYNK model is analysed within the cost and factor demand function framework in a Translog specification with constant returns to scale and perfect competition. Autonomous technical change is specified for all input factors (i.e. the factor biases) and also as the driver of TFP (total factor productivity).

2.2.1. Substitution in a K,L,E,M^m^,M^d^ model

The model is set up with inputs of capital (K), labor (L), energy (E), imported (M^m) and domestic non-energy materials (M^d), and their corresponding input prices p_K, p_L, p_E, p_{Mm} and p_{Md}. Each industry faces a unit cost function for the price (p_Q) of output Q, with constant returns to scale

$$\log p_Q = \alpha_0 + \sum_i \alpha_i \log(p_i) + \frac{1}{2}\sum_i \gamma_{ii} (\log(p_i))^2 + \sum_{i,j} \gamma_{ij} \log(p_i)\log(p_j) + \alpha_t t + \frac{1}{2}\alpha_{tt} t^2 + \sum_i \rho_{ti} t \log(p_i) \tag{19}$$

where p_Q is the output price (unit cost), p_i, p_j are the input prices for input quantities x_i, x_j, and t is the deterministic time trend, TFP is measured by α_t, and α_{tt}. Shepard's Lemma yields the cost share equations in the Translog case, which in this case of five inputs can be written as:

$$\begin{aligned}
v_K &= [\alpha_K + \gamma_{KK} \log(p_K / p_{Md}) + \gamma_{KL} \log(p_L / p_{Md}) + \gamma_{KE} \log(p_E / p_{Md}) + \gamma_{KM} \log(p_{Mm} / p_{Md}) + \rho_{tK} t] \\
v_L &= [\alpha_L + \gamma_{LL} \log(p_L / p_{Md}) + \gamma_{KL} \log(p_K / p_{Md}) + \gamma_{LE} \log(p_E / p_{Md}) + \gamma_{LM} \log(p_{Mm} / p_{Md}) + \rho_{tL} t] \\
v_E &= [\alpha_E + \gamma_{EE} \log(p_E / p_{Md}) + \gamma_{KE} \log(p_K / p_{Md}) + \gamma_{LE} \log(p_L / p_{Md}) + \gamma_{EM} \log(p_{Mm} / p_{Md}) + \rho_{tE} t] \\
v_M &= [\alpha_M + \gamma_{MM} \log(p_{Mm} / p_{Md}) + \gamma_{KM} \log(p_K / p_{Md}) + \gamma_{LM} \log(p_L / p_{Md}) + \gamma_{EM} \log(p_E / p_{Md}) + \rho_{tM} t]
\end{aligned} \tag{20}$$

The homogeneity restriction for the price parameters $\sum_i \gamma_{ij} = 0$, $\sum_j \gamma_{ij} = 0$ has already been imposed in (20), so that the terms for the price of domestic intermediates p_{Md} have been omitted. The immediate ceteris paribus reaction to price changes is given by the own and cross price elasticity. These own- and cross- price elasticities for changes in input quantity x_i are given as:

$$\varepsilon_{ii} = \frac{\partial \log x_i}{\partial \log p_i} = \frac{v_i^2 - v_i + \gamma_{ii}}{v_i} \tag{21}$$

$$\varepsilon_{ij} = \frac{\partial \log x_i}{\partial \log p_j} = \frac{v_i v_j + \gamma_{ij}}{v_i} \tag{22}$$

Here, the v_i represent the factor shares in equation (19), and the γ_{ij} the cross-price parameters. The rate of factor bias, i.e. the impact of t on factor x_i without taking into account TFP is given by:

$$\frac{d \log x_i}{dt} = \frac{\rho_{ti}}{v_i} \tag{23}$$

Factor prices are exogenous for the derivation of factor demand, but are endogenous in the system of supply and demand. Some factor prices are directly linked to the output prices p_Q which are determined in the same system. All user prices are the weighted sum of the domestic price p^d and the import price, p^m. The import price of commodity i in country s is given as the weighted sum of the commodity prices of the k sending countries ($p^{d,k}$). Once the (user specific) import prices for intermediate goods are given, the price vectors of total domestic ($\mathbf{p}_{Md}$) and imported ($\mathbf{p}_{Mm}$) intermediate inputs by industry can be calculated. Within the bundle of intermediate inputs (M^m and M^d), which comprises 55 non-energy industries/commodities, Leontief technology is assumed. These bundles are defined by the 'use structure matrices' ($\mathbf{S}_{\mathrm{NE}}^{\mathrm{m}}$ and $\mathbf{S}_{\mathrm{NE}}^{\mathrm{d}}$) with column sum of unity.

$$\mathbf{p}_{\mathrm{Mm}} = \mathbf{p}^{\mathrm{m}} \mathbf{S}_{\mathrm{NE}}^{\mathrm{m}} \qquad \mathbf{p}_{\mathrm{Md}} = \mathbf{p}^{\mathrm{d}} \mathbf{S}_{\mathrm{NE}}^{\mathrm{d}} \tag{24}$$

The price of capital is based on the user cost of capital: $u_K = p_{CF}(r + \delta)$ with p_{CF} as the price of investment goods an industry is buying, r as the deflated benchmark interest rate and d as the aggregate depreciation rate of the capital stock K. The investment goods price p_{CF} can be defined as a function of the domestic commodity prices and import prices, given the input structures for investment, derived from the capital formation matrix for domestic ($\mathbf{B}_{\mathrm{K}}^{\mathrm{d}}$) and imported ($\mathbf{B}_{\mathrm{K}}^{\mathrm{m}}$) investment demand:

$$\mathbf{p}_{CF} = \mathbf{p}^{m}\mathbf{B}_{K}^{m} + \mathbf{p}^{d}\mathbf{B}_{K}^{d} \tag{25}$$

The price of labour is endogenous as well and determined in the labour market (see section 2.4). The prices of energy types are assumed to be determined at world markets for energy and are therefore treated as exogenous. A specific feature of capital is that two prices of this input can be formulated: (i) the ex post rate of return to K (derived from operating surplus) and (ii) the ex ante rate of return to K, i.e. the user cost. In economic terms, that represents an imperfect capital market, which can be in disequilibrium (see: Jorgenson, et al., 2013). It is assumed that after the base year, this adjustment takes place instantaneously.

All data for the production system are derived from the WIOD (World Input Output Database) dataset that contains World Input Output Tables (WIOT) in current and previous year's prices, Environmental Accounts (EA), and Socioeconomic Accounts (SEA). For energy the data in physical units (TJ) by energy type and user (s. above) are used. Energy prices by energy type are exogenous, like in the household block of the model. The systems of output price and factor demand equation by industry across the India have been estimated applying the Seemingly Unrelated Regression (SUR) estimator for the balanced panel under cross section fixed effects. The estimation results yield values for the own and cross price elasticity for capital, labour, energy, and imported intermediates respectively. The average (un-weighted) own price elasticity of labour as well as of energy is about -0.5, while the own price elasticity of imported intermediates (-0.75) and capital (-0.95) is considerably higher (Table 3). For energy intensive industries the own price elasticity of energy is lower, but the substitution elasticity between energy and capital is slightly higher than on average. Though, also on average, capital and energy are substitutes (though in several sectors complementary). The rate of factor bias (equation (23)) in general is very low, and technical progress slightly energy using and labour saving. Like in the consumption model the elasticity values have been used by inverting the elasticity equations ((21), (22) and (23)) together with factor share data for the India (one economy) to calibrate the production system and derive parameter values for γ_{ij} and ρ_{ti}.

2.2.2. Energy inputs in production and the domestic indirect CO_2e footprint of households

The aggregate E comprises four energy industries/commodities. In a second nest, the factor E is split up into aggregate categories of energy (coal, oil, gas, renewable, electricity/heat) in a Translog model. The unit cost function of this model determines the bundle price of energy, p_E , and the cost shares of the five aggregate energy types:

$$\log p_E = \alpha_0 + \sum_i \alpha_{E,i} \log(p_{E,i}) + \frac{1}{2}\sum_i \gamma_{E,ii}\left(\log(p_{E,i})\right)^2 + \sum_{i,j} \gamma_{E,ij} \log(p_i)\log(p_j) + \sum_i \rho_{tE,i} t \log(p_{E,i}) \tag{26}$$

$$v_{E,i} = \left[\alpha_{E,i} + \sum_{i,j} \gamma_{E,ij} \log(p_{E,i}) + \rho_{tE,i} t\right] \tag{27}$$

In some cases the elasticity of inter-fuel substitution is very close to zero, but most industries show a value of straying around -0.5. The cross price elasticity also show negative signs in a large number of industries, indicating complementarity between fuels.

The set of five energy categories of the model of inter-fuel substitution needs to be directly linked to two parts of the model: (i) the energy accounts by industry and detailed fuel category (26) in physical units (TJ) and (ii) the energy commodities and industries of the use table in monetary units. The first link is carried out in the same way as described above for households, i.e. by deflating with a price per unit of physical input (TJ) and applying sub-shares in physical terms. The second link is carried out by applying changes in the structure of the five energy inputs to the use structure matrix of the factor *E*.

The GHG emissions by industry are therefore derived in a similar way as in the case of households. One main difference is that the GHG emissions by industry do not only comprise CO_2 emissions stemming from energy input, but also CH_4 and N_2O emissions (both measured in CO_2e). These emissions are directly linked via a (row) vector of fixed emission factors per unit of output ($\mathbf{em}_{GHG,j}$) to the gross output in constant prices of the industries. The data source for these emissions is the Environmental Accounts (EA) of the WIOD database.

A matrix of energy input in physical units by industry is further constructed, whose elements represent the energy costs in each industry *j*, ($v_{E,ij}E_j$) divided by given energy prices $p_{E,i}$ and multiplied by the corresponding sub-shares s_{eij}, $s_{eij}\dfrac{v_{E,ij}E_j}{p_{E,i}}$. Applying the same (row) vector of fixed CO_2 emission factors per unit of energy type ($\mathbf{em}_{GHG,e}$) as in the consumption block to this energy matrix and the (row) vector of fixed emission factors per unit of output ($\mathbf{em}_{GHG,j}$) yields the (row) vector of domestic CO_2 emissions by industry $\mathbf{EM}_{GHG,j}$:

$$\mathbf{EM}_{GHG,\,j} = \mathbf{em}^{d}_{GHG,\,e}\left[\mathbf{E}_{e}\right] + \mathbf{em}^{d}_{GHG}\,\mathbf{q} \tag{28}$$

Note that the *indirect* domestic CO_2e footprint of households by quintile is given by the sum of the energy and the output impact of consumption by quintile $\left(\frac{d\sum_j \mathbf{E_j}}{d\mathbf{c_q}} + \frac{d\sum_j \mathbf{q_j}}{d\mathbf{c_q}}\right)$. In that case we assume that the change dc_q corresponds to the full consumption of a quintile. Without price changes, the first term in brackets is just proportional to the second term (output impact of consumption of a quintile).

2.3. Trade and Domestic Output

The commodity balance for non-energy commodities is defined by applying the use structure matrices $\mathbf{S}^{m}_{NE}$ and $\mathbf{S}^{d}_{NE}$ (equation (24)) as well as the diagonal matrices of the factor shares in equation (20), $\hat{\mathbf{V}}_{D}$ and $\hat{\mathbf{V}}_{M}$. Multiplying the use structure matrix with the corresponding factor share matrix and with the column vector of output in current prices gives the sum of intermediate demand by commodity. The procedure for energy commodities is the same, with use structure matrices $\mathbf{S}^{m}_{E}$ and $\mathbf{S}^{d}_{E}$ (where the column sum over both matrices yields one), and diagonal matrix $\hat{\mathbf{V}}_{E}$. The full commodity balance is given by adding the column vectors of domestic consumption ($\mathbf{c}^{d}$), capital formation ($\mathbf{cf}^{d}$) and public consumption ($\mathbf{cg}^{d}$). Capital formation is endogenous as well and derived from capital demand by industry in the Translog model, applying the capital formation matrix (equation (25)). The (column vector) of the domestic output of commodities in current prices, $\mathbf{p}^{D}\mathbf{q}^{D}$, is transformed into the (column vector) of output in current prices, $\mathbf{p}_{Q}\mathbf{q}$, by applying the market shares matrix, C (industries * commodities) with column sum equal to one:

$$\mathbf{p}^{D}\mathbf{q}^{D} = \left[\hat{\mathbf{V}}_{D}\mathbf{S}^{\mathbf{d}}_{\mathbf{NE}}\right]\mathbf{p}_{Q}\mathbf{q} + \left[\hat{\mathbf{V}}_{E}\mathbf{S}^{\mathbf{d}}_{\mathbf{E}}\right]\mathbf{p}_{Q}\mathbf{q} + \mathbf{c}^{d} + \mathbf{cf}^{d} + \mathbf{ex}^{d} + \mathbf{st}^{d} + \mathbf{cg}^{d} \tag{29}$$

$$\mathbf{p}_{\mathrm{Q}}\mathbf{q} = \mathbf{C}\mathbf{p}_{\mathrm{D}}\mathbf{q}_{\mathrm{D}} \tag{30}$$

The final demand categories in ($\mathbf{c}^{\mathrm{d}}$, $\mathbf{cf}^{\mathrm{d}}$, $\mathbf{ex}^{\mathrm{d}}$, $\mathbf{st}^{\mathrm{d}}$ and $\mathbf{cg}^{\mathrm{d}}$) comprise energy and non-energy commodities, are all in current prices and are all – except stock changes ($\mathbf{st}^{\mathrm{d}}$) – endogenous. The export vector $\mathbf{ex}^{\mathrm{d}}$ is calibrated with price elasticity of unity for all commodities and therefore is constant in current prices. The vector of public consumption $\mathbf{cg}^{\mathrm{d}}$ is determined in the public sector block of the model in order to close the model with a predetermined public deficit.

Imports by commodity are in this model determined by the sum of final and intermediate demand by commodity. For this purpose, an import shares matrix for final demand, $\mathbf{M}^{\mathbf{f}}$ is introduced and applied to the total final demand matrix, $\mathbf{F}$ (consisting of the columns of final demand, $\mathbf{c}$, $\mathbf{cf}$, $\mathbf{ex}$, $\mathbf{st}$, $\mathbf{cg}$). The elements of matrix F are treated as constant and could alternatively be modelled via the Armington elasticity. Note that the major part of imports (i.e. intermediate goods) is variable and reacts upon prices. Total imports by commodities $\mathbf{IM}$ are in this framework given by imports of final demand, both energy and non-energy commodities imports and of intermediate inputs (energy), as well as non-energy (the symbol $\otimes$ represents element by element multiplication of two matrices.):

$$\mathbf{IM} = \mathbf{M}^{\mathbf{f}} \otimes \mathbf{F} + \left[\hat{\mathbf{V}}_{\mathrm{M}}\mathbf{S}^{\mathbf{m}}_{\mathbf{NE}}\right]\mathbf{p}_{\mathrm{Q}}\mathbf{Q} + \left[\hat{\mathbf{V}}_{\mathrm{E}}\mathbf{S}^{\mathbf{m}}_{\mathbf{E}}\right]\mathbf{p}_{\mathrm{Q}}\mathbf{Q} \tag{31}$$

2.3.1. The Imported Indirect CO_2e footprint of Households

The GHG emissions of imports (in the rest of the world) by import commodity *i* are given by a (row) vector of average coefficients of GHG emissions by one unit of import in India ($\mathbf{em}^{\mathrm{m}}_{\mathrm{GHG}}$) derived from a MRIO (multi-regional input-output) model (Arto, et al., 2014). The total imported *indirect* CO_2e footprint of the economy is therefore given as:

$$\mathbf{EM}^{\mathrm{m}}_{\mathrm{GHG}} = \mathbf{em}^{\mathrm{m}}_{\mathrm{GHG}}\mathbf{IM} \tag{32}$$

The imported *indirect* CO_2e footprint of households by quintile is therefore determined by $\frac{d\mathbf{M}}{d\mathbf{c}_{\mathbf{q}}}$, where $d\mathrm{c}_{\mathrm{q}}$ again stands for the full consumption of a quintile.. This is the sum of the final demand import effect (captured in $\mathbf{M}^{\mathbf{f}}$)

and the intermediate demand import effect, which is proportional to the output impact $\frac{d\mathbf{q}}{d\mathbf{c_q}}$.

2.4. Labour Market

The labour market is characterized by wage bargaining, formalized in wage curves by industry. These wage curves are specified as the employee's gross wage rate per hour by industry, i.e. $w_t (1 - t_L)$. The labour price (index) of the Translog model is then defined by adding the employers' social security contribution to that. Combining the meta-analysis of Folmer (2019) on the empirical wage curve literature with a basic wage bargaining model from Boeters and Savard (2013) gives a specification for the sectoral hourly wages. These functions describe the responsiveness of hourly wages to labour productivity (industry, aggregate), consumer prices, hours worked per employee, and the rate of unemployment. The parameter estimated for labour productivity in the wage curve therefore is conditional on this impact of working time on hourly wages.

Wage data including hours worked are taken from WIOD Sectoral Accounts and are complemented by labour force data from The Central Statistics Office (CSO). The wage equations have been estimated for India panel. The un-weighted average across industries of the long-run unemployment elasticity is about 0.06. The long-run productivity elasticity of wages is only about 0.3, whereas the consumer price elasticity is close to unity (0.8).

2.5. Government and Model Closure

The public sector balances close the model and show the main interactions between households, firms and the general government. Taxes from households and firms are endogenized via tax rates and the path of the deficit per GDP share according to Indian stability programs is included as a restriction. Wage income of households is taxed with social security contributions (tax rates t_{wL} and t_L) and wage income plus operating surplus accruing to households are taxed with income taxes (tax rate t_Y). Additionally, households' gross profit income is taxed with tax rate t_r. Taxes less subsidies are not only levied on private consumption, but also on the other final demand components in purchaser prices ($\mathbf{f}_{pp}$, comprising capital formation, changes in stocks, exports, and public consumption) as well as on gross output. The expenditure side of government is made up of transfers to households (Tr), public investment (cf_{gov}) and public consumption (*cg*). Additionally, the government pays interest with interest rate r_{gov} on the stock of public debt, D_{gov}.

The model is closed by further fixing the public budget constraint, that defines the future path of government net lending to GDP ($p_Y Y$). Linking public investment with a fixed ratio (w_{cf}) to public consumption and introducing the net lending to GDP constraint, public consumption is then derived as the endogenous variable that closes the model:

$$
\begin{aligned}
cg(1+w_{cf}) &= \Delta D_{gov,t} / p_y Y - r_{gov,t} D_{gov,t-1} - Tr + (t_{wL} + t_L) w_t H_t \\
&+ t_Y (w_t H_t + \Pi_{h,t}) + t_r r_t A_{t-1} + \hat{\mathbf{T}}_{\mathrm{N}} \left[\mathbf{c}_{\mathrm{pp,t}} + \mathbf{f}_{\mathrm{pp,t}} + \mathbf{p}_{\mathrm{Q,t}} \mathbf{Q}_{\mathrm{t}} \right]
\end{aligned} \tag{33}
$$

3. The CO_2e Footprint and Income: Simulations with the DYNK Model

3.1. The Economic and CO_2e footprint Impact of Quintiles

In this analysis, the DYNK model described above has been used for calculating the carbon footprint of the different household income groups. The total CO_2e footprint of a quintile (q) is the sum of the direct CO_2e footprint, the indirect domestic CO_2e footprint, and the indirect imported CO_2e footprint of this quintile, where $d\mathrm{c}_{\mathrm{q}}$ corresponds to the full consumption of a quintile:

$$
\frac{d\mathbf{EM}_{\mathbf{GHG}}}{d\mathbf{c}_{\mathbf{q}}} = \mathbf{EM}_{\mathrm{GHG,q}} + \frac{d\sum_j \mathbf{EM}_{\mathbf{GHG,j}}}{d\mathbf{c}_{\mathbf{q}}} + \frac{d\mathbf{EM}_{\mathrm{GHG}}^{\mathrm{m}}}{d\mathbf{c}_{\mathbf{q}}} \tag{34}
$$

Note that the first term captures just the direct CO_2 emissions of the respective quintile, whereas the other two terms include indirect effects on CO_2 emissions which partly are due to consumption in other quintiles. This is the main difference between the approach used here and the standard MRIO analysis of footprint. These induced effects that are taken into account in the second and third term in equation (34) comprise also endogenous impacts on other final demand components, partly induced by income, partly by price effects. The price effects are due to wage reactions to employment effects and their repercussion on the whole price system. As can be deduced from the results presented in Table 1, though consumption of each quintile will create disposable income in the other four quintiles through a production/income multiplier, the consumption reactions induced by these income effects will be very different.

The income induced in the bottom income quintile by consumption in the top income quintile for example converts into consumption with a much higher MPC than the other way round. From Table 1 we can even conclude that pure income effects in the top income quintile will not increase consumption significantly, if no wealth effects are induced for this income group as well.

The footprint is calculated in the following by introducing five exogenous demand shocks separately into the DYNK model from 2015 to 2025 which are equivalent to the consumption vector of the five income quintiles, i.e. to $d\mathbf{c}_q$ in (34). The problem is that all consumption is in principle endogenous in the model, so that double counting or over-determination might occur. One method to deal with that would have been to make consumption of each quintile in each simulation exogenous. One potential problem with this method is that this changes the model structure and truncates links and feedbacks in the model. The other method – chosen here – is to subtract the impact of induced consumption in the quintile that should be fixed exogenously. This subtraction also is biased in the sense that it does not take into account the indirect and induced effects from this induced consumption in the same quintile, but bears the advantage that it does not alter the model structure. Indirect induced CO_2e footprint of the same quintile is subtracted by applying the same emission coefficients per unit of output to the value that results in the model simulation for induced domestic ($d\mathbf{c}^{\mathrm{d}}_{\mathrm{q,ind}}$) and imported ($d\mathbf{c}^{\mathrm{m}}_{\mathrm{q,ind}}$) consumption. For domestic indirect footprint physical energy coefficients per unit of output have been calculated, $\left[\mathbf{E}_{\mathrm{e}}\mathbf{q}^{-1}\right]$. The other GHG footprint (CH_4 and N_2O) as well as indirect imported footprint are already directly linked to output and imports, so the application is straightforward.

$$\frac{d\mathbf{EM}_{\mathbf{GHG}}}{d\mathbf{c}_{\mathbf{q}}} = \mathbf{EM}_{\mathrm{GHG,q}} + \frac{d\sum_{j}\mathbf{EM}_{\mathbf{GHG,j}}}{d\mathbf{c}_{\mathbf{q}}} + \frac{d\mathbf{EM}^{\mathrm{m}}_{\mathrm{GHG}}}{d\mathbf{c}_{\mathbf{q}}} - \\ - \mathbf{em}^{\mathrm{d}}_{\mathrm{GHG,e}}\left[\mathbf{E}_{\mathrm{e}}\mathbf{q}^{-1}\right]d\mathbf{c}^{\mathrm{d}}_{\mathrm{q,ind}} - \mathbf{em}^{\mathrm{d}}_{\mathrm{GHG}}\,d\mathbf{c}^{\mathrm{d}}_{\mathrm{q,ind}} - \mathbf{em}^{\mathrm{m}}_{\mathrm{GHG}}\,d\mathbf{c}^{\mathrm{m}}_{\mathrm{q,ind}} \tag{35}$$

This measure of a corrected CO_2e footprint from the model simulations is taken in the following for analyzing the link between income distribution and footprint. Table 4 shows the aggregate results of the model simulations, namely the economic and environmental impact of the full consumption vector of each quintile in 2025, compared to a baseline scenario. As has been said above already, in this simulation all final demand categories are endogenous and together determine the impact on GDP, together with the IO linkages. The demand shock that corresponds to the consumption vector of each quintile induces some private consumption. As expected, this effect is larger in the case of the bottom quintiles and smaller for the top quintiles. For the top 20% income group this induced consumption effect turns out even negative. The employment impact and the movement towards full employment, especially in the case of the 4^{th} and 5^{th} quintiles, induce wage and price reaction, which in turn affect final demand negatively. In the case of exports this results in a significant demand reduction. These effects show that the consumption of households needs to be seen simultaneously with the other demand categories. Lower consumption in India would ceteris paribus lead to higher price competitiveness, which would shift the footprint to exports, i.e. to consumption in the rest of the world.

The impacts of direct CO_2e footprint of all five income groups in Table 4 add up to the total (100%) of direct household emissions. The impacts of indirect CO_2e footprint include the imported footprint and therefore add up to more than double of the domestic emission from production. From Table 4 one can already conclude that in these simulations the indirect footprint is important for all income groups and increases less with income than the direct footprint. This last result is different from what the literature has found until now. In the case of the top income group the CO_2e footprint in India and in the rest of the world amounts to more than 70% of Indian emissions.

The induced income effects across the other quintiles for the consumption of each quintile are visible in Table 5. The consumption of bottom quintiles induces income for higher income groups, but – as could be seen from Table 4 – that does not induce so much additional consumption. Partly this is also due to price effects resulting from the consumption demand. The total induced income impact in Table 5 can be compared with the direct share of the quintiles in disposable income. This relationship can be interpreted as the income multiplier of each quintile. For the bottom income group this multiplier more than doubles the income weight of the group: the 1^{st} quintile has a share of about 6% in disposable income and induces 5.2% in total disposable income due to its consumption activity. This multiplier decreases when moving to higher income groups. For the middle (3^{rd} quintile) it is 15% direct income share to 10% induced income and for the top it changes to 45% direct vs. about 20% induced.

3.2. The Relationship between CO_2e footprint and Income Distribution

The difference in the MPC between income groups and the difference in the structure of the consumption vectors determines the different structures of income, consumption and CO_2e footprint (Figure 1). The bottom income quintile has a share of 6% in disposable income, 7% in consumption expenditure and 8% in the CO_2e footprint, whereas the top income quintile has a share of 45% in disposable income, 42% in consumption expenditure and 37% in the carbon footprint of all households. Except for the top income group, all other groups exhibit shares in the CO_2e footprint which are higher than those in consumption. This is an indication for a 'Kuznet effect', i.e. with higher income the consumption structure changes in a way that leads to a less than proportional increase in CO_2e footprint. This 'Kuznet effect' is continuous and rather small when moving from one quintile to the other between the first and the fourth quintile and then exhibits a larger shift when moving from the fourth to the fifth quintile. For the fourth quintile the share in income is 22% and the share in the CO_2e footprint is 24%, whereas for the fifth quintile the corresponding values are 45% (income) and 37% (CO_2e footprint). That means that within the fifth quintile some heterogeneity concerning income and CO_2e footprint might exist which could only be further analysed by applying more disaggregate income groups, like for example deciles.

In absolute terms, the average CO_2e footprint of Indian households according to our model simulations is 36.8 t CO_2e per household or 15.7 t CO_2e per capita (Figure 2). The bottom income group in India has less than half of this footprint, namely 6.1 t CO_2e per capita and the top income group has less than double (29.2 t CO_2e per capita). This result also corroborates the 'Kuznet effect'.

Two important issues discussed in the literature in this context are the relative importance of direct and indirect footprint and the income elasticity of the footprint. The objective in both cases is to better understand potential counterbalancing effects to the level effect that determines the larger footprint of top income households. These effects could comprise directly and indirectly less emission intensive consumption structures of rich household groups and a different income elasticity that compensate for the dominating effect of much higher consumption levels of these households.

The standard result of the literature is that for bottom income households direct emissions have a higher share and for top income emissions from heating and driving become less important compared to indirect emissions. As Table 6 reveals that does not hold for the simulation results with the DYNK model. Indirect emissions play a more important role (in relative terms) for bottom income households. The main reason for this seems to be the CH_4 emissions from agricultural products. It can be expected that this effect would even be magnified, if the agricultural sector would be further disaggregated. The emissions - either via energy input or directly – are linked to the monetary value of the agricultural and food industry output. Rich households consume high quality/high price products in a larger amount, the production of which is not necessarily more energy/emission intensive than the same product with a lower quality. The share of indirect CO_2e footprint amounts to 91% for the bottom income group and decreases continuously with moving to higher income groups and finally reaches 86% for the top income group. The order across income groups is therefore different from the literature, but our values for the share of indirect emissions lie within the range of the literature which is between 70% and 90% (Parikh et al., 2019 and Weber and Matthews, 2007).

The income elasticity of CO_2e has been widely researched, partly only with econometric methods applied to aggregate data, partly by applying econometrics to results of IO analysis, as in Weber and Matthews (2007). Chakravarty *et al.* (2019) define a range of the income elasticity of CO_2 emissions of 0.8 to 1. Chancel and Piketty (2015) use income elasticity values for assigning national emissions to income group and – in response to the values found in the literature – apply a range between 0.6 and 1.5 with a core value of 0.9, which according to their review corresponds to the mean value in the literature. It must be noted that the literature so far (to our knowledge) has derived values for the income elasticity of CO_2e either from econometric studies only or from applying econometrics ex post to the outcome of IO analysis. This methodology does not integrate the effects of household behavior into the IO analysis that measures the CO_2e footprint and therefore does not take into account feedback mechanisms and interactions between the household sector and the production structure. In this study the household sector is fully integrated into the IO structure of the DYNK model and relevant feedbacks between consumption, other endogenous final demand components and the production structure of the Indian economy are taken into account. The income elasticity of the CO_2e footprint is then calculated on the results of the model simulations. It is defined as the coefficient of the logarithmic difference of the CO_2e footprint to the logarithmic difference of income between two quintiles:

$\frac{\log\left(d\mathbf{EM}_{\mathbf{GHG}}/d\mathbf{c}_{\mathbf{q+1}}\right)-\log\left(d\mathbf{EM}_{\mathbf{GHG}}/d\mathbf{c}_{\mathbf{q}}\right)}{\log\left(yd_{q+1}\right)-\log\left(yd_{q}\right)}$. In Table 6 the values for the first quintile, i.e. an income elasticity of 1.32 for direct CO_2e footprint and 0.89 for the indirect CO_2e footprint, define the reaction of the footprint when moving from the average income of the first quintile to the average income of the second quintile. The income elasticity of the direct CO_2e footprint is still above unity for the second quintile and then decreases to a value of 0.69. Again, the shift when moving from the fourth to the fifth quintile is larger than in all other cases of moving from one quintile to the next. This can again be seen as an indication that further disaggregating the top 20% households of the income distribution could be worthwhile. The results lead us to assume that within this group the income elasticity might decrease continuously as well and for the last step of 10% or 5% of the income distribution might be considerably smaller. The income elasticity of the indirect CO_2e footprint is always below unity and decreases from 0.89 for the first quintile to 0.62 for the fourth quintile. As can be easily seen, these values are in general within the range of the literature except for direct emissions. It must – though – be noted here that a large part of the literature does either not differentiate between direct and indirect emissions or not include direct emissions. This high income elasticity of the direct CO_2e footprint at the bottom of the income distribution of households needs to be seen in the context of the relatively high MPC of low income households for durables (Table 1). The durable stock enters energy consumption (and thereby direct CO_2 emissions) with a unitary elasticity (equations (8) to (10) and Table 2).

Table 1: Excess sensitivity of consumption w.r.t. lagged disposable income (without profit income)

Sensitivity, low									
	1st quintile		2nd quintile		3rd quintile		4th quintile		5th quintile
$\text{dlog}(C_{dur})$	0.45	***	0.38	***	0.30	**	0.21		0.14
	(0.15)		(0.16)		(0.16)		(0.16)		(0.16)
$\text{dlog}(C_{nondur})$	0.94	***	0.76	***	0.58	***	0.38	***	-0.03
	(0.41)		(0.20)		(0.15)		(0.12)		(0.13)
Sensitivity, high									
	1st quintile		2nd quintile		3rd quintile		4th quintile		5th quintile
$\text{dlog}(C_{dur})$	0.44	***	0.40	**	0.33	***	0.26	**	0.20
	(0.13)		(0.14)		(0.14)		(0.14)		(0.14)
$\text{dlog}(C_{nondur})$	1.02	***	0.86	***	0.69	***	0.49	***	0.09
	(0.37)		(0.18)		(0.14)		(0.12)		(0.09)

*, **, and *** indicate significance at the 10%, 5% , and 1% level, respectively

Table 2: Price and expenditure elasticity of energy and non-energy demand of households (Indian panel 2005-2021, Indian cross section, 2020/2021)

Nondurable Consumption	own price elasticity	expenditure elasticity Time series	Cross section
Food	-0.14	0.85	0.61
Clothing	-0.64	1.04	1.28
Furniture/equipment	-1.06	1.11	1.46
Health	-0.83	0.98	1.20
Communication	-0.89	0.96	0.68
Recreation/accomodation	-0.50	1.08	1.27
Financial Services	-0.94	1.33	1.00
Other	-0.68	1.09	1.00
Energy Consumption	own price elasticity	durable stock elasticity	
Transport fuel	-0.77	1.00	
Heating	-0.87	1.00	
Electricity	-0.81	1.00	

Table 3: Parameters for factor demand (price elasticity, factor bias) and wage function

Production	own price elasticity	cross price elasticity, E/K	rate of factor bias
K, all industries	-0.95		0.00
L, all industries	-0.51		-0.01
E, all industries	-0.53		0.02
E, energy intensive	-0.37	0.20	0.00
all industries		0.15	
M(m)	-0.75		0.02
Wage curve	long-run elasticity		
Consumer price	0.82		
Productivity	0.27		
Unemployment rate	-0.06		

More insights in what might be driving the small 'Kuznet effect' in our results can be gained by looking into the commodity structure of consumption on the one hand and the indirect CO_2e footprint of quintiles on the other hand (Table 7). As can be seen, rich households exhibit considerably lower shares of

Table 4: Macroeconomic impact of consumption by quintile

	1st quintile	2nd quintile	3rd quintile	4th quintile	5th quintile
GDP, const. prices	2.7	3.6	4.0	4.2	4.5
Private Consumption, const. prices	0.6	0.6	0.5	0.2	-0.2
Capital formation, const. prices	0.0	0.0	0.1	0.1	0.1
Exports, const. prices	-4.6	-7.7	-10.4	-13.7	-21.1
Employment (persons)	4.9	7.2	8.7	10.3	13.7
Unemployment rate (% points)	-4.2	-6.3	-7.7	-9.0	-10.5
GHG emissions, direct	5.4	11.5	17.7	24.8	40.5
GHG emissions, indirect	18.6	31.1	41.3	53.6	83.6
GHG emissions, total	15.3	26.2	35.4	46.5	72.9

Table 5: Cross quintile income impact of consumption by quintile

	1st quintile	2nd quintile	3rd quintile	4th quintile	5th quintile
Total	5.2	8.1	10.4	12.9	19.6
1st quintile		5.7	7.5	9.7	15.4
2nd quintile	4.6		9.3	11.7	18.2
3rd quintile	4.9	7.7		12.3	19.1
4th quintile	5.2	8.1	10.3		19.8
5th quintile	5.7	8.8	11.2	13.9	

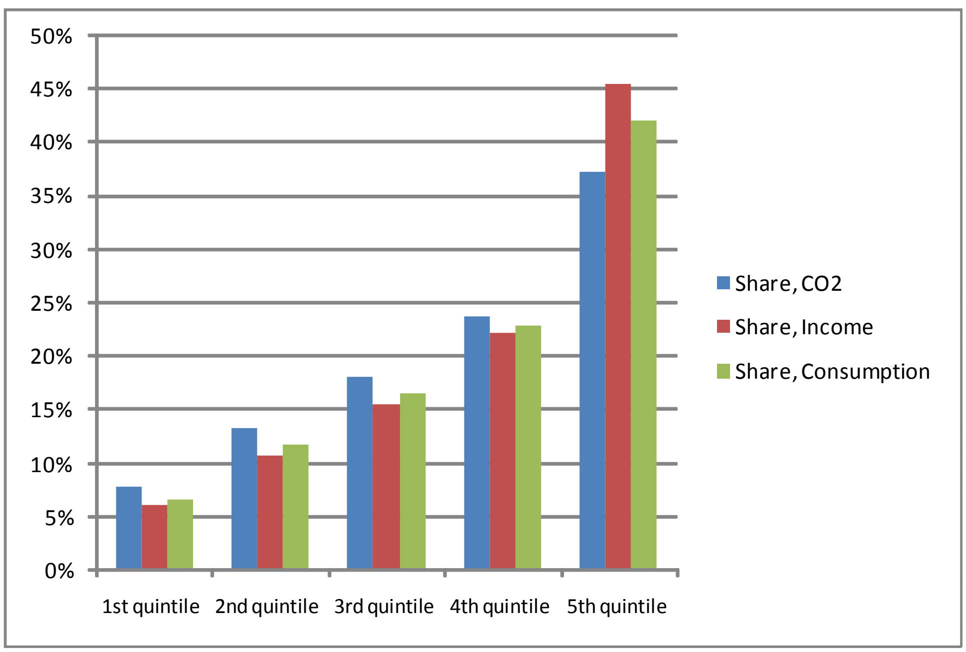

Figure 1: Income, Consumption and CO_2e footprint by quintiles (shares in %)

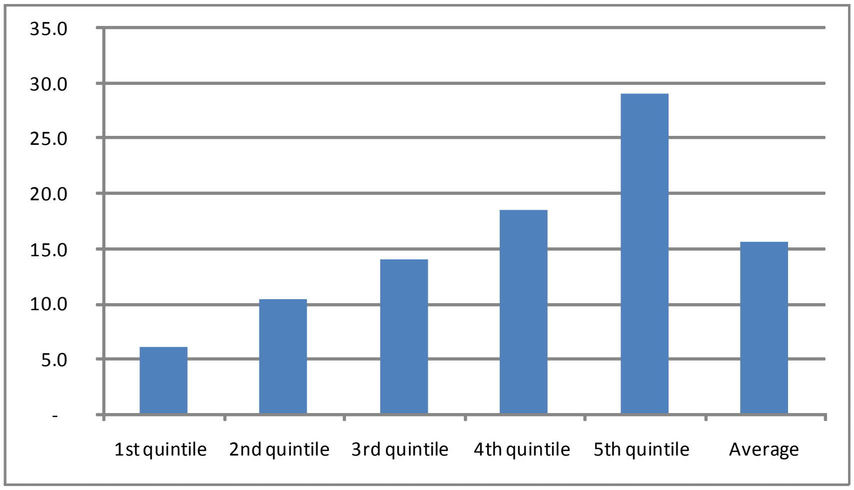

Figure 2: CO_2e footprint by quintiles (in t CO_2e per capita)

Table 6: Direct and indirect CO_2e footprint: structure and income elasticity by quintile

	1st quintile	2nd quintile	3rd quintile	4th quintile	5th quintile
Shares (%)					
Direct	8.7	10.9	12.5	13.3	13.8
Indirect	91.3	89.1	87.5	86.7	86.2
Income Elasticity					
Direct	1.32	1.18	0.95	0.69	
Indirect	0.89	0.78	0.74	0.62	

Table 7: Structure of indirect CO_2e footprint and consumption by quintile

	1st quintile	2nd quintile	3rd quintile	4th quintile	5th quintile
Agriculture, hunting and related services					
share in consumption	3.07	2.92	2.71	2.48	2.02
share in indirect emissions	8.02	7.58	7.17	6.76	6.10
Food products and beverages					
share in consumption	15.85	14.87	13.59	12.14	9.38
share in indirect emissions	4.31	4.12	3.95	3.80	3.56
Coke, refined petroleum products					
share in consumption	4.79	5.37	5.88	6.23	5.88
share in indirect emissions	3.73	3.71	3.76	3.77	3.68
Chemicals, chemical products					
share in consumption	2.00	2.33	2.43	2.56	3.01
share in indirect emissions	8.63	8.66	8.68	8.73	9.03
Radio, television and communication equipment					
share in consumption	0.56	0.68	0.73	0.79	0.85
share in indirect emissions	3.49	3.52	3.53	3.55	3.68
Motor vehicles, trailers					
share in consumption	2.15	2.85	3.54	3.99	5.71
share in indirect emissions	2.04	2.08	2.13	2.17	2.23
Electrical energy, gas, steam and hot water					
share in consumption	2.37	3.25	3.56	3.87	3.76
share in indirect emissions	11.93	12.86	13.05	13.23	12.73

food and agricultural products in the consumption structure, which are not fully compensated by the higher shares of other emission intensive products (gasoline/diesel, electricity, air transport) in their consumption basket.

4. Conclusions

The objective of this study is fully integrating household behavior of five household income groups into a hybrid model (between CGE and econometric IO) and deriving the CO_2e footprint of different income groups from model simulation results. The CO_2e footprint calculated not only takes into account endogenous intermediate demand like in traditional static IO analysis, but also induced consumption in the other groups and other endogenous final demand, as well as wage and price effects due to the demand pull.

The direct and indirect CO_2e footprint of the five groups exhibit several aspects of a small 'Kuznets effect': the share of the top income group in income (45%) is much larger than its share in the CO_2e footprint (37%) and vice versa for the bottom income group (6% in income and 8% in footprint). In per capita terms the bottom income CO_2e footprint is more than 2.5 times smaller than the average per capita footprint (15.7 t CO_2e), whereas the top income footprint is less than twice as large. There is a strong indication in all results that the top 20% income group should be further disaggregated, as one observes a significant shift in all results between the fourth and the fifth quintile. The 'Kuznets effect' is mainly driven by other indirect GHG emissions (CH_4) linked to agricultural production and the relatively high share of food consumption at the bottom of the income distribution. This effect would even be magnified, if the agricultural sector would be further disaggregated. Rich households consume agricultural products with higher prices, but not necessarily with higher energy/emission intensity.

There are several aspects in the results that underline the importance of the general philosophy in this paper of integrating household behavior consistently into the production (IO) structure. The different marginal propensity of consumption for nondurable and durable goods plays an important role in explaining the differences in income vs. CO_2e footprint shares as well as in the heterogeneity of the income elasticity of the direct CO_2e footprint. Another important aspect is the difference of consumption in other income groups induced by the consumption of each income group.

Several results of this analysis are different from what the literature has found by applying aggregate econometric analysis or only static IO analysis.

One applies to the share of indirect emissions by income groups and the other to the income elasticity of the CO_2e footprint.

We find – in contrast to the standard result of the literature – that indirect emissions play a more important role (in relative terms) for bottom income households. The main reason for this seems to be the CH_4 emissions from agricultural products. The income elasticity of the direct and indirect CO_2e footprint in this study takes into account macroeconomic (or general equilibrium) feedbacks and therefore is not limited to the ceteris paribus condition that needs to hold for the elasticity values estimated in the literature. It is calculated on the results of the model simulations and can be interpreted as the relative reaction of the footprint when moving from the average income of one quintile to the next. The income elasticity of the direct CO_2e footprint is 1.32 for the first quintile and still above unity for the second quintile and then decreases to a value of 0.69. The income elasticity of the indirect CO_2e footprint is always below unity and decreases from 0.89 for the first quintile to 0.62 for the fourth quintile.

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