EPiC Series in Education Science
Volume 6, 2024, Pages 164–178
Proceedings of the NEMISA Digital Skills Summit and Colloquium 2024

Modelling the Impact of Digital Skills on Employment with a Macroeconomic Agent-Based Model

Dino Giovannoni[1], Evert Knoesen[2], and Jan Mentz[3]

[1] Belgium Campus iTversity, Pretoria North, South Africa.
giovannoni.d@belgiumcampus.ac.za
[2] Rhodes Business School, Rhodes University, Makhanda, South Africa
e.knoesen@ru.ac.za
[3] Belgium Campus iTversity, Pretoria North, South Africa.
mentz.j@belgiumcampus.ac.za

Abstract

This paper investigates how widespread strategic adoption of digital skills, technology and knowledge by firms would affect employment, inequality and the economy in general. A macroeconomic agent-based model (MABM) was developed to simulate micro-level interactions between economic agents in different markets, giving rise to emergent macroeconomic features. Agents representing individuals in the economy acquire different levels of skills as they progress through an education system. Based on a firm's level of technological sophistication, it will employ a workforce that aligns with its skills requirements. The simulations show that if firms in the economy adopt higher levels of technology in their operations, higher levels of unemployment may emerge, in particular for the sector of the population with low levels of digital skills. The education system would need to be transformed to provide an inclusive, quality education that is aligned with the current and future needs of industry.

Keywords: Agent-based modelling, Digital skills, Digital transformation, Unemployment, Inequality

1 Introduction

As the world becomes increasingly knowledge-based and interconnected through information and communication technologies (ICT), there is a growing need for people to be equipped with a broad range of digital and technological skills to enable meaningful participation in both the workforce and broader society [45]. Today, digital skills encompass more than the ability to simply operate devices. There is an ever-increasing need for the ability to navigate the digital world, from critical online information gathering to creative content creation, and from seamless online collaboration to responsible digital citizenship [23]. As the globalized, increasingly complex world becomes ever more intertwined with technology, digital skills unlock doors to education, employment, and meaningful participation in society. Digital transformation, while promising efficiency and growth, also casts a dark shadow of a potetial rise in unemployment.

An economy is a highly complex system of interacting agents, who change and adapt to each other's behaviour in myriad ways. The process of constructing and analysing models is a means of understanding complex real-world phenomena. In most cases, it is necessary to simplify the system or consider only certain aspects of it in order to better model it [24]. An economic modelling technique that has attracted considerable interest is agent-based modelling (ABM) [19, 40]. This is due to the fact that micro-level properties, behaviours and interactions are implemented for a large number of autonomous software agents, giving rise to emergent macro-level phenomena [17]. In macroeconomic agent-based modelling, macroeconomic features naturally emerge from microeconomic behaviour [8, 38].

The question "*how would the widespread adoption of digital technologies and knowledge by industry affect economic indicators such as unemployment and inequality?*" is of particular importance for an emerging economy such as South Africa. In the research project on which this paper is based, a macroeconomic ABM was developed, as detailed in Section 4, in order to simulate the impact of the widespread adoption of advanced technologies within an economy. Individuals within the simulation are assumed to acquire skills through their lifetimes; while firms are assumed to want to employ suitably skilled workers to satisfy their production requirements. The simulation provides potential outcomes of employment and inequality measures, and therefore serves as a testbed for understanding the macroeconomic impact resulting from shifts in the adoption of digital technologies.

2 Digital skills

In the modern fast-paced business environment, computers and ICT technology are no longer mere tools, they have become the very lifeblood of modern operations [14]. From streamlining communication, to the use of data analytics in decision making, to automating tasks and driving innovation, computing and ICT technologies permeate every facet of an organization, from marketing and sales to finance, production and customer service. Digital transformation has reshaped and redefined the workplace, demanding a new breed of employees equipped with a broad range of digital skills [14, 36]. These skills go beyond basic technical proficiency and the ability to simply use software or operate digital devices; they encompass critical thinking, problem-solving, and the ability to leverage technology for strategic advantage [23, 44]. There is a growing need for *digital excellence*, that encapsulates a range of skills beyond technological skills, including critial thinking, creativity, flexibility, collaborative capabilities, the ability to effectively communicate, and social skills [45]. Grundke, et al. [27] identified six generic job related skill indicators, categorised as cognitive skills (including ICT related skills, advanced numeracy skills, accounting and selling skills); non-cognitive skills (managing, communication and self-organisation); and socio-emotional skills (such as readiness to learn and creative problem solving). Digital proficiency has become the new currency to leverage success in the modern business world. Without it, businesses risk falling behind, while those who embrace digital transformation and empower their workforce with the appropriate skills have the potential to thrive in the dynamic digital age.

As businesses increasingly rely on digital and ICT technologies for their core functions, the need for employees equipped with appropriate digital skills has become paramount. Automation threatens repetitive jobs, and ever evolving skillsets leave many unprepared. Particular groups, like low-skilled workers and older individuals, are becoming progressively more vulnerable to higher levels of unemployment [6]. Adoption of sophisticated technologies may widen income gaps with dire consequences for inequality, fuels unemployment, and potentially puts increasing strain on social safety nets. Mitigation may require adaptation to the education system, reskilling initiatives, robust social support, and creating a culture of lifelong learning [15].

3 Agent-based modelling

Agent-based modelling is a computational approach for simulating the behaviour of a large number of autonomous agents within an artificial environment, where the agents interact with each other and their environment [40]. It has become an increasingly useful tool in the study of complex adaptive systems, particularly in social systems including areas such as economics, sociology, geography, ecology and environmental sciences [9, 22]. There are typically three parts in an agent-based model: *agents* as the active elements in the model, the artificial *environment* in which the agents operate and a *scheduler* that defines the timing of events in the simulation. The fundamental element of an ABM is an *agent*, that can be defined as a discrete, heterogeneous, software object with a set of unique defining properties; that exists within some artificial environment; is capable of autonomous action governed by a set of behavioural rules; and interacts with other agents and the environment in order to meet its objectives [40]. Each agent would have its own unique decision-making rules, based on their own characteristics and properties. The simulated environment may also be attributed with characteristics that may either be evolved externally or altered based on interactions with the agents. A key feature of AMBs is that any governing equations are embedded in the models of individual agents or the environment. Typically, agents do not have access to global information and have limited computational capabilities, making them 'simple' [5].

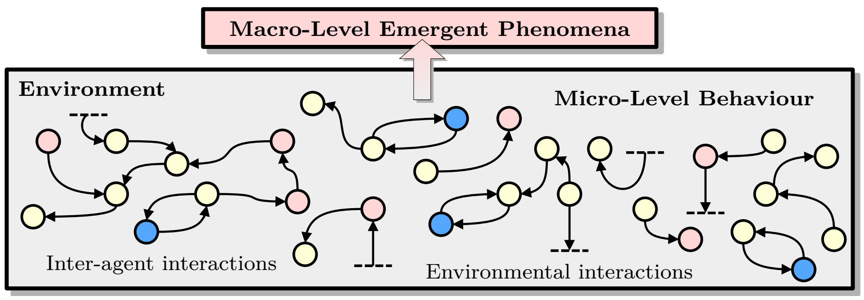

Figure 1: The concept of an agent-based model.

Agent-based modelling is a 'bottom-up' approach to modelling, where the micro-level properties, behaviours, decisions and interactions of each of the various agents are modelled [26]. An important consequence of the ABM approach is the concept of *emergent phenomena* where aggregated structures may arise from simple rules [19]. Explicit modelling of the behaviour of individual agents and interactions between agents results in emergent macro-level phenomena, as represented in Figure 1. Behavioural rules are explicitly incorporated within an agent, describing how the agent makes decisions under different circumstances. Macro-level phenomena then emerge from the aggregated results of all the micro-level interactions between a large number of agents [40]. ABMs thus provide a way to interrogate the relationship between micro-level behaviour and macro-level phenomena [21].

ABMs have become a popular approach to economic modelling due to the fact that its agents are usually governed by simple rules and collectively interact in complex ways [3, 11]. An ABM enables the incorporation of multiple theoretical models, the exploration of potential causal effects, the creation of heterogeneous economic agents, scalability, and the inclusion of social dynamics effects by exploring different behavioural rules [10, 29]. An advantage of agent-based models is that there is no need to assume equilibrium conditions, since any resulting equilibria emerge endogenously through the interactions of agents [21]. Additionally, there is also no need to assume that individual agents will attempt to seek an optimal condition. A wide variety of economic applications have been analysed using ABMs, including: emergent macroeconomic phenomena [20, 28, 33], financial markets [25], the role of technology in economic growth [34], the effect of inflation on macroeconomic performance [2], the role of banks [3], economic policy decision making [13, 18, 37], consumer behaviour [35, 43], and the dynamic behaviour of various types of firms [4, 16, 31].

4 The model

The macroeconomic agent-based model that has been developed is based on a simplified economy consisting of various types of agents and markets as illustrated in Figure 2. There are 5 types of agents in the model: many individuals, several consumer firms (C-firms), a single capital firm (K-firm), other countries, and government. The agents interact via three markets: a product market, a foreign market and a labour market.

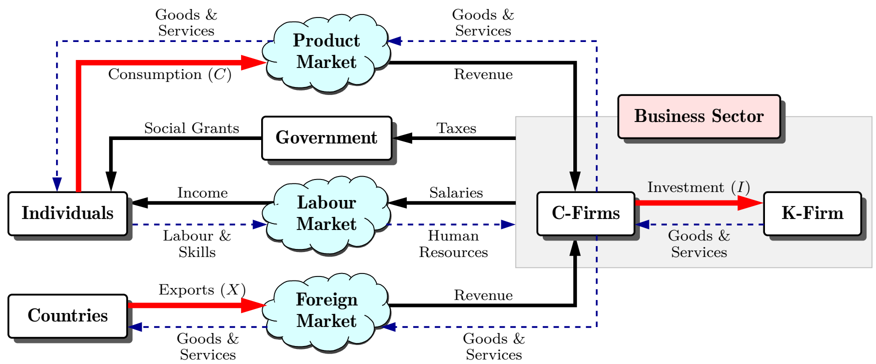

Figure 2: The economic model used as the basis for the simulation.

4.1 The individuals

The consumers in the economic model are *individual* agents, that also serve as the labour force for firms. An individual is characterized by several parameters, including age, status (passive, employed, unemployed, retired), skill level, demand for goods and services, available cash, and accumulated wealth. The collection of all individuals constitutes a population that grows at a predefined growth rate. This differs from other MABM models that have a constant population size [4, 28, 33]. Each individual is born, will age, and eventually die in such a way as to maintain an approximate half-normal distribution of ages.

Throughout the life of the individual, its status and role within the economy will change, as shown in Figure 3. The status attribute changes as the individual ages, makes choices about education, and whether or not they are employed. As a youth (child, at school or studying), the individual is a *passive* participant in the economy, but is progressing through an education system, developing skills required by industry. During the individual's youth, the individual will accumulate skills at a level defined by how far they progress through the education system. As indicated in Figure 3, if the individual does not complete their basic schooling, they will be assumed to have no digital skills. If they complete basic schooling, they will have only a basic level of skills. If they achieve a low-level higher education (such as a bachelors degree), they will have an intermediate level of skills and, finally if they complete a postgraduate qualification, they will have an advanced skill level. This results in the definition of a set of 4 possible skill levels, indexed by a variable s. In the simulation, the decisions are based on random choices which are regulated by various progression probabilities between each stage. For example, for a progression probability of 0.4 from *school* to *studying*, means that there is a 60% chance that the individual will make a decision not to study further.

Once the individual has moved beyond the youth phase, they then move on to become consumers, receiving income from various sources. The unemployed receive social grants, the employed receive salaries, and the retired make use of their accumulated savings. Employed individuals will save a percentage of their salary, with various propensity-to-save factors based on their skill levels. Any remaining cash is then used to purchase goods and services from the product market.

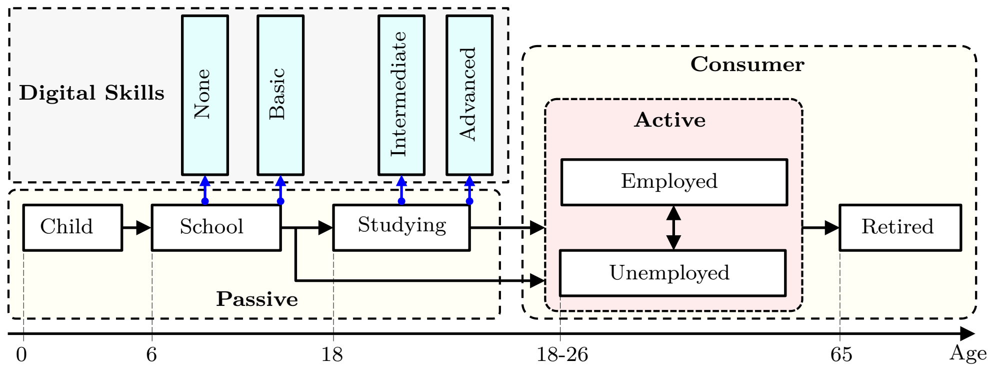

Figure 3: The evolution of the status attributes for individuals.

There are two types of goods available in the product market: *essential* goods and *luxury* goods. Depending on the disposable income of individuals and their acquired level of education, an individual will decide on a unique mix of goods to purchase from the market. This *basket* of goods defines the product market demand, and is analogous to the "consumption bundle" used by Ashraf et al. [3]. Higher-income individuals will have a basket with more luxury items, while low-income individuals will have a basket with more essential items.

4.2 The consumer firms

The second major class of agents in the model are firms that produce consumer goods. A fixed number of consumer firms are created, with each firm producing a single product. A single capital-producing firm, serves as a supplier of capital equipment or knowledge infrastructure to consumer firms. The parameters used to characterize a consumer firm are outlined in Figure 4, and include the *product* produced by the firm, the base sales *price* for the product, the labour skills *composition*, its investment in *capital* and *knowledge*, and a level of *technological sophistication*. A firm chooses to produce one of two possible types of products: *essential* goods or *luxury* goods, thus defining two market sectors. Each product sector is assumed to have a similar market structure in terms of product homogeneity, pricing, generic labour requirements, productivities, etc.

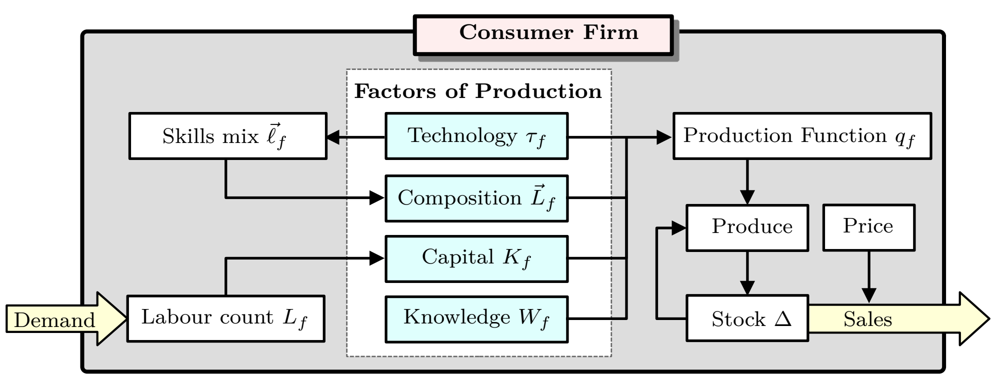

Figure 4: An overview of the consumer firm properties contributing towards production.

4.2.1 Knowledge and technological sophistication

A crucial factor for a firm is the kind of technologies it employs in its operations. The firm may be labour intensive using relatively unsophisticated technologies, or it may adopt advanced manufacturing technologies. The technological capabilities of a firm can be defined in terms of two complementary variables: *technological sophistication* and *knowledge*:

- **Technological sophistication:** Each firm will choose to adopt a particular level of technology in their operations. They will each choose a level of technological sophistication, which may include aspects such as choices in production methods, automation technologies, planning systems, service delivery processes, financial management, etc. Within the model, each firm is initialized with a level of technological sophistication, τ, with a value between 0 and 1. The lower limit, $\tau \approx 0$, represents a firm using very low levels of technological sophistication in its operations, while $\tau = 1$ represents the industry's *technological frontier* [1]. The technology variable is used to establish the required labour skills mix, which then determines the labour composition of the firm (see Figure 4). Conceptually, the idea is that a firm with a high value of τ will require a workforce with a more advanced "mix" of digital skills (see section 4.2.2 for details).
- **Knowledge:** The knowledge variable, W, encapsulates all of the historically accumulated knowledge of a firm, including 'know-how', systems, procedures, associated infrastructure, etc. Since firms would choose to invest in the accumulation of knowledge, it is treated as an asset, measured in currency units [12]. Although knowledge is an intangible asset, it may provide a firm with a significant competitive advantage over its competitors through higher levels of productivity and efficiency [32]. Section 4.2.3 shows how knowledge has been incorporated in the firm's production function through various productivity parameters. An important difference between capital and knowledge is that knowledge does not depreciate over time.

4.2.2 Labour composition

In general, there are two aspects of its labour composition that a firm needs to consider: the total number of employees and the skill levels of the employees [7]. In the model, it is assumed that the total labour count is determined by demand, while the required skills mix is determined by the level of technological sophistication of the firm. Since a consumer firm would need to adapt its production output in response to market conditions, in the short term the total labour count, L_f, is adjusted based on market demand.

A firm that adopts advanced technologies will need a workforce with higher levels of expertise. Technological sophistication, τ, establishes the required composition of skills for a firm, described by a *skills mix vector*, $\vec{\ell}_f$ A company with advanced technical capabilities will need fewer people with low skill levels and more workers with higher skill levels. For each skill level, s, a continuous function $\ell_{fs}(\tau)$ (with values between 0 and 1), is used to define the proportion of workers required at that skill level. For a firm, f, the desired mix of qualifications for labour is constructed as a vector, $\vec{\ell}_f$ where each element is a function of the firm's technological sophistication, $\vec{\ell}_f = (\ell_{f1}(\tau)\ \ell_{f2}(\tau)\ \ell_{f3}(\tau)\ \ell_{f4}(\tau))$. Since each of the vector components, $\ell_{fs}(\tau)$, represents the required proportion of a firm's workforce with a skill s, they must sum to 1. For example, if $\vec{\ell}_f = (0.4, 0.3, 0.2, 0.1)$, then the skills requirements for the workforce are: 40% with no skills, 30% with basic skills, 20% with intermediate skills, and 10% with advanced skills.

The various functions used for $\ell_{fs}(\tau)$ are shown in Figure 5. These functions are constructed so that as τ increases, there is a decrease in the requirement for unskilled labour, while skilled labour becomes more desirable. The required labour for a firm is then obtained as the total number of employees multiplied by the skill-mix vector, resulting in the *labour composition vector*, $\vec{L}_f(\tau_f) = L_f\, \vec{\ell}_f(\tau_f)$. The total labour composition vector is used as the basis for the labour demand in the labour market. For example, if $\vec{\ell}_f = (0.4, 0.3, 0.2, 0.1)$ and the required number of employees is $L_f = 50$, then the desired labour composition of the firm is 20 workers with no skills, 15 workers with basic skills, 10 workers with intermediate skills, and 5 workers with advanced skills. Three labour composition vectors are used: a

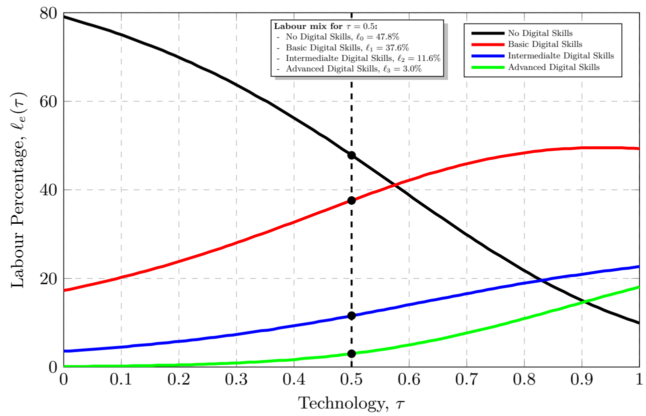

Figure 5: Digital skills mix functions used in the simulation to determine the labour composition based on technological sophistication.

requirements vector used to define the desired labour composition, a *possesses* vector indicating the actual employee composition, and a *needs* vector that defines the change in labour. The *requirements* vector is adjusted based on technological sophistication and product demand as outlined above. Each month the firm will calculate its labour *needs* as the difference between the *requirements* and what it *possesses*. The firm will then either lay off workers or try to employ new workers in the labour market based on the *needs* vector.

4.2.3 Production

The mathematical relationship between the input factors of production and the production output capacity of a firm are defined by a *production function* [30, 39]. A production function hides the operational details within a firm, focusing on the most significant factors of production and how they contribute towards output. The production capacity for each firm is assumed to depend on the total labour composition, $\vec{L}_f$, the available capital, K_f, and the level of accumulated knowledge, W_f, giving rise to a production function $q_f^{\max}(K_f, \vec{L}_f, W_f)$. A Cobb-Douglas type production function is used to model the production capacity of firms [38, 39, 41]. The production function used in the model is given by

$$q_f^{\max} = C_f \left(A_f^{\mathrm{K}}(W_f)K_f\right)^{\alpha_f} \left(\sum_s A_{fs}^{\mathrm{L}}(W_f)L_{fs}(\tau_f)\right)^{1-\alpha_f}, \tag{1}$$

where C_f is an overall production scaling parameter, A_f^{K} is the capital productivity, A_{fs}^{L} are the labour productivities for each skill level, and α_f is the output elasticity for capital. The production function provides the maximum possible output for the firm, while the actual production in a month, $q_f(t)$, is calculated as the difference between the production capacity and the available stock.

The modelled components of technological capabilities, knowledge, W, and technological sophistication, τ, affect the production function in different ways. The key concepts are that accumulated knowledge influences productivity, while technological sophistication influences labour composition. Capital and labour productivities are assumed to be functions of knowledge, and for simplicity, a linear relationship is assumed between knowledge, W_f, and each of the productivity parameters A_f^{K} and A_{fs}^{L}.

4.2.4 Investment

Every 1 to 3, years a firm would invest any accumulated profits to expand its production capacity. The firm could strategically invest in one of the three factors of production: capital, K, expanding its workforce, L, or knowledge development, W. A single simulation parameter, the *capital-labour investment probability*, ξ, is used to regulate the choice. The parameter defines the probability that a firm would invest in either capital or labour. For example, with $\xi = 0.4$, there is a 40% probability that a firm would invest in capital, a 40% probability that a firm would invest in labour, and a 20% probability that a firm would invest in knowledge. This value of $\xi = 0.4$ serves as the baseline simulation. Adjusting this simulation parameter would cause a global economic shift in investment priorities. *Explored* simulations would also be conducted by considering a change of the parameter ξ to a value of 0.35. This would shift the investment probabilities to more strongly favour investment in knowledge and associated technological investments.

5 Simulation results

The ABM simulations were run over 50 years, with 20 Monte-Carlo runs for each simulation scenario and output variables averaged over all Monte-Carlo runs. Two simulation scenarios were considered: a baseline simulation (with the capital-labour investment probability parameter $\xi = 0.4$) and an explored simulation (with $\xi = 0.35$) representing a shift towards greater investment in knowledge and technology. The simulations were initialised with an initial population of 2,500 individuals, an unemployment rate of 25%, and a population growth rate of 1.5% per annum. Only one capital firm was used, while 15 consumer firms were created in the essential goods sector and 10 firms in the luxury goods sector. The various educational progression probabilities (discussed in section 4.1) were set to values representing fairly poor progression through the system and kept constant between the two scenarios. The sections that follow provide the results for the two simulation scenarios.

5.1 Unemployment

Figure 6 displays the overall unemployment rate under both simulation scenarios. Higher widespread adoption of technology within the economy appears to be linked to a long-term rise in the overall unemployment rate.

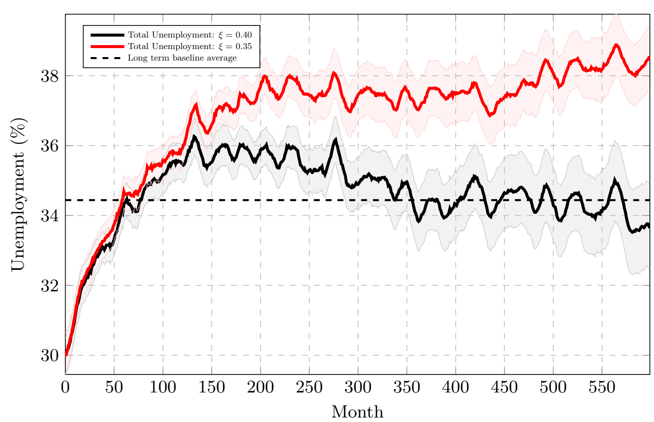

Figure 6: Comparison of the total unemployment for the two simulation scenarios. Shaded regions indicate uncertainty bounds.

The unemployment profile takes on a nuanced perspective in Figure 7. While the adoption of digital technologies brings progress and increased productivities (see section 5.6), the impact on different skill levels is far from uniform. Individuals with limited digital skills face a concerning rise in unemployment as firms embrace higher levels of technological sophistication. This finding echoes broader observations that the rise of digital technologies often comes at the expense of low-skilled workers, whose employment prospects decline with increased investment in digital technologies [6].

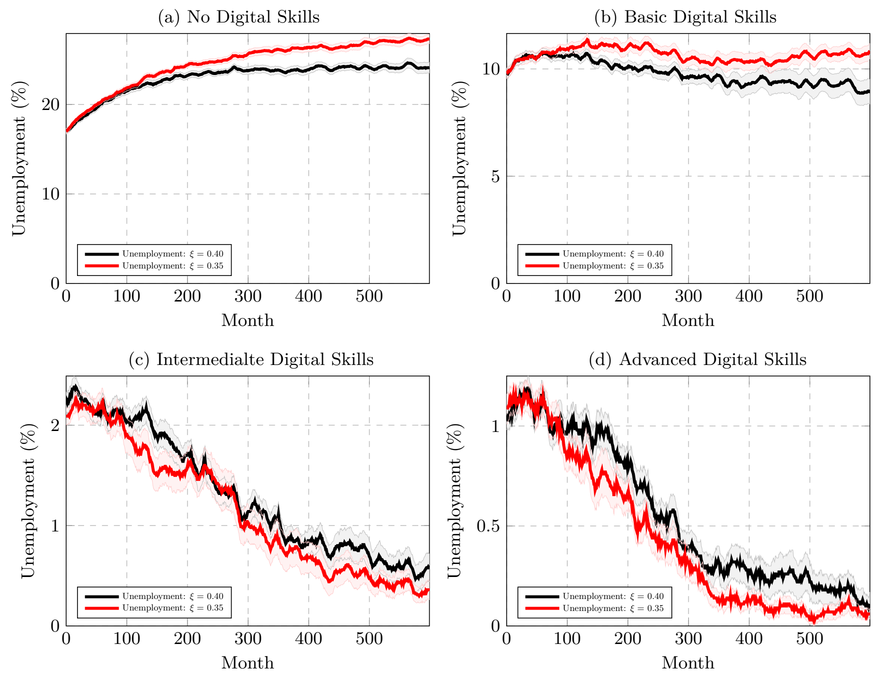

Figure 7: Comparison of unemployment for the simulation scenarios and different digital skill levels. Shaded regions indicate uncertainty bounds.

5.2 Income inequality

Figure 8 reveals a crucial finding: the Gini index, a measure of income inequality, does not show a significant difference between the two simulation scenarios. The results are aligned with South Africa's current Gini coefficient range of 0.65-0.67 [42], suggesting that the simulated population mirrors the real-world situation. Notably, Figure 8 implies that investments in technology have not yet translated into significant reductions in inequality within the simulated population. Therefore, the simulations suggest that within an economy, technological sophistication alone is insufficient to address entrenched inequality, possibly requiring a broader set of policy interventions.

5.3 Labour counts

Figure 9 reveals a noteworthy trend: both consumer goods sectors experience a sizeable decrease in the total labour force under the explored scenario. This suggests the potential for significant job losses across these sectors, as manifested in the overall unemployment rate. The essential goods sector shows the most pronounced decrease in workforce. This signals a possible overall decrease in demand for basic goods, suggesting that low-income households, facing increased financial strain, may be cutting back on basic necessities.

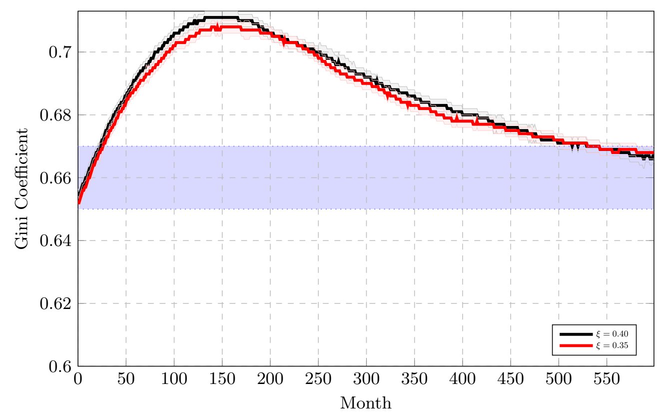

Figure 8: The Gini coefficient obtained from the simulations. The blue shaded region shows the range of Gini coefficients for South Africa [42].

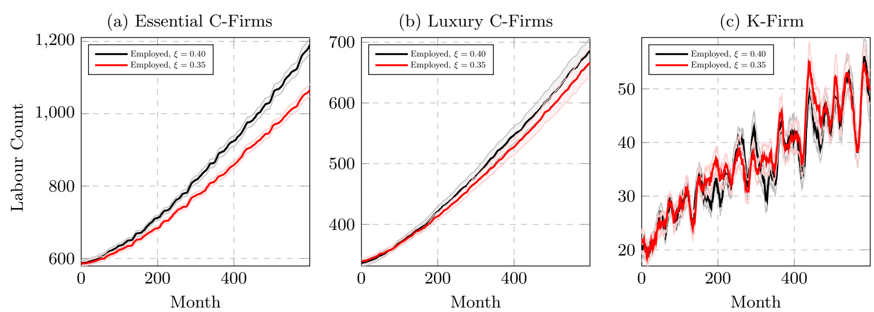

Figure 9: A comparison of the firm labour for all sectors from the simulation scenarios. Shaded regions indicate uncertainty bounds.

5.4 Labour composition

Plots of the labour composition (as a percentage of the total labour force) of all firms between the two scenarios are shown in Figure 10. While Figure 10 reveals a universal shift towards highly skilled labour, it also exposes the potential trade-offs of technological advancement. Both scenarios see a decline in unskilled workers, raising concerns about job displacement for those with limited digital skills. However, the explored scenario, with its increased focus on technology adoption, shows a more dramatic decrease, highlighting the potential impact of automation on low-skilled jobs. On the other hand, the technology-focused scenario also exhibits a significant surge in the demand for highly skilled workers, suggesting the creation of new opportunities for those with specialized expertise. This complex picture underscores the need for a nuanced approach to technological advancement, ensuring that it benefits all segments of the workforce through reskilling and upskilling initiatives.

5.5 Factors of production

Figure 11 sheds light on how different investment strategies impact the factors of production. By normalizing all factors to their initial values, we can clearly see contrasting trends across the scenarios for both sectors. The baseline simulations, favouring capital and labour investments due to a higher value of the *capital-labour investment probability* parameter, ξ, unsurprisingly show faster growth in

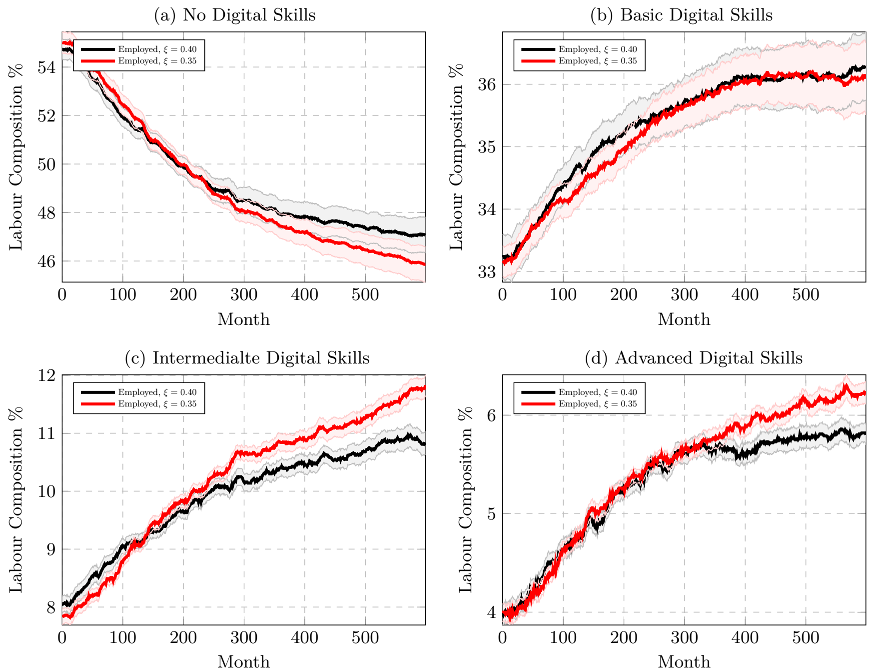

Figure 10: A comparison of the total labour composition by digital skill level for the simulation scenarios. Shaded regions indicate uncertainty bounds.

those areas. However, the explored simulations, pushing for knowledge and technology investments, reveal a significant increase in aggregate investment in those factors, representing an overall shift towards a more knowledge-driven economy.

5.6 Labour & capital productivities

The production function used in the model (Equation (1)) considers two key productivity parameters: capital productivity, A_f^{K}, and labour productivity, A_{fe}^{L}. These parameters play a crucial role in determining the production capacity of the firms in the economy under the different scenarios. Figure 12 depicts the relationship between aggregate production capacity and total labour, with both variables normalized to their initial values. The slope of each curve represents the aggregate efficiency of labour for each scenario and economic sector. As can be seen, the explored scenario curve is steeper than the baseline scenario curves in both sectors. This indicates that for a given percentage increase in labour, the explored scenario, with higher levels of technological sophistication, experiences a larger increase in production output. This suggests that labour productivity is higher in the explored scenario.

Figure 13 follows a similar format, but this time examines the relationship between aggregate production capacity and total capital. Here again, the explored scenario curve exhibits a steeper slope, indicating that for a given percentage increase in capital, the explored scenario experiences a larger increase in production output. This suggests that capital productivity is also higher in the explored scenario, meaning that capital is being used more effectively to generate output.

Overall, Figures 12 and 13 reveal that both labor and capital productivity are higher in the explored scenario compared to the baseline scenario. The implication is that the explored scenario leads to a more efficient and productive economy capable of generating more output with the same resources. Technology has delivered in that efficiencies and productivities have increased.

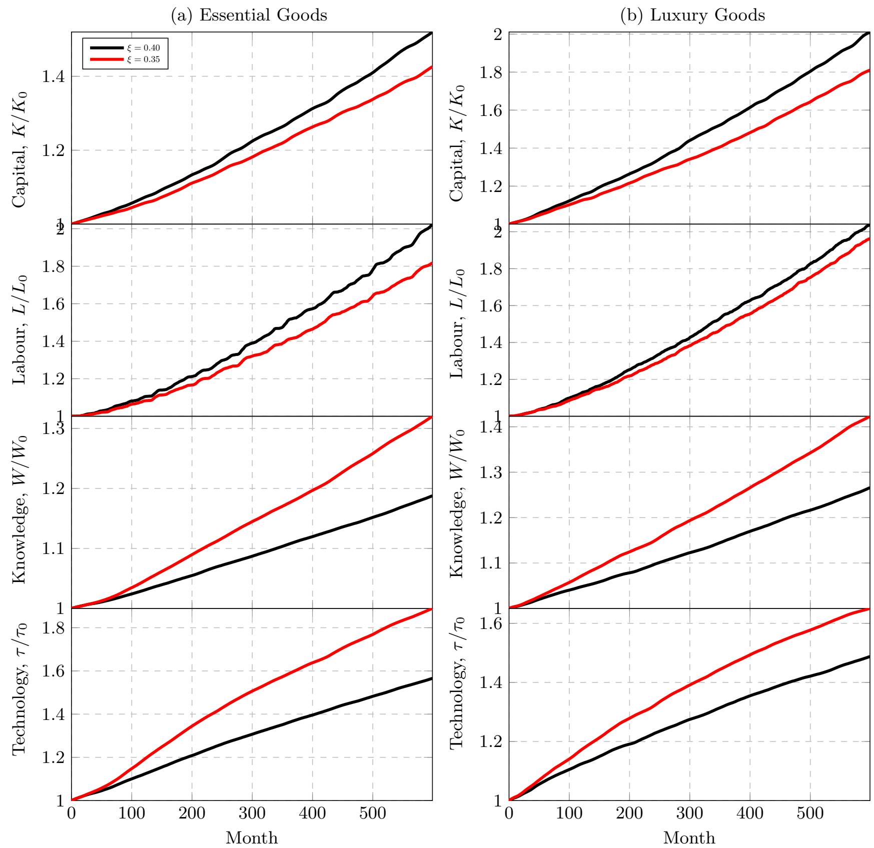

Figure 11: Relative changes in the factors of production for the two simulation scenarios.

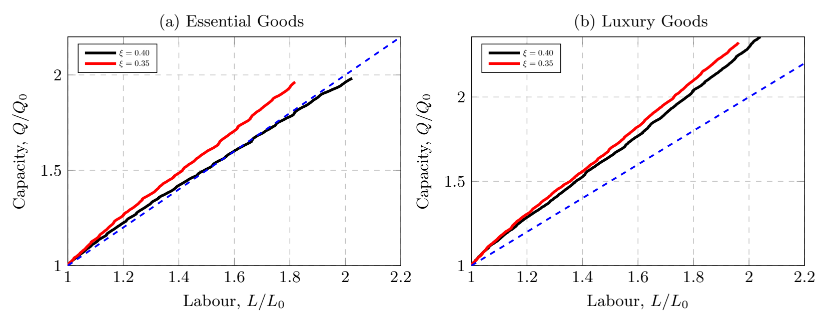

Figure 12: Change in capacity vs labour for the two simulation scenarios. Data is normalised to the initial values, Q_0 and L_0.

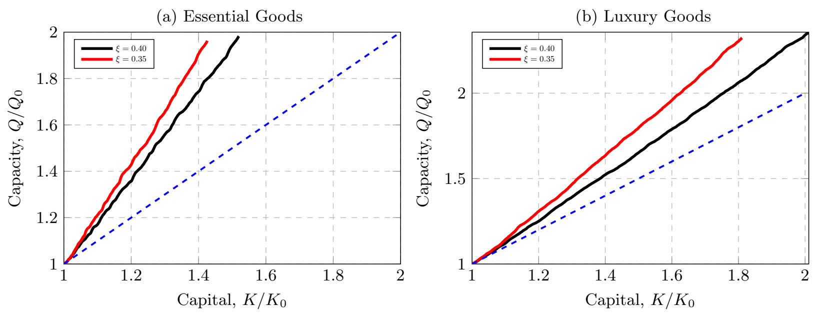

Figure 13: Change in capacity vs capital for the two simulation scenarios. Data is normalised to the initial values, Q_0 and K_0.

6 Conclusions

As firms within an economy embrace more advanced technologies, skill requirements inevitably shift. This poses a challenge for developing economies, as our macroeconomic agent-based model suggests. The simulations indicate that while long-term investment in technology may boost overall economic efficiencies and productivities, it could come at the cost of higher unemployment, especially for those lacking the necessary skills. This raises concerns about a widening gap between the skills needed in the evolving workplace and the skills possessed by low-skilled workers, potentially leading to their exclusion from the economic benefits of technological progress.

Furthermore, the results show that simply transitioning to a more technologically sophisticated economy is unlikely to be sufficient to solve entrenched high levels of income inequality. While technology plays an important role in improving economic productivity, it is essential to address the underlying social and economic factors that contribute to the various types of inequalities, such as access to education, skills development, healthcare, and resources. Tackling these issues will require a comprehensive set of policies beyond just technological investment.

In short, the widespread adoption of digital technologies and knowledge by industry is no silver bullet for addressing the triple threat of persistently high unemployment, inequality and poverty in a country like South Africa.

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