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Harnessing Technological Innovation for Poverty Reduction: Sectoral and Microsimulation Insights from Cameroon and the DRC

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ABSTRACT

This study investigates Cameroon and the Democratic Republic of Congo, both contending with significant technological disparities—defined as variations in capital-augmenting technological capacity across sectors that influence productivity and growth potential. Using data from the year 2015, the analysis employs a dynamic computable general equilibrium (CGE) model combined with a microsimulation approach. The study examines how capital-augmenting technological innovation (TI)-that is, improvements in the efficiency of capital use-affects key macroeconomic variables such as GDP growth, wage rates, consumption patterns, and household welfare. Results from the CGE simulations reveal that increased TI positively influences GDP growth through contributions from agriculture, industry, and transport sectors. Welfare and income effects benefit households engaged in innovative sectors, while investment and consumption responses differ across activities. At the micro level, higher TI reduces poverty rates in both countries, especially within agriculture, industry, and transport. The findings highlight the importance of targeted investments in technology-intensive sectors to maximise TI's benefits for growth, income distribution, and poverty reduction. Policymakers are encouraged to foster innovation-friendly environments, support entrepreneurship, and promote inclusive growth strategies that enhance labour market outcomes and long-term welfare.

Keywords: Technological Innovation and Poverty; Technological Innovation and Sectoral Productivity; Technological Innovation and Microsimulation; Computable General Equilibrium Model; Central Africa

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1. Introduction

The alleviation of poverty stands as a pivotal objective within the scope of sustainable development. This initiative has given rise to several attempts to forecast poverty trends [1]. Wilson et al. [2] demonstrated that poverty reduction is more effective than economic growth in reducing income inequality. Both the African Union's Agenda 2063 and the United Nations' Agenda 2030 endorse the crucial role of science, technology, and innovation in pursuing inclusive and sustainable development [3]. These agendas highlight the significance of science, technology, and innovation as fundamental drivers of progress and prosperity. In alignment with this, the Science, Technology, and Innovation Strategy for Africa 2024 (STISA–2024) was introduced, serving as a comprehensive framework aimed at propelling Africa towards an innovation-centric economy [3].

Numerous studies have demonstrated the poverty–reducing potential of technological innovation. A significant body of literature explores the impact of technological innovation on economic growth, with seminal works by authors such as Romer [4] and Solow [5] laying the theoretical groundwork. Subsequent research emphasizes innovation as a catalyst for inclusive growth and poverty reduction [6]. Extensive empirical evidence highlights the positive influence of technological innovation on economic growth and investment [7–11]. These advancements further contribute to enhanced social welfare and broader employment opportunities [12–16]. Specific mechanisms, such as labor–saving innovations and the widespread adoption of new technologies, fundamentally shape modern employment dynamics [17–19]. Beyond macroeconomic growth, addressing poverty involves direct enhancements to farmers' welfare alongside indirect benefits gained through increased employment and higher wages [20, 21]. Sachs [22] points out the pivotal role of scientific and technological advancements in substantially reducing extreme poverty globally. Berdegue and Escobar's [23] research illustrates how technological innovation can directly enhance the well–being of farming households, with outcomes varying based on integration within agricultural markets. Moreover, technological innovation yields secondary benefits for impoverished populations by influencing factors such as food prices, employment prospects, and interconnected relationships across various sectors of the economy. However, gaps persist in sector–specific investigations of the impact of technological innovation on poverty, as well as the integration of the spatial distribution of households to examine the effects of technological innovation on both urban and rural poverty.

In this study, technological innovation is specifically conceptualised and measured as a capital-augmenting technological advancement. This means the focus is on innovations that increase the productivity of the capital stock within the economy's production structure. In the context of the applied Dynamic Computable General Equilibrium (CGE) model, this is operationalised through a simulation shock that increases the efficiency parameter associated with the capital input across key productive sectors. This particular conceptualisation is chosen because it directly addresses the capital deficit and low absorptive capacity typical of Sub-Saharan African economies like Cameroon and the DRC, allowing the analysis to trace how improved efficiency in capital usage (e.g., better machinery, improved infrastructure utilisation, or more effective production processes) translates through the economy to affect wages, prices, and ultimately, household poverty across rural and urban divides.

This paper explores the role of technological innovation in alleviating poverty in Cameroon and the Democratic Republic of Congo (DRC), two nations grappling with significant technological underdevelopment and prevalent poverty. Despite ongoing efforts to bridge the innovation gap, these countries, typical of many emerging economies in Sub–Saharan Africa, continue to lag behind in technological advancement. For instance, the Democratic Republic of Congo (DRC) witnessed an increase in its research and development expenditure from 0.07% of GDP in 2009 to 0.40% in 2015, as reported by the World Bank. However, despite notable strides, challenges remain. The Global Innovation Index highlights a concerning decline in Cameroon's innovation index from 27.8 in 2015 to 23.90 in 2019, plummeting further to 15.1 points in 2022. In that year, Cameroon ranked 18th among 25 surveyed sub–Saharan African countries and stood at 121st out of 132 globally. The distribution of poverty rates in Cameroon is as follows: 55.19% in rural areas, 21.81% in urban centres, and an average of 37.5% across the entire nation, according to data from the ECAM 4 database. In the Democratic Republic of Congo, prevailing poverty rates are delineated as 80.02% in rural regions, 43.19% in urban hubs, and a comprehensive national average of 63.4%, according to EDS–RDC (2013–2014) database.

Cameroon and the Democratic Republic of Congo (DRC) form a comparative pair because they represent divergent structural conditions in Central Africa under which capital-augmenting technological change may operate differently. Cameroon, as a lower-middle-income economy with more diversified agro-industrial activities and moderately stable macro-indicators [24], contrasts with the DRC, a low-income, resource-rich economy marked by large-scale natural-resource extraction, conflict fragility and weaker institutional capacity [25]. This juxtaposition allows testing of the hypothesis that the same increase in capital-augmenting technological innovation will yield differing outcomes depending on baseline absorptive capacity, market depth, sectoral structure and governance [26, 27]. By comparing these two countries, the study addresses how heterogeneity in technology adoption, factor usage and institutional environments mediate the transmission from innovation to GDP growth, labour-wage changes, consumption and household welfare across different African contexts [28].

A clear contrast emerges when comparing key demographic, macroeconomic and structural indicators. Demographically, the DRC's population (estimated over 100 million) is roughly four times that of Cameroon (around 28 million) and features a younger median age and higher growth rate — factors that intensify labour-market and human-capital dynamics. Macroeconomically, Cameroon records a higher GDP per capita (approx. USD 1700 in recent years) and a more diversified export base, compared to the DRC whose GDP per capita remains among the lowest globally despite large mineral rents [29, 30]. The DRC suffers from higher inflation, currency depreciation and frequent conflict-related disruptions to basic services [31]. In terms of welfare, the DRC's poverty headcount rate is extremely high (~72.9%) compared to ~23% in Cameroon under an extreme international poverty line ($2.15 PPP) [24, 32], while Cameroon's Gini coefficient of 42.2 underlines significant inequality [33]. These structural differences—population scale and growth patterns, GDP per capita and macro-volatility, conflict and institutional fragility, poverty and inequality burdens—directly affect how capital-augmenting technological innovation diffuses within firms/sectors, how labour and capital markets respond, and how inclusive the welfare impacts are across households.

Comparing poverty levels between Cameroon and the Democratic Republic of Congo requires rigorous harmonization of measurement assumptions to ensure valid cross-country comparability. In this study, poverty estimates rely on nationally representative data sources—the Fourth Cameroon Household Survey (ECAM 4) and the Demographic and Health Survey for the DRC (EDS-RDC 2013–2014)—which provide detailed information on household consumption and income. To achieve consistency across countries, all monetary values were adjusted for country-specific inflation using official Consumer Price Index (CPI) series and converted into a common purchasing power framework (PPP) for the base year 2015, in line with the World Bank's International Comparison Program methodology [34]. This adjustment ensures that differences in price levels and inflation dynamics do not distort welfare comparisons. Additionally, spatial price variations between urban and rural consumption baskets were explicitly taken into account to capture heterogeneity in living costs and consumption structures within each country [35]. By adopting these methodological refinements, the study upholds transparency and cross-country comparability, ensuring that the observed poverty differentials between Cameroon and the DRC reflect true structural and welfare disparities rather than artefacts of inflation, exchange-rate volatility, or spatial price inconsistencies.

To assess the impacts of technological innovation on poverty reduction and address the gap highlighted above, this study adopts a novel approach, analysing macro, meso, and micro aspects through a dynamic Computable General Equilibrium (CGE) analysis methodology. The macro– and meso–level analysis explores the effects of capital–augmenting technological advancement on key economic variables, including GDP growth, wage rates, consumption patterns, overall household welfare, and sectoral output. The micro–level investigation delves into household poverty impacts, particularly within the domains of agriculture, industry, and transport. This expanded scope enables a nuanced exploration of the differential effects of technological innovation on poverty across diverse sectors, yielding insights crucial for targeted policy interventions.

The paper's structure is as follows: after the introduction, Section 2 documents the literature on technological innovation and poverty. This is followed by the presentation of the methodology in Section 3. Section 4 presents and discusses the simulation results. Finally, Section 5 concludes the study.

2. Literature Review

Alleviating poverty stands as a crucial pillar of the Sustainable Development Goals. The literature has extensively addressed the role of technological innovation (TI) in achieving this goal. Karagozoglu & Brown[36] argue that governments should actively stimulate technological progress through various means like direct financial support, high–tech purchases, tax policies, and patent protection. This can lead to a healthy balance between social and private rates of return, ultimately reducing poverty. Numerous works have examined the impact of TI on various macroeconomic indicators such as economic growth, investment, welfare, and employment.

From an economic growth perspective, Romer[4] and Solow[5] stand as the pioneering authors who laid the theoretical groundwork for understanding how TI affects economic growth. While not explicitly addressing the technical aspect, their work illuminated a phenomenon where enhancing labour and capital inputs becomes a driving force behind economic expansion within the classical framework. Later, George et al.[6] constructed a similar theoretical framework, placing innovation at the heart of inclusive growth. They perceived innovation as a catalyst that not only generates but also enhances opportunities, leading to improved well–being and the alleviation of poverty. Expanding upon these foundational concepts, a plethora of empirical studies have emerged, providing robust evidence of the positive impact of TI on economic growth[7–11]. Further research demonstrates how these advancements stimulate investment and improve broader welfare metrics[12–16]. Additionally, the literature explores the nuanced relationship between innovation and long-term employment stability[17, 18]. For instance, Zhou & Luo[10] showed that the synergy between technological innovation and education yields a delayed yet ultimately positive impact on economic growth.

Regarding investment, various studies have shown a positive relationship between TI and investment[37–41]. For instance, Khan et al.[38] indicated that public–private partnership investment reacts positively to TI in the long–term. Loukil[39] explored a reverse relation, showing the existence of a threshold between foreign direct investment (FDI) and TI. Thus, there is a certain level of FDI that fosters TI, beyond which its impact becomes negative. Building on these investment dynamics, recent scholarship has further explored how infrastructure and policy frameworks support these technological transitions[42, 43].

On the welfare front, many authors have investigated this issue[44–48]. They generally converge on the idea that TI improves overall welfare. For instance, Barnett[44] emphasised that maximising welfare results from conditions that shift the supply curve and increase dynamic efficiency. However, welfare improvement is closely tied to better employment conditions.

The effect of TI on employment is of major concern for workers[49]. These authors demonstrated that TI has a positive but small impact on employment based on data from six OECD countries. This finding is consistent throughout the literature. Specifically, studies focusing on technological displacement and skill-biased changes support this trend[50–52], while research emphasizing the compensatory effects of market expansion further validates these outcomes[53–55]. In a more specific study, Bogliacino & Pianta[56] established that innovation positively affects job creation in both the manufacturing and services sectors. This success can be attributed to increased demand and wages. This success can be attributed to increased demand and wages. Similarly, Benavente & Lauterbach[57] demonstrated that product innovation positively affects employment in Chile. However, the evidence did not suffice to draw conclusions on the efficacy of sectoral investment in innovation on employment outcomes. Acar & Sever[58] found that innovation in exportable products triggers job creation in Turkey.

Yet, Vivarelli[19] provides an overview of how TI influences employment and poverty. He identifies direct and indirect mechanisms through which TI shapes employment dynamics. Generally, innovative efforts must focus on reducing production costs to produce the same output with fewer production inputs, particularly labour. Consequently, the widespread adoption of new machines may lead to the replacement of workers in some or all tasks. However, the availability of robots necessitates additional production. This results in a shift of workers from industries that employ robots downstream to sectors engaged in producing these robots upstream, thereby countering the initial negative impact on employment[59]. Vivarelli[19] identifies three primary pathways through which this equilibrium is achieved: prioritizing profitability, integrating labour–saving technologies in the capital goods sector, and implementing new machines either through additional investments or by substituting obsolete ones. This perspective aligns with Dosi et al.'s[60] viewpoint, further solidifying the orientation toward the concept of TI.

Regarding the issue of poverty, existing literature converges on the idea that TI positively affects poverty alleviation. De Janvry et al.[20], investigating the contribution of technological change in agriculture to poverty reduction, highlighted two main channels through which this is possible: direct and indirect effects. The direct effect involves the improved welfare of poor farmers who adopt TI. This improvement arises from increased production for home consumption, higher gross revenue from sales, lower production costs, reduced yield risks, lower exposure to harmful chemicals, and enhanced natural resource management. The indirect effect involves an increase in employment and wages.

Dhrifi[21] found that a 1% increase in TI reduces poverty by 0.31%. In contrast, Si et al.[61] emphasised that technology development promotes social and economic development, generating new approaches and solutions for poverty reduction while challenging existing poverty research theories. The potential of investing in TI is exemplified by Sachs[22], who suggested that such investments could assist the most impoverished nations in halving their poverty rates by 2015. Beyond its role in stimulating economic growth, technology can augment food supplies, curtail morbidity and mortality, particularly within developing nations, and enhance access to water and energy for disadvantaged communities[21].

Zameer et al.[62], Wang & Tan[63], and Ye et al.[64] further explained that, aside from TI, financial innovation can also reduce poverty, and this applies not only to specific household groups. It is noteworthy, however, that Srinivas & Sutz[65] contextualize TI as a process whose relevance is shaped by the socio–economic circumstances in which it is embedded. Nonetheless, Smith et al.[66] emphasized that even amidst the diversity among various developing countries, appropriate technology initiatives share common characteristics. These included low capital cost, utilisation of local materials, job creation through local skills and labour, affordability for small groups, local understanding, control and maintenance, collective use and collaboration, and avoidance of patents and property rights.

In recent literature, the focus on TI and poverty has increasingly shifted towards climate change and energy poverty[67, 68]. Nonetheless, the fundamental observation remains unchanged. These studies pinpoint two notable limitations: firstly, to the best of our knowledge, none of them have thoroughly investigated the impact of technological innovation on poverty within specific sectors of the economy. Here, we address this gap by focusing on three sectors: agriculture, industry, and transport. The significance of this lies in the potential heterogeneity between diverse economic sectors within a nation, resulting in varying levels of poverty and necessitating tailored approaches. The second limitation pertains to the integration of the residential zone. While microsimulation studies often cover this dimension[69, 70], there remains an absence of research concerning the connection between TI and poverty based on household location. We remedy this situation by investigating the rural and urban impacts, which yield significant disparities depending on the selected country. To address these limitations, we describe in the following section the methodology employed, which utilises a specific tool that accounts for sectoral impacts. This explains why we have chosen to give precedence to the dynamic Computable General Equilibrium (CGE) analysis in this study.

3. Methodology

In this study, we assess the effects of technological innovation on poverty reduction using the top–down Microsimulation approach, a methodology pioneered by Chen & Ravallion[71]. This method involves integrating product and factor price changes derived from a Computable General Equilibrium (CGE) model into a microsimulation household model. The following sub-sections detail the necessary data, the CGE model's features, and the poverty measurement approach.

3.1. Data Sources and Social Accounting Matrix Structure

3.1.1. Data Sources

The foundation of this research rests on two primary data sources: the Social Accounting Matrices (SAMs) and the Household Survey Data for Cameroon and the Democratic Republic of Congo (DRC). The SAMs for both countries were constructed using data from the reference year of 2015. This year was selected due to the optimal availability of harmonised data required for SAM creation and alignment with the corresponding household surveys. The raw data for the SAMs were sourced from National Accounts Statistics, Input-Output Tables, Balance of Payments, and Government Finance Statistics. These raw matrices were subsequently modified and aligned with the specific PEP-w-t SAM structure to ensure full compatibility with the model.

For the microsimulation, we utilise the fourth edition of Cameroon Households Data Survey (ECAM) for Cameroon and the comparable comprehensive household survey for the DRC (EDS–RDC). These surveys are crucial as they provide detailed household-level information on factor endowments, income sources, and expenditures. Cameroon data (Fourth Household Survey) are from 2014. And DRC (Demographic and Health Survey) data are from 2013-2014.

3.1.2. SAM Structure

According to Hossain et al.[72] a SAM is a square matrix that illustrates the inter-linkages among domestic sectors and interactions with the rest of the world, ensuring that the sum of each account's columns aligns with its corresponding row sums. The SAMs employed in this study consist of a total of 49 accounts. This disaggregated structure includes five accounts for factors of production (Skilled Labour, Unskilled Labour, Land, Natural Resources, and Capital), ten accounts for various economic activities (such as Agriculture, Mining, Food, Industries, Utilities, Consumption, Trade, Transport, Services, and Public Administrations), twenty commodity accounts (ten exportable and ten domestic), four economic agent accounts (representative household, firms, Government, and the Rest of the World), as well as accounts for direct tax, import tariff, indirect tax, factor income earning, factor income uses, accumulation, and inventory.

3.2. CGE Model Description

Over the past decades, CGE models have gained significant popularity, particularly due to their capability to analyse sectoral impacts[73] as well as households' level effects within a microsimulation framework. As described by Lemelin[74], a CGE model comprises a system of simultaneous equations that establish relationships between variables, with some being endogenous and determined within the model, while others remain exogenous. This study uses the dynamic CGE module of the PEP network, specifically the PEP–1–t version developed by Decaluwé et al.[75]. This model is a system of simultaneous equations based on neoclassical economic principles.

3.2.1. Brief Description of the Model

The schematic diagram (see **Figure 1**) presents the dynamic structure of the PEP-1-t CGE model, highlighting the flow of goods, factors, and income across agents and markets. The representative agent allocates income across labor (α_H), capital services (α_G), and foreign transfers (α_R), reflecting the initial endowment shares. Labor (LD_D) and capital (KD_D) are used in production, with substitution governed by elasticities σ_{LD} and σ_{CD}. The goods market aggregates supply and demand, with household consumption captured by β, government demand by σ_M, and exports by σ_Θ. The government collects taxes and transfers income abroad via α_{RT}, while the rest of the world interacts through trade and transfers, modulated by θ_0. This schematic complements the algebraic formulation by clarifying the role of each coefficient in shaping equilibrium and intertemporal dynamics.

3.2.2. Key Equations of the Model

Sectoral output is modelled using a Constant Elasticity of Substitution (CES) nested structure. At the initial level, output is a combination of value added and Intermediate Inputs[76]. Intermediate inputs follow a Leontief specification as a fix proportion of sectoral output as shown by the following equation:

$$DI_{i,j,t} = io_j.CI_{j,t} \tag{1}$$

With $DI_{i,j,t}$ the intermediate demand of commodity i by sector j; $CI_{j,t}$ the total intermediate demand by sector j computed by:

$$CI_{j,t} = io_j.XS_{j,t} \tag{2}$$

Where $XS_{j,t}$ represents the output of sector j.

Value added $VA_{j,t}$, is in turn, a CES function of the five factors of production. Firms minimise production costs subject to this function to determine factor demand. Its final formula is given by:

$$\begin{aligned} VA_{j,t} = B_j^{va}\Big[&\vartheta_j^{va}.LDC_{j,t}^{-\rho_j^{va}} \\ &+ \left(1-\vartheta_j^{va}\right).KDC_{j,t}^{-\rho_j^{va}}\Big]^{-\frac{1}{\rho_j^{va}}} \end{aligned} \tag{3}$$

Where $LDC_{j,t}$ and $KDC_{j,t}$ represent the composite labor and composite capital respectively; ρ_j^{va} is the CES elasticity of substitution parameter; ϑ_j^{va} the distributive parameter; and B_j^{va} the scale parameter.

The representative household maximises utility subject to its budget constraint. Consumption demand is determined using the Linear Expenditure System (LES), which allows for both subsistence consumption and income-elastic demand.

$$C_{i,h,t} = \frac{PC_{i,t}.Cmin_{i,h,t} + \gamma_{i,h}^{LES}(CTH_{h,t} - \sum_i PC_{i,t}.Cmin_{i,h,t})}{PC_{i,t}} \tag{4}$$

Where $C_{i,h,t}$ represents the consumption demand for commodity i by household h; $Cmin_{i,h,t}$ the subsistence consumption; $CTH_{h,t}$ the total consumption by household h; and $PC_{i,t}$ the market price of composite commodity. $\gamma_{i,h}^{LES}$ is the LES parameter.

The model adopts the standard trade specifications. For imports, the Armington[77] specification is used, assuming domestically produced goods and imported goods are imperfect substitutes (CES aggregation, Equation 5). For exports, domestic producers allocate their output between the domestic and foreign markets using a Constant Elasticity of Transformation (CET) function, assuming domestic and export goods are imperfect transforms (see Equation 6).

$$\begin{aligned} Q_{j,t} = B_j^m \Big[& \vartheta_j^m . D_{j,t}^{-\rho_j^m} \\ & + \left(1 - \vartheta_j^m\right) . IM_{j,t}^{-\rho_j^m} \Big]^{-\frac{1}{\rho_j^m}} \end{aligned} \tag{5}$$

Where $Q_{j,t}$ represents the composite commodity; $IM_{j,t}$ the imports and ρ_j^m; ϑ_j^m; $B_j^m$the CES elasticity of substitution, distributional parameter and the scale parameter respectively.

$$\begin{aligned} XS_{j,t} = B_j^{xs} \Big[& \vartheta_j^{ex} . D_{j,t}^{\rho_j^{ex}} \\ & + \left(1 - \vartheta_j^{ex}\right) . EX_{j,t}^{\rho_j^{ex}} \Big]^{1/\rho_j^{ex}} \end{aligned} \tag{6}$$

$XS_{j,t}$ represents the sectoral output; $EX_{j,t}$ the exports and ρ_j^{ex}; ϑ_j^{ex}; B_j^{ex} the CET elasticity of substitution, distributional parameter and the scale parameter respectively.

The macroeconomic closure ensures that the model is fully defined: investment is savings-driven, the government budget closure is achieved by adjusting the indirect tax rate.

3.2.3. Calibration and Validation Process

The model is calibrated to the SAM data for the benchmark year, 2015, ensuring it perfectly replicates all financial flows recorded in the matrix. Key elasticity parameters and marginal propensity parameters are sourced from the established literature and adapted to align with the economic characteristics of Cameroon and the DRC. For validation, we simulate a baseline scenario without the technological shock and we make sure that the benchmark is reached. The model's dynamic projections for key macroeconomic indicators such as GDP growth and inflation are compared against historical trends and independent economic forecasts for the simulation period (2015–2040) to confirm that the model's trajectory is economically plausible.

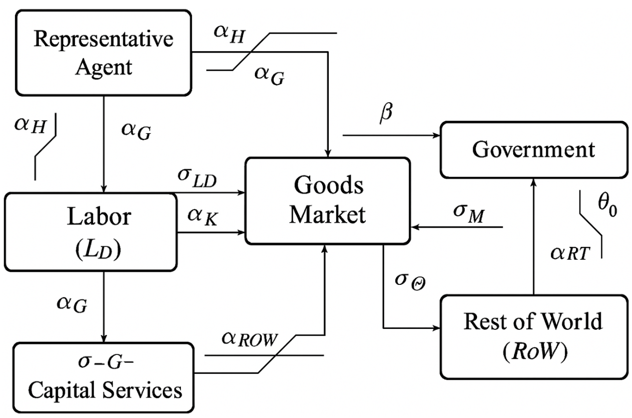

Figure 1. Schematic sketch of the model.

Source: The authors.

3.3. Technological Innovation Scenarios and Simulation

3.3.1. Simulating Technological Innovation

The core equation of the simulation is Equation (3), which is adjusted using the technological parameter as shown below:

$$\begin{aligned} VA_{j,t} = B_j^{va} \Big[& \vartheta_j^{va} . A_{j,t}^L . LDC_{j,t}^{-\rho_j^{va}} \\ & + \left(1 - \vartheta_j^{va}\right) . A_{j,t}^K . KDC_{j,t}^{-\rho_j^{va}} \Big]^{-\frac{1}{\rho_j^{va}}} \end{aligned} \tag{7}$$

Where $A_{j,t}^L$ and $A_{j,t}^K$ are the technological parameters related to labor and capital respectively initially set at the unity. Any change in only one factor signifies Harrod–neutral technological progress, while a change in both coefficients in the same proportions reflects Hicks-neutral technological progress. This methodology can be accessed in Lennox & Parrodo[78].

In this study, our emphasis is directed towards technological advancements that enhance capital productivity. Capital–augmenting technological change defines a distinct form of technological advancement that enhances the productivity and operational efficiency of capital goods, including machinery, equipment, and tools. Notably, this form of progress does not directly impact the quality of labour. Instead, its primary effect is directed towards enhancing the production process, refining the inherent capabilities of capital–intensive factors, thereby facilitating enhancements in overall output. Hence, only the coefficient $A^K_{j,t}$ is considered in our simulations.

3.3.2. Scenarios and Simulation Implementation

Following the precedent description, we centre our attention on three sectors: agriculture, industry, and transport. Regarding agriculture, innovation involves the use of advanced machinery like tractors, combine harvesters, and automated irrigation systems. Within the industrial sector, this encompasses automated assembly lines, Computer-Aided Design, and other pertinent technologies. In the field of transportation, innovation in a developing country context involves intelligent traffic signals, real–time traffic monitoring systems, automated toll payment systems, as well as e-ticketing and cashless payments solutions for enhanced traffic management.

We introduce a marginal increment to $A^k_{j,t}$, keeping i constant. Our simulation commences in 2023 with a growth rate of 20%. Subsequently, we assume a gradual reduction in this rate over the temporal span in an arithmetic progression, ultimately reaching 2040, where no shock is introduced. To achieve this, we have derived an equation to accurately compute the rate to be applied, as presented below:

$$Coef(t) = 1.2 + t\frac{1-1.2}{18} \tag{8}$$

By employing an iterative algorithm with time indexing t, the outcomes presented in **Table 1** were derived.

Table 1. Marginal increase rate in the TI.

Year	2023	2024	2025	2026	2027	2028	2029	2030	2031
Rate applied	1.2	1.188	1.176	1.165	1.153	1.141	1.129	1.118	1.106
Year	2032	2033	2034	2035	2036	2037	2038	2039	2040
Rate applied	1.094	1.082	1.071	1.059	1.047	1.035	1.024	1.012	1

Source: Authors.

Hence, the following scenarios are examined:

- Scenario 1: Total Economy–wide Technological Innovation:

Within this scenario, we introduce modifications to the coefficient $A^k_{j,t}$ through an iterative algorithm. Specifically, $A^k_{j,t}$ is adjusted as $A^k_{j,t} = A^k_{j,t} \cdot (1 + Coef(t))$. Notably, this intervention is limited to three key sectors, namely agriculture, industry, and transport.

- Scenario 2: Agricultural Sector Technological Innovation

In this case, the technological innovation focuses solely on the agricultural sector. Here, $A^k_{j,t}$ transforms into $A^k_{'agri',t} = A^k_{'agri',t} \cdot (1 + \text{Coef(t)})$;

- Scenario 3: Industrial Sector Technological Innovation

Within this scenario, the technological innovation is exclusive to the industrial sector. Accordingly, $A^k_{j,t}$ takes on the form $A^k_{'ind',t} = A^k_{'ind',t} \cdot (1 + Coef(t))$;

- Scenario 4: Transport Sector Technological Innovation

This scenario is characterised by technological adjustments solely within the transport sector. Thus, $A^k_{j,t}$ is transformed to $A^k_{'tran',t} = A^k_{'tran',t} \cdot (1 + \text{Coef(t)})$.

Furthermore, we assess the robustness of our findings through a sensitivity analysis. In this regard, we implemented a 50% augmentation in the substitution parameter values within the value–added equation. For the sake of simplicity, we conducted this assessment exclusively for scenario 1. The outcomes of this analysis are presented in tables in section 4.2. Notably, the primary observation deduced from this exercise is the consistency of our results with respect to exogenous parameters, as evidenced by the absence of significant changes.

3.4. Microsimulation Model

A microsimulation model (MSM) is a modeling technique used to analyse the distributional impacts, including poverty and inequalities, of economy-wide shocks or policies. According to Abouna[79], a MSM is a partial equilibrium model addressing the limitations of CGE models to account for the distributional impacts analyses. Microdata on households' income and expenditure are necessary to conduct a microsimulation analysis. MSMs stem from the household income generated model[80]. The link from CGE simulations to the microsimulation model is made by feeding price changes, sectoral output and sectoral employment as inputs for the household-level analysis. In this study, we assess the effects of technological innovation on poverty reduction using the top–down microsimulation approach developed by Chen & Ravallion[71]. This method involves integrating product and factor price changes from a CGE model into a microsimulation household model[79, 81]. The adjusted household incomes (or expenditures) are then used with the calculated poverty lines to compute the Foster Geer Thorbecke (FGT) index developed by Foster et al.[82]. The general formula is given by:

$$P_\alpha = \frac{1}{n} \sum_{i=1}^{q} \left[\frac{\mathcal{Z} - y_i}{\mathcal{Z}} \right]^\alpha \tag{9}$$

Where n is the population size, $\mathcal{Z}$ the poverty line, y_i the income of the $i^{'}s$ individual, q the total number of individuals whose income is below the poverty line, α is the poverty level, which takes three values (0 for incidence, 1 for depth and 2 for severity).

To conduct sectoral analyses, we begin by examining various scenarios within the CGE model. The resulting impacts on households' income, expenditures, and factor prices are then incorporated into the households' data survey, where poverty lines are initially computed for both countries under investigation. The research assesses the poverty levels among households engaged in the agricultural, industrial, and transport sectors, considering the degree of technological innovation within each respective sector. Additionally, sensitivity analysis is performed using the CGE results. In the second scenario, the focus is solely on technological innovation in the agricultural sector. All poverty analyses are carried out using the DASP package of Stata software. The implementation is more precisely done following the steps:

- The CGE-generated changes in factor and commodity prices are applied to the initial micro-data.
- New Household Income: The change in factor prices is used to calculate the new total income for each household.
- New Consumption: The change in commodity prices is used to calculate the new real value of each household's consumption expenditure.
- Poverty analysis: The new real consumption/income is then compared against the harmonized poverty lines to calculate post-shock poverty indicators at the household level.

4. Results and Discussion

To assess the effects of technological innovation on poverty reduction, it is essential to conduct both macro and micro analyses. The macro impacts focus on overall changes in GDP growth, investment, and the wage rate, while the meso and micro impacts delve into the impacts on sectoral output, and households, including household income and consumption. Consequently, this section is divided into two parts: the first part presents the primary findings from the CGE analysis, while the second part explores poverty–related aspects.

4.1. Macro and Sectoral Impact of CGE Analysis

4.1.1. GDP Impacts

Tables 2 and **3** illustrate the macroeconomic impact of technological innovation (TI) in Cameroon and DR Congo across various scenarios. In Cameroon, **Table 2** shows that a 20 percent increase in TI drives consistent GDP growth from 6.71 (2023) to 9.16 (2040). Enhanced TI in Agriculture yields incremental growth from 1.81 (2023) to 2.11 (2040), emphasising its role in agricultural productivity. Increased TI in Industry is anticipated to contribute to GDP, ranging from 0.81 (2023) to 1.18 (2040). Transport–related TI boosts connectivity, with GDP rising from 0.26 (2023) to 0.32 (2040). In DR Congo, **Table 3** indicates that an economy–wide TI expansion would raise GDP from 5.85 (2023) to 7.89 (2040). Agricultural TI would lead to GDP growth from 1.62 (2023) to 1.82 (2040), while Industrial TI would raise GDP by 0.66 (2023), reaching 0.89 (2040). Transport–driven TI would lead to GDP growth from 0.92 (2023) to 1.11 (2040), highlighting technology's trade–facilitating role.

Table 2. Macro impact of technological innovation for Cameroon.

		Scenario 1 (Economy–Wide)				Scenario 2 (Agriculture)				Scenario 3 (Industry)				Scenario 4 (Transport)			
		2023	2030	2035	2040	2023	2030	2035	2040	2023	2030	2035	2040	2023	2030	2035	2040
Welfare		35.46	26.95	26.51	26.14	6.10	4.55	4.52	4.51	4.01	3.22	3.25	3.27	1.51	1.08	1.04	1.00
GDP		6.71	7.85	8.57	9.16	1.81	1.91	2.01	2.11	0.81	0.98	1.09	1.18	0.26	0.29	0.31	0.32
Income		5.47	5.37	5.40	5.50	−0.92	−0.72	−0.61	−0.53	1.03	1.08	1.12	1.16	0.47	0.47	0.48	0.50
Investment		13.26	13.48	13.47	13.57	1.10	1.29	1.38	1.45	0.81	0.98	1.09	1.18	0.22	0.20	0.21	0.21
Output	Agriculture	6.29	7.35	8.10	8.76	−0.40	−0.06	0.19	0.41	1.23	1.34	1.44	1.52	0.23	0.24	0.25	0.26
	Industry	10.75	12.57	13.60	14.40	2.51	2.61	2.68	2.75	2.64	2.93	3.16	3.35	0.07	0.09	0.11	0.12
	Transport	8.37	10.92	12.40	13.53	2.65	2.69	2.73	2.77	0.70	0.96	1.14	1.29	3.26	3.53	3.73	3.88
HH Cption*	Agriculture	4.96	5.33	5.74	6.18	−4.08	−3.48	−3.14	−2.86	1.37	1.37	1.39	1.43	0.38	0.38	0.39	0.39
	Industry	3.34	4.58	5.43	6.12	2.40	2.40	2.44	2.48	−1.83	−1.60	−1.44	−1.28	0.23	0.28	0.30	0.33
	Transport	8.98	10.71	11.42	11.83	4.87	4.69	4.54	4.40	0.73	1.03	1.18	1.28	−2.90	−2.81	−2.65	−2.48
Wage	Agriculture	4.39	3.84	3.61	3.51	−2.34	−2.07	−1.95	−1.86	1.20	1.19	1.21	1.23	0.48	0.47	0.48	0.50
	Industry	4.38	3.95	3.76	3.69	−1.23	−1.03	−0.94	−0.87	1.00	1.02	1.05	1.07	0.42	0.42	0.43	0.44
	Transport	4.38	3.97	3.79	3.72	−1.04	−0.85	−0.76	−0.69	0.96	0.99	1.02	1.05	0.41	0.41	0.42	0.43

Source: Authors.

Table 3. Macro impact of technological innovation for DR Congo.

		Scenario 1 (Economy−Wide)				Scenario 2 (Agriculture)				Scenario 3 (Industry)				Scenario 4 (Transport)			
		2023	2030	2035	2040	2023	2030	2035	2040	2023	2030	2035	2040	2023	2030	2035	2040
Welfare		32.56	24.55	23.97	23.46	6.15	4.42	4.31	4.22	2.96	2.36	2.38	2.39	4.78	3.46	3.36	3.29
GDP		5.85	6.92	7.47	7.89	1.62	1.69	1.76	1.82	0.66	0.76	0.83	0.89	0.92	1.00	1.06	1.11
Income		3.17	3.16	3.33	3.52	−0.93	−0.84	−0.79	−0.75	1.04	1.09	1.13	1.15	1.20	1.26	1.32	1.36
Investment		8.39	8.25	8.29	8.42	0.62	0.66	0.68	0.69	1.34	1.47	1.55	1.62	0.56	0.60	0.65	0.69
Output	Agriculture	5.92	6.68	7.20	7.65	−0.25	0.00	0.18	0.34	0.63	0.73	0.80	0.86	0.85	0.91	0.96	1.01
	Industry	12.64	13.71	14.21	14.61	1.59	1.66	1.68	1.70	4.44	4.71	4.91	5.07	0.62	0.72	0.81	0.90
	Transport	10.38	12.16	13.01	13.64	2.06	2.10	2.13	2.15	0.97	1.18	1.35	1.49	3.69	3.92	4.10	4.25
HH Cption*	Agriculture	4.12	4.42	4.79	5.15	−3.47	−3.08	−2.85	−2.66	0.77	0.83	0.88	0.91	1.16	1.21	1.26	1.30
	Industry	4.92	5.95	6.34	6.59	2.95	2.90	2.86	2.81	−1.55	−1.42	−1.29	−1.16	0.31	0.38	0.44	0.49
	Transport	8.30	8.88	9.06	9.20	4.42	4.25	4.11	4.01	0.75	0.88	0.96	1.01	−4.69	−4.48	−4.19	−3.93
Wage	Agriculture	2.06	1.46	1.39	1.43	−2.30	−2.16	−2.10	−2.06	1.02	1.05	1.07	1.08	1.16	1.20	1.25	1.28
	Industry	2.16	1.68	1.63	1.67	−1.37	−1.27	−1.23	−1.20	0.89	0.93	0.95	0.97	0.94	0.98	1.02	1.05
	Transport	2.18	1.71	1.67	1.71	−1.21	−1.12	−1.08	−1.05	0.86	0.90	0.93	0.95	0.91	0.94	0.98	1.01

*HH Cption: Household Consumption.
Source: Authors.

These findings are consistent with several works [7–11]. For instance, Zhou & Luo [10] showed that technological innovation has a positive impact on economic growth. Among targeted technological innovation strategies for specific sectors, scenario 2 stands out for generating the highest GDP growth, especially when technological innovation is exclusively focused on the agricultural sector. Therefore, within the framework of a single–target approach to sectoral innovation, both countries have much to gain by directing investments towards agricultural activities, considering the significant role agriculture plays in their respective GDPs.

These findings of robust GDP growth underpin the foundational theories of Solow [5] and Romer [4], who established technological advancement as a primary driver of economic expansion. They are further corroborated by a wealth of empirical studies [7, 10]. The particularly strong performance of the agricultural sector scenario aligns with the view of George et al. [6], who see innovation as a catalyst for inclusive growth, given agriculture's significant share of employment in these economies. However, as our subsequent poverty analysis will reveal, this aggregate GDP growth does not automatically translate into equitable poverty reduction, highlighting a critical nuance often overlooked in macro-level analyses.

4.1.2. Income and Welfare Effects

A widespread enhancement of technological innovation (TI) would have a beneficial impact on household income both in the short and long terms, particularly benefiting those employed within innovative firms [83]. In Cameroon, a 20%

TI increase would lead to an income rise ranging from 5.47 (2023) to 5.50 (2040) (see **Table 2**). Correspondingly, in DR Congo, these figures would range from 3.17 (2023) to 3.52 (2040) (see **Table 3**). When examined at the sectoral level, increased TI in Agriculture would initially correlate with decreased income (–0.92 in 2023 in Cameroon and –0.93 in DR Congo), but this trend would gradually improve to –0.53 and –0.75, respectively, by 2040. Conversely, Industry and Transport–focused TI exhibits consistent income growth, signifying a positive technological influence. Notably, the income effect of industry–related TI is more pronounced than that of transport–related TI in Cameroon, while the opposite is observed in DR Congo.

In terms of well–being, a 20% overall increase in Total Income (TI) across the economy would lead to a welfare enhancement ranging from 35.56 (2023) to 26.16 (2040) in Cameroon, and 32.56 (2023) to 23.46 (2040) in DR Congo. The sectors of Agriculture, Industry, and Transport all contribute to the rise in welfare, with Agriculture displaying the most significant influence in both nations. In Cameroon, Industry holds the second–highest impact on welfare, while in DR Congo, it is the Transport sector that showcases the second most substantial effect after Agriculture. These findings are in alignment with an extensive body of literature that stresses the pivotal role played by TI in enhancing overall societal well-being [42–46]. However, to effectively harness the potential of this positive trajectory, it is imperative to acknowledge the significance of improved employment conditions, which can substantially influence the shift of the supply curve of producers [44].

4.1.3. Investment Effects

In the case of Cameroon, the simulation results highlight a consistent positive impact of TI on investment across all scenarios and timeframes. Specifically, a 20% economy–wide increase in TI would result in a 13.26% increase in investment in 2023, rising incrementally to 13.57% by 2040. Moreover, Scenario 2 (Agriculture) exhibits the most substantial growth in investment, starting at 1.10 in 2023 and reaching 1.45 in 2040. The subsequent scenarios, Industry (Scenario 3) and Transport (Scenario 4), also contribute to the increasing investment trend.

Similarly, for DR Congo, the findings reveal a positive and upward trend in investment across all scenarios and years. The economy–wide scenario shows investment values starting at 8.39 in 2023 and progressing to 8.42 by 2040. In Scenario 2, investment increases from 0.62 in 2023 to 0.69 in 2040. Moreover, unlike Cameroon, Scenario 3 demonstrates a significant impact, with investment rising from 1.34 in 2023 to 1.62 in 2040. Scenario 4 also contributes positively to the investment landscape. The consistent positive impact of TI on investment across all scenarios aligns with the established body of work by scholars such as Omri [37] and Khan et al. [38]. Specifically, the significant investment triggered by economy-wide and industrial TI resonates with Khan et al. [38], who demonstrated that public-private partnership investment reacts positively to TI. The divergent results between Cameroon and the DRC, where industry-driven investment is more potent in the latter, also reflect the contingent nature of this relationship, echoing Loukil's [39] finding that the impact of investment channels (like FDI) on TI and vice-versa can be non-linear and subject to specific economic thresholds.

4.1.4. Consumption Effects

Household consumption demonstrates varied patterns across sectors and scenarios. In the economy–wide scenario, consumption steadily increases from 4.12 (2023) to 5.15 (2040), reflecting the favourable cross–sectoral impact of technology. Conversely, the Agriculture scenario presents a contrasting trajectory for households involved in the agricultural sector, showing a decline from –4.08 (2023) to –2.86 (2040) in Cameroon (–3.47 in 2023 to –2.66 in 2040 in DR Congo). On the other hand, a positive trend emerges for households active in the industry and transport sectors, showcasing the spill–over effect of technology. This trend is evident in Scenarios 3 and 4, where an increase in TI within a sector leads to a reduction in consumption within that sector but a rise in consumption in other sectors. In terms of the economy-wide perspective, the increase in consumption substantiates the previously emphasised improvement in welfare. This outcome stands in contrast to the conclusions drawn by Dhrifi [21], who found that a 1% change in agricultural productivity results in a modest 0.09% increase in household consumption. This disparity might stem from variations in the applied methodology. Unlike the approach taken by Dhrifi [21], the current study adopts the capital-augmenting framework put forth by Lennox & Parrodo [78], in which capital plays a central role in propelling productivity, in contrast to the labour factor.

4.1.5. Wage and Output Effects

Wage trends exhibit a diverse range of patterns that vary across different sectors and scenarios. In the context of the economy–wide scenario, wages demonstrate a robust upswing across all sectors. However, the expansion of TI within the agricultural sector yields a negative impact on wages. In contrast, an increase in TI within the industry and transport sectors corresponds to wage increases. The observed negative impact of agricultural TI on wages provides a stark, real-world illustration of the labour-substitution mechanism theorized by Vivarelli [19], where capital-augmenting technological change leads to the replacement of workers in some or all tasks. This finding challenges the more optimistic consensus of studies that found a generally positive, if small, impact of TI on employment [49, 50]. It suggests that in developing economies with large, low-skilled agricultural labour forces, the initial effect of modernisation can be disruptive. This supports Vivarelli's [19] argument that innovative efforts focused solely on cost-cutting can reduce labour demand, creating a tension between productivity gains and employment stability. The subsequent long-term recovery in agricultural output, however, hints at the compensatory mechanisms he also describes, where new industries and investments may eventually absorb displaced labour [59]. Notably, the introduction of TI contributes to job losses within the agricultural sector, driven by a notable increase in the utilisation of machines over human labour [19]. This effect can be termed as a substitution effect. Conversely, there is a concurrent rise in the prices of agricultural products, which diminishes real incomes and consequently dampens demand. This phenomenon can be termed as a 'scale effect' [84]. Moreover, increased investments in machines elevate the costs of production inputs and the final products, subsequently reducing the demand for agricultural output. Yet, Vivarelli [19] demonstrates that innovative efforts must concentrate on reducing production costs to achieve the same output with fewer production inputs, particularly labour. This finding shows that capital-augmenting technological change assumes a reverse role in affecting wages in the agricultural sector of developing countries.

In Cameroon, a diverse range of output trends becomes apparent across various sectors and scenarios. The expansion of TI at the economy–wide level leads to a consistent upward trajectory in output, progressing from 6.29 (2023) to 8.76 (2040). Within the Agriculture sector, the increase in TI presents a nuanced pattern, initially resulting in a short–term output decline (–0.40 in 2023), followed by a subsequent long–term increase (0.41 in 2040). A decline in demand for agricultural output is a direct outcome of the decrease in employment due to the capital–labour substitution, leading to a consequential loss in consumer income. Furthermore, the expansion of TI in the Industry sector correlates with consistent growth in output, rising from 1.23 (2023) to 1.52 (2040). Notably, in Scenario 4 (Transport), a substantial increase in output is observed, transitioning from 0.23 (2023) to 3.88 (2040).

Similarly, in DR Congo, output trends mirror those observed in Cameroon across different sectors and scenarios. In Scenario 1, output shows improvement from 5.92 (2023) to 7.65 (2040). Agriculture displays a comparable trend, shifting from –0.25 (2023) to 0.34 (2040), indicating the potential of technology to enhance agricultural output over the long term. The industry sector maintains a growth trajectory, with output increasing from 0.63 (2023) to 0.86 (2040). Noteworthy growth is also evident in the Transport sector, where output experiences a significant upswing, rising from 0.85 (2023) to 4.25 (2040). Our finding corroborates that of Oltra & Flor [85], who discovered that the technological opportunities within the industry and a systematic approach to Research and Development (R&D) positively influence firms' output innovation. This correlation is typically a direct outcome of the capital-augmenting approach implemented in this study.

4.2. Poverty Findings

4.2.1. Impact at the National Level

Table 4 presents simulation results that elucidate the projected effects of heightened technology adoption on poverty rates in Cameroon and the DR Congo, spanning from 2023 to 2040, encompassing various sectors. The data is presented as percentage changes in poverty rates. Both countries demonstrate diminished national poverty rates owing to technological advancements, as evident by the negative changes.

In scenario 1, a consistent downward trajectory in poverty rates is observed: ranging from –2.61% to –2.62% for Cameroon and from –3.17% to –4.21% for the DR Congo. These figures feature the positive role of technology in the reduction of poverty. Within the agricultural sector, poverty rates experience a decline: ranging from –2.30% to –2.73% in Cameroon and from –3.18% to –4.10% in the DR Congo. This emphasises the poverty-mitigating effect of technology for households reliant on agriculture. Similarly, the industry and transport sectors exhibit encouraging trends in poverty rates, credited to overarching technological advancement across the economy, thereby suggesting a positive technological influence. This finding resonates with the studies conducted by Zameer et al.[62] and Ye et al.[64], which delved into the pivotal role of technological innovation and financial innovation in reducing poverty.

Table 4. Impact at the national level (values in percentage).

			Cameroon				DR Congo			
			2023	2030	2035	2040	2023	2030	2035	2040
Scenario 1	Economy–wide	Global	−2.61	−2.56	−2.58	−2.62	−3.17	−3.74	−4.04	−4.21
		Agriculture	−2.30	−2.54	−2.73	−2.73	−3.18	−3.63	−3.86	−4.10
		Industry	−1.41	−2.08	−2.59	−2.96	−7.44	−7.64	0.00	−7.79
		Transport	−4.46	−5.30	−5.59	−5.79	−5.62	−6.60	−7.03	−7.41
Scenario 2	Agriculture	Global	0.48	0.38	0.33	0.28	−0.88	−0.91	−0.94	−0.99
		Agriculture	2.38	2.02	1.87	1.70	0.14	0.00	−0.09	−0.19
		Industry	−1.04	−1.04	−1.06	−1.07	−0.84	−0.89	−0.91	−0.92
		Transport	−2.23	−2.14	−2.05	−1.97	−1.12	−1.16	−1.20	−1.23
Scenario 3	Industry	Global	−0.49	−0.52	−0.55	−0.57	−0.37	−0.43	−0.46	−0.48
		Agriculture	−0.66	−0.66	−0.68	−0.69	−0.35	−0.41	−0.45	−0.48
		Industry	1.03	0.89	0.82	0.71	−2.35	−2.45	−2.58	−2.67
		Transport	−0.33	−0.49	−0.57	−0.63	−0.52	−0.62	−0.70	−0.78
Scenario 4	Transport	Global	−0.24	−0.24	−0.24	−0.24	−0.49	−0.54	−0.58	−0.59
		Agriculture	−0.21	−0.21	−0.21	−0.21	−0.47	−0.48	−0.51	−0.55
		Industry	−0.16	−0.18	−0.18	−0.20	−0.35	−0.40	−0.46	−0.48
		Transport	1.72	1.66	1.50	1.41	−2.02	−2.13	−2.23	−2.29
Sensitivity		Global	−1.97	−2.19	−2.51	−2.81	−3.36	−3.35	−3.47	−3.62
		Agriculture	−1.63	−2.30	−2.88	−3.29	−3.04	−3.21	−3.40	−3.65
		Industry	−4.69	−5.48	−5.88	−6.16	−3.77	−3.49	−3.75	−3.90
		Transport	−4.69	−5.48	−5.88	−6.16	−5.16	−6.10	−6.31	−6.07

Source: Authors from DASP Stata package.

In Cameroon, the transport sector displays the greatest potential for poverty reduction, outpacing the agricultural and industry sectors. In DR Congo, it is the industry sector that witnesses the most substantial decline. In terms of overall impact, technology has a more pronounced influence in DR Congo compared to Cameroon, resulting in a faster reduction of poverty rates in DR Congo due to its higher initial poverty level in comparison to Cameroon.

As shown in **Table 4**, an expansion of agricultural technological innovation (TI) leads to an increase in global poverty and poverty within the agricultural sector in both the short and long terms for Cameroon. This result contrasts with those of Dhrifi[21] and De Janvry et al.[20], who suggested that TI in agriculture implies direct benefits to households. The finding that agricultural TI can increase poverty, particularly in Cameroon, introduces a critical nuance to the literature. This stands in contrast to the direct and indirect poverty reduction channels identified by De Janvry et al.[20] and the clear negative correlation found by Dhrifi[21], who concluded that a 1% increase in TI reduces poverty by 0.31%. The discrepancy can be traced to our modelling of a specific type of innovation. Our capital-augmenting shock prioritises machinery over labour, making the negative direct effect (job displacement) immediate and potent, potentially overwhelming the positive indirect effects (lower prices, new jobs in other sectors) in the short-to-medium term. This powerfully validates the perspective of Srinivas & Sutz[65] that TI is not a panacea but a contextual process whose impacts are shaped by the socio-economic circumstances it is embedded in. In this context, a technology that is not appropriate lacking the characteristics of low capital cost and job creation using local skills as outlined by Smith et al.[66] can have adverse distributional consequences, even while boosting aggregate output.

On the other hand, Dhrifi [21] found that a 1% increase in technology leads to a decrease in poverty by 0.31%. For the DR Congo, overall global poverty declines, but within the agricultural sector, there is a short-term increase followed by a long-term decrease.

The findings further indicate that if technological innovation were to expand within the transport sector, there would be a rise in poverty, specifically within the transport industry in Cameroon. However, this localised effect contrasts with the broader impact on poverty and the other sectors, both of which would experience a decrease. On the other hand, in DR Congo, an increase in technological innovation within the transport sector is associated with a reduction in poverty. This positive outcome highlights the potential for technology to alleviate poverty challenges in the sector.

De Janvry et al. [20] argue that technology presents significant potential for alleviating poverty in smallholder agriculture. To effectively leverage technology for poverty reduction, the technological approach should be integrated into a comprehensive strategy for rural development and poverty reduction. This explains the common trend that emerges in both countries concerning the industrial sector. In both Cameroon and DR Congo, an increase in TI within the industrial sector is associated with a reduction in poverty rates. This underlines a consistently positive relationship between technological advancements and poverty reduction within the industrial sector across these nations.

4.2.2. Impact on Rural Poverty

Table 5 provides an insightful perspective on how TI impacts rural areas, measured in percentage changes. Over the assessed years, the percentage change in poverty rates at the global level fluctuates between –3.22% and –3.33% for Cameroon, and between –3.18% and –4.18% for DR Congo. The result underlines the potential of technological innovation as a powerful tool for poverty reduction within these nations.

Table 5. Impact in rural area (values in percentage).

			Cameroon				DR Congo			
			2023	2030	2035	2040	2023	2030	2035	2040
Scenario 1	Economy–wide	Global	−3.33	−3.22	−3.27	−3.33	−3.18	−3.76	−4.04	−4.18
		Agriculture	−2.87	−3.20	−3.49	−2.87	−3.19	−3.66	−3.86	−4.08
		Industry	−1.84	−2.71	−3.29	−3.72	−6.93	−7.62	−7.81	−7.96
		Transport	−5.54	−6.61	−7.11	−7.29	−5.66	−6.69	−7.13	−7.59
Scenario 2	Agriculture	Global	0.41	0.41	0.39	0.31	−0.91	−0.92	−0.95	−0.98
		Agriculture	2.31	1.94	1.78	1.63	0.14	0.00	−0.09	−0.19
		Industry	−1.34	−1.34	−1.38	−1.41	−0.85	−0.92	−0.92	−0.94
		Transport	−2.83	−2.77	−2.65	−2.56	−1.09	−1.14	−1.17	−1.20
Scenario 3	Industry	Global	−0.64	−0.66	−0.72	−0.76	−0.39	−0.45	−0.48	−0.51
		Agriculture	−0.83	−0.83	−0.87	−0.87	−0.37	−0.44	−0.47	−0.50
		Industry	1.05	0.87	0.76	0.66	−2.37	−2.47	−2.61	−2.71
		Transport	−0.43	−0.64	−0.76	−0.83	−0.54	−0.64	−0.73	−0.80
Scenario 4	Transport	Global	−0.33	−0.33	−0.33	−0.33	−0.52	−0.57	−0.61	−0.61
		Agriculture	−0.31	−0.31	−0.31	−0.31	−0.50	−0.51	−0.54	−0.58
		Industry	−0.25	−0.27	−0.27	−0.29	−0.36	−0.43	−0.48	−0.51
		Transport	1.63	1.59	1.47	1.43	−2.05	−2.17	−2.26	−2.33
Sensitivity		Global	−2.46	−2.27	−2.36	−2.42	−3.34	−3.33	−3.47	−3.61
		Agriculture	−2.56	−2.81	−3.16	−3.58	−3.07	−3.25	−3.42	−3.69
		Industry	−2.13	−2.87	−3.66	−4.17	−2.81	−3.50	−3.77	−3.89
		Transport	−5.89	−6.90	−7.46	−7.81	−5.04	−5.63	−6.09	−6.33

Source: Authors from DASP Stata package.

At the national level, **Table 4** shows that the expansion of agricultural TI has notable implications for rural poverty dynamics in both Cameroon and DR Congo. For Cameroon, this expansion results in an amplification of global rural poverty and increased poverty rates within the agricultural sector, persisting across both short and long–term projections. Conversely, the scenario plays out differently in DR Congo. Here, the overarching trend showcases a decline in overall global rural poverty. However, this trend within the agricultural sector is nuanced. In the short term, there is a notable increase in poverty within the agricultural sector, followed by a subsequent decrease in the long term. These findings suggest that a wise and effectively executed implementation of technology in the agricultural industry is essential. According to Dhahri and Omri [86], alleviating poverty and hunger in developing economies hinges on the development of the agricultural sector. Interestingly, a contrasting pattern emerges when examining the industry sector in both countries. In this sector, an upsurge in technological innovation corresponds to decreased rural poverty rates. This reveals a positive correlation between technological advancements within industry and the improvement of rural poverty circumstances in these regions. Regarding transportation, the results at the rural level reflect those observed at the national level.

4.2.3. Impact on Urban Poverty

As shown in **Table 6**, Cameroon and DR Congo see declining urban poverty rates globally due to an economy–wide increased technological innovation, with values ranging from approximately –1.98% to –4.28%. This suggests a promising potential for reducing urban poverty rates in both countries across various sectors, such as agriculture, industry, and transport. In the transport sector, negative changes (around –3.51% to –7.00%) also suggest positive strides in improving urban poverty rates. Overall, the simulation consistently points out how advanced technologies can enhance living conditions and economic well–being in urban areas.

Table 6. Impact in urban area (values in percentage).

			Cameroon				DR Congo			
			2023	**2030**	**2035**	**2040**	**2023**	**2030**	**2035**	**2040**
Scenario 1	Economy–wide	Global	−1.98	−1.98	−1.98	−1.99	−3.14	−3.69	−4.05	−4.28
		Agriculture	−1.79	−1.96	−2.05	−2.31	−3.16	−3.56	−3.87	−4.14
		Industry	−1.02	−1.52	−1.98	−2.29	−6.60	−7.02	−7.24	−7.40
		Transport	−3.51	−4.14	−4.25	−4.47	−5.54	−6.37	−6.78	−7.00
Scenario 2	Agriculture	Global	0.53	0.35	0.27	0.26	−0.82	−0.86	−0.92	−0.99
		Agriculture	2.43	2.09	1.96	1.76	0.14	0.00	−0.09	−0.19
		Industry	−0.77	−0.77	−0.77	−0.77	−0.80	−0.84	−0.86	−0.88
		Transport	−1.70	−1.57	−1.52	−1.45	−1.19	−1.22	−1.25	−1.29
Scenario 3	Industry	Global	−0.37	−0.40	−0.40	−0.40	−0.31	−0.37	−0.41	−0.42
		Agriculture	−0.51	−0.51	−0.51	−0.53	−0.31	−0.34	−0.40	−0.42
		Industry	1.01	0.92	0.86	0.75	−2.28	−2.41	−2.50	−2.57
		Transport	−0.24	−0.37	−0.40	−0.46	−0.46	−0.57	−0.63	−0.73
Scenario 4	Transport	Global	−0.16	−0.16	−0.16	−0.16	−0.42	−0.48	−0.52	−0.54
		Agriculture	−0.13	−0.13	−0.13	−0.13	−0.41	−0.42	−0.45	−0.49
		Industry	−0.09	−0.11	−0.11	−0.13	−0.31	−0.33	−0.41	−0.42
		Transport	1.79	1.72	1.54	1.39	−1.95	−2.06	−2.15	−2.21
Sensitivity		Global	−1.37	−1.30	−1.30	−1.35	−3.42	−3.40	−3.49	−3.63
		Agriculture	−1.45	−1.65	−1.94	−2.12	−1.96	−3.14	−3.36	−3.56
		Industry	−1.19	−1.79	−2.20	−2.51	−5.68	−6.46	−6.70	−6.91
		Transport	−3.62	−4.23	−4.48	−4.70	−5.56	−6.11	−6.21	−6.37

Source: Authors from DASP Stata package.

In summary, the conclusions drawn from the rural level analysis closely mirror the observations made at both the national and urban levels, particularly concerning the interplay between technological innovation and poverty reduction on a global scale, across various sectors, and over different timeframes. Although the extent of the poverty impact may vary, the fundamental trends hold consistently. It is noteworthy that rural poverty demonstrates a more rapid decline compared to urban poverty. This disparity can be attributed to the significant concentration of impoverished households in rural regions. The consistent pattern highlighted by the simulation shows how the adoption of advanced technologies can lead to better living conditions and improved economic well–being in urban and rural areas.

5. Conclusions

This research investigates the potential of technological innovation to reduce poverty in Cameroon and the Democratic Republic of Congo, nations challenged by considerable technological underdevelopment and elevated poverty levels. To tackle this issue, the study employs a dynamic Computable General Equilibrium analysis to evaluate how TI influences diverse economic factors, encompassing GDP growth and household well–being. It further examines poverty implications on a broader scale, analysing macro, meso, and micro levels, with specific attention to agriculture, industry, and transport sectors.

Through the analysis of these particular cases and a concentration on capital-augmenting technological advancements that enhance sectoral productivity, the paper introduces a novel approach for studying the impacts of technological innovation on poverty reduction across diverse economic facets. This methodology provides insightful perspectives that can shape precise policy interventions and deepen our understanding of how TI can successfully diminish poverty in emerging economies.

The findings reveal that increased TI positively influences GDP growth, with agriculture, industry, and transport sectors all contributing. The welfare and income effects also demonstrate positive trends, benefiting households employed in innovative firms. Investment and consumption effects vary across sectors, with agriculture experiencing an initial income decline but later improvement, while industry and transport sectors consistently show positive influences. Wage and output effects reveal nuanced patterns, with TI affecting employment dynamics and production outputs across sectors. Overall, the results highlight the potential of TI to enhance economic growth, income, and welfare, particularly through targeted investments in key sectors, presenting valuable insights for policy formulation and poverty reduction strategies.

The poverty findings reveal that increased TI has a positive impact on poverty reduction in Cameroon and DR Congo. Across sectors and timeframes, both countries experience reduced national poverty rates, particularly in agriculture, industry, and transport. In Cameroon, the transport sector shows the most potential for poverty reduction, while in DR Congo, the industry sector witnesses a substantial decline. An expansion of agricultural TI, however, leads to short–term global poverty increase in Cameroon and short–term sectoral increase followed by long–term decrease in DR Congo. Conversely, industry–related TI consistently correlates with decreased poverty rates in both nations. The impact is mirrored in rural and urban areas, where agricultural TI has varied effects. In urban areas, both countries see declining poverty rates due to economy–wide TI, highlighting its potential to improve living conditions.

The results of the analysis present significant policy implications for harnessing technological innovation (TI) as a means to drive economic growth, enhance well-being, and reduce poverty in Cameroon and DR Congo. The macro and meso impacts underline the necessity for targeted and actionable investments in key sectors, such as agriculture, industry, and transport, to maximise the positive influence of TI on GDP growth, household income, and consumption. Policymakers should focus on creating an enabling environment that encourages innovation and research and development within these sectors, whilst adopting concrete implementation guidance.

For agriculture, targeted investments must prioritise capital-augmenting innovations that directly boost smallholder productivity and improve supply chain efficiency. This involves funding for climate-smart technologies and subsidising or providing affordable loans for innovative storage and efficient processing equipment to reduce post-harvest losses. Implementation should proceed through the establishment of Technology Adoption Funds to offer matching grants or low-interest loans to farmer cooperatives and Small and Medium-sized Enterprises (SMEs), supported by enhanced extension services that train farmers on the use and maintenance of new technologies, ensuring sustained use and maximum impact.

In the industry sector, investments should aim at modernising existing manufacturing processes and fostering the growth of high-value-added light industries. This can be achieved by implementing Industry-specific R&D Tax Credits for domestic firms and establishing Innovation Hubs or

Industrial Parks with reliable infrastructure and shared high-tech equipment accessible to SMEs at subsidised rates. Given the strong poverty reduction potential in DR Congo, the government should establish Sectoral Competitiveness Clusters to link resource extraction with local processing through technology transfer programmes. Crucially, this must be paired with investment in Vocational Training Centres to offer specialised courses in industrial automation and machinery operation to adapt the workforce to technological changes and mitigate potential negative wage effects.

Regarding the transport sector, investments should focus on using technology to improve connectivity, efficiency, and safety, lowering the cost of trade and facilitating market access. Priority should be given to the digitalisation of logistics and trade facilitation, investing in national single-window systems for customs clearance and electronic cargo manifests to reduce transit times. Furthermore, deploying drone technology or sensor networks for real-time monitoring of road and rail networks, particularly in Cameroon, where the sector shows the highest poverty reduction potential, will allow for predictive maintenance and rapid repair. These large-scale technology deployments should explore Public-Private Partnership (PPP) models for financing, prioritising the linking of key agricultural production zones with urban markets and ports to ensure that the gains from technological efficiency directly benefit the rural poor.

The consistent positive consumption effects in the industry and transport sectors point to the potential of technology-driven supply chain enhancements and increased trade connectivity. The observed positive trends in well-being and income effects suggest that policies promoting innovation and entrepreneurship should be prioritised, particularly to support innovative firms and their employees. The nuanced wage and output effects call for a careful approach to managing the labour market impacts of TI. Policies must focus on reskilling and upskilling the workforce to adapt to technological changes, particularly in sectors, like agriculture where capital–labour substitution may lead to job losses. Regarding poverty reduction, policymakers should prioritise initiatives that enhance technological adoption, especially in sectors with the highest poverty reduction potential. Efforts should be made to promote inclusive growth that benefits both urban and rural areas, with a focus on agricultural innovation and industry-driven poverty reduction strategies.

The present study, while contributing valuable insights, presents certain limitations that could guide future research. An avenue for future research lies in exploring the depth of poverty, considering the distance between the poverty line and poor households. Additionally, investigating the severity of poverty, particularly addressing inequalities among the poor, could offer a more nuanced understanding. A crucial aspect not covered in this study pertains to the discussion of funding sources that would facilitate the effective implementation of the examined policies. Future research could explore the financial mechanisms and resources required to support the integration of TI-driven strategies.

Author Contributions

R.N.T.: Conceptualisation, Methodology, Software, Formal Analysis, Investigation, Data Curation, Writing – Original Draft Preparation (Methodology, Results). E.T.N.: Writing – Original Draft Preparation (Introduction, Results & Discussion, Conclusion), Writing–Review & Editing, Visualisation, Project Administration. G.Z.N.: Writing – Original Draft Preparation (Literature Review), Writing – Review & Editing (Discussion). All authors have read and agreed to the published version of the manuscript.

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Conflicts of Interest

The authors declare no conflict of interest.

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