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The Economics of AI and Robotics: A Scenario Analysis of Automation, Employment, Poverty, Taxation and Income Distribution in a Hypothetical Three-Sector Economy

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The Economics of AI and Robotics: A Scenario Analysis of Automation, Employment, Poverty, Taxation and Income Distribution in a Hypothetical Three-Sector Economy

Preprint-Working Paper for Discussion

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Abstract. *This study examines how the deepening of artificial intelligence (AI) and robotics, defined as the progressive replacement of human workers by machines, affects output, employment, poverty and income distribution. Drawing on the economics of prediction and general-purpose technologies, the task-based theory of automation, growth theory, the literature on factor shares and Keynesian demand constraints, we construct a hypothetical economy, Solvania, with 30 million inhabitants, GDP per capita of US$25,000, 6% unemployment, a 5.3% poverty rate and three sectors: agriculture (30% of output and employment), automobile manufacturing (20%) and services (50%). A macro-sectoral model linked to a 150,000-household microsimulation, implemented in Python, traces a gradual scenario, in which automation reaches 25% of jobs within five years and 50% by year 20, and a rapid scenario, in which it reaches 80% in agriculture and manufacturing and 60% in services within ten years. Both paths raise GDP strongly, to US$1.57 trillion by year 20 (gradual) and US$1.39 trillion by year 10 (rapid), but the gains are distributed very unequally. In the rapid scenario unemployment reaches 47.2%, the labour share falls from 60% to 19.9%, the Gini coefficient rises from 0.369 to 0.621 and poverty more than triples to 17.3%, while median income rises by only 8%. A policy package combining an automation levy that finances a universal dividend, universal income support, accelerated reinstatement and work sharing reduces poverty to 0.7%, lowers the Gini to 0.408 and raises GDP by a further 16%. The results are robust to alternative assumptions and support redistributive and labour-market institutions established before the fastest phase of automation.*

Keywords: *economics of AI and robotics, automation, technological unemployment, labour share, inequality, poverty, universal basic income, microsimulation*

JEL classification: *D31, E24, H23, I32, J23, J31, O33*

1. Introduction

Concern that machines will make human labour redundant is almost as old as industrial economics. David Ricardo added a chapter "On Machinery" to the third edition of his *Principles*, conceding that the substitution of machinery for labour could be injurious to workers (Ricardo, 1821), and John Maynard Keynes coined the phrase "technological unemployment" to describe job losses that outrun society's ability to find new uses for labour (Keynes, 1930). For most of the twentieth century these fears proved exaggerated: productivity growth raised living standards and new occupations absorbed displaced workers (Autor, 2015; Mokyr et al., 2015).

The current wave of AI and robotics has revived the debate for three reasons. First, the range of tasks that machines can perform now extends from routine manual work to cognitive, linguistic and interpersonal activities (Brynjolfsson & McAfee, 2014; Eloundou et al., 2024). Second, empirical studies find measurable negative effects of industrial robots on local employment and wages (Acemoglu & Restrepo, 2020), even where aggregate employment is sustained through reallocation (Dauth et al., 2021). Third, the labour share of income has declined in many economies (Karabarbounis & Neiman, 2014; Autor et al., 2020), raising the prospect that the gains from automation accrue mainly to the owners of capital (Piketty, 2014; Moll et al., 2022). The International Monetary Fund estimates that almost 40% of global employment, and around 60% in advanced economies, is exposed to AI (Cazzaniga et al., 2024).

These questions define the rapidly growing field of the economics of AI and robotics, which examines how intelligent machines alter the costs of prediction and physical work, the organisation of production, market structure, the demand for labour, the distribution of income and the design of public policy (Agrawal et al., 2018; Furman & Seamans, 2019). The field draws on growth theory, labour economics, industrial organisation, public finance and development economics, and treats AI and robotics not simply as new tools but as general-purpose technologies whose economic effects depend on institutions and policy choices (Trajtenberg, 2019; Acemoglu & Johnson, 2023).

Existing studies typically estimate the exposure of occupations or the historical effect of robot adoption. Fewer studies trace, within one internally consistent framework, how different speeds of automation propagate through sectoral output, employment, trade, factor shares, household incomes and poverty, and how policy can alter those outcomes. This study contributes such an analysis for a stylised economy and makes the full model available as Python code, so that every table and figure can be reproduced and every assumption varied. To achieve these objectives, the following research questions (RQs) are formulated:

> **RQ1.** *How do sectoral and aggregate GDP respond when AI and robotics replace a rising share of human jobs at different speeds?*
>
> **RQ2.** *What happens to employment, poverty and income distribution as automation deepens?*
>
> **RQ3.** *Which policy combinations deliver the highest standard of living with the least increase in poverty?*

The remainder of this paper is structured as follows. Section 2 reviews the theory and evidence on the economics of AI and robotics. Section 3 describes the hypothetical economy, the scenario design, the model and its Python implementation. Section 4 presents results for both scenarios, the policy simulation and sensitivity tests. Section 5 discusses the findings in light of theory, Section 6 sets out policy recommendations and Section 7 concludes. The Appendix documents the code.

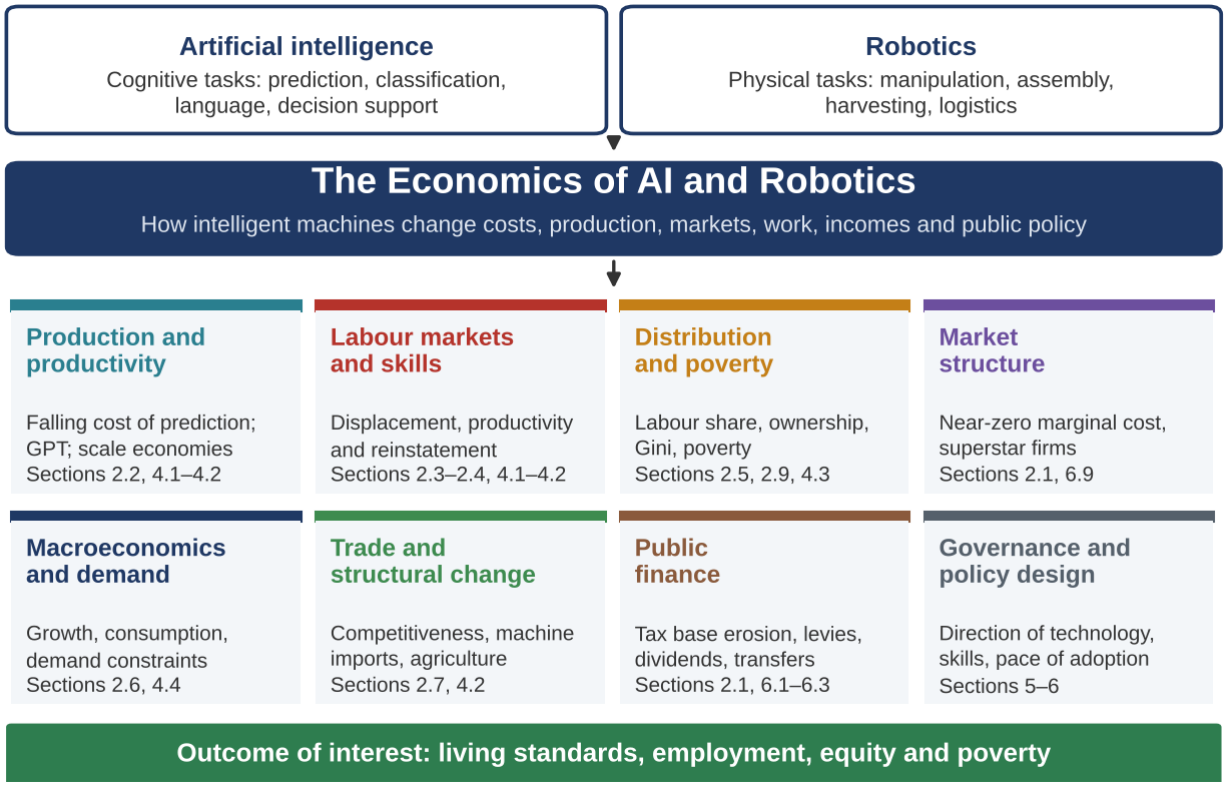
2. Theoretical Framework and Literature Review

2.1 The Economics of AI and Robotics: Concept and Scope

The economics of AI and robotics is the branch of economics that analyses how intelligent machines, namely software systems that perform cognitive tasks such as prediction, classification, language processing and decision support, and robots that perform physical tasks such as manipulation, assembly and harvesting, change the costs of production, the organisation of firms and markets, the demand for labour, the distribution of income and the role of the state (Furman & Seamans, 2019). Figure 1 summarises its main pillars and shows where each is addressed in this article.

Figure 1

Conceptual Framework: The Economics of AI and Robotics



Note. Elaborated on the basis of Agrawal et al. (2018), Furman and Seamans (2019) and Acemoglu and Restrepo (2019).

AI as a fall in the cost of prediction

Agrawal, Gans and Goldfarb (2018) characterise AI as a technology that dramatically reduces the cost of prediction, that is, of filling in missing information from available data. Basic price theory then yields clear implications: as the price of prediction falls, its use expands into activities not previously framed as prediction problems; the value of complements such as data, human judgment and the ability to act on predictions rises; and the value of substitutes, including human prediction and routine cognitive work, falls. Brynjolfsson and Mitchell (2017) show that tasks suitable for machine learning are spread across most occupations, so AI reorganises jobs task by task rather than eliminating whole occupations at once.

Robots as labour-substituting capital

Robots are capital goods that perform physical tasks. Their economic effect depends on their relative price and on the elasticity of substitution between capital and labour. In a constant elasticity of substitution (CES) production function with AI and robotic capital K and labour L,

$$Y = A\left[\alpha K^{(\sigma-1)/\sigma} + (1-\alpha) L^{(\sigma-1)/\sigma}\right]^{\sigma/(\sigma-1)} \quad (1)$$

where A is total factor productivity, α a distribution parameter and σ the elasticity of substitution. When σ exceeds one, a decline in the relative price of capital raises the capital share and lowers the labour share of income. Karabarbounis and Neiman (2014) estimate σ at about 1.25 and attribute roughly half of the global decline in the labour share to cheaper investment goods, a mechanism that AI and robotics are likely to intensify.

General-purpose technology and innovation

General-purpose technologies (GPTs) are pervasive, improve over time and spawn complementary innovations across the economy (Bresnahan & Trajtenberg, 1995). AI displays all three characteristics (Trajtenberg, 2019) and may also be a new "method of invention" that raises the productivity of research itself (Cockburn et al., 2019). Because GPTs require complementary investment in skills, organisation and intangible capital, their productivity gains typically arrive with a lag (Brynjolfsson et al., 2019).

Digital cost structure and market power

AI systems have high fixed costs of development and data acquisition but near-zero marginal costs of replication and distribution (Goldfarb & Tucker, 2019). Combined with data network effects, in which more users generate more data and better models, these features create strong economies of scale and scope that favour large firms (Varian, 2019). The resulting concentration can generate economic rents and contribute to the rise of superstar firms and the fall in the labour share (Autor et al., 2020). The question of who owns the machines and the data therefore becomes central to income distribution (Freeman, 2015).

Public economics of AI and robotics

AI and robotics also raise public-finance and welfare questions. Tax systems that rely heavily on labour income lose revenue as work is automated, and tax codes that favour capital can encourage excessive automation (Acemoglu et al., 2020). Displacement imposes adjustment costs on workers and communities that markets do not compensate automatically, while skills and new-task creation have public-good characteristics. Korinek and Stiglitz (2019) show that the gains from AI can make everyone better off only if accompanied by appropriate redistribution, and Acemoglu and Johnson (2023) argue that public policy can shape the direction of technological change itself.

2.2 Growth Theory and the Productivity Effect of Automation

In the neoclassical growth model, sustained increases in output per worker come from technological progress rather than capital accumulation alone (Solow, 1956). Solow (1957) attributed the bulk of the growth in US output per hour to technical change, and endogenous growth theory models that progress as the outcome of deliberate investment in ideas (Romer, 1990). AI and robotics can be interpreted both as capital deepening and as a general-purpose technology that raises total factor productivity. Aghion, Jones and Jones (2019) show that automation can accelerate growth, but that growth may remain constrained by "Baumol" sectors where productivity is hard to raise, echoing Baumol's (1967) theory of unbalanced growth. Brynjolfsson, Rock and Syverson (2019) argue that measured productivity gains from AI may lag adoption because firms must first invest in complementary intangible capital, while Nordhaus (2021) finds little evidence so far of an imminent growth singularity.

Automation can also exploit economies of scale. Kaldor's (1966) interpretation of Verdoorn's law holds that productivity growth in manufacturing rises with output growth, and trade models with increasing returns show how scale lowers unit costs and expands exports (Krugman, 1979). These mechanisms motivate the larger productivity uplift assumed for the automobile sector in our model.

2.3 The Task-Based Framework: Displacement, Productivity and Reinstatement

Modern analysis of automation builds on the task-based approach, in which production requires a continuum of tasks that can be allocated to labour or capital (Zeira, 1998; Autor et al., 2003; Acemoglu & Autor, 2011). Autor, Levy and Murnane (2003) showed that computerisation

substitutes for routine tasks and complements non-routine problem-solving and interpersonal tasks. Acemoglu and Restrepo (2018, 2019) formalise three effects of automation on labour demand:

- *Displacement effect (negative):* machines take over tasks previously performed by workers, reducing labour's task content of production.
- *Productivity effect (positive):* lower costs raise output and demand for labour in non-automated tasks.
- *Reinstatement effect (positive):* new tasks in which labour has a comparative advantage are created, restoring labour's share.

In stylised form, the change in aggregate labour demand can be decomposed as:

$$\Delta \ln L^d \approx \text{Productivity effect} - \text{Displacement effect} + \text{Reinstatement effect} \quad (2)$$

Whether automation raises or lowers wages and employment depends on the relative magnitude of these terms. Acemoglu and Restrepo (2019) warn that "so-so technologies", which displace workers without generating large productivity gains, are especially harmful, and that US employment growth since the late 1980s has been characterised by faster displacement and slower reinstatement than in earlier decades. Acemoglu and Johnson (2023) emphasise that the direction of technological change is a social choice rather than a technical inevitability.

2.4 Skill-Biased Change, Polarisation and Displaced Workers

The canonical supply-and-demand model of relative wages attributes rising skill premia to technology that favours skilled labour (Katz & Murphy, 1992), with education determining whether workers keep pace in a "race between education and technology" (Goldin & Katz, 2008). Autor and Dorn (2013) document job polarisation, as middle-skill routine occupations decline and employment grows at the top and in low-wage services. The costs of displacement are persistent: Jacobson, LaLonde and Sullivan (1993) find that displaced workers suffer long-lasting earnings losses. These findings justify our assumption that displacement falls first on lower-skill households and that remaining workers earn a modest complementarity premium.

2.5 Factor Shares, Capital Ownership and Inequality

Kaldor (1961) listed the approximate constancy of factor shares among the stylised facts of growth, yet the labour share has fallen across many countries since the early 1980s. Karabarbounis and Neiman (2014) attribute roughly half of this decline to the falling relative price of investment goods, which encourages substitution of capital for labour, while Autor et al. (2020) link it to the rise of highly productive "superstar" firms. Piketty (2014) argues that when the return on capital exceeds the growth rate, wealth becomes increasingly concentrated. Moll, Rachel and Restrepo (2022) show that automation raises returns to wealth, so inequality increases beyond what wage effects alone imply. Freeman (2015) summarises the distributional stakes: those who own the robots will capture the gains unless ownership is broadened. Kuznets (1955) hypothesised that inequality first rises and then falls during structural transformation; whether automation produces a new Kuznets-type upswing depends on institutions.

2.6 Aggregate Demand and Macroeconomic Constraints

A purely supply-side view neglects the demand channel. In Keynesian theory, output is constrained by aggregate demand, which depends on household income (Keynes, 1936). If automation redistributes income from workers with high propensities to consume towards capital owners with low propensities, consumption demand for domestically produced services may weaken. Sachs and Kotlikoff (2012) show that "smart machines" can reduce the welfare of

younger generations, and Berg, Buffie and Zanna (2018) find that automation raises output but can depress real wages for extended periods. Korinek and Stiglitz (2019) conclude that AI can make everyone better off only if accompanied by sufficient redistribution. Our model therefore includes a demand drag that links unemployment and income replacement to sectoral output.

2.7 Structural Change, Agriculture and Trade

Dual-economy theory describes how labour moves from low-productivity agriculture into modern sectors (Lewis, 1954). Automation of agriculture reverses the usual logic: labour is released without a modern sector ready to absorb it. Rodrik (2016) documents "premature deindustrialisation" in developing economies, where manufacturing employment peaks at lower income levels than in earlier industrialisers. Services, historically the absorber of displaced labour (Baumol, 1967), are now themselves exposed to AI (Eloundou et al., 2024). In open economies, automation can raise export competitiveness while increasing imports of robots, semiconductors and software, affecting the trade balance.

2.8 Empirical Evidence on Exposure and Impacts

Frey and Osborne (2017) estimated that 47% of US employment was at high risk of computerisation, but task-based estimates are much lower: Arntz, Gregory and Zierahn (2016) find around 9% of jobs at high risk across OECD countries because most occupations contain non-automatable tasks. Graetz and Michaels (2018) estimate that industrial robots raised annual labour productivity growth by about 0.36 percentage points across 17 countries while reducing hours worked by low-skilled workers. Acemoglu and Restrepo (2020) find that one additional robot per thousand workers reduces the employment-to-population ratio by about 0.2 percentage points and wages by about 0.42% in US local labour markets. Bessen (2019) shows that automation raised employment in industries where demand was price-elastic but reduced it once demand became saturated. For generative AI, Brynjolfsson, Li and Raymond (2023) report a 14% average productivity increase among customer-support agents, concentrated among less experienced workers, and Eloundou et al. (2024) estimate that around 80% of US workers could have at least 10% of their tasks affected by large language models. The OECD (2019) stresses that the future of work depends heavily on adjustment policies.

2.9 Measuring Poverty and Inequality

We measure inequality with the Lorenz curve (Lorenz, 1905) and the Gini coefficient (Gini, 1912), and poverty with the headcount ratio, the first member of the Foster–Greer–Thorbecke family of poverty measures (Foster et al., 1984). Following Sen (1999), we treat median disposable income and the poverty rate, rather than GDP per capita alone, as better indicators of the standard of living. Table 1 links each mechanism to its representation in the model and to the associated policy levers.

Table 1
Theoretical Mechanisms, Their Representation in the Model and Associated Policy Levers

Mechanism	Key references	Model representation	Policy lever
Productivity and scale effect	Solow (1957); Kaldor (1966); Krugman (1979); Graetz & Michaels (2018)	Sector output uplift κ_s per point of automation; highest in automobile	Competition policy; domestic AI capacity
Displacement effect	Zeira (1998); Acemoglu & Restrepo (2018, 2020)	Human jobs fall in proportion to automation share	Pace management; tax neutrality
Reinstatement effect	Acemoglu & Restrepo (2019); Autor (2015); Bessen (2019)	Share ρ_t of displaced workers enter new tasks	Retraining; job guarantee; care economy
Skill bias and polarisation	Katz & Murphy (1992); Autor & Dorn (2013); Goldin & Katz (2008)	Displacement falls first on low-skill households	Lifelong learning accounts
Capital share and ownership	Karabarbounis & Neiman (2014); Piketty (2014); Moll et al. (2022)	Profits concentrated in top decile	Automation levy; dividend fund; broad ownership
Demand constraint	Keynes (1936); Berg et al. (2018); Korinek & Stiglitz (2019)	Output drag from unemployment net of income support	Universal income floor
Trade and structural change	Lewis (1954); Rodrik (2016)	Exports scale with tradable output; imports of machines	Industrial and rural policy

Note. Compiled from the literature reviewed in Section 2.

3. Methodology

3.1 The Hypothetical Economy

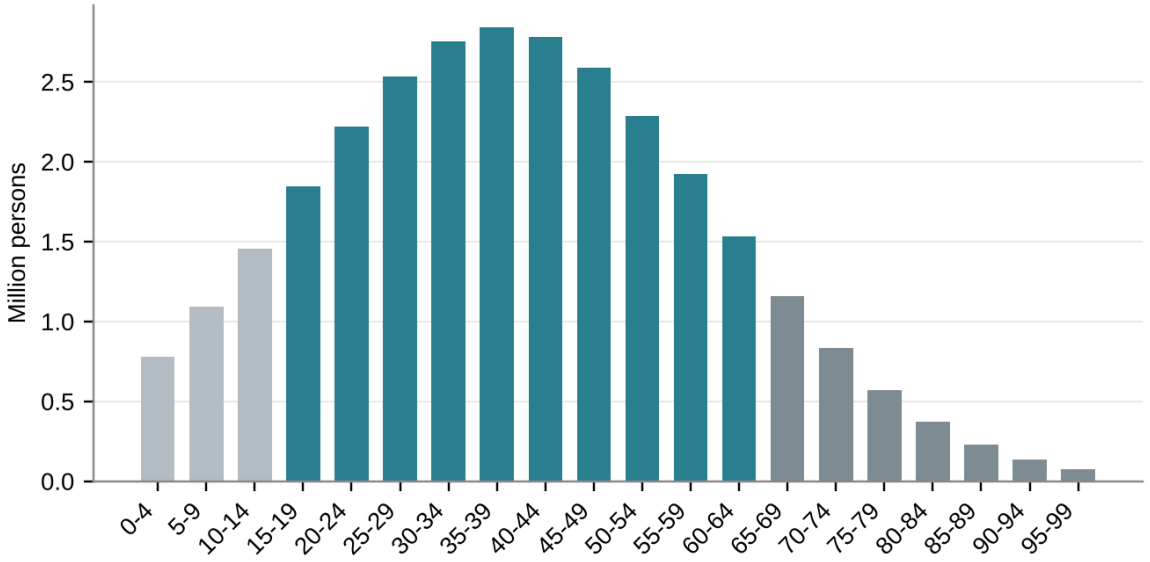
Solvania is a closed-form, stylised economy calibrated to resemble an upper-middle to high income country. Table 2 summarises the baseline. The age distribution follows a truncated normal (bell-shaped) curve with mean 38 years and standard deviation 22 years, giving 11.1% of the population under 15, 77.7% aged 15 to 64 and 11.2% aged 65 and over (Figure 2). A labour-force participation rate of about 64% of the working-age population yields 15 million workers. Employment shares equal output shares, so output per worker is initially identical (US$53,191) in all sectors.

Table 2
Baseline Characteristics of the Solvanian Economy (Year 0)

Indicator	Agriculture	Automobile	Services
Sectoral structure			
Share of GDP and employment	30%	20%	50%
Value added (US$ billion)	225	150	375
Employment (million)	4.23	2.82	7.05
Initial automation rate	5%	5%	5%
Macroeconomic and social indicators (whole economy)			
Population / labour force	30 million	15 million	
GDP / GDP per capita	US$750 bn	US$25,000	
Unemployment / poverty rate	6.0%	5.3%	
Exports / imports (% of GDP)	10%	10%	
Labour share of GDP / Gini coefficient	60%	0.369	

Note. Model calibration.

Figure 2
Population by Five-Year Age Group (Millions)



Note. Normal distribution, mean 38, standard deviation 22, truncated at 0 and 100 years.

3.2 Scenario Design

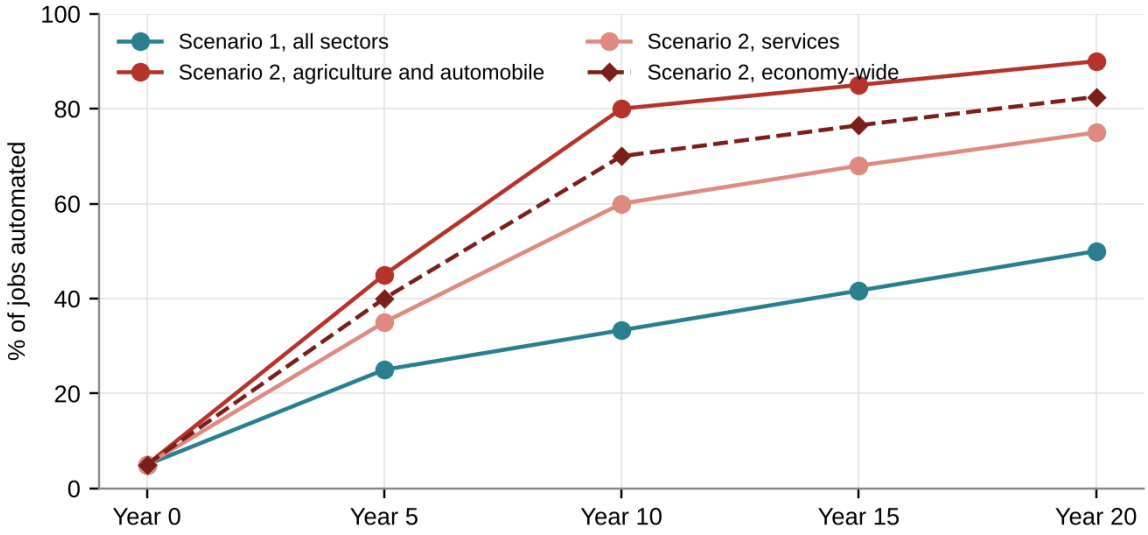
Automation deepening is defined as the share of jobs previously performed by humans that are performed by AI and robotics. Two scenarios are simulated over years 0, 5, 10, 15 and 20 (Table 3, Figure 3). In Scenario 1 (gradual), automation rises uniformly across sectors to 25% by year 5 and 50% by year 20. In Scenario 2 (rapid), automation reaches 80% in agriculture and automobile manufacturing and 60% in services by year 10. Because services employ half the workforce, these sectoral rates imply an employment-weighted rate of 70.0% at year 10; the economy-wide threshold of 75% is crossed by year 15 (76.5%). A policy variant of each scenario is examined in Section 4.4.

Table 3
Automation Rates by Scenario, Sector and Year (% of Jobs)

Scenario and sector	Year 0	Year 5	Year 10	Year 15	Year 20
Scenario 1: gradual deepening					
All sectors	5.0	25.0	33.3	41.7	50.0
Scenario 2: rapid deepening					
Agriculture	5.0	45.0	80.0	85.0	90.0
Automobile	5.0	45.0	80.0	85.0	90.0
Services	5.0	35.0	60.0	68.0	75.0
Economy-wide (weighted)	**5.0**	**40.0**	**70.0**	**76.5**	**82.5**

Note. Scenario assumptions.

Figure 3
Automation Paths Under the Two Scenarios



Note. Scenario assumptions.

3.3 Model Structure

The model has two layers: a macro-sectoral block that determines employment, output, trade and factor incomes, and a household microsimulation that converts these aggregates into a distribution of disposable income. Figure 4 summarises the transmission mechanism and Figure 5 the sequence of calculations. For sector $s \in$ {agriculture, automobile, services} in year t, human employment is:

$$H_{s,t} = H_{s,0} \times (1 - a_{s,t}) \,/\, (1 - a_{s,0}) \tag{3}$$

where $a_{s,t}$ is the automation rate. Displaced workers, $D_t = \Sigma_s (H_{s,0} - H_{s,t})$, are divided among new-task employment, exit from the labour force and unemployment:

$$N_t = \rho_t D_t, \quad X_t = \chi D_t, \quad U_t = U_0 + D_t - N_t - X_t \tag{4}$$

$$u_t = U_t \,/\, (L_0 - X_t) \tag{5}$$

where ρ_t is the reinstatement rate, χ the labour-force exit share and L_0 the initial labour force. Sectoral value added combines background growth g, a productivity and scale uplift κ_s (Section 2.2) and a Keynesian demand drag δ_s (Section 2.6) mitigated by the income replacement ratio θ:

$$Y_{s,t} = Y_{s,0}\,(1+g)^t\,[1 + \kappa_s(a_{s,t} - a_{s,0})]\,[1 - \delta_s(1-\theta)\,\max(0, u_t - u_0)] \tag{6}$$

$$GDP_t = \Sigma_s\, Y_{s,t} + \pi_N\, N_t\,(1+g)^t \tag{7}$$

where π_N is value added per new-task worker. Exports scale with tradable output (agriculture and automobile) and a competitiveness term, while imports rise with purchases of machines, chips and software:

$$EX_t = EX_0\,(Y^T_t \,/\, Y^T_0)\,[1 + \varepsilon(\bar{a}^T_t - a_0)], \quad IM_t = m_0\, GDP_t\,[1 + \mu(\bar{a}_t - a_0)] \tag{8}$$

Wages of remaining workers include a complementarity premium ω, and the labour share is the wage bill divided by GDP:

$$w_{s,t} = w_0(1+g)^t[1 + \omega(a_{s,t} - a_0)], \quad LS_t = [\Sigma_s\, H_{s,t}\, w_{s,t} + N_t\, w_{N,t}] \,/\, GDP_t \tag{9}$$

The residual, capital income, is partly distributed to households according to a concentrated wealth distribution in which the top decile receives 65%. In the microsimulation, 150,000 synthetic households (each representing one labour-force member and one dependant) are

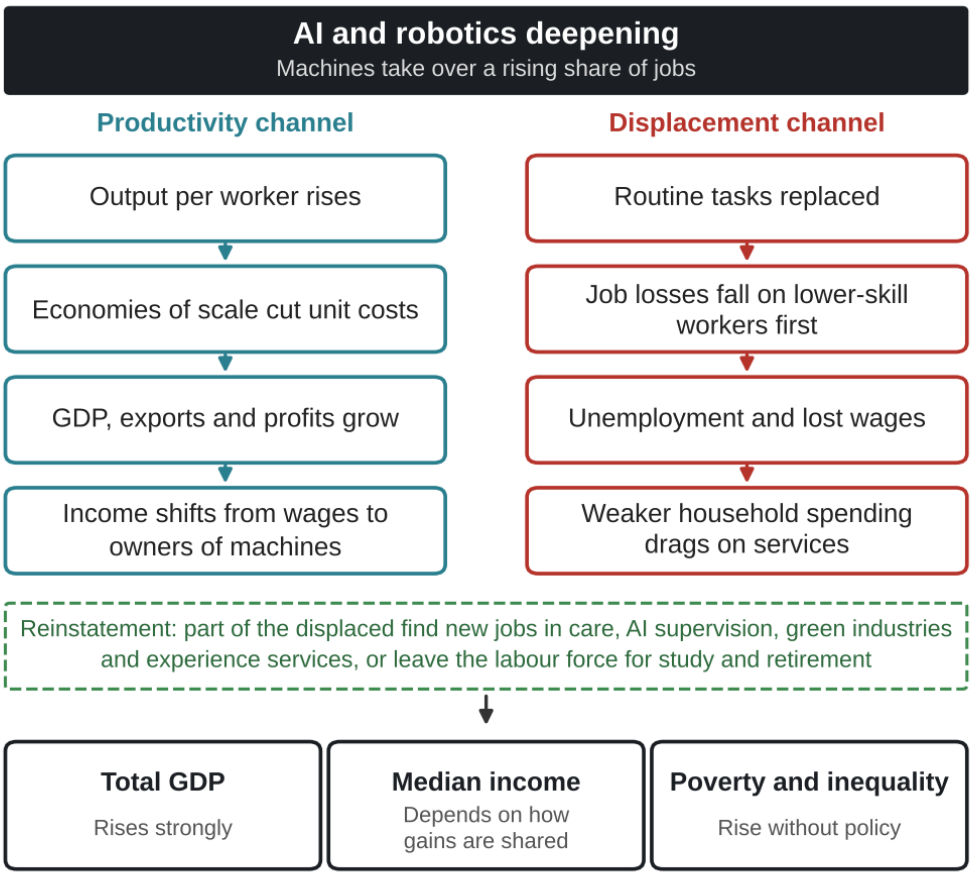
ranked by a latent skill score correlated with wages and wealth; displacement falls on the lowest-ranked workers first. Household income comprises wages, capital income, unemployment benefits or social assistance, and, in policy runs, a universal dividend. Poverty and inequality are then computed as:

$$P_0 = (1/n)\,\Sigma_i\, 1(y_i < z), \quad G = [2\,\Sigma_i\, i \cdot y_{(i)}] \,/\, [n\,\Sigma_i\, y_i] - (n+1)/n \tag{10}$$

where y_i is disposable income per person, $y_{(i)}$ incomes sorted in ascending order and z an absolute poverty line of US$5,060 per person per year held constant in real terms and calibrated to reproduce the baseline poverty rate of about 5%.

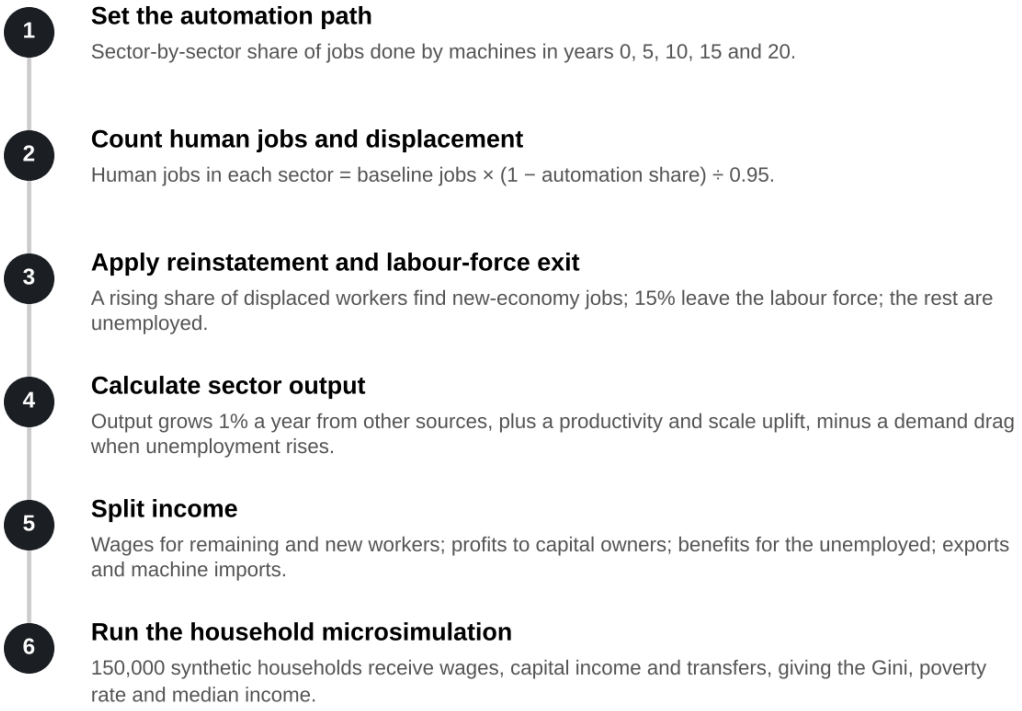
Figure 4

Transmission Mechanism From AI and Robotics Deepening to Economic and Social Outcomes



Note. Elaborated on the basis of Acemoglu and Restrepo (2019) and Korinek and Stiglitz (2019).

Figure 5
Sequence of Model Calculations



Note. Elaborated on the basis of the model in Section 3.3.

3.4 Python Implementation and Household Microsimulation

The model is implemented in Python 3 with NumPy and Matplotlib. The core module holds the baseline, scenario paths, parameters, the macro-sectoral block (Equations 3 to 9), the microsimulation and the statistics of Equation 10; a run script executes both scenarios with and without policy, the sensitivity cases of Section 4.5 and the Lorenz curves, and writes every result to a single file from which all tables and figures are produced. The core module is listed in the Appendix.

The macro block is deterministic and reproduces Equations 3 to 9 exactly. In the microsimulation each synthetic household receives a latent skill z_i drawn from a standard normal distribution and an employability rank equal to z_i plus noise with standard deviation 0.2. Households are allocated in rank order to legacy-sector jobs; labour-force exits are drawn at random from the remaining households; the best-ranked of the rest are reinstated in new tasks and the remainder are unemployed. Legacy wages are log-normal in skill (dispersion 0.42) around the sectoral wage of Equation 9; new-task wages are log-normal with dispersion 0.3 around $w_{N,t}$. A share of 55% of capital income reaches households, allocated by a wealth index correlated with skill and rescaled so that the top decile receives 65%. Without policy, half of the unemployed (drawn at random) receive unemployment benefit of US$9,600 per household and the rest receive social assistance of US$4,000; households that leave the labour force receive US$9,600 in pension or study support. The household parameters were chosen by grid search to reproduce the baseline poverty rate, Gini coefficient, median income and quintile shares. The random seed is fixed, so all results are exactly reproducible.

3.5 Calibration

Parameters are illustrative but informed by the literature (Table 4). They are not econometric estimates for any specific country; Section 4.5 tests their influence on the results.

Table 4
Parameter Values and Theoretical or Empirical Motivation

Parameter	Value	Motivation
Productivity and scale uplift κ_s	Agriculture 0.9; automobile 1.5; services 1.1	Graetz & Michaels (2018); Kaldor (1966)
Background growth g	1% per year	Solow (1956)
Reinstatement rate ρ_t, years 5/10/15/20	Gradual 0.40/0.52/0.60/0.65; rapid 0.20/0.28/0.36/0.42	Acemoglu & Restrepo (2019); Dauth et al. (2021)
Labour-force exit share χ	0.15 (0.18 to 0.19 with policy)	Jacobson et al. (1993)
Demand-drag coefficients δ_s	Agriculture 0.25; automobile 0.35; services 0.60	Keynes (1936); Berg et al. (2018)
Income replacement ratio θ	0.30 (0.65 with policy)	Illustrative; see OECD (2019)
New-task output / wage	US$45,000 / US$30,000 (US$34,000 with policy)	Autor & Dorn (2013)
Complementarity wage premium ω	0.30	Autor et al. (2003)
Export competitiveness ε; import elasticity μ	0.5; 0.4	Krugman (1979)
Top-decile share of capital income	65%; 55% of capital income reaches households	Piketty (2014); Moll et al. (2022)
Unemployment support (no policy)	US$9,600 per household for 50% of unemployed; US$4,000 assistance otherwise	Illustrative
Wage dispersion; rank noise	0.42; 0.2	Calibrated to baseline distribution
Poverty line z	US$5,060 per person per year	Foster et al. (1984)

Note. Values as coded in the model (see Appendix).

4. Results

The results are organised to address the three research questions formulated in the Introduction: Sections 4.1 to 4.3 answer RQ1 and RQ2, and Sections 4.4 and 4.5 answer RQ3.

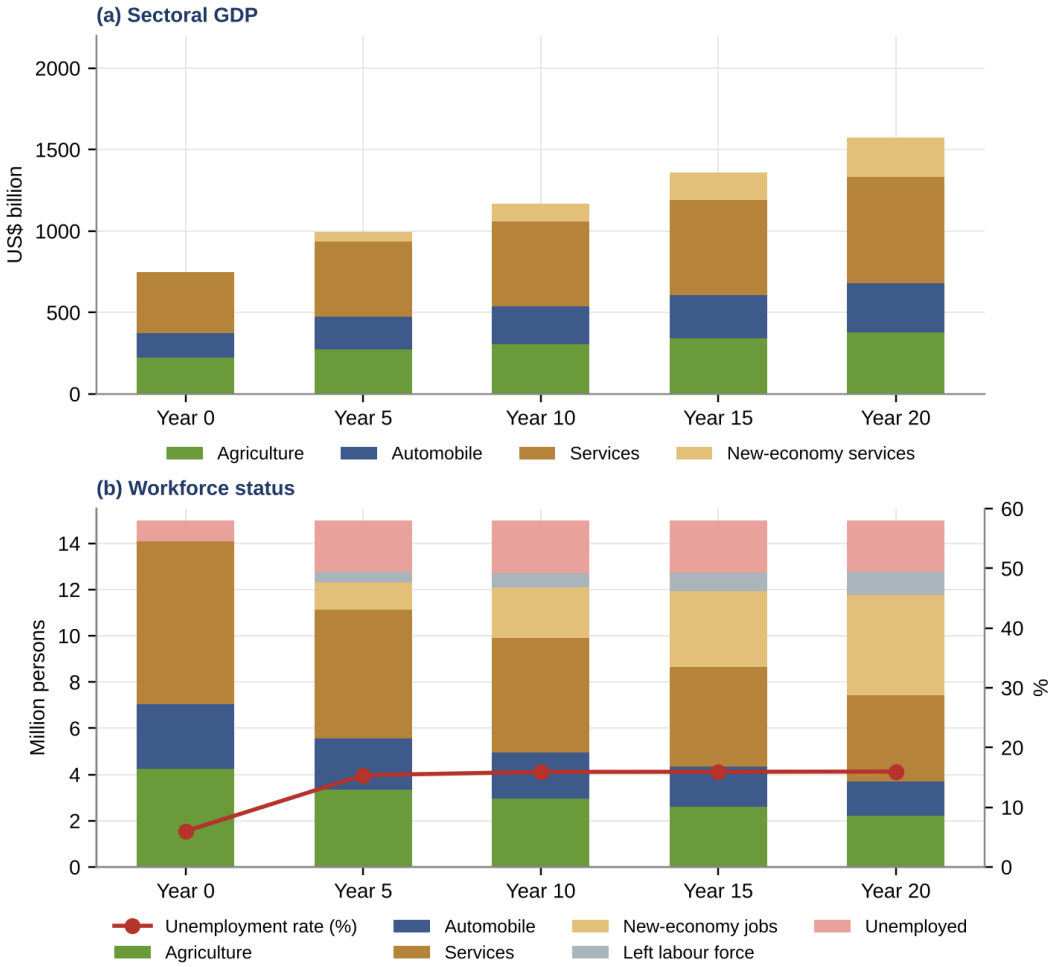
4.1 Scenario 1: Gradual Deepening

Table 5 reports the full results. In the first five years automation rises from 5% to 25%, displacing about 2.97 million workers while 1.19 million find new-task employment. Unemployment rises from 6.0% to 15.4% and poverty roughly doubles from 5.3% to 11.1%, affecting 3.3 million people. At the same time the productivity effect dominates the macroeconomic picture: GDP grows by almost one third to US$993 billion.

As reinstatement strengthens, unemployment stabilises at about 16% and new-task employment reaches 4.34 million by year 20. GDP rises to US$1,572 billion, or US$52,396 per capita, a 110% increase on the baseline. Yet the labour share falls from 60.0% to 31.0%, median income per person rises by only 43% and the Gini coefficient increases from 0.369 to 0.520. The bottom quintile's income share falls from 7.2% to 2.8%, while the top quintile's rises from 44.6% to 57.2%. Poverty peaks at 11.1% in year 5 and declines only gradually, to 9.0%, by year 20, as rising capital income and new-task wages lift some households back above the line.

Figure 6

Scenario 1: Sectoral GDP (US$ Billion) and Workforce Status (Million Persons)



Note. Model simulations. The line in panel (b) is the unemployment rate (right axis).

Table 5

Scenario 1 (Gradual Deepening): Simulation Results

Indicator	Year 0	Year 5	Year 10	Year 15	Year 20
A. Automation rate (% of jobs performed by AI and robotics)					
Agriculture	5	25	33	42	50
Automobile	5	25	33	42	50
Services	5	25	33	42	50
Economy-wide (employment-weighted)	5.0	25.0	33.3	41.7	50.0
B. Labour market (million persons unless stated)					
Human employment, agriculture	4.23	3.34	2.97	2.60	2.23
Human employment, automobile	2.82	2.23	1.98	1.73	1.48
Human employment, services	7.05	5.57	4.95	4.33	3.71
New-task (reinstated) employment	0.00	1.19	2.19	3.27	4.34
Exit from labour force	0.00	0.45	0.63	0.82	1.00
Unemployed	0.90	2.24	2.29	2.26	2.24
Unemployment rate (%)	**6.0**	**15.4**	**15.9**	**15.9**	**16.0**
C. Output and external sector (US$ billion, constant prices)					
Agriculture value added	225	274	307	341	379
Automobile value added	150	200	230	263	299
Services value added (incl. new tasks)	375	518	629	756	894

Indicator	Year 0	Year 5	Year 10	Year 15	Year 20
Gross domestic product	**750**	**993**	**1,166**	**1,361**	**1,572**
GDP per capita (US$)	25,000	33,094	38,876	45,359	52,396
Exports	75	104	123	143	166
Exports (% of GDP)	10.0	10.5	10.5	10.5	10.6
Imports	75	107	130	156	185
Imports (% of GDP)	10.0	10.8	11.1	11.5	11.8
Trade balance	0	−3	−7	−13	−19
D. Distribution and welfare					
Labour share of GDP (%)	60.0	43.6	38.7	34.5	31.0
Gini coefficient	**0.369**	**0.454**	**0.478**	**0.499**	**0.520**
Poverty headcount ratio (%)	**5.3**	**11.1**	**10.6**	**9.7**	**9.0**
Persons in poverty (million)	1.6	3.3	3.2	2.9	2.7
Median disposable income per person (US$)	15,981	17,781	19,366	21,088	22,835
Income share, bottom quintile (%)	7.2	4.1	3.5	3.2	2.8
Income share, top quintile (%)	44.6	51.2	53.4	55.3	57.2

Note. Model simulations. Constant US dollars.

4.2 Scenario 2: Rapid Deepening

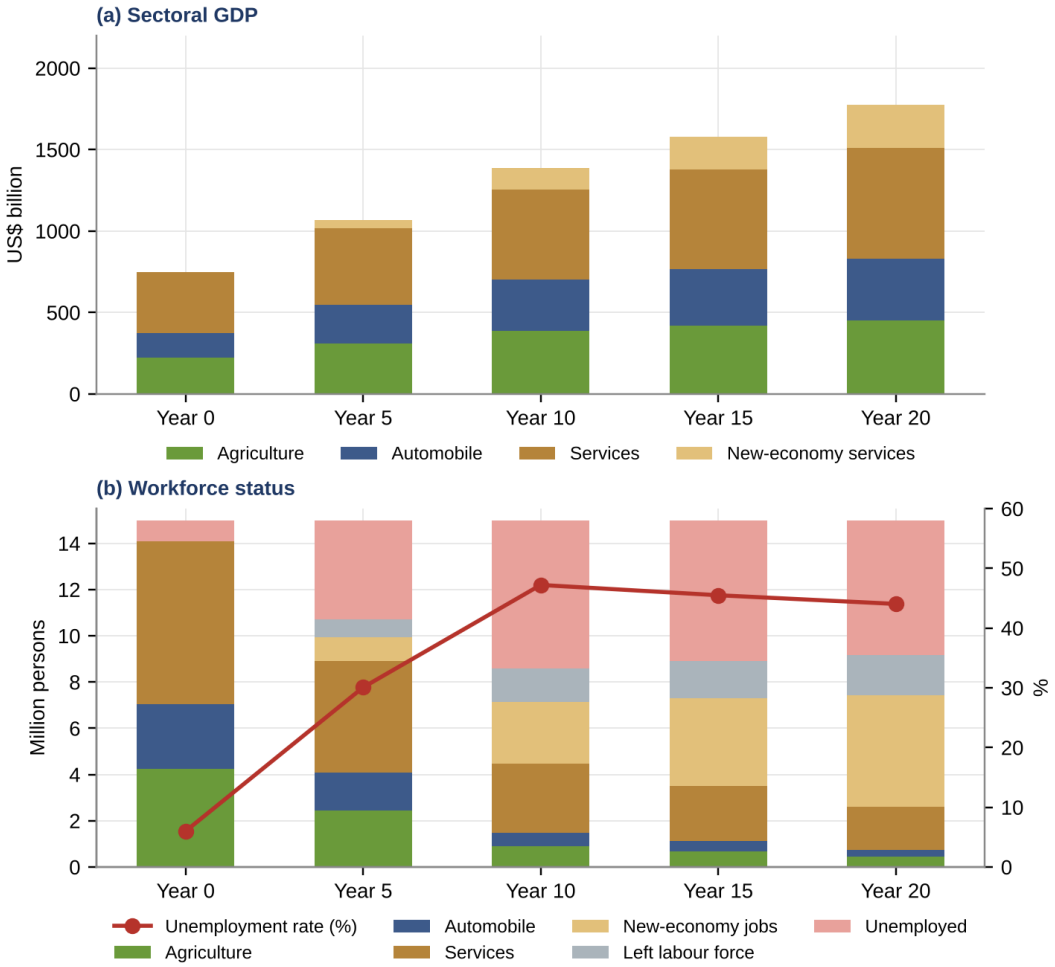
Rapid automation produces a labour-market shock (Table 6). By year 10, human employment in the original three sectors falls from 14.1 million to 4.45 million. Only 2.70 million displaced workers are reinstated, 1.45 million leave the labour force and 6.40 million are unemployed, an unemployment rate of 47.2%. Displacement overwhelms reinstatement, the configuration that Acemoglu and Restrepo (2019) identify as most damaging for labour.

Aggregate output nevertheless expands strongly. Agricultural value added rises by 72% to US$386 billion and automobile value added more than doubles to US$317 billion, reflecting economies of scale. GDP reaches US$1,387 billion at year 10, 19% higher than in the gradual scenario at the same date. Exports increase to 13.9% of GDP and imports to 12.6%, producing a trade surplus of about US$19 billion. However, the demand drag limits services: legacy services value added grows far less than technology alone would permit, because unemployed households cut consumption.

Distributional outcomes deteriorate sharply. The labour share collapses to 19.9%, the Gini coefficient reaches 0.621 and poverty rises to 17.3% (5.2 million people). Median income per person is only 8% above its baseline level despite an 85% increase in GDP per capita, a clear decoupling of aggregate prosperity from typical living standards. Between years 10 and 20, GDP continues to rise to US$1,776 billion, but unemployment remains above 40% and the Gini coefficient reaches 0.637. Poverty eases only slowly, to 14.2% by year 20, as growing capital income reaches part of the population; it remains more than two and a half times its baseline level.

Figure 7

Scenario 2: Sectoral GDP (US$ Billion) and Workforce Status (Million Persons)



Note. Model simulations. The line in panel (b) is the unemployment rate (right axis).

Table 6

Scenario 2 (Rapid Deepening): Simulation Results

Indicator	Year 0	Year 5	Year 10	Year 15	Year 20
A. Automation rate (% of jobs performed by AI and robotics)					
Agriculture	5	45	80	85	90
Automobile	5	45	80	85	90
Services	5	35	60	68	75
Economy-wide (employment-weighted)	5.0	40.0	70.0	76.5	82.5
B. Labour market (million persons unless stated)					
Human employment, agriculture	4.23	2.45	0.89	0.67	0.45
Human employment, automobile	2.82	1.63	0.59	0.45	0.30
Human employment, services	7.05	4.82	2.97	2.37	1.86
New-task (reinstated) employment	0.00	1.04	2.70	3.82	4.83
Exit from labour force	0.00	0.78	1.45	1.59	1.73
Unemployed	0.90	4.28	6.40	6.10	5.85
Unemployment rate (%)	**6.0**	**30.1**	**47.2**	**45.5**	**44.0**
C. Output and external sector (US$ billion, constant prices)					
Agriculture value added	225	308	386	418	452
Automobile value added	150	237	317	346	378
Services value added (incl. new tasks)	375	520	684	814	946

Indicator	Year 0	Year 5	Year 10	Year 15	Year 20
Gross domestic product	**750**	**1,066**	**1,387**	**1,579**	**1,776**
GDP per capita (US$)	25,000	35,525	46,228	52,623	59,189
Exports	75	131	193	214	237
Exports (% of GDP)	10.0	12.3	13.9	13.6	13.3
Imports	75	121	175	203	233
Imports (% of GDP)	10.0	11.4	12.6	12.9	13.1
Trade balance	0	+9	+19	+11	+4
D. Distribution and welfare					
Labour share of GDP (%)	60.0	34.0	19.9	18.3	16.9
Gini coefficient	**0.369**	**0.532**	**0.621**	**0.629**	**0.637**
Poverty headcount ratio (%)	**5.3**	**16.5**	**17.3**	**15.6**	**14.2**
Persons in poverty (million)	1.6	5.0	5.2	4.7	4.3
Median disposable income per person (US$)	15,981	17,611	17,230	18,661	19,894
Income share, bottom quintile (%)	7.2	2.8	2.3	2.2	2.0
Income share, top quintile (%)	44.6	56.8	65.1	65.9	66.7

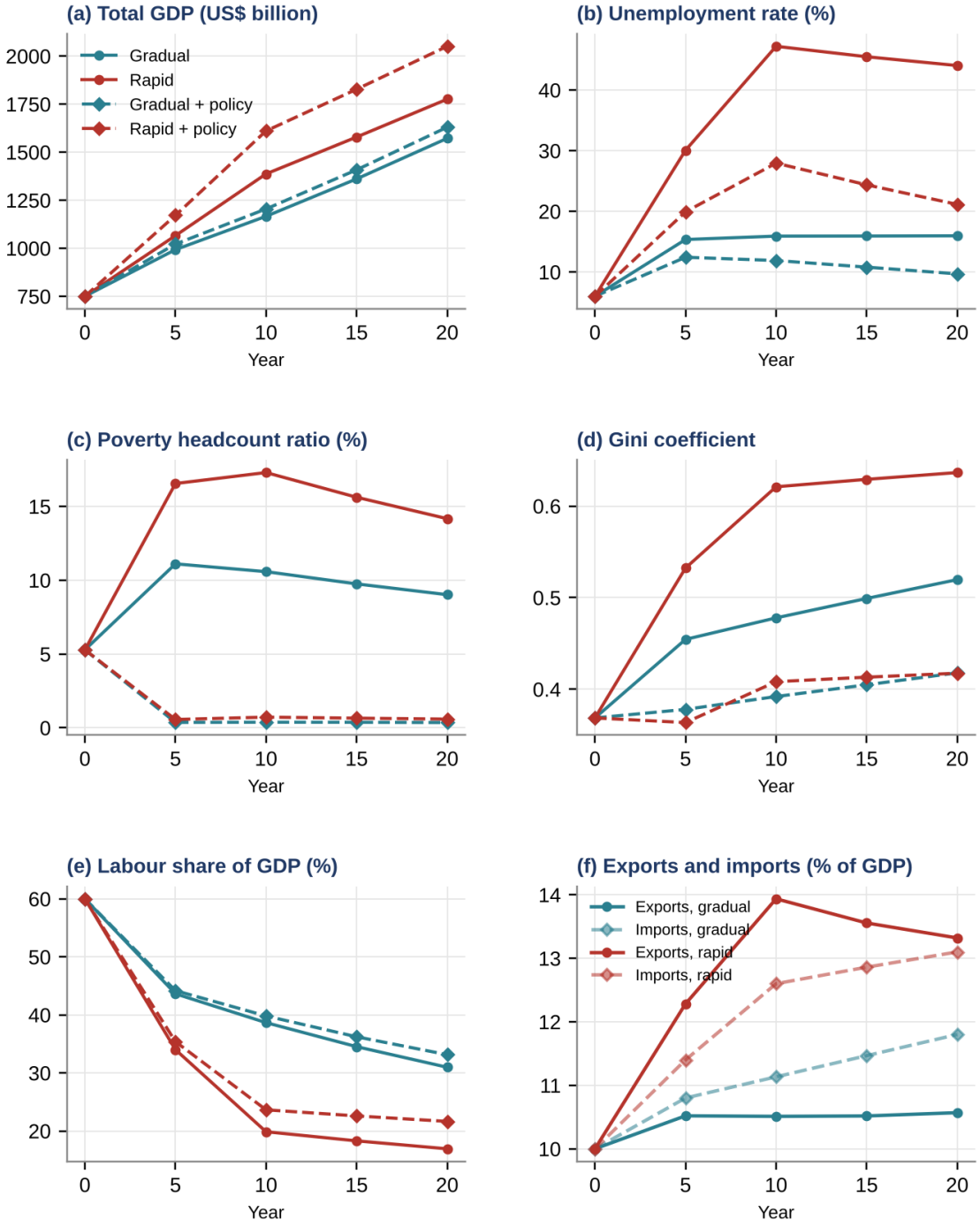
Note. Model simulations. Constant US dollars.

4.3 Comparative and Distributional Analysis

Figure 8 compares the two scenarios. Faster automation yields higher GDP at every horizon but also higher unemployment, poverty and inequality. The decoupling between GDP per capita and median income (Figure 9) is the central empirical signature of the model: automation raises average income through the productivity effect while the displacement effect and the shift from wages to profits prevent those gains from reaching the median household. Lorenz curves (Figure 10) show that the bottom half of the population receives 26.3% of income at baseline but only 10.8% at year 10 of the rapid scenario.

Figure 8

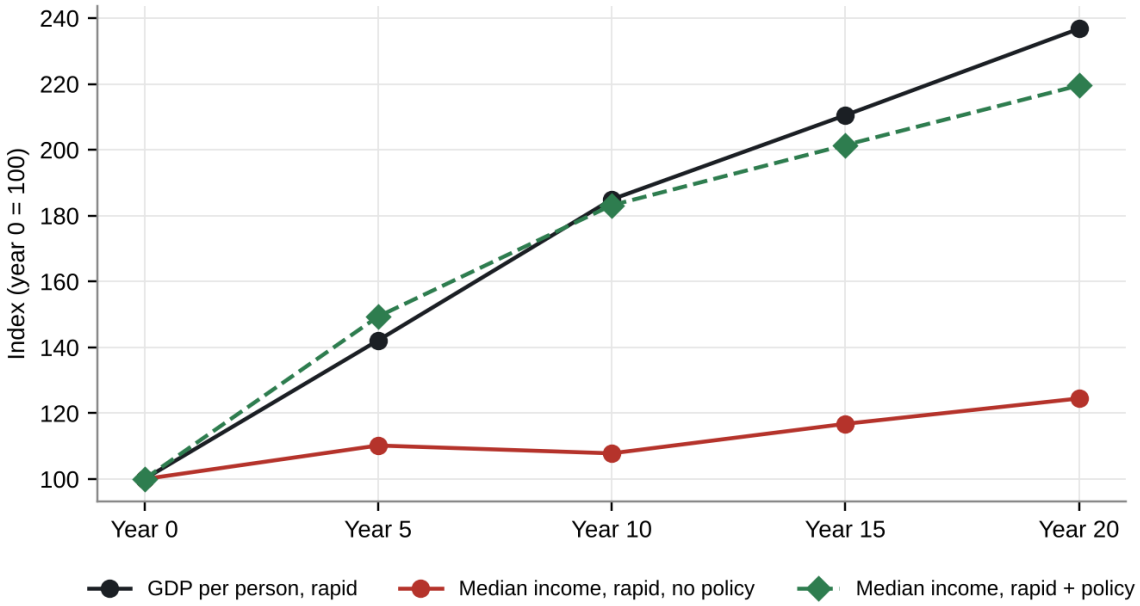
Comparative Indicators: GDP, Unemployment, Poverty, Gini, Labour Share and Trade



Note. Model simulations. Solid lines: no policy; dashed lines: policy package (Section 4.4).

Figure 9

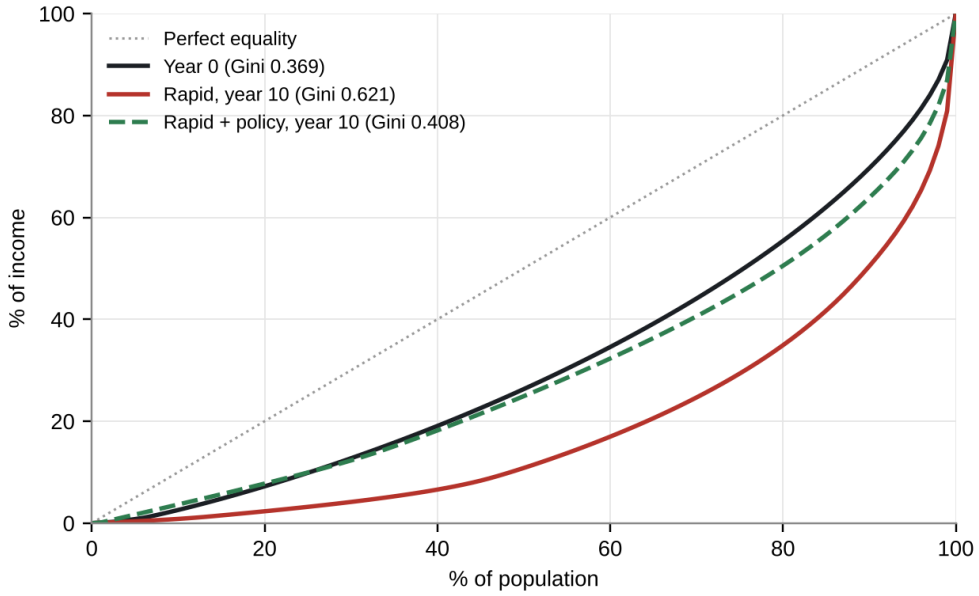
GDP per Capita and Median Disposable Income per Person, Index (Year 0 = 100)



Note. Model simulations, rapid scenario.

Figure 10

Lorenz Curves: Baseline, Rapid Scenario and Rapid Scenario With Policy (Year 10)



Note. Model simulations. Gini coefficients: baseline 0.369; rapid 0.621; rapid with policy 0.408.

4.4 Policy Simulation

Guided by the theory in Section 2, the model was re-run with a policy package that acts on each channel of Figure 4. The package comprises: (i) an automation levy of 10% (gradual) or 20% (rapid) of capital income, financing a universal dividend paid to every resident; (ii) universal income support of US$14,000 (gradual) or US$16,000 (rapid) per household for the unemployed and for those who leave the labour force, raising the income replacement ratio from 0.30 to 0.65; (iii) retraining and job-creation programmes that raise the reinstatement rate by 10 points (gradual) or 22 points (rapid), for example from 0.28 to 0.50 at year 10 in the rapid scenario,

with a wage floor of US$34,000 for new-task jobs; and (iv) work sharing that retains 5% to 6% of otherwise displaced workers in existing roles, while lifelong-learning and early-retirement options raise the exit share to 0.18 to 0.19. A 2.5% share of households is assumed to be excluded from transfer systems.

Table 7
Outcomes With and Without the Policy Package

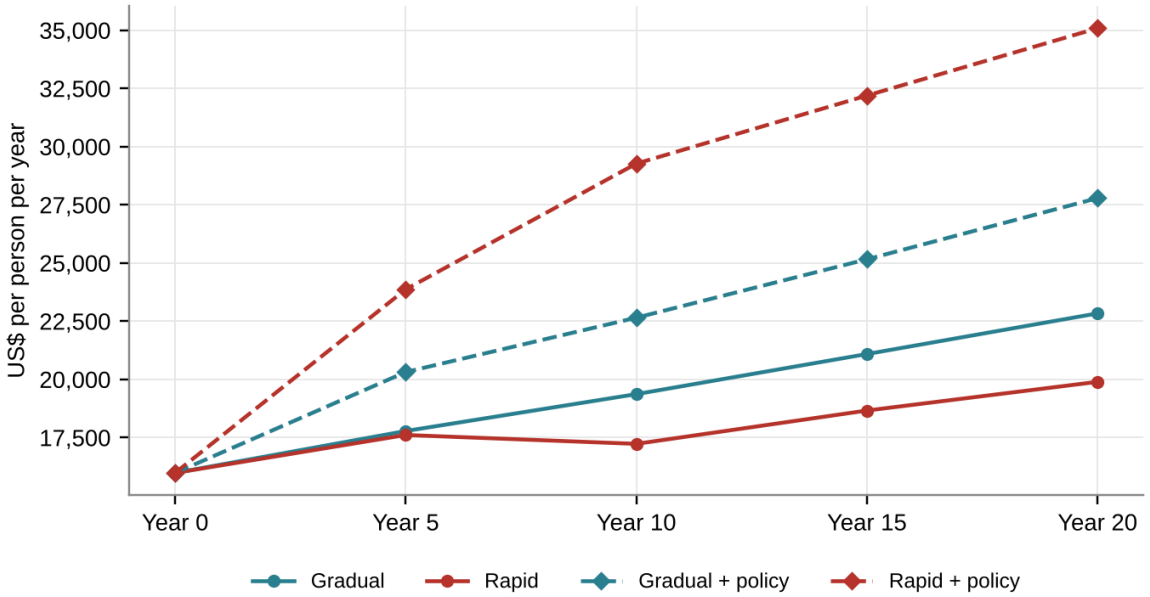
Indicator	Gradual, no policy, yr 20	Gradual + policy, yr 20	Rapid, no policy, yr 10	Rapid + policy, yr 10	Rapid, no policy, yr 20	Rapid + policy, yr 20
GDP (US$ billion)	**1,572**	**1,630**	**1,387**	**1,611**	**1,776**	**2,051**
GDP per capita (US$)	52,396	54,324	46,228	53,684	59,189	68,363
Unemployment rate (%)	16.0	9.7	47.2	28.0	44.0	21.2
Poverty headcount ratio (%)	**9.0**	**0.4**	**17.3**	**0.7**	**14.2**	**0.6**
Persons in poverty (million)	2.7	0.1	5.2	0.2	4.3	0.2
Gini coefficient	**0.520**	**0.418**	**0.621**	**0.408**	**0.637**	**0.418**
Median income per person (US$)	**22,835**	**27,786**	**17,230**	**29,269**	**19,894**	**35,085**
Bottom quintile share (%)	2.8	6.7	2.3	7.8	2.0	7.4
Labour share of GDP (%)	31.0	33.1	19.9	23.6	16.9	21.6
Dividend per person (US$/year)	0	3,632	0	8,198	0	10,713
Automation levy (% of GDP)	0.0	6.7	0.0	15.3	0.0	15.7

Note. Model simulations.

In the rapid scenario at year 10, the package reduces poverty from 17.3% to 0.7%, unemployment from 47.2% to 28.0% and the Gini coefficient from 0.621 to 0.408, while raising median income from US$17,230 to US$29,269 (+70%). GDP is 16% higher (US$1,611 billion) because stronger household incomes relieve the demand constraint and more workers are productively reinstated. In the gradual scenario at year 20, poverty falls from 9.0% to 0.4% and median income rises from US$22,835 to US$27,786. The levy raises 6.7% of GDP in the gradual case and 15.3% in the rapid case; the latter is large, but it is drawn from a capital share of roughly 76% of GDP.

Figure 11

Median Disposable Income per Person Under Four Scenario Runs (US$)



Note. Model simulations.

4.5 Sensitivity Analysis

Table 8 tests the robustness of the results to the most uncertain parameters: the productivity uplift, the reinstatement rate and the strength of the demand drag. Higher productivity raises GDP but also inequality, because the additional output accrues largely to capital. Lower reinstatement has the largest effect on unemployment (raising it to 54.3% at year 10 of the rapid scenario), while weaker productivity gains produce the highest poverty rate because less income is generated for distribution. In every case, poverty in the rapid no-policy scenario lies between 15.4% and 19.7%, whereas with the policy package it remains below 1%. The qualitative conclusions are therefore robust.

Table 8

Sensitivity of Key Results to Alternative Assumptions

Assumption	S1 yr 20 GDP	S1 yr 20 poverty %	S1 yr 20 Gini	S2 yr 10 GDP	S2 yr 10 poverty %	S2 yr 10 Gini	S2 + policy poverty %
Central assumptions	**1,572**	**9.0**	**0.520**	**1,387**	**17.3**	**0.621**	**0.7**
Productivity uplift 50% lower	1,348	9.9	0.490	1,122	19.7	0.596	0.8
Productivity uplift 50% higher	1,795	8.3	0.544	1,652	15.4	0.640	0.7
Reinstatement 10 points lower	1,515	10.9	0.533	1,308	18.9	0.632	0.8
Reinstatement 10 points higher	1,629	7.0	0.506	1,466	15.5	0.609	0.6
No demand drag	1,615	8.9	0.525	1,568	16.0	0.634	0.7
Demand drag doubled	1,529	9.2	0.514	1,206	18.9	0.605	0.7

Note. Model simulations. GDP in US$ billion. S1 = gradual scenario; S2 = rapid scenario. Productivity cases scale κ_s by 0.5 or 1.5; reinstatement shifts ρ_t by 10 percentage points; demand-drag cases set δ_s to zero or double it.

5. Discussion

The simulations are consistent with the central proposition of the task-based framework: the labour-market consequences of automation depend less on the level of technology than on the race between displacement and reinstatement (Acemoglu & Restrepo, 2019). In the gradual scenario, reinstatement has time to catch up and unemployment stabilises; in the rapid scenario displacement races ahead and the economy settles into a high-unemployment equilibrium even as output grows.

The results also illustrate the core propositions of the economics of AI and robotics set out in Section 2.1. The falling cost of prediction and physical work raises output strongly, particularly in the automobile sector where economies of scale are greatest, consistent with the view of AI and robotics as general-purpose technologies (Bresnahan & Trajtenberg, 1995; Agrawal et al., 2018). At the same time, the substitution of machines for labour pushes the capital share from 40% to around 80% of GDP in the rapid scenario, the outcome predicted by a CES framework with an elasticity of substitution above one (Karabarbounis & Neiman, 2014). Because the returns to machines and data are concentrated, the distributional consequences are determined largely by ownership and policy rather than by technology alone.

Second, the results illustrate how automation can produce a modern analogue of the rising segment of Kuznets' (1955) inverted-U. Unlike the historical transition from agriculture to industry, however, there is no automatic mechanism in the model that brings inequality back down: the Gini coefficient rises monotonically in both no-policy scenarios. This supports the argument of Piketty (2014) and Moll, Rachel and Restrepo (2022) that, when capital income is concentrated, technology-driven growth tends to widen inequality unless institutions intervene.

Third, the demand channel matters for growth itself. The finding that redistribution raises GDP in the rapid scenario accords with Keynesian theory (Keynes, 1936) and with Korinek and Stiglitz (2019), who argue that the gains from AI can be shared in a Pareto-improving way. It also corresponds to the Kaldor–Hicks compensation principle (Kaldor, 1939; Hicks, 1939): automation passes the potential compensation test, because winners gain enough to compensate losers, but welfare improves in practice only if compensation is actually paid.

Fourth, the external sector shows that productivity gains in tradable sectors improve competitiveness, consistent with increasing-returns trade theory (Krugman, 1979), but that rising imports of machines can erode the trade balance over time, as occurs by year 20 in three of the four runs. Finally, the decoupling of median income from GDP per capita underlines Sen's (1999) argument that aggregate output is an incomplete measure of development.

5.1 Limitations

The model is deliberately stylised. Parameters are illustrative rather than estimated; the economy has no explicit capital accumulation, financial sector, government budget constraint or general-equilibrium price adjustment; population and labour supply are held constant; the microsimulation has no tax system and no behavioural responses, such as changes in labour supply due to the dividend, although evidence from the Alaska Permanent Fund suggests such effects on employment are small (Jones & Marinescu, 2022). The household-block parameters were calibrated only to the baseline distribution, so distributional results at later dates are model outputs, not targets. The results should therefore be read as an illustration of mechanisms rather than as forecasts for any real country.

6. Policy Recommendations

The analysis suggests that the objective of policy should not be to halt automation, whose productivity gains are substantial, but to ensure that those gains reach households faster than jobs disappear. Table 9 organises the recommendations into three phases, and Sections 6.1 to 6.10 describe them.

Table 9
Phased Policy Roadmap

Prepare (years 0 to 2)	Cushion and retrain (years 3 to 10)	Share and redesign (years 10 to 20)
Automation impact monitoring by sector and region	Automation levy and AI Dividend Fund	Universal AI dividend for every resident
Remove tax bias that favours machines over workers	Wage insurance for displaced workers	Broad ownership of robots and data
Launch lifelong learning accounts	Care, green and public-service job programmes	Competition rules against AI monopolies
Universal unemployment insurance	Shorter working week and job sharing	Education built around human skills

Note. Derived from the simulation results and the literature reviewed in Section 2.

6.1 Share the Automation Dividend

Establish a sovereign AI Dividend Fund financed by a levy on automation profits, public equity stakes in major AI and robotics platforms and taxes on data rents, and distribute a universal dividend. Evidence from the Alaska Permanent Fund indicates that universal cash transfers need not reduce employment (Jones & Marinescu, 2022), and reviews of basic income find potential for poverty reduction (Banerjee et al., 2019; Van Parijs & Vanderborght, 2017). In the model this is the single most effective lever for poverty reduction.

6.2 Restore Tax Neutrality Between Labour and Capital

Tax systems that tax labour heavily while granting generous allowances for equipment and software encourage excessive automation (Acemoglu et al., 2020). Reduce employer social contributions on low- and middle-wage jobs and raise effective taxation of capital income. Optimal-tax analyses support a temporary robot tax while incumbent workers cannot easily change occupations (Guerreiro et al., 2022; Costinot & Werning, 2023).

6.3 Build a Universal Income Floor

Make unemployment insurance universal, extend its duration during structural transitions and introduce wage insurance for displaced workers who accept lower-paid jobs, reflecting the persistent earnings losses documented by Jacobson et al. (1993). Atkinson (2015) proposes complementary measures such as a participation income.

6.4 Accelerate Reinstatement Through Skills and New Tasks

Provide funded lifelong-learning accounts, sector transition councils for agriculture, automobile manufacturing and services, and training stipends, so that education keeps pace with technology (Goldin & Katz, 2008). Direct public research and procurement towards technologies that create new tasks for workers rather than merely replacing them (Acemoglu & Johnson, 2023).

6.5 Expand Employment in Human-Centred Services

An ageing population will require more health care, long-term care and education, sectors in which Baumol-type labour intensity persists (Baumol, 1967). A public employment guarantee in care, green infrastructure and community services can absorb displaced workers.

6.6 Share Working Time

Shorter standard working weeks, phased retirement and sabbaticals can spread remaining work across more people, realising the potential Keynes (1930) foresaw for shorter hours as productivity rises.

6.7 Broaden Capital Ownership

Promote employee share ownership, cooperatives and pension-fund investment in domestic automation so that more households receive capital income (Freeman, 2015).

6.8 Protect Rural and Agricultural Communities

In the rapid scenario 3.3 million of 4.2 million agricultural jobs disappear. Support farmer cooperatives that jointly own robotic equipment, robotics-as-a-service for smallholders, rural broadband and agro-processing that retains value in rural regions (Lewis, 1954; Rodrik, 2016).

6.9 Maintain Competition and a Sustainable External Balance

Apply competition policy to prevent monopoly rents in AI platforms (Autor et al., 2020) and develop domestic capacity in robotics, semiconductors and software to limit import dependence.

6.10 Manage the Pace of Automation and Monitor Outcomes

Require advance notice and co-financed retraining before large-scale automation, stagger public incentives across sectors and publish a real-time labour-market and distribution dashboard. The gradual scenario delivers markedly better social outcomes than the rapid one even before policy is applied.

7. Conclusion

Using the analytical lens of the economics of AI and robotics, a hypothetical three-sector economy and a household microsimulation grounded in the task-based theory of automation, this study has shown that AI and robotics deepening can dramatically increase national output while leaving the typical household little better off and substantially increasing poverty and inequality (RQ1 and RQ2). In the rapid scenario, GDP per capita rises by 85% in ten years, median income by only 8%, and poverty more than triples. The technology is not the source of the problem; the distribution of its rewards is.

A coherent policy package, combining an automation dividend, a universal income floor, accelerated reinstatement, work sharing and broader capital ownership, transforms the same technological shock into higher growth, a median income 70% higher than the no-policy path and near-zero poverty (RQ3). The principal lesson for policymakers is to build these institutions before the fastest phase of automation arrives. Future research should embed these mechanisms in a dynamic general-equilibrium model with capital accumulation, fiscal constraints and empirically estimated parameters for specific countries; the open Python implementation is designed to make such extensions straightforward.

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Appendix. Python Implementation of the Model

The model runs in Python 3 with NumPy and Matplotlib. Running the run script reproduces every result in Tables 2 to 8 and writes them to one results file; the figure script draws Figures 2 to 11. The core module is listed below.

```
"""
Solvania model: macro-sectoral block + 150,000-household microsimulation.
Implements Section 3 of "The Economics of AI and Robotics" (this article).

Equation numbers refer to the paper.
"""
import numpy as np

# ---------------------------------------------------------------- baseline (Table 2)
YEARS = [0, 5, 10, 15, 20]
SECT = ['Agriculture', 'Automobile', 'Services']
POP = 30.0                      # million persons
L0 = 15.0                       # labour force, million
U0 = 0.90                       # unemployed, million (6.0%)
E0 = L0 - U0                    # 14.1 million employed
u0 = U0 / L0
GDP0 = 750.0                    # US$ billion
H0 = np.array([0.30, 0.20, 0.50]) * E0      # employment by sector
Y0 = np.array([0.30, 0.20, 0.50]) * GDP0    # value added by sector
LS0 = 0.60                       # labour share
w0 = LS0 * GDP0 * 1e9 / (E0 * 1e6)          # average wage, US$
EX0 = 0.10 * GDP0; m0 = 0.10                # exports and import ratio
TRAD = [0, 1]                    # tradable sectors: agriculture, automobile

# ---------------------------------------------------------------- scenarios (Table 3)
PATH = {
    'gradual': np.array([[5, 25, 100/3, 125/3, 50]] * 3) / 100,
    'rapid':   np.array([[5, 45, 80, 85, 90],
                         [5, 45, 80, 85, 90],
                         [5, 35, 60, 68, 75]]) / 100,
}

# ---------------------------------------------------------------- parameters (Table 4)
KAPPA = np.array([0.9, 1.5, 1.1])            # productivity and scale uplift
DELTA = np.array([0.25, 0.35, 0.60])         # demand-drag coefficients
RHO = {'gradual': [0, 0.40, 0.52, 0.60, 0.65],
       'rapid':   [0, 0.20, 0.28, 0.36, 0.42]}
G = 0.01                                     # background growth
CHI = 0.15                                   # labour-force exit share
THETA = 0.30                                 # income replacement ratio
PI_N = 45_000.0                              # value added per new-task worker
W_N = 30_000.0                               # new-task wage
OMEGA = 0.30                                 # complementarity wage premium
EPS, MU = 0.5, 0.4                           # export competitiveness, import elasticity

# policy package (Section 4.4)
POLICY = {
    'gradual': dict(levy=0.10, support=14_000, keep=0.05, d_rho=0.10, chi=0.18),
    'rapid':   dict(levy=0.20, support=16_000, keep=0.06, d_rho=0.22, chi=0.19),
}
THETA_POL = 0.65
W_N_POL = 34_000.0
EXCLUDED = 0.025

# no-policy income support (Table 4)
UB, UB_COVER, SA = 9_600.0, 0.50, 4_000.0
EXIT_INC = 9_600.0                           # pension / study support for labour-force exits

POV_LINE = 5_060.0                           # US$ per person per year



def macro(sc, pol=False, kap=1.0, rho_shift=0.0, dscale=1.0):
    """Macro-sectoral block, equations (3)-(9). Returns one dict per year."""
    a = PATH[sc]
    P = POLICY[sc]
    th = THETA_POL if pol else THETA
    out = []
    for j, t in enumerate(YEARS):
        H = H0 * (1 - a[:, j]) / (1 - a[:, 0])                          # (3)
        if pol and j > 0:
            H = H + P['keep'] * (H0 - H)                                 # work sharing
        D = (H0 - H).sum()
        rho = RHO[sc][j] + rho_shift + (P['d_rho'] if pol and j > 0 else 0)
        rho = min(max(rho, 0.0), 0.95)
        chi = (P['chi'] if pol else CHI) if j > 0 else 0.0
        N = rho * D; X = chi * D; U = U0 + D - N - X                     # (4)
        u = U / (L0 - X)                                                 # (5)
        gf = (1 + G) ** t
        da = a[:, j] - a[:, 0]
```

```
        Y = Y0 * gf * (1 + KAPPA * kap * da) * (1 - DELTA * dscale * (1 - th) * max(0, u - u0))  # (6)
        YN = PI_N * N * 1e6 / 1e9 * gf
        gdp = Y.sum() + YN                                                  # (7)
        aT = (a[TRAD, j] * H0[TRAD]).sum() / H0[TRAD].sum()
        abar = (a[:, j] * H0).sum() / E0
        ex = EX0 * (Y[TRAD].sum() / Y0[TRAD].sum()) * (1 + EPS * (aT - 0.05))   # (8)
        im = m0 * gdp * (1 + MU * (abar - 0.05))
        w = w0 * gf * (1 + OMEGA * da)                                      # (9)
        wN = (W_N_POL if pol and j > 0 else W_N) * gf
        wb = (H * 1e6 * w).sum() / 1e9 + N * 1e6 * wN / 1e9
        out.append(dict(t=t, a=a[:, j].copy(), abar=abar, H=H, D=D, N=N, X=X, U=U, u=u,
                        Y=Y, YN=YN, gdp=gdp, ex=ex, im=im, w=w, wN=wN, wb=wb,
                        LS=wb / gdp, cap=gdp - wb))
    return out



# ------------------------------------------------------------------ microsimulation
NH = 150_000                    # synthetic households (1 worker + 1 dependant)
PERS = 2.0
HH_W = L0 * 1e6 / NH            # real households represented by each synthetic one

# calibration of the household block (chosen to reproduce the baseline distribution)
CAL = dict(sig=0.42, lam=0.20, beta=1.3, nu=1.0, phi=0.55, top=0.65)

rng = np.random.default_rng(2026)
z = rng.standard_normal(NH)                         # latent skill
rank = z + CAL['lam'] * rng.standard_normal(NH)     # employability rank
ORDER = np.argsort(-rank)                           # highest rank first
wealth = np.exp(CAL['beta'] * (z + CAL['nu'] * rng.standard_normal(NH)))
exit_draw = rng.random(NH)
cover_draw = rng.random(NH)
excluded = rng.random(NH) < EXCLUDED



def wealth_weights(wt, top):
    """Rescale wealth so that the top decile receives `top` of capital income."""
    thr = np.quantile(wt, 0.9)
    t = wt >= thr
    w = wt.copy()
    w[t] *= top / w[t].sum()
    w[~t] *= (1 - top) / w[~t].sum()
    return w



WW = wealth_weights(wealth, CAL['top'])



def micro(m, sc, pol=False, levy=0.0):
    """Disposable income per person for each synthetic household."""
    nH = int(round(NH * m['H'].sum() / L0))
    nN = int(round(NH * m['N'] / L0))
    nX = int(round(NH * m['X'] / L0))
    emp = ORDER[:nH]
    rest = ORDER[nH:]
    ex = rest[np.argsort(exit_draw[rest])][:nX]          # exits drawn at random
    remain = np.setdiff1d(rest, ex)
    remain = remain[np.argsort(-rank[remain])]
    new = remain[:nN]                                    # best-ranked reinstated first
    un = remain[nN:]


    inc = np.zeros(NH)
    avgw = (m['H'] * m['w']).sum() / m['H'].sum()
    e = np.exp(CAL['sig'] * z[emp]); inc[emp] = e / e.mean() * avgw
    if len(new):
        e = np.exp(0.3 * z[new]); inc[new] = e / e.mean() * m['wN']


    cap_pool = m['cap'] * 1e9 * (1 - levy) * CAL['phi']
    inc += WW * cap_pool / HH_W                          # capital income per household


    if pol:
        sup = POLICY[sc]['support']
        inc[un] += sup
        inc[ex] += sup
        div = levy * m['cap'] * 1e9 / (POP * 1e6)        # universal dividend per person
        tr = np.full(NH, div * PERS)
        tr[excluded] = 0.0
        inc[un[excluded[un]]] -= sup
        inc[ex[excluded[ex]]] -= sup
        inc += tr
    else:
        div = 0.0
        inc[un] += np.where(cover_draw[un] < UB_COVER, UB, SA)
        inc[ex] += EXIT_INC
    return inc / PERS, div
```

```
def stats(y):
    s = np.sort(y); n = len(s); i = np.arange(1, n + 1)
    gini = 2 * (i * s).sum() / (n * s.sum()) - (n + 1) / n
    q = n // 5
    return dict(pov=(y < POV_LINE).mean(), gini=gini, med=float(np.median(y)),
                q1=s[:q].sum() / s.sum(), q5=s[-q:].sum() / s.sum(),
                b50=s[:n // 2].sum() / s.sum())



def run(sc, pol=False, **kw):
    rows = []
    for j, m in enumerate(macro(sc, pol, **kw)):
        p = pol and j > 0
        levy = POLICY[sc]['levy'] if p else 0.0
        y, div = micro(m, sc, pol=p, levy=levy)
        r = dict(m); r.update(stats(y)); r.update(div=div, levy_gdp=levy * m['cap'] / m['gdp'],
                                                  gdppc=m['gdp'] / POP * 1000, y=y)
        rows.append(r)
    return rows
```