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Generative AI

Catalyst for Growth or Harbinger of Premature De-Professionalization?

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Abstract

This paper presents a multi-sector growth model to elucidate the general equilibrium effects of generative artificial intelligence on economic growth, structural transformation, and international production specialization. Using parameters from the literature, the paper employs simulations to quantify the impacts of artificial intelligence across various scenarios. The paper introduces a crucial distinction between high-skill, highly digitalized, tradable services and low-skill, less digitalized, less-tradable services. The model's key propositions align with empirical evidence, and the simulations yield novel and sobering predictions. Unless artificial intelligence achieves widespread cross-sector adoption and catalyzes paradigm-shifting innovations that fundamentally reshape consumer preferences, its growth benefits may be limited. Conversely, its disruptive impact on labor markets could be profound. This paper highlights the risk of "premature de-professionalization", where artificial intelligence likely shrinks the space for countries to generate well-paid jobs in high-skill services. The analysis portends that developing countries failing to adopt artificial intelligence swiftly risk entrapment as commodity exporters, potentially facing massive youth underemployment, diminishing social mobility, and stagnating or even declining living standards. The paper also discusses artificial intelligence's broader implications on inequality, exploring multiple channels through which it may exacerbate or mitigate economic disparities.

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Generative AI: Catalyst for Growth or Harbinger of Premature De-Professionalization?

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1 Introduction

Artificial Intelligence (AI), particularly recent advances in generative AI, has sparked intense debate about its potential impact on economic growth, labor markets, and global trade patterns. Estimates and projections of AI's economic effects vary widely. Goldman Sachs (2023) predicts that generative AI could increase global GDP by 7%, equivalent to US$ 7 trillion over a decade. Acemoglu 2024 provides a more conservative estimate, predicting a GDP increase of only 0.9% to 1.1% over the next decade. D. Autor 2024 argues that generative AI offers a unique opportunity to expand the middle class by enabling middle-skill workers to perform higher-stake decision-making tasks currently reserved for elite experts. In contrast, Frey and Osborne 2024 suggests that by lowering barriers to entry in cognitive occupations, generative AI will increase competition, eventually driving down wages and causing significant labor market disruptions. If generative AI tools commodify expertise and reduce the returns to specialized skills, individuals may be less incentivized to acquire advanced expertise, leading to further downsides to productivity and wages (Capraro et al. 2024).

While discourse on AI's economic impact predominantly focuses on advanced economies, its influence on developing countries and global production patterns remains uncertain and profound. Korinek and Stiglitz 2021 warn that AI could worsen the terms of trade for developing countries by eroding their labor-cost advantage, potentially leading to further impoverishment. Conversely, AI might reduce geographical and language barriers, shrink human capital gaps, and increase outsourcing of cognitive tasks to these nations, potentially diminishing income disparities with wealthier countries. However, this optimistic outcome hinges on rapid AI adoption in developing countries—a prospect hampered by low labor costs and significant barriers such as poor infrastructure, education, and regulatory frameworks.

Given AI's varied impacts across industries and countries, a nuanced analysis is required. This paper examines generative AI's potential effects on economic growth, labor markets, and inequality through the lens of structural transformation and global production specialization, aiming to offer insights into how AI may reshape economies and societies worldwide.

Structural transformation—the reallocation of economic activities across sectors—is integral to economic growth. Decades ago, economists noted a decline in the share of agriculture in both employment and output, a temporary rise in manufacturing, and a long-term shift towards services (Kuznets 1957).

Multi-sector growth models offer unique advantages for studying AI's impact. The dominant growth models in economics have historically been single-sector constructs (Solow 1956; Romer 1986; Lucas Jr 1988; Aghion and Howitt 1992; Grossman and Helpman 1991). These models have proved powerful and appealing, though they are not without limitations. Such models emphasized the importance of capital, labor, education, and innovation in driving growth, but overlook the differences and intricate inter-linkages between sectors. Consequently, single-sector models fall short in elucidating how an economy's compositional structure relates to its growth trajectory. The economic complexity theory (Hidalgo and Hausmann 2009) shows that a country's industrial composition and specialization patterns strongly influence its growth prospects. Understanding the complex interplay between growth and structural transformation is essential for formulating policies that enable sustainable development at scale (Gollin and Kaboski 2023).

I construct a simple multi-sector growth model to conceptualize the distinct channels through which AI influences growth and structural transformation. The model builds on recent structural transformation frameworks (Rodrik 2016; Comin, Lashkari, and Mestieri 2021; Matsuyama 2019) and incorporates non-homothetic preferences, where income elasticities of demand vary across sectors. The economy has four sectors: agriculture (A), manufacturing (M), high-skill services (Sh), and low-skill services (Sl). Labor is the only factor of production. The model initially assumes a closed economy, later extending to an open economy context. It also explores various model extensions, transitioning from exogenous to endogenous growth and incorporating inter-sectoral productivity linkages. The model's propositions are strongly supported by empirical evidence.

High-skill services include information and communication technology (ICT) services, finance and insurance, and professional, scientific, and technical services. The term "high-skill" serves as a shorthand for sectors characterized by high levels of skill, income, tradability, and digitalization. These industries significantly differ from other service sectors across all four dimensions. Based on data from the U.S. and China, these three industries exhibit the highest average earnings, ICT service input intensity, trade intensity, and the largest share of employees with advanced degrees (master's or higher). Other services are classified as low-skill services. Although education and healthcare also have a high proportion of employees with advanced degrees, they are considered low-skill due to their low tradability and digitalization.

AI affects growth and structural transformation through three distinct channels:

1. Demand: AI creates radically new products and shifts consumer preferences. It reshapes utility functions by altering income elasticities for certain sectors and changing the elasticity of substitution across sectors.

2. Supply: AI affects relative prices across sectors. While previous technologies primarily affected the goods-producing sector and routine tasks, generative AI targets high-skill services, particularly

cognitive and creative tasks (Eloundou et al. 2023; Gmyrek, Berg, and Bescond 2023).

3. International production specialization: AI changes comparative advantages among countries. Nations that adopt generative AI early can enhance their comparative advantage in high-skill services. Additionally, generative AI has been shown to improve the productivity of less-skilled, less-experienced workers (Brynjolfsson, Li, and Raymond 2023; Noy and W. Zhang 2023; Peng et al. 2023; Dell'Acqua et al. 2023), potentially enabling developing countries to compete in high-skill services and replace more expensive labor in developed nations.

Using model parameters sourced from the literature, the paper quantifies AI's potential impact through simulations. I explore three scenarios regarding AI's influence:

1. Short-term/pessimistic: AI exclusively increases labor productivity growth in high-skill services.

2. Medium-term/neutral: AI enhances labor productivity growth across all four sectors, with the most substantial increase observed in high-skill services.

3. Long-term/optimistic: AI not only boosts labor productivity in all sectors but also catalyzes the creation of revolutionary products, fundamentally altering societal preferences.

The simulations reveal several novel and sobering findings:

1. The recent rise in high-skill services employment share in many countries will eventually stagnate or decline, following a hump-shaped curve similar to manufacturing. Although higher incomes increase demand for high-skill services, advances in AI will reduce the need for white collar workers, shifting job concentration to low-skill services.

2. AI will further limit the potential for creating quality jobs in the high-skill services sector, particularly in developing countries. Similar to premature de-industrialization, AI will cause "premature de-professionalization", where high-skill services employment peak earlier and at lower income levels.

3. Small open economies face a critical juncture with AI adoption. Failure or delay in embracing AI technologies risks eroding existing comparative advantages in high-skill services and manufacturing, or impeding the development of such advantages. These countries may consequently find themselves trapped as commodity exporters, with employment heavily concentrated in agriculture and low-skill services. In contrast, successful and timely AI adoption could catalyze the development of comparative advantages in manufacturing or high-skill service sector.

4. Unless AI is widely adopted across sectors and drives transformative innovations that permanently shift consumer preferences, its growth benefits will likely be underwhelming. Even with a 50% increase in labor productivity growth in high-skill services, real income sees only a modest initial boost of 0.046 percentage points, which gradually diminishes over time. After 100 years, real income is just 2.4% higher than without AI. If AI enhances productivity across all four sectors, real income at year 100 is 19% higher. In the most optimistic scenario, real income at year 100 is 28% higher than the baseline.

The paper then addresses the limitations of the model and considers how generative AI might influence growth and inequality more broadly. The model's exclusion of capital overlooks a key aspect of AI's impact: automation, job displacement, and the declining labor income share. Additionally, by omitting intermediate inputs, the model may underestimate the demand for high-skill services. The assumption of homogeneous, freely mobile labor across sectors, which leads to equalized incomes, diverges from reality and provides little insight into income inequality. Generative AI could lower entry barriers for certain high-skill service jobs, potentially driving down average wages and reducing income inequality across industries and occupations. However, it may also influence incentives for education and skill acquisition. If AI shrinks the share of high-skill, well-paid jobs and depresses wages in these fields, individuals may become less motivated to invest in higher education, which could hinder long-term growth and limit social mobility.

The paper contributes to the growing body of literature on the economic impacts of AI in several ways.

First, to the best of my knowledge, it is the first study to analyze the effects of generative AI through the lens of structural transformation and international production specialization. Unlike many existing studies that focus on occupational exposure based on current tasks, this model incorporates demand-side factors, rooted in non-homothetic preferences across sectors. This broader approach captures AI's potential to reshape task content and create new occupations, offering a more holistic view at the macroeconomic level.

Second, this paper advances traditional structural transformation models by introducing a critical distinction between high-skill, highly digitalized, tradable services and low-skill, less digitalized, non-tradable services. This differentiation yields deeper insights into the uneven impact of AI across service sectors and occupations, as well as its implications for economic growth and inequality.

Third, alongside non-homothetic preferences, this study explores a new demand-side channel through which AI may drive growth: shifting consumer preferences. One scenario models AI as a catalyst for game-changing new products and industries, permanently altering income elasticity in certain sectors and the elasticity of substitution across sectors. Combined with the channel of international production specialization, this approach offers rich insights into AI's varied economic impacts across different types of countries.

Fourth, the paper uses simulations to illuminate the general equilibrium effects of AI on economic growth and labor markets under various scenarios, quantifying the scale of these effects. Consistent with Acemoglu 2024, the results suggest that AI's short- to medium-term growth impact will likely be modest.

Notably, this paper is the first to predict AI's potential to reduce opportunities for well-paid jobs in high-skill services. This could be particularly harmful for late AI adopters and developing countries, a phenomenon I dub as "premature de-professionalization". It underscores the diminishing prospects for developing economies to foster high-skill service employment, cautioning that those slow to adopt AI risk being relegated to commodity exporters, facing large scale youth underemployment, reduced social mobility, and potential declines in living standards.

The rest of the paper is organized as follows: Section 2 presents stylized facts about structural transformation, the divergence between high- and low-skill services, and AI's disproportionate effects on high-skill services. Section 3 introduces the four-sector growth model and derives several empirically supported propositions. Section 4 simulates the baseline model using parameters from the literature and quantifies AI's potential impact through three channels across three scenarios. Section 5 discusses model limitations and the broader implications of AI for growth and inequality. Section 6 concludes.

2 Stylized Facts

2.1 Structural transformation

Demand side driver: Different income elasticities across sectors

Differences in income elasticities of demand across sectors are a key driver of structural transformation. Economists have long studied systematic variations in the sectoral composition of demand as income changes, a concept explored through Engel curves. Typically, services exhibit higher income elasticities than agricultural and manufactured goods (1). As a result, non-homothetic preferences across sectors can explain the shift in consumer spending from food and manufacturing to services, observable in both real and nominal terms (Kongsamut, Rebelo, and Xie 2001; Foellmi and Zweimüller 2008; Boppart 2014; Comin, Lashkari, and Mestieri 2021).

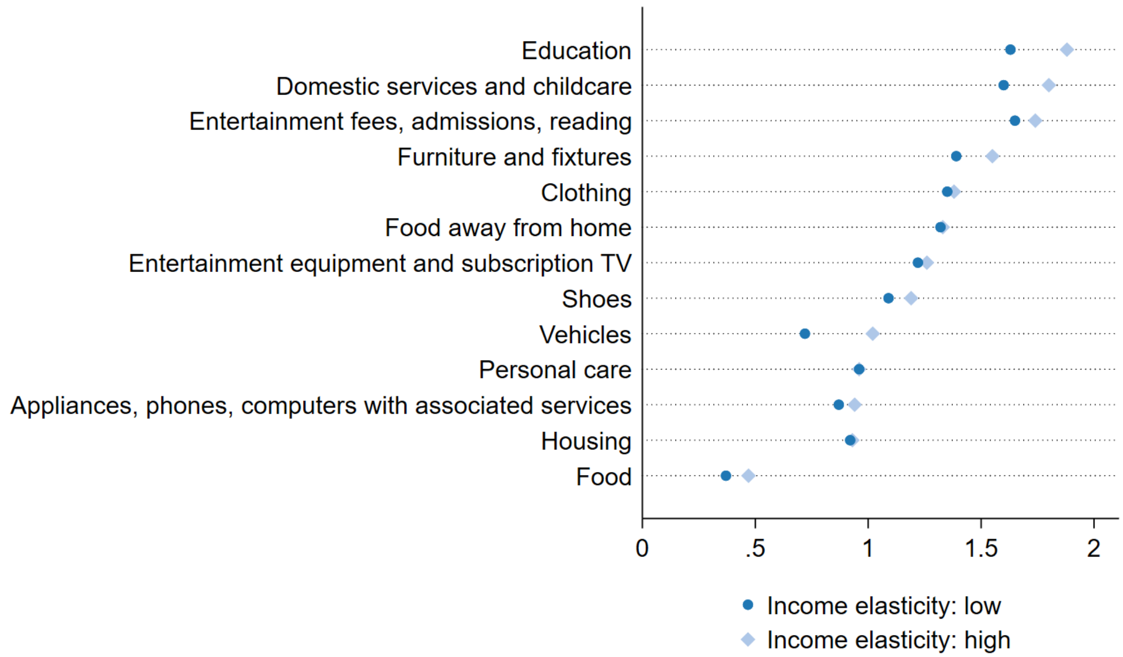


Figure 1: Estimated income elasticity by goods type

Note: Based on US data from Aguiar and Bils 2015

Supply side driver: Different productivity growth across sectors

Changing relative prices across sectors is a key supply-side force affecting structural transformation. Changes in relative prices are primarily driven by the heterogeneity in sectoral productivity growth rates. Empirical estimates show significant variations in productivity growth rates across sectors (Martin and Mitra 2001; Duarte and Restuccia 2010; Lawrence and Edwards 2013). If sectoral demand is inelastic, rapid productivity growth and subsequent price declines in a sector can lead to reduced share of spending and employment in that sector. Historically, productivity growth in agriculture and manufacturing has exceeded that in the service sector, partly explaining the declining share of manufacturing in rich countries with high manufacturing productivity (Ngai and Pissarides 2007). This mechanism, often referred to as the Baumol's disease, describes how economic activity shifts from industries with faster productivity growth to those with slower growth (Baumol 1967). Additionally, Acemoglu and Guerrieri 2008 highlight cross-sectoral differences in factor intensity and capital deepening as causes of relative price changes.

Globally, average annual labor productivity growth during 1950-2010 was the highest in agriculture (3%), followed by manufacturing (2.8%), high-skill services (1.5%), and the lowest in low-skill services (1.1%) (Figure 2). Productivity growth varies significantly across country income groups. Among high-income countries, labor productivity growth in agriculture and manufacturing is above 4%, more than twice the growth rate in high-skill and low-skill services (around 1.5%). In upper middle-income countries, agriculture and manufacturing report the highest labor productivity growth of around 3%, followed by 2% in high-skill services, and 1.2% in low-skill services. In lower middle-income and low-income countries, agricultural productivity growth is only 1.5%, followed by high-skill services at 1.2%. Productivity growth in manufacturing is only 0.7%, and a mere 0.4% in low-skill services.

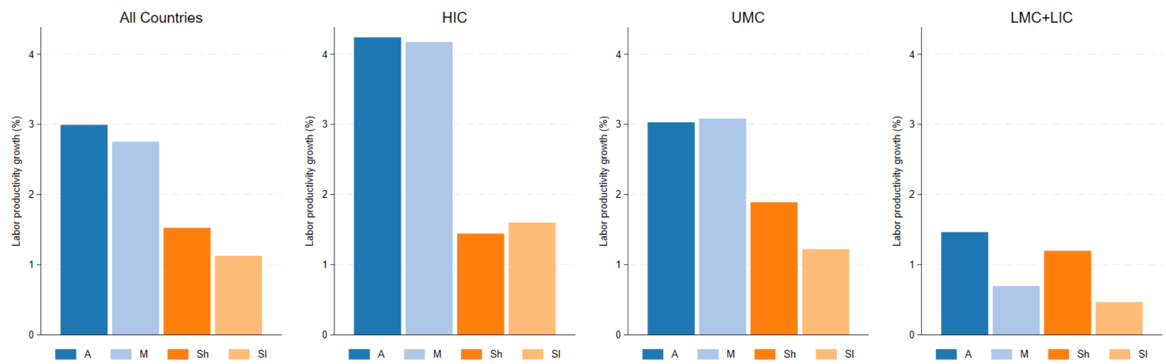


Figure 2: Labor productivity growth across sectors

Source: GGDC 10-sector Database. Labor productivity is calculated as value-added at 2005 fixed prices in each sector divided by sectoral employment. See Appendix A for more details.

International production specialization and premature de-industrialization

Technology-enabled globalization has impacted the dynamics of employment and output shares through patterns of international specialization. Advances in transportation and communication technologies in the late 20th century enabled production unbundling, outsourcing, and offshoring on a massive scale, leading to unprecedented growth in international trade and investment. Many studies have documented the effects of trade and multinational corporations' offshoring on de-industrialization in the US (D. H. Autor, Dorn, and Hanson 2013; Acemoglu, D. Autor, et al. 2016; Boehm, Flaaen, and Pandalai-Nayar 2020). Such forces may be even stronger for smaller developing countries, which typically act as price takers in world markets. Theory suggests that international trade can create patterns of structural change distinct from closed economy models (Matsuyama 2009; Matsuyama 2019). Globalization amplifies, rather than reduces, the power of endogenous domestic demand composition differences as a driver of structural transformation (Matsuyama 2019). A recent line of work has documented pronounced trends toward earlier de-industrialization in developing countries (Dasgupta and Singh 2007; Rodrik 2016).

Most high-income countries have experienced a continuous decline in agricultural employment share, which had fallen below 3% by 2010. The manufacturing sector initially saw an increase in employment share, peaking at around 30% before beginning to decline (Figure 3). Concurrently, the high-skill services sector has gradually increased its employment share, with some countries already reaching a peak or stagnation point of approximately 20%. By 2010, low-skill services had come to dominate employment, accounting for 70%-85% of total jobs.

The rapid productivity growth in agriculture, along with industrialization and urbanization, began more than 150 years ago in Western Europe and the United States. During this period, domestic supply and demand forces played a much more significant role than global trade. When globalization accelerated in the 1990s, most high-income countries had already transitioned to service-dominated economies, enjoying a comparative advantage in producing and exporting high-skill tradable services.

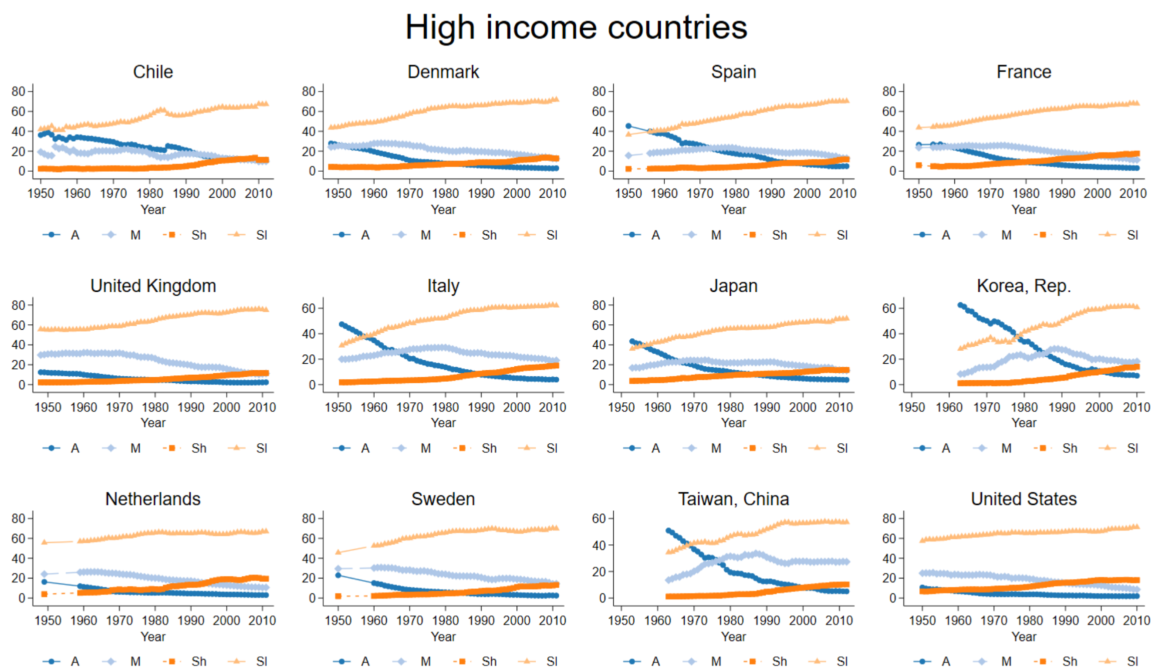


Figure 3: Sectoral employment share - High income countries

Upper-middle-income countries, on the other hand, exhibit patterns of premature de-industrialization in their structural transformation. Agricultural employment share has declined over time and has been surpassed by employment in low-skill services. Manufacturing employment in these countries has peaked at around 20%, a significantly lower level than the peak reached in high-income countries, and at a lower real income level. The employment share in high-skill services has begun to increase in some of these countries but remains well below the levels seen in high-income nations, as shown in Figure 4.

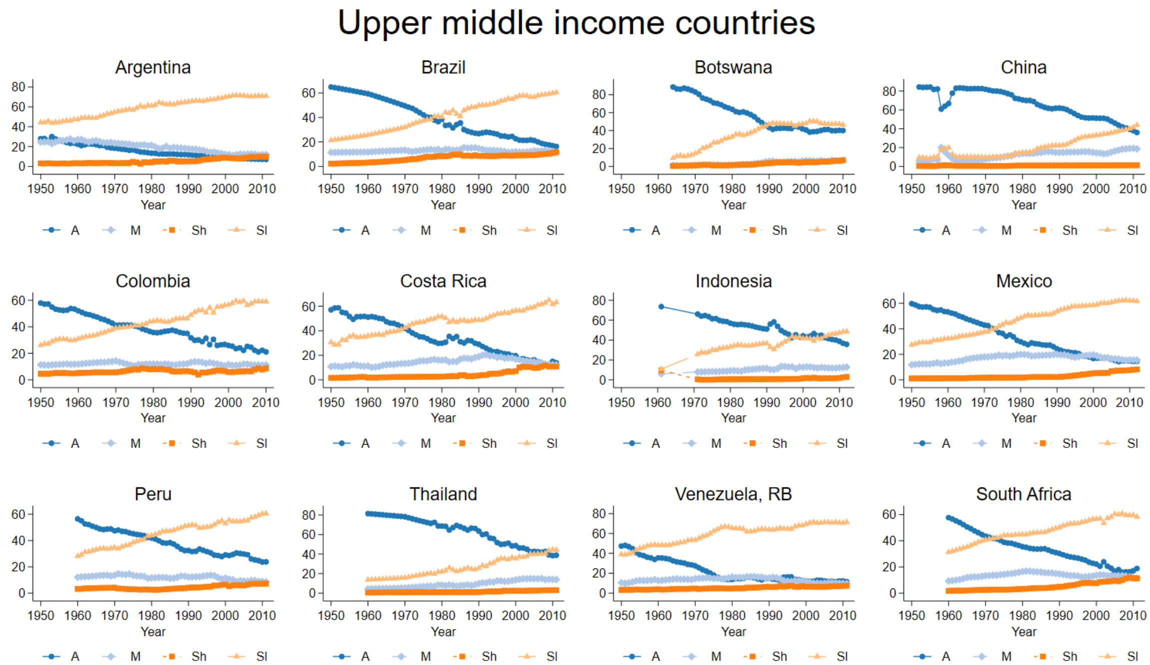


Figure 4: Sectoral employment share - Upper middle income countries

Lower-middle-income and low-income countries maintain extremely low and stagnant employment shares in manufacturing and high-skill services (Figure 5). In most of these nations, agriculture still accounted for more than half of total employment by 2010. Unlike the high-income country trajectory of moving from farms to factories and then to offices, labor freed from agriculture in these lower-income countries tends to move directly into low-skill services. These low-skill service jobs are predominantly concentrated in retail, restaurants and hotels, and personal services sectors, presenting significant challenges for long-term economic development and individual prosperity. Such jobs typically offer limited opportunities for learning, skills upgrading, and technological advancement, which are crucial for driving productivity growth and innovation. Moreover, these sectors generally have low export potential, restricting a country's ability to generate foreign exchange and participate effectively in the global economy. Unlike manufacturing or high-skill services, which often benefit from economies of scale and technological progress, many low-skill service jobs are less amenable to such efficiency gains. This can lead to stagnant wages and living standards in these economies, or even deteriorating terms of trade.

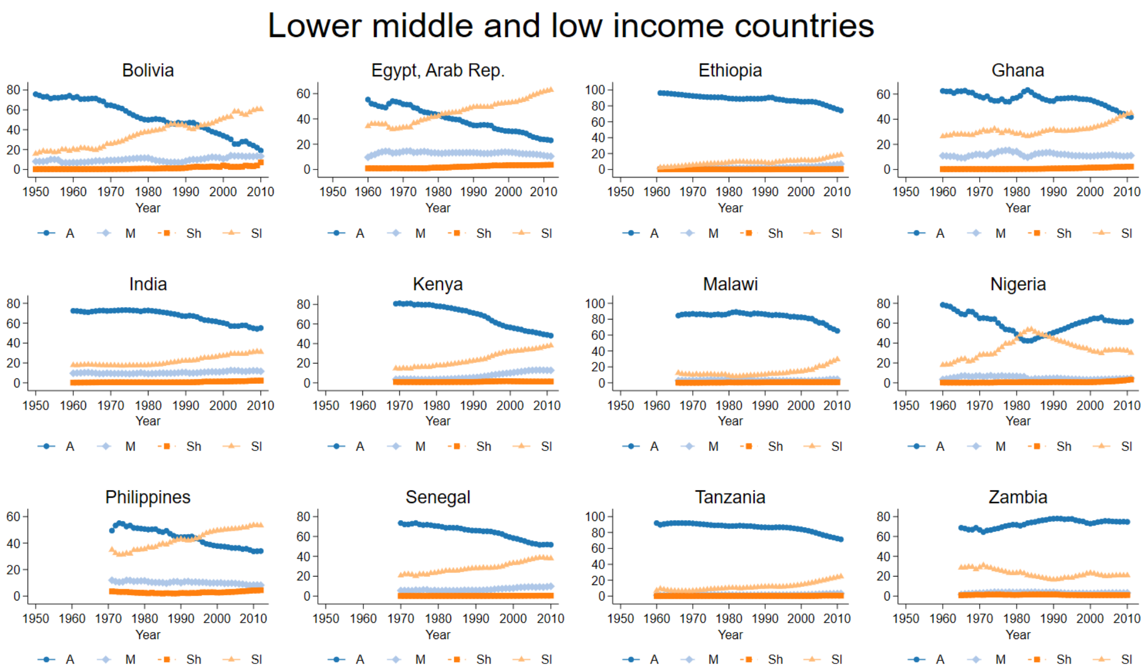


Figure 5: Sectoral employment share - Lower middle and low income countries

These diverse patterns of structural transformation across different income groups highlight the complex interplay of domestic and global factors in shaping economic development trajectories.

2.2 Divergence within the service sector

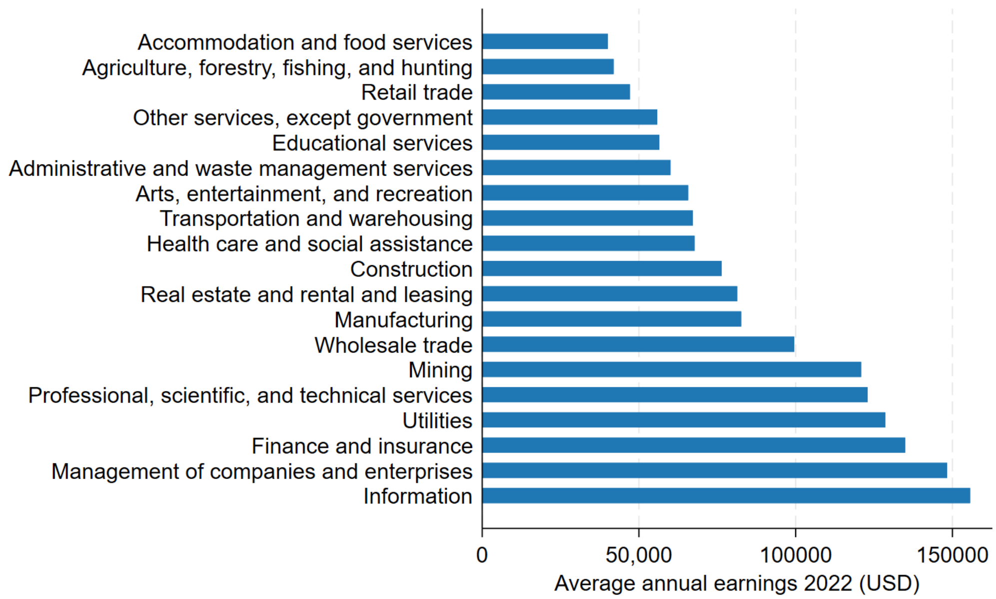
Distinct characteristics of high-skill and low-skill services

The diverse nature of activities and jobs within the servics sector necessitates a more granular level of analysis. The service sector is an extensive category encompassing a wide range of activities not classified under agriculture or manufacturing. The subsectors and occupations in services are highly varied, ranging from low-skill jobs such as cashiers and cleaners to highly specialized roles like software engineers, fund managers, lawyers, and surgeons. Globally, services now contribute to half of GDP and account for over 60% of employment. In high-income countries, the service sector represents three-quarters of both employment and GDP. Even in low-income countries, services accounted for around one-third of GDP and employment in 2022. However, the service sector is often treated as a residual category after agriculture and manufacturing, an afterthought in economic measurement. Many countries still use the outdated three-sector framework in economic accounting, and structural transformation models often focus on these broad sectors, offering limited insight into the increasingly service-based global economy.

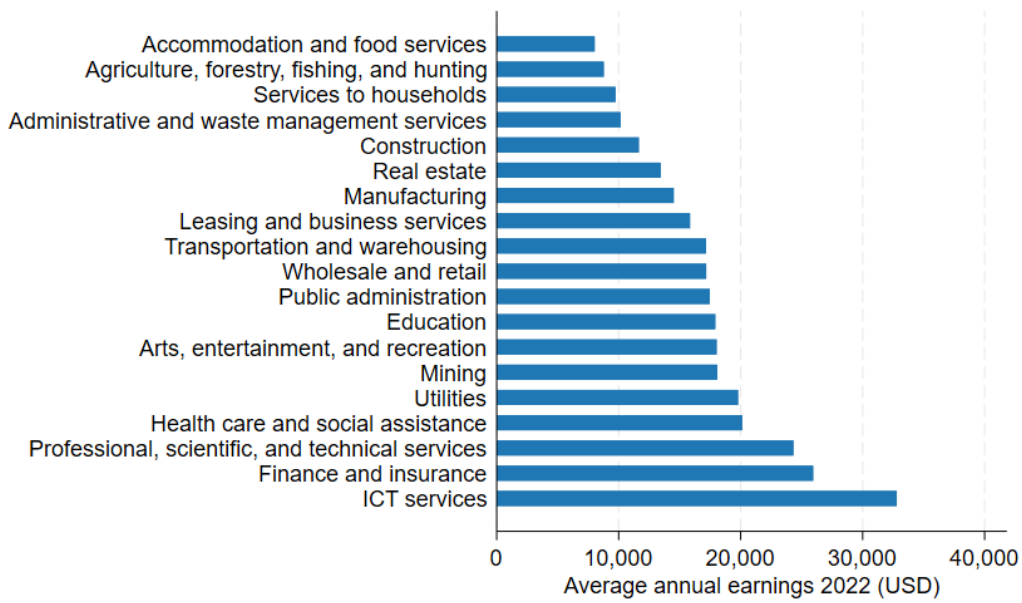
Rising income inequality within industries, especially among different service industries, further underscores the need to distinguish various types of services in economic research. Card, Rothstein, and Yi 2024 have documented significant heterogeneity in industry wage premiums in the US, showing that workers in higher-paying industries possess higher observed and unobserved skills, thus widening between-industry wage inequality. Haltiwanger, Hyatt, and Spletzer n.d. found that most of the rise in earnings inequality in the US is due to increasing between-industry inequality, with the disparity particularly pronounced in the service sector.

High-skill, highly digitalized, tradable service industries, such as information and communication technology (ICT) services, financial services, and professional and business services, are pulling further ahead of other service industries. In 2022, the average annual earnings in the information, finance and insurance, and professional service sectors exceeded US$120,000 in the US, placing them among the top five highest-earning industries. In China, ICT services, finance and insurance, and professional services were the top three highest-earning industries in 2022. In both countries, the highest and lowest earning industries are in the service sector, with ICT services being the highest paying and accommodation and food services the lowest (Figure 6).

This growing disparity in earnings across industries and occupations has led to significant differences in returns to education across majors, thereby influencing the supply of skills. Median and average earnings vary greatly by students' college majors, even among similar students (Altonji, Blom, and Meghir 2012; Andrews, Imberman, and Lovenheim 2017; Andrews and Stange 2019; Arcidiacono, Hotz, and Kang 2012; Hamermesh and Donald 2008). Indeed, the mean earnings differences across majors are at least as large as the earnings gap between high school and college graduates. Recently, engineering and computer science majors have yielded the highest returns for students, followed by business, health, and STEM fields (L. Zhang, Liu, and Hu 2024). Consequently, students have increasingly abandoned humanities in favor of fields like computer science and business. The share of tertiary graduates majoring in ICT programs has risen in most countries between 2016 and 2022, and numerous certificate programs, coding bootcamps, and online platforms have emerged to meet the surging demand. On Coursera, computer science and business are the most popular course categories and degree programs.



(a) United States



(b) China

Figure 6: Average income by industry 2022

In the US, professional services, ICT services, finance and insurance are among the top seven industries with the highest share of employees with at least Master's degree in 2023 (Figure 7). Using the share of IT services in total intermediate input cost (IT services input intensity) as a proxy for digitalization level, ICT services, professional services, and finance and insurance are also the top three most digitalized industries based on Trade in Value Added (TiVA) data (Figure 8). ICT services, professional services, finance and insurance are also the most tradable services in addition to transportation and warehousing, wholesale and retail, and administrative support services (Figure 9).

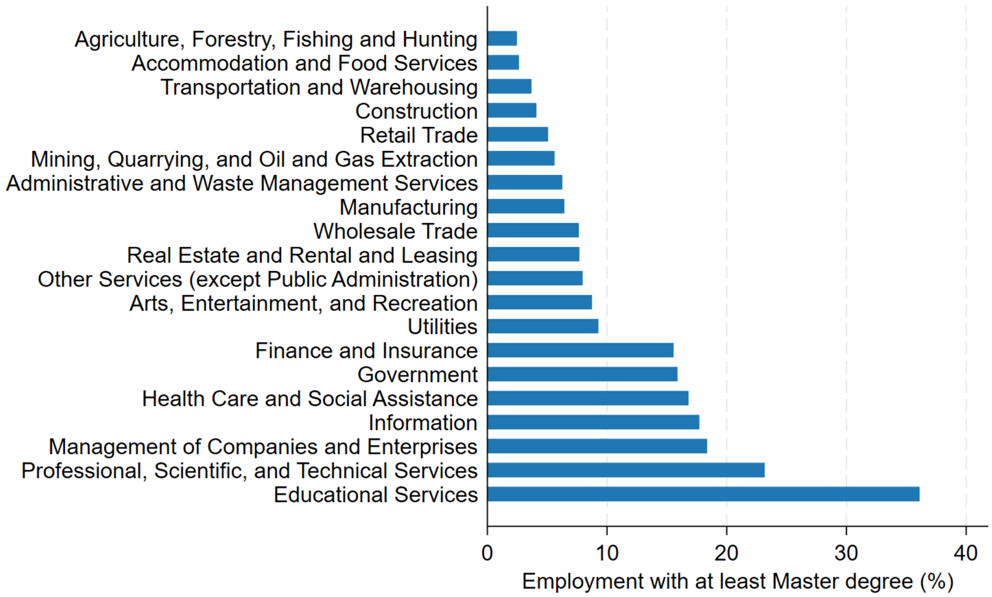


Figure 7: Share of employment with advanced degree by industry, US 2023

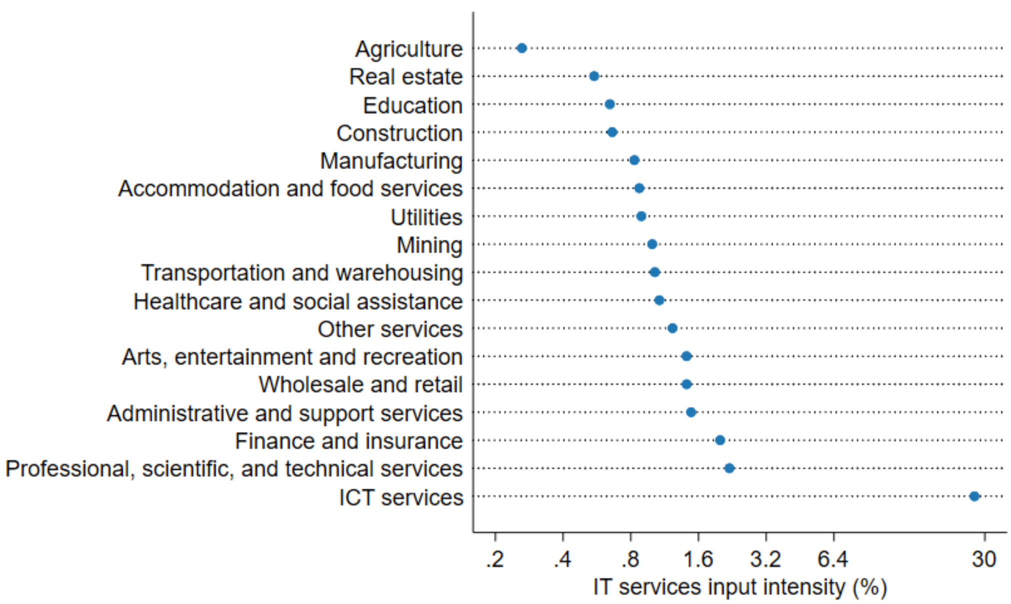


Figure 8: IT services input intensity by industry, 2020

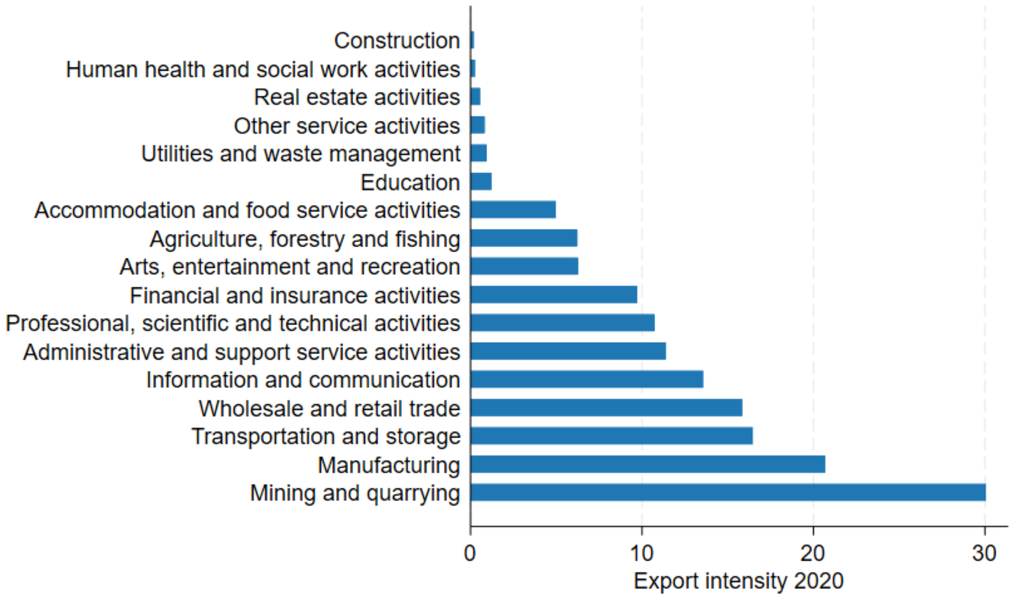


Figure 9: Export intensity by industry, 2020

2.3 Generative AI predominantly boosts productivity in high-skill services

Generative AI is poised to have an outsized impact on white collar jobs in high skill services. Unlike previous waves of digital technologies, generative AI does not just speed up routine tasks or make predictions by recognizing data patterns. Its power to synthesize and generate ideas and content overlaps with a significant portion of tasks in white collar occupations. Several papers have measured occupational exposure to generative AI (Eloundou et al. 2023; Gmyrek, Berg, and Bescond 2023; World Economic Forum (2023); Melina et al. 2024), the top exposed jobs are consistently services occupations, mostly in high-skill service sector. Based on Gmyrek, Berg, and Bescond 2023 and the employment share of each occupation across industries using US data in 2023, this paper constructed an industry level exposure to generative AI. Finance and insurance industry has the highest exposure with an exposure index above 0.5, followed by management of companies and enterprises, ICT services, and professional services (Figure 10).

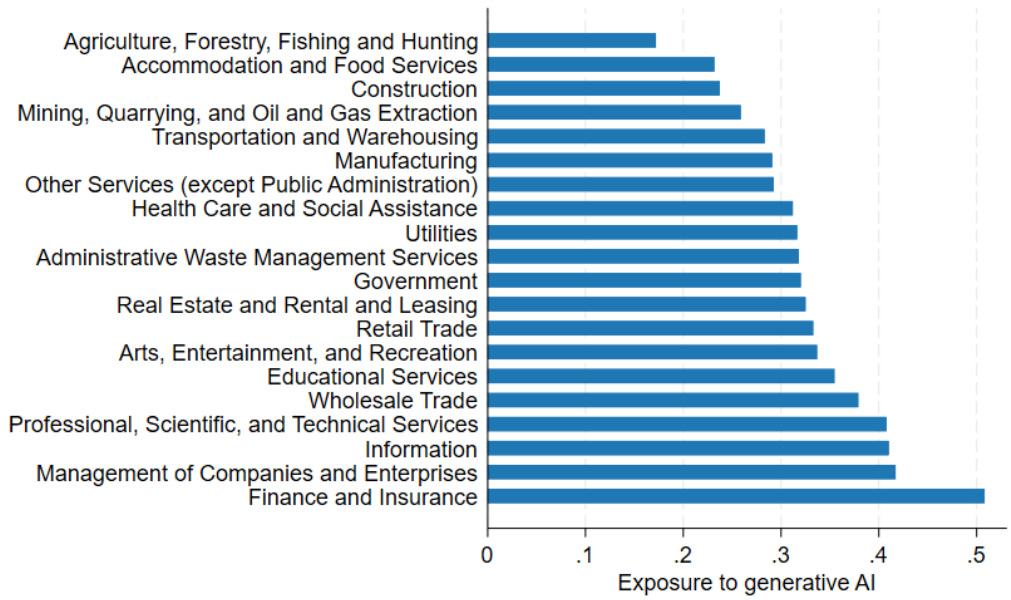


Figure 10: Industry exposure to generative AI

Empirical evidence from several experiments demonstrates that generative AI tools can significantly boost labor productivity in certain cognitive tasks and occupations, particularly for lower-skilled and less-experienced workers. Brynjolfsson, Li, and Raymond 2023 find that access to generative AI increases productivity by 14% for call center agents, with a 34% improvement for novice and low-skilled workers. Peng et al. 2023 report that generative AI enables programmers to complete tasks 56% faster than their peers. Noy and W. Zhang 2023 show that generative AI reduces task completion time by 37% and enhances quality by 0.45 standard deviations for white-collar workers engaged in professional writing tasks. Dell'Acqua et al. 2023 find that management consultants using generative AI completed 12% more tasks, worked 25% faster, and improved task quality by 40%.

3 The Model

Motivated by the above stylized facts, I present a bare-bones multi-sector growth model to analyze the effect of AI on economic growth, structural transformation and trade patterns for different types of countries. I begin with a closed economy model, detailed as follows.

3.1 Closed economy

Suppose there are four sectors in the economy: (1) agriculture (A), (2) manufacturing (M), (3) low-skill, less-digitalized, non-tradable services (Sl), which includes utilities, construction, transportation and warehousing, retail and wholesale, accommodation and food services, recreational and personal services, healthcare, education, administrative support, real estate and rental, and (4) high skill, highly digitalized, tradable services (Sh), including professional, scientific, and technical services, finance and insurance, and ICT services. Labor is the single non-tradable factor of production.

Demand

The economy has a representative consumer that lives indefinitely. The consumer's aggregate consumption (or welfare) at time t is denoted by C_t, which combines four sectoral goods: C_{At}, C_{Mt}, C_{Sht}, and C_{Slt}. The individual only cares about current consumption and spends all the income at time t on consumption.

The representative consumer has the implicit utility function:

$$\sum_i \Omega_i^{\frac{1}{\sigma}} C_t^{\frac{\varepsilon_i - \sigma}{\sigma}} C_{it}^{\frac{\sigma-1}{\sigma}} = 1 \tag{1}$$

σ is the elasticity of substitution across sectors, and ε_i is the income elasticity for good i. Ω_i is a time invariant constant for good i. $i \in \{A, M, S_l, S_h\}$. If $\varepsilon_i \;= 1$ for all ı, equation 1 becomes the standard homothetic CES, which is directly explicitly additive. By letting ε_i depend on i, this class of utility functions, no longer directly explicitly additive but still directly implicitly additive, allows the income elasticity to differ across sectors, while keeping the constant elasticity of substitution across sectors, σ, as a separate parameter. This makes it possible to control for the income elasticity differences without affecting the price elasticity, which helps to isolate the role of income elasticity differences (Matsuyama 2019).

As in standard CES utility functions, when σ<1, the four sectoral outputs are gross substitutes. When σ >1, they are gross complements. In this model, we assume 0<σ<1. If $\varepsilon_i \geq \sigma$ for any i, real income C_t is strictly increasing with C_{it}.

The consumer chooses $C_{it}, i \in \{A, M, Sh, Sl\}$, to maximize C_t, subject to the budget constraint: the total expenditure, $E_t = \sum_i P_{it} C_{it}$, must be less than or equal to the individual's total wage income, w_t.

$$E_t = P_t C_t = \sum_i P_{it} C_{it} \leq w_t \tag{2}$$

P_t is the aggregate price level at time t.

Demand for the products of each sector can be derived:

$$C_{it} = \Omega_i \left(\frac{P_{it}}{P_t} \right)^{-\sigma} C_t^{\varepsilon_i} \tag{3}$$

Consumption of good i strictly decreases with its relative price, and strictly increases with real income. And the model assumes income elasticity for the four sectors satisfy the following:

$$0<\sigma = \varepsilon_A<\varepsilon_M<\varepsilon_{Sh}<\varepsilon_{Sl} \tag{4}$$

This assumption draws upon various estimates of sectoral income elasticities from existing literature (Comin, Lashkari, and Mestieri 2021; Young 2013; Aguiar and Bils 2015). As incomes rise, consumer expenditure patterns tend to shift from goods to services, reflecting a growing preference for experiences over material possessions. Food exhibits the lowest income elasticity, as even the wealthiest individuals have finite nutritional needs. Similarly, manufactured goods have a limited income elasticity, as the utility gained from owning multiple TVs, smartphones, or cars diminishes beyond a certain point.

The challenge lies in estimating the income elasticity for high skill services. First, a major portion of financial services, ICT services, professional, scientific, and technical services primarily cater to businesses rather than individual consumers, making it difficult to derive income elasticity from household expenditure surveys. As an economy's real income level increases, businesses become more sophisticated, driving up demand for these services to enhance productivity. Second, households often consume such services indirectly through other products or services, making it challenging to isolate and accurately measure the expenditure on these services. Third, some of these services like legal and accounting services are purchased infrequently, such expenses often fall out of the regular expenditures that surveys typically focus on. Fourth, some digital services could be accessed for free or through non-monetary means (e.g., data sharing), which is not captured in traditional expenditure surveys.

By far the highest income elasticity is observed in non-tradable, low-skill services including housing, education, healthcare, tourism, and personal services. Aguiar and M. Bils (2015) estimated that income elasticity in US households is 0.4-0.5 for food, 1-1.5 for manufactured goods, 1.2-1.3 for entertainment equipment and television subscription, 1.65 for entertainment fees, admissions, and reading, 1.6-1.8 for childcare, and 1.6-1.9 for education, as shown in Section 2, Figure 1. These results corroborate the model assumption in Equation 4.

Equation 3 yields the below: consumption of good i relative to good j decreases with relative price and increases with the relative income elasticity. As real income increases, consumption of goods with the highest income elasticity increases disproportionately.

$$log\left(\frac{C_{it}}{C_{jt}}\right) = log\left(\frac{\Omega_i}{\Omega_j}\right) - \sigma log\left(\frac{P_{it}}{P_{jt}}\right) + (\varepsilon_i - \varepsilon_j)\, logC_t \tag{5}$$

Supply

Labor is the only input in production. There is a fixed one unit of labor in each period, allocated across the four sectors to produce the four kinds of goods: $L_{At} + L_{Mt} + L_{Slt} + L_{Sht} = 1$. Supply for each sector is determined by the following production function, which has constant return to scale:

$$Y_{it} = X_{it} L_{it} \tag{6}$$

Y_{it} denotes the quantity of output for sector i at time t. X_{it} reflects labor productivity in sector i. Technology is initially assumed to be exogenous. While sectoral technology growth can be endogenous, the potential for labor productivity growth in each sector is largely determined by the inherent characteristics of the sector. For instance, the production of largely homogenous goods, such as in agriculture and manufacturing, can be significantly enhanced through the use of machinery and economies of scale, leading to substantial labor productivity growth. In contrast, low-skill, non-tradable services are often customized based on unique contexts, require face-to-face interactions, rely on unstructured physical movement or manual dexterity, making them difficult to automate or produce in large volumes. Baumol's classic example illustrates this point: it still takes a string quartet the same amount of time to play a piece today as it did when Mozart wrote it. Therefore, there are valid reasons to assume that potential labor productivity growth across sectors is exogenous. I also demonstrate that moving from exogenous to endogenous growth does not affect equilibrium pathways later in this section.

Labor productivity in each sector X_{it} grows at a constant rate over time. Let productivity growth rate in each sector be τ_i. Initial productivity level is normalized to one $X_{i0} = 1$. Then productivity for each sector at time t can be written as $X_{it} = e^{\tau_i t}$. Sectoral productivity growth satisfies the following: productivity grows the fastest in the agriculture sector, followed by manufacturing, and high skill services, and grows the slowest in the low-skill service sector.

$$0 \leq \tau_{Slt} < \tau_{Sht} < \tau_{Mt} < \tau_{At} \tag{7}$$

L_{it} is labor input for sector i at time t. All the revenue will be paid to the individual as wage, and wage rate is the same across sectors.

Equilibrium

There are four market-clearing conditions for the four sectors: consumption must equal production in each sector: $C_{it} = Y_{it}$.

Total nominal income of the economy at time t is the value of all goods produced (always equal to total expenditure, as the economy has no savings), which equals the sum of labor income from each sector:

$$P_t C_t = \sum_i P_{it} Y_{it} = w_t \sum_i L_{it} = w_t \tag{8}$$

Let the share of nominal output for good i be ω_{it}, the model implies that sectoral nominal output share will equal employment share:

$$\omega_{it} = \frac{P_{it} Y_{it}}{P_t Y_t} = \frac{Y_{it}}{X_{it}} = L_{it} \tag{9}$$

Y_t is the same as C_t, denoting real income.

The rest of the paper use sectoral employment/expenditure/nominal output share interchangeably, or simply refer to it as sectoral share.

Under the given technology, demand and supply in the four sectors will pin down price and output in each sector. As the model can only determine relative prices, let agricultural goods be the numeraire, $P_{At} \equiv 1$.

Solving the equilibrium yields the following:

Proposition 1 *Output/consumption in each sector is determined by two separate forces: the supply side force and the demand side force. Production/consumption in each sector grows monotonously over time.*

$$Y_{it} = C_{it} = X_{it} L_{it} = \Omega_i X_{it}^{\sigma} Y_t^{\varepsilon_i - \sigma} \tag{10}$$

The supply side force (price effect, X_{it}^{σ} in equation 10) increases output/consumption through productivity growth. The demand side force (income effect, $Y_t^{\varepsilon_i - \sigma}$ in equation 10) increases output/consumption through higher demand resulting from real income growth.

The agricultural sector exhibits a unique dynamic: its income elasticity equals the elasticity of substitution ($\varepsilon_A = \sigma$), output/consumption is only influenced by the supply side force.

$$\Delta log \left(\frac{Y_{it}}{Y_{jt}} \right) = \sigma \left(\tau_i - \tau_j \right) t + \left(\varepsilon_i - \varepsilon_j \right) \Delta log Y_t \tag{11}$$

Changes in the relative quantity of output/consumption between sectors i and j, $\frac{Y_{it}}{Y_{jt}}$, is determined by: (1) difference in sectoral productivity growth rate and time, $\sigma\left(\tau_i-\tau_j\right)t$; and (2) difference in sectoral income elasticities and real income growth, $\left(\varepsilon_i-\varepsilon_j\right)\Delta logY_t$.

Proposition 2 *Relative price between sector i and j is inverse to their productivity levels. Sectors with higher productivity have lower relative prices.*

$$\frac{P_{it}}{P_t}=\frac{Y_t}{X_{it}} \tag{12}$$

$$log\left(\frac{P_{it}}{P_{jt}}\right)=(\tau_j-\tau_i)t \tag{13}$$

Relative prices are only driven by supply-side forces in the form of differential rates of productivity growth. As agricultural product is set as the numeraire and agriculture sector has the highest productivity growth, prices for all other sectors will grow monotonously over time:

$$P_{it}=\frac{X_{At}}{X_{it}}=e^{(\tau_A-\tau_i)}t$$

Proposition 3 *For non-agricultural sectors, sectoral employment/expenditure/nominal output share monotonously increases with real income/welfare, and monotonously decreases with productivity.*

Employment/expenditure/nominal output share of agriculture monotonously decreases over time. For both manufacturing and high-skill tradable service sectors, employment share exhibits an inverted U-pattern over time. Share of low-skill, nontradable services rises monotonously.

$$\omega_{it}=L_{it}=\Omega_i X_{it}^{\sigma-1}Y_t^{\varepsilon_i-\sigma} \tag{14}$$

The dynamics of sectoral employment share can be derived:

$$\Delta logL_{it}=\left(\varepsilon_i-\sigma\right)\Delta logY_t+\left(\sigma-1\right)\tau_i \tag{15}$$

In the agriculture sector, where $\varepsilon_A=\sigma$, the employment share decreases at a constant rate over time, as $\Delta logL_{At}=\left(\sigma-1\right)\tau_A<0$.

For other sectors, the first item (income effect) is positive but decreasing over time, while the second term (price effect) is negative and constant. Given the sectoral income elasticity assumption in 4 and sectoral productivity growth assumption in 7, both manufacturing and high-skill service sectors exhibit an inverted U-pattern in employment share over time. Conversely, the employment share in low-skill, nontradable services rises monotonously.

Higher labor productivity in any sector reduces its employment share. For manufacturing and high-skill services, increased labor productivity leads to an earlier, lower peak in employment share, reached at a lower real income level.

This model explains the phenomenon of premature de-industrialization in developing countries, even without direct trade shocks. As these countries industrialize, they can leverage cutting-edge manufacturing technology embodied in imported machinery and equipment. The resulting higher productivity means fewer workers are needed to produce the required output at any given income level.

Furthermore, Proposition 3 predicts a shrinking capacity for job creation in the high-skill service sector and a premature decline in its employment share in developing countries.

As total labor input is fixed:

$$\sum_i L_{it} \Delta log L_{it} = 0$$

The real income growth rate can be derived below:

$$\Delta log Y_t = \Delta log C_t = \frac{(1-\sigma)\left(\tau_A L_{At} + \tau_M L_{Mt} + \tau_{Sh} L_{Sht} + \tau_{Sl} L_{Slt}\right)}{L_{At}\left(\varepsilon_A - \sigma\right) + L_{Mt}\left(\varepsilon_M - \sigma\right) + L_{Sht}\left(\varepsilon_{Sh} - \sigma\right) + L_{Slt}\left(\varepsilon_{Sl} - \sigma\right)} \tag{16}$$

Real income growth is determined by four key factors: sectoral composition, sectoral productivity growth, sectoral income elasticity, and the elasticity of substitution.

Proposition 4 *As an economy transitions from sectors with high productivity growth to those with low productivity growth, its real income growth rate decreases. In the long run, the growth rate is constrained by the sector exhibiting the slowest technological progress.*

Equation 15 demonstrates that higher productivity growth in any sector invariably increases real income growth in each period. The agriculture sector, assumed to have the highest labor productivity growth and the lowest income elasticity, contributes significantly to real income growth when it has a higher initial employment share. In the long term, the employment share in the low-skill service sector approaches one, and the real income growth rate converges to $\frac{(1-\sigma)\tau_{Sl}}{(\varepsilon_{Sl}-\sigma)}$. This convergence highlights the importance of productivity growth in the low-skill service sector for sustaining long-term economic growth.

From exogenous to endogenous growth

The model can be extended by relaxing the assumption of exogenous and constant productivity growth in each sector. Following Matsuyama 2019, sectoral productivity growth is assumed to be proportional to the employment share in that sector. This assumption is intuitive: as a sector becomes more important in an economy, more research and development efforts are directed towards it. Productivity growth is proportional to sectoral employment share rather than sectoral consumption share (which are equal in a closed economy), as an economy needs to maintain a critical mass of employment in the sector to transmit the tacit knowledge required for production. Under this assumption:

$$\Delta log X_{it} = \eta_i L_{it} \tag{17}$$

Changes in sectoral employment and nominal output share become:

$$\Delta log \omega_{it} = \Delta log L_{it} = (\sigma - 1)\, \eta_i L_{it} + (\varepsilon_i - \sigma)\, \Delta log Y_{it} \tag{18}$$

All four propositions from the exogenous growth model remain valid. The agriculture sector's employment share continues to decrease monotonically over time, albeit no longer at a fixed rate. The rate of decrease gradually declines and converges to zero as the agricultural employment share shrinks.

For manufacturing and high-skill services, the first term (supply-side force through productivity growth) is negative and follows a U-shaped pattern, while the second term (demand-side force through higher real income) is positive and decreasing. The net growth starts positive, decreases to below zero, then increases and gradually converges to zero. Employment share in both sectors first increases and then decreases.

For the low-skill service sector, the first term is negative and decreasing, while the second term is positive and decreasing. The net growth remains positive and eventually converges to zero.

Real income growth is given by:

$$\Delta log Y_t = \Delta log C_t = \frac{(1 - \sigma)\left(\sum_i \eta_i L_{it}^2\right)}{\sum_i (\varepsilon_i - \sigma)\, L_{it}} \tag{19}$$

As the economy transitions from agriculture-dominated to low-skill services-dominated, the denominator increases over time. If $\eta_{Sl} < \eta_A$, the numerator decreases over time, resulting in positive but decreasing real income growth.

3.2 Open economy

Now consider a global economy comprising multiple countries of varying sizes at different stages of development. Each country has a representative consumer with identical preferences defined by equation 1, and consumption in each sector is determined by equation 3. Production in sector i of country j is given by $Y_{it}^{j} = X_{it}^{j} L_{it}^{j}$, where countries differ in their technology levels and productivity growth rates across sectors.

Agriculture, manufacturing, and high-skill services are tradable, eliminating the need for domestic supply to equal domestic demand. Global demand and supply determine prices for each type of tradable good, with the price of agricultural goods normalized to one. For simplicity, assume zero trade costs. The relationship between consumption and production can be expressed as:

$$C_{it}^{j} = \lambda_{it}^{j} Y_{it}^{j}, \lambda_{it} \geq 0 \tag{20}$$

where λ_{it}^{j}>1 indicates that country j is a net importer of goods in sector i at time t, and λ_{it}^{j}<1 denotes that country j is a net exporter.

In any country j producing all four types of goods simultaneously, the wage rate must be equal across sectors, and the marginal revenue product of labor should be consistent across sectors: $w = P_A X_A = P_M X_M = P_{Sh} X_{Sh} = P_{Sl} X_{Sl}$. This condition ensures labor market equilibrium within each country, as workers would otherwise shift to sectors offering higher wages.

This section examines two extreme cases, as outlined in Rodrik 2016: the large country case and the small country case. In the large country case, prices are determined endogenously by domestic economic developments, with net trade flows acting as exogenous shocks. In the small country case, the economy is a price taker in world markets due to its limited size.

For the large country case, changes in sectoral employment share are given by:

$$\Delta log L_{it} = (\sigma - 1)\, \tau_i + (\varepsilon_i - \sigma)\, \Delta log Y_t - \Delta log \lambda_{it} \tag{21}$$

Economic growth is determined by:

$$\Delta log Y_t = \frac{(1-\sigma) \sum_i \tau_i L_{it} + \sum_i \Delta log \lambda_{it} L_{it}}{\sum_i L_{it} \left(\varepsilon_i - \sigma\right)} \tag{22}$$

Trade balance requires that expenditure on imported goods equals income earned from exports:

$$\sum_i P_{it}\left(C_{it} - Y_{it}\right) = \sum_i P_{it} Y_{it}\left(\lambda_{it} - 1\right) = 0,\ i \in \{A, M, Sh\} \tag{23}$$

Proposition 5 *In a large open economy:*

1. A positive (negative) productivity shock in sector i leads to lower (higher) employment and nominal output share in that sector, and higher (lower) real income.

2. A positive trade shock increasing net exports in sector i ($\Delta log\lambda_{it}$<0) increases employment and nominal output share in that sector while reducing them in at least one other tradable sector. A negative trade shock has the opposite effect.

3. If a trade shock shifts employment from high to low productivity growth sectors, real income growth slows in each period. Conversely, if it shifts employment from low to high productivity growth sectors, real income growth accelerates in each period.

A positive trade shock that increases net exports in sector i has an effect similar to a higher relative price of good i, shifting consumption away from that sector.

Proposition 6 *In a small open economy:*

1. A positive productivity shock in a tradable sector attracts more labor to that sector, increasing exports and purchasing power for other tradable goods, thus raising welfare/real income. Conversely, a negative productivity shock reduces labor in the affected sector, increases reliance on imports, and decreases real income.

2. An increase in the global price of tradable sector i reduces domestic consumption while increasing production, leading to higher net exports in sector i and increased net imports in at least one other tradable sector.

3. A decrease in the global price of tradable sector i increases consumption while reducing employment in that sector, resulting in higher net imports and increased net exports in at least one other tradable sector.

In the small country case, prices for tradable goods are exogenous. Consumption across the four sectors at a given real income level is largely determined by global prices (Equation 24).

$$C_{it} = \Omega_i \left(\frac{P_{it}}{P_t}\right)^{-\sigma} C_t^{\varepsilon_i} = \Omega_i \left(\frac{P_{it}}{E_t}\right)^{-\sigma} C_t^{\varepsilon_i - \sigma} \tag{24}$$

$$C_{it} = \lambda_{it} Y_{it} = \lambda_{it} X_{it} L_{it} \tag{25}$$

In an open economy, a small country j has a comparative advantage in producing good i if its theoretical domestic price $P_{it}^{j} = \frac{X_{At}^{j}}{X_{it}^{j}}$ is below the global price P_{it}. This leads to labor reallocation from other tradable sectors to sector i to capitalize on the higher global price, resulting in exports of surplus production and imports of other tradable goods. The term "theoretical domestic price" is used because the actual domestic price must equal the global price in the absence of trade costs.

Conversely, if the theoretical domestic price exceeds the global price for good i, country j has a comparative disadvantage. In this case, country j will import good i and shift labor from sector i to the sector with the highest comparative advantage.

Consider a small open economy with a comparative advantage in agriculture. This economy allocates labor only to two sectors: agriculture and nontradable low-skill services. The equal wage rate condition implies: $P_{At}X_{At} = X_{At} = P_{Slt}X_{Slt} = P_tC_t$.

Trade balance requires that expenditure on imported manufactured goods and high-skill services equals income from agricultural net exports:

$$P_{Mt}C_{Mt} + P_{Sht}C_{Sht} = P_{At}\left(Y_{At} - C_{At}\right) \tag{26}$$

$$\Omega_M P_{Mt}^{1-\sigma} X_{At}^{\sigma} C_t^{\varepsilon_M - \sigma} + \Omega_{Sh} P_{Sht}^{1-\sigma} X_{At}^{\sigma} C_t^{\varepsilon_{Sh} - \sigma} = X_{At}L_{At} - \Omega_A X_{At}^{\sigma} C_t^{\varepsilon_A - \sigma} \tag{27}$$

For low-skill nontradable services, consumption and production must be equal:

$$C_{Slt} = \Omega_{Slt} X_{Slt}^{\sigma} C_t^{\varepsilon_{Sl} - \sigma} = X_{Slt}L_{Slt} \tag{28}$$

Solving these equations yields:

$$\sum_i \Omega_i X_{At}^{\sigma-1} P_{it}^{1-\sigma} C_t^{\varepsilon_i - \sigma} = 1 \tag{29}$$

An increase in global prices for manufacturing or high-skill services reduces the real income of the agriculture exporter, as it can import fewer of these goods. Conversely, a decrease in these global prices raises the country's real income. Higher domestic productivity in agriculture or low-skill services unambiguously increases the real income level.

This simple model illustrates how global price changes and domestic productivity improvements affect a small open economy specializing in agriculture, highlighting the importance of terms of trade and sectoral productivity in determining overall economic well-being.

3.3 Model validation and AI impact channels

Most of the six model propositions are intuitive and have been observed for an extended period. Rigorous empirical analysis, presented in Appendix A, strongly supports these propositions. The analysis draws upon multiple datasets covering the past seven decades, providing robust evidence for the model's validity.

The model demonstrates how technology influences relative prices, nominal and real outputs, sectoral employment shares, as well as real income levels and growth trajectories. It also highlights the distinct effects of technology on large and small open economies through trade. Given that generative AI primarily enhances productivity in high-skill services, the model predicts the following:

- Impact on real income: If AI's productivity gains are confined to the high-skill service sector, the aggregate growth effect will be limited, as this sector represents a relatively small share of total output and employment. However, AI's growth impact will be significantly greater if it drives productivity increases across all sectors.

- Impact on sectoral composition: AI's effect on sectoral employment shares is ambiguous, contingent on its impact on real income and sectoral productivity. In general, AI tends to accelerate the shift toward low-skill services. If its productivity impact is most pronounced in high-skill services, as evidence suggests, it will result in an earlier and lower peak in high-skill services employment at a lower real income level. Similar to the phenomenon of premature deindustrialization, generative AI could lead to "premature de-professionalization" in many developing countries.

- Impact on comparative advantage and trade: In large open economies, AI is unlikely to alter comparative advantage, as productivity changes are offset by corresponding shifts in relative prices. Over time, AI is expected to reduce employment in high-skill services and drive down global relative prices in this sector. For small open economies, AI presents an opportunity to gain comparative advantage in high-skill services, increasing production, exports, and employment in this sector.

The analysis above assumes that AI does not alter consumer preferences. In the following section, I use model parameters drawn from the literature and empirical evidence to quantify AI's impact under various scenarios. Beyond exploring different productivity boost scenarios, I introduce a more ambitious scenario in which AI creates entirely new products and industries, leading to a permanent shift in consumer preferences.

4 Simulating AI's Impact

This section begins by simulating economic growth and structural transformation patterns in both closed and open economy settings as a baseline. All simulations assume exogenous growth. Appendix B provides additional simulations using varied productivity growth parameters, as well as endogenous growth models with and without inter-sectoral productivity spillovers. The simulated growth and structural transformation patterns closely align with trends observed in the stylized facts, further validating the model's credibility.

4.1 Model parameters and baseline

Closed economy baseline

First consider a closed economy with exogenous productivity growth. Model parameters are shown in Table 1. The elasticity of substitution is assumed to be 0.5 based on Comin, Lashkari, and Mestieri 2021. Income elasticities across the four sectors are also based on Comin, Lashkari, and Mestieri 2021 and Aguiar and Bils 2015. Labor productivity growth rate is 8% in agriculture (A), 4% in manufacturing (M), 2% in high-skill services (Sh), and 1% in low-skill services (Sl). The sector constant Ω_i is 0.9 for A, 0.05 for M, 0.01 for Sh, and 0.04 for Sl. These values correspond to the initial employment share.

Elasticity of Substitution: $\sigma = 0.5$			
Income Elasticity			
$\varepsilon_A = 0.5$	$\varepsilon_M = 1.4$	$\varepsilon_{Sh} = 1.6$	$\varepsilon_{Sl} = 1.8$
Labor Productivity Growth			
$\tau_A = 8\%$	$\tau_M = 4\%$	$\tau_{Sh} = 2\%$	$\tau_{Sl} = 1\%$
Sector constant			
$\Omega_A = 0.9$	$\Omega_M = 0.05$	$\Omega_{Sh} = 0.01$	$\Omega_{Sl} = 0.04$

Table 1: Baseline Model Parameters

The simulated real income, sectoral employment and nominal output share over 100 years (T=100) is shown in Figure 11. As discussed previously, real income growth declines over time and gradually converge to $\frac{(1-\sigma)\tau_{Sl}}{\varepsilon_{Sl}-\sigma} = 0.38\%$.

Agriculture employment share drops dramatically from 90% at t=0 to around 2% at t=100. Manufacturing share peaks at 17% at t=28 (when real income is 7.4) and decreases to 8% at t=100. High-skill services share ascends from 1% at t=0 to a peak of 8% at t=60 (when real income is 11.4), and gradually declines to 7% at t=100. Low-skill services share grows from 4% in the beginning to 83% at t=100. Real income (or welfare) starts at 1 and reaches 15 at t=100. Real income, which can be interpreted as thousands of US dollars, increases from \$1,000 to \$15,000 over the century. This baseline simulation thus depicts an economy experiencing both significant structural transformation and economic growth.

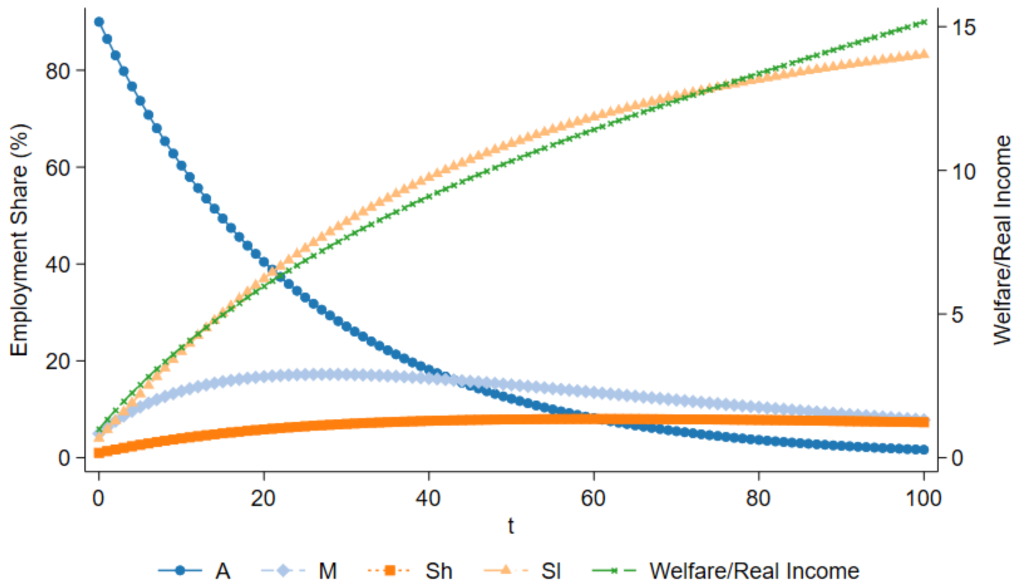


Figure 11: Closed economy baseline

The simulated trajectory closely mirrors the United States' growth and structural transformation from 1700 to 1950. During this period, U.S. GDP per capita rose from approximately \$1,000 to \$15,000 (based on the Maddison Project Database 2023). Key sectoral shifts include:

- Agriculture: Employment share plummeted from 80% in the 1700s to 5% by the 1950s, further declining to 2% in the 2000s.
- Low-skill services: Gradually increased to 50% by the 1950s, reaching 66% in the 2000s.
- Manufacturing: Grew from 3% in the early 1800s to over 20% in the 1950s, then decreased to 10% by the 2000s (Lebergott 1966.
- High-skill services: Expanded from virtually zero in the 1700s to 6% in 1950, surging to 20% since the 2000s.

The recent surge in high-skill services employment in the U.S., partly driven by exports, explains why the actual figure exceeds the simulated projection.

Large open economy baseline

The simulation now shifts to an open economy case. Building upon the parameters in the closed economy, consider a large open economy experiencing a positive trade shock in the high-skill service sector, with $\Delta log \lambda_{Sht} = -0.005$ in each period. Assume net trade in the agriculture sector remains at zero. Figure 12 illustrates the simulation results.

High-skill services share continues to rise throughout the simulation period and reaches 12.1% at t=100, driven by the positive trade shock. Manufacturing employment share reaches its peak (16.3% at t=24, real income at 6.7) earlier and at a lower level compared to the baseline (peak of 17% at t=28, real income at 7.4). It subsequently remains below the scenario 1 level in each period, reflecting the economy's increasing reliance on imported manufactured goods. For agriculture and low-skill services, employment share mirrors the closed economy level in each period.

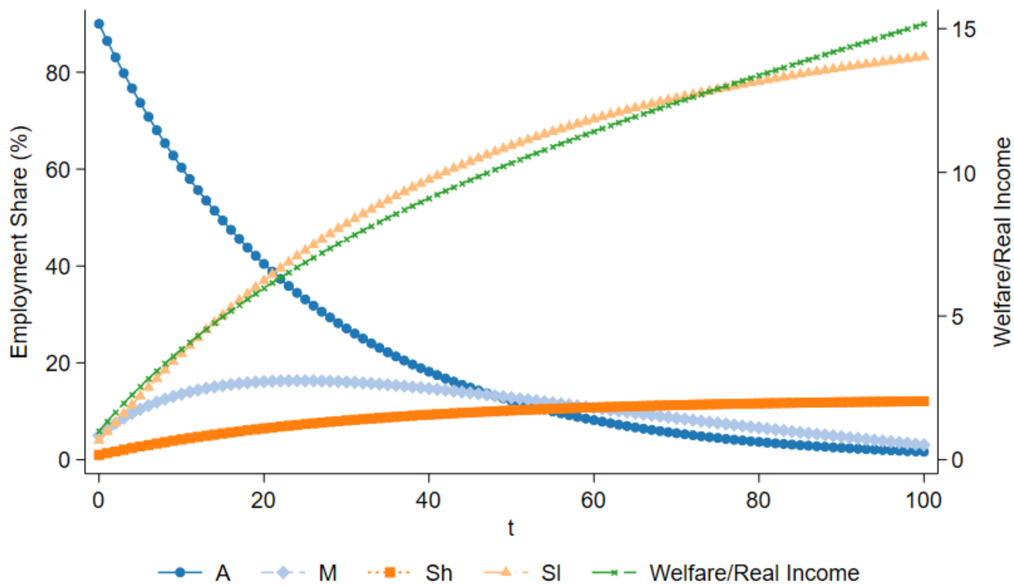
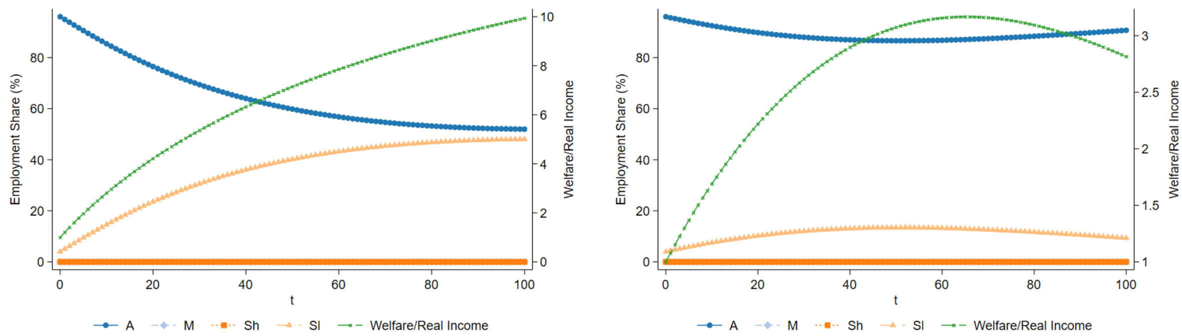


Figure 12: Large open economy, net exporter of high-skill services

Structural transformation patterns in most high-income countries align closely with the predictions from both the closed baseline model and the large open economy model, as illustrated in Figure 3.

Small open economy baseline

For simplicity, this paper only simulates the case of an agricultural exporter in two sub-scenarios: high and low agriculture productivity growth. This small economy produces only agricultural products and low-skill services. Manufacturing and high-skill services are entirely imported. Sectoral income elasticities, elasticity of substitution, sector constants, and global prices for tradable sectors remain as in the closed economy baseline. Low-skill services productivity growth is set at 1%. Two agricultural productivity growth scenarios: high-growth (a): 5%. Low-growth (b): 2%. Simulation results are shown in Figure 13.



(a) High growth

(b) Low growth

Figure 13: Small open economy: agriculture exporter

In both cases, the country exports surplus agricultural goods in exchange for manufactured goods and high-skill services. The outcomes differ significantly based on agricultural productivity growth:

High growth scenario (a):

Efficiency gains in agriculture fully compensate for growth in global manufacturing and high-skill services prices. The economy requires a decreasing share of labor in agriculture to meet export demands. Continuous economic growth occurs, with labor shifting from agriculture to low-skill services. Structural transformation patterns in lower-middle income and low-income countries closely resemble this case, as depicted in Figure 5. Relatively closed lower-income countries follow the closed economy low growth pattern in Appendix B.

Low growth scenario (b):

Global prices for manufactured goods and high-skill services rise faster than agricultural productivity growth. The economy eventually struggles to maintain import levels of manufactured goods and high-skill services. Agricultural employment share initially decreases, then increases to finance growing import expenses. Real income ultimately decreases due to persistently rising global prices for other tradable goods.

4.2 Three scenarios on AI's impact

Generative AI could affect economic growth and structural transformation through multiple channels. This subsection focuses on three primary mechanisms: enhanced productivity growth, the creation of demand for novel products, and international trade. The first two mechanisms affect model parameters, while the third is simulated in the open economy model.

I examine three distinct scenarios:

1. AI exclusively increases labor productivity growth in the high-skill service sector. This scenario is the most plausible in the short term, given that finance, information and communication technology (ICT), and professional services demonstrate the highest occupational exposure to generative AI (Figure 10).

2. AI enhances labor productivity growth across all four sectors, with the most substantial increase observed in high-skill services. This scenario is likely to transpire in the medium to long term, as generative AI becomes widely integrated into machinery, robotics, and production processes across sectors, enabling more sophisticated interactions with the physical world.

3. AI not only boosts labor productivity in all sectors but also catalyzes the creation of revolutionary products and industries, leading to a permanent increase in the income elasticity for high-skill services and higher elasticity of substitution between broad sectors. This scenario envisions a transformative future where AI fundamentally alters societal preferences and consumption patterns. Imagine a world where:

    - The boundaries between physical and virtual realities blur, with individuals spending an increasing portion of their income on immersive metaverse experiences and hyper-realistic AI-generated entertainment.
    - Every household is equipped with versatile, AI-powered robots that handle a wide array of tasks, from intricate housework to personalized healthcare and eldercare.
    - AI-driven personal assistants evolve into indispensable life companions, offering not just task management but also emotional support and intellectual stimulation.
    - Novel AI-human collaborative professions emerge, redefining traditional notions of work and creativity.
    - AI-engineered sustainable technologies revolutionize energy consumption and environmental preservation, creating new economic sectors centered on eco-friendly innovations.

    This scenario, while highly speculative, may only materialize in the longer term if AI capabilities continue to advance exponentially and reshape the fabric of society and the economy.

For simplicity, the simulation in this section is based on the exogenous growth model. Results from the endogenous growth model yield very similar outcomes.

AI's impact: Closed economy

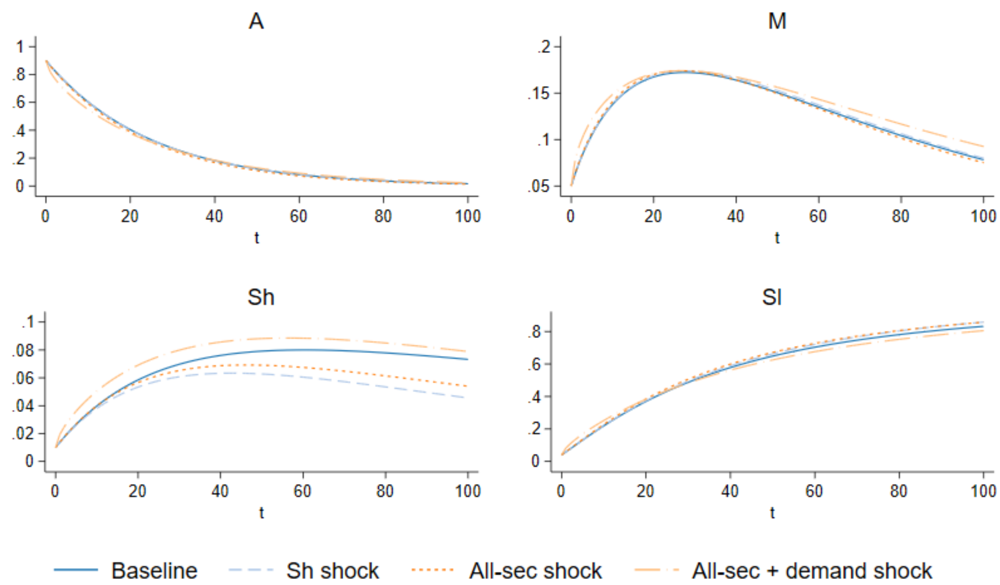
I begin by examining a closed economy setting. The parameters for the three generative AI scenarios are as follows:

- Baseline: $\varepsilon_{Sh} = 1.6$
- High-skill services (Sh) shock: 50% increase in τ_{Sh}
- All-sector shock: 50% increase in τ_{Sh}, 5% increase in τ_A, 10% increase in τ_M, 40% increase in τ_{Sl}
- All-sector + demand shock: 50% increase in τ_{Sh}, 5% increase in τ_A, 10% increase in τ_M, 40% increase in τ_{Sl}, ε_{Sh} increases from 1.6 to 1.7, σ increases from 0.5 to 0.6

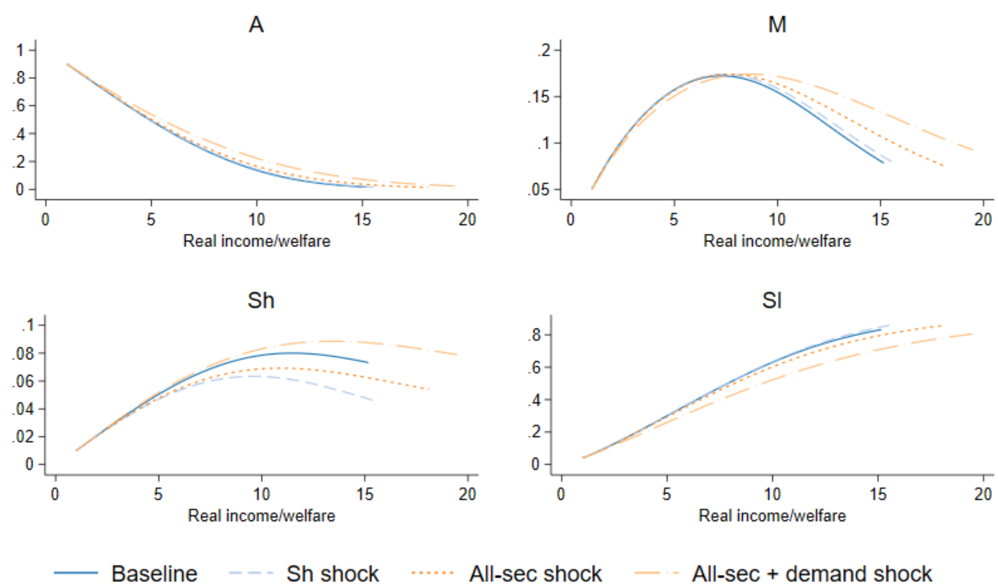
Figure 14 illustrates the impact of generative AI on sectoral employment share under different scenarios. Subfigure (a) depicts changes over time, while subfigure (b) shows changes relative to real income.

In the scenario where generative AI only boosts productivity growth by 50% in high-skill services, agricultural employment share remains the same as in the baseline model in each period. Manufacturing and low-skill services experience slightly higher employment shares in each period and at the same income level. High-skill services employment share peaks earlier but at a significantly lower level, with this peak occurring at a lower real income level. Overall real income growth surpasses the baseline scenario in each period, albeit the increase is very modest.

When generative AI boosts productivity growth across all sectors, agriculture share declines more rapidly, manufacturing share peaks earlier at a higher level, with this peak occurring at a higher real income level. High-skill services share is lower than the baseline but higher than in the high-skill services shock scenario. Real income at each period exceeds both the baseline and high-skill services shock scenarios.



(a) By time



(b) By income

Figure 14: AI impact: closed economy

In the scenario where generative AI also increases income elasticity for high-skill services and the elasticity of substitution, employment in high-skill services increases to meet higher demand, reaching a higher peak at a higher real income level. However, due to accelerated productivity growth, the high-skill services employment share subsequently declines more rapidly than in the baseline scenario. Low-skill services employment share is initially higher but grows more slowly, the share becomes the lowest level among all four scenarios after a certain time.

The magnitude of the growth impact attributable to generative AI is illustrated in Figure 15.

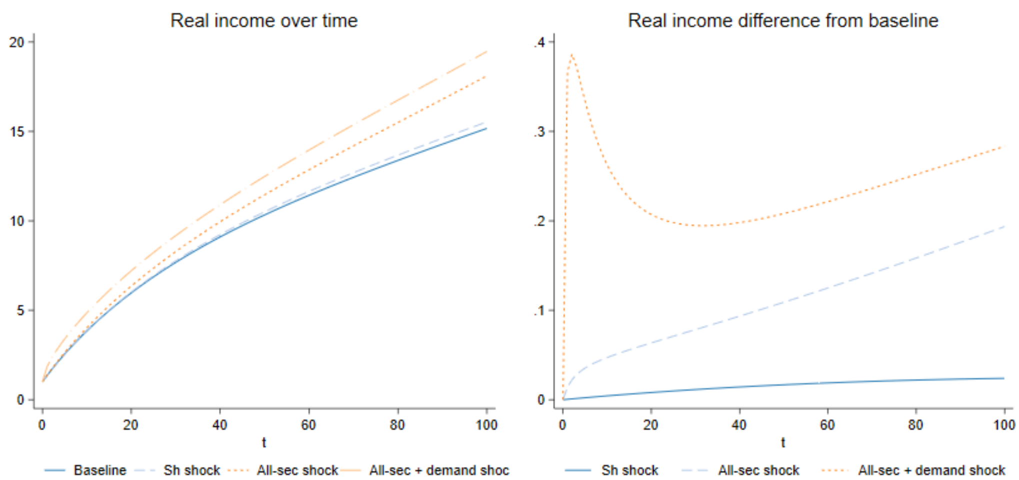


Figure 15: AI growth impact: closed economy

The results reveal varying degrees of aggregate growth impact across different scenarios:

1. AI impact limited to high-skill services: Even with a substantial 50% increase in labor productivity growth in high-skill services, the real income growth rate experiences a modest initial boost of 0.046 percentage points at t=0. This increase diminishes monotonically over time. By t=100, the real income level is only 2.4% higher than in the baseline model, indicating a relatively limited long-term impact.

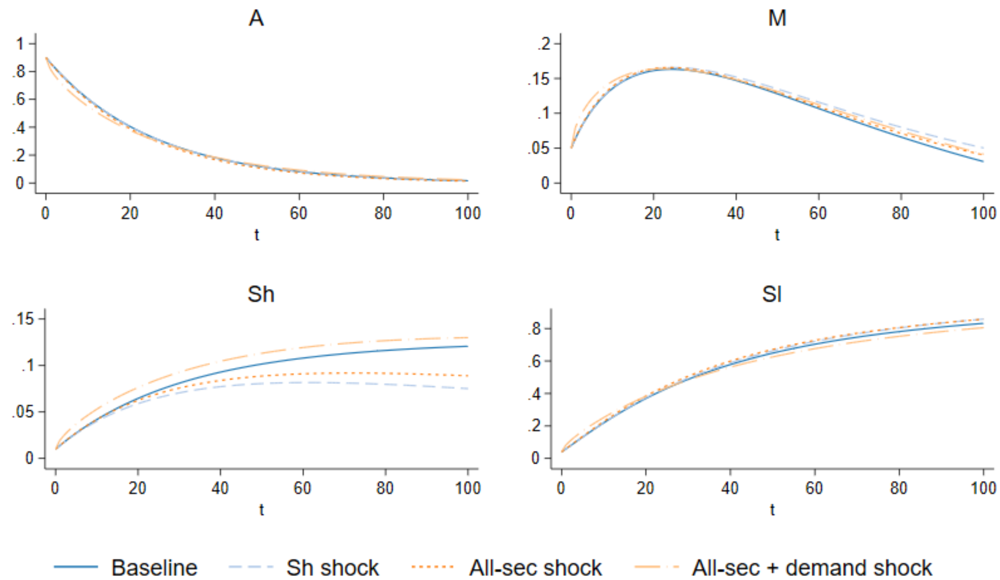
2. AI-driven productivity growth across all sectors: When generative AI enhances productivity across all sectors, the growth impact is considerably more pronounced. The growth rate differential relative to the baseline scenario is approximately 0.15 percentage points. This translates into a 19% higher real income level at t=100 compared to the baseline, demonstrating a more meaningful and sustained economic effect.

3. AI boosting productivity and transforming preferences: In the most optimistic scenario, where AI not only accelerates productivity growth across sectors but also catalyzes game-changing products and industries, the economic impact is the most dramatic. Initially, real income growth surges by 37% compared to the baseline. While this differential initially declines, it subsequently experiences a secondary increase. By t=100, the real income level stands 28% higher than the baseline scenario, underscoring the potential for AI to drive significant long-term economic transformation.

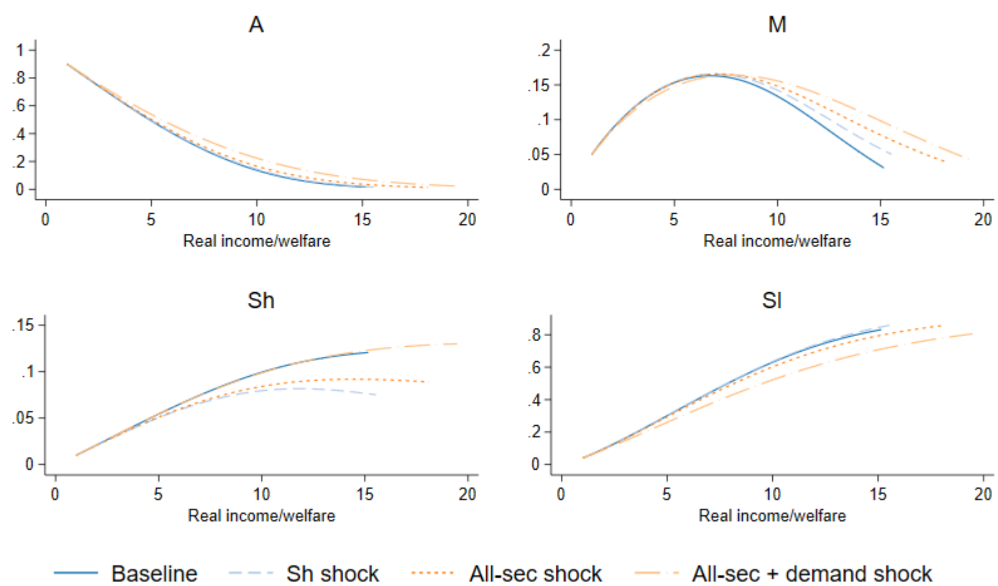
These findings highlight the varying potentials of AI to influence economic growth, with the most substantial impacts emerging from widespread adoption and innovation across multiple sectors.

AI impact: Open economy

In the context of a large open economy that exports an increasing share of high-skill services it produces, advances in AI are poised to propel real income growth. Initially, exports can sustain employment in the high-skill service sector. However, this growth trajectory faces two inevitable constraints: (1) global demand growth will eventually plateau; (2) the continuous enhancement of AI capabilities exerts downward pressure on high-skill services employment. The relentless progression of AI technology will ultimately precipitate a decline in high-skill services employment, unless AI fundamentally alters consumer preferences as described in scenario 3. Even in this optimistic scenario, where AI spawns new markets and shifts consumption patterns, the high-skill services employment share will eventually peak and decrease, albeit at a more gradual pace. The magnitude of the growth impact in the large open economy mirrors that of the closed economy model. This suggests that the domestic structural changes driven by AI have a more profound influence on economic growth than the expansion of export markets for AI-enhanced services.



(a) By time



(b) By income

Figure 16: AI impact: large open economy

For a small open economy to engage in production across all four sectors, the following equilibrium condition must be satisfied:

$$X_{At}^{D} = P_{Mt}^{G} X_{Mt}^{D} = P_{Sht}^{G} X_{Sht}^{D} = P_{Slt}^{D} X_{Slt}^{D} \tag{30}$$

where superscript D denotes domestic values and G denotes global values.

If a small open economy originally produces all four products, then AI causes a reduction in the global price of high-skill services P^G_{Sht} without a compensatory increase in domestic productivity X^D_{Sht}, the economy will stop producing high-skill services. Consequently, the economy would shift to exporting agriculture and manufacturing products in exchange for high-skill services. If AI also reduces the global price for manufacturing while domestic productivity X^D_{Mt} fails to increase proportionally, the economy will also drop out of manufacturing production. The small economy would be transformed into a commodity exporter. The only types of jobs left will be in agriculture and low-skill services.

Figure 17 shows the impact of AI on a small commodity exporter. Assume that AI increases labor productivity growth in agriculture from 5% to 6%, and in low-skill services from 1% to 1.2%. Despite the country's inability to generate employment in manufacturing and high-skill service sectors, the AI-driven productivity improvements in agriculture still yield economic benefits: accelerated decline in agriculture employment and associated urbanization; growth in real income, albeit probably at a lower rate compared to a more diversified economy.

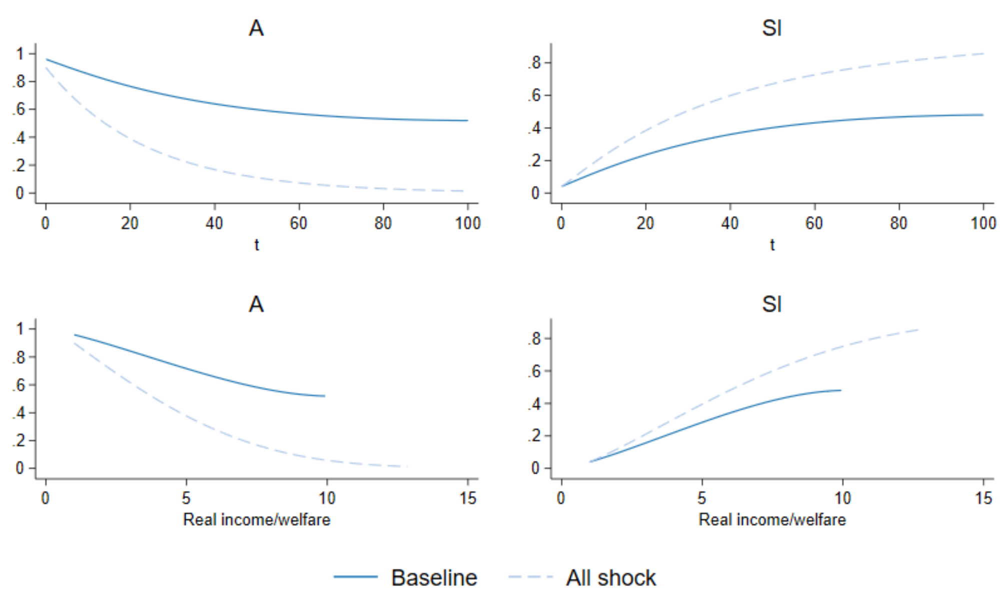


Figure 17: AI impact: small commodity exporter, exogenous growth

Conversely, if the small open economy successfully integrates AI into its production, it may develop a comparative advantage in manufacturing or high-skill services. This scenario would result in a labor shift from agriculture to these more innovative sectors. Importantly, to develop such a comparative advantage, the small economy need not match the frontier economy's productivity levels in manufacturing or high-skill services. Instead, it just need to satisfy the following condition: $P_{it}^{D} = \frac{X_{At}^{D}}{X_{it}^{D}} \leq P_{it}^{G} = \frac{X_{At}^{G}}{X_{it}^{G}}$, where i represents either the manufacturing or high-skill service sector.

5 AI's Broader Implications

The model and simulations presented thus far have illuminated the complex interplay among AI, economic growth, and sector composition, highlighting AI's differential impact on various types of countries under diverse scenarios. A country's industrial specialization pattern not only shapes its growth prospects (Hidalgo and Hausmann 2009) but also profoundly influences inequality. Next I discuss the limitations of this simple model and how AI may affect growth and inequality more broadly.

Firstly, the model's omission of capital overlooks a crucial dimension of AI's economic impact. AI is likely to further enrich capital owners at the expense of workers, exacerbating a trend already observed in many advanced economies. Digital transformation, automation, and rising industry concentration have contributed to falling labor income shares (D. Autor et al. 2017; Karabarbounis and Neiman 2014; Eden and Gaggl 2019). AI technologies tend to concentrate economic rents among a small cadre of superstar firms, leveraging network effects, economies of scale and scope, and control of core assets to generate significant first-mover advantages (Azoulay, Krieger, and Nagaraj 2024). The adoption of digital technologies and AI often favors large companies. This scale dependence in IT demand further accentuates the rise in concentration and the labor share decline (Lashkari, Bauer, and Boussard 2024). As AI capabilities expand by leaps and bounds, a broader spectrum of jobs could face automation or heightened competition due to lower entry barriers, potentially widening the chasm between labor and capital owners (Frey and Osborne 2024).

Secondly, the model's exclusion of intermediate inputs in production may underestimate the demand for high-skill services. Many high-skill services, such as business software and professional and technical services, are integral to business production. AI breakthroughs are likely to catalyze business investment in the technology and complementary factors, potentially bolstering employment in high-skill services for a period. Some futurists have long speculated that technological progress will ultimately liberate humanity from mundane labor, leaving only creative pursuits - art, science, entrepreneurship - as viable occupations. The McKinsey Global Institute (2023) projects that generative AI will augment workers in high-skill services, forecasting significant employment growth in STEM fields, business and legal professions, and creative industries between 2022 and 2030.

However, the perpetual growth of high-skill services employment share seems implausible and has already plateaued in some net-exporting countries. Furthermore, developing nations can hardly rely on high-skill services to generate substantial employment opportunities for their bulging youth populace. Figure 18 illustrates the trends in high-skill services employment across economies at various income levels. While many countries experienced rapid growth in this sector thanks to accelerating digital transformation, growth has moderated or stagnated in several nations, including the United States, the largest high-skill services exporter. Among middle- and low-income countries, high-skill services employment share has also stalled in Mexico, Türkiye, Bolivia, the Philippines, and Viet Nam in recent years. Around 13%-20% of the workforce in high-income countries engages in high-skill services. This share drops considerably to 6%-10% in upper middle-income countries, and plummets further to a mere 0%-4% in lower middle and low-income countries. Notably, even in developing countries renowned for their high-skill services exports, such as India and the Philippines, this sector's contribution to overall employment remains surprisingly modest, accounting for no more than 3% of jobs.

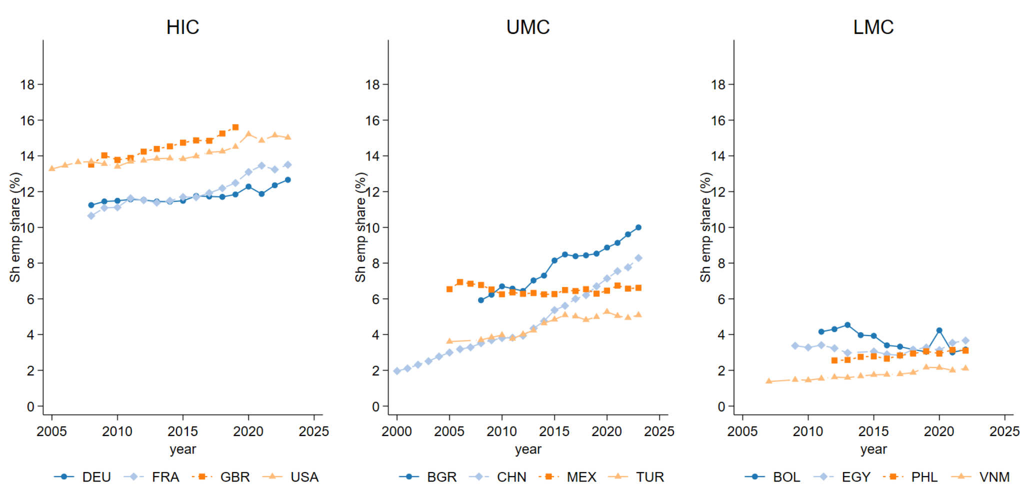


Figure 18: High-skill services employment share trends

The inherent characteristics of high-skill services occupations suggest an intrinsic limit to job creation within this sector. Unlike goods-producing sectors or less scalable low-skill services, high-skill services predominantly generate knowledge, ideas, data, and digital products. These outputs are often non-rival and have zero marginal cost, leading to a "winner-takes-all" dynamic where a few superstar firms can satisfy global demand. This phenomenon is evident in the limited number of dominant search engines, social media platforms, investment funds, and professional services firms needed worldwide. A stark comparison illustrates this point: Mercedes-Benz, a leading automotive manufacturer, employs over 170,000 people globally, while OpenAI, creator of the widely-used ChatGPT, operates with merely a few hundred employees despite serving hundreds of millions of users.

Third, the model's assumption of zero trade costs oversimplifies reality. AI is poised to reduce trade costs by bridging language and cultural barriers, potentially stimulating global trade and investment in specific sectors. Developing countries with comparative advantages in manufacturing and high-skill services that successfully adopt AI stand to benefit significantly. Generative AI may catalyze a new wave of services outsourcing and offshoring, creating opportunities for some developing nations, albeit with limited job creation potential.

Fourth, the model's assumption of homogeneous, freely mobile labor across sectors, resulting in equalized income, diverges from reality and fails to offer insights on inequality. Substantial wage disparities exist across industries, with between-industry income inequality emerging as a major driver of broader inequality (Eckert, Ganapati, Walsh, et al. 2019; Haltiwanger, Hyatt, and Spletzer 2023). Individual intentionally sort into different sectors and occupations based on their characteristics. Agricultural workers often lack the education and skills necessary for transitioning to manufacturing or high-skill services. Similarly, manufacturing and low-skill service workers face significant barriers to entering high-skill services. Geographical constraints further impede cross-sector job mobility, particularly for rural residents with limited local job diversity. Generative AI may lower entry barriers for certain high-skill service jobs, potentially suppressing average wages and reducing inter-occupational income inequality.

Recent studies on the distributional effects of generative AI within occupations yield mixed results. Some research indicates that newer, less skilled workers benefit more from generative AI (Brynjolfsson, Li, and Raymond 2023; Noy and W. Zhang 2023; Peng et al. 2023; Dell'Acqua et al. 2023). Conversely, other evidence suggests that AI and ChatGPT have significantly reduced translation tasks and earnings, with more pronounced negative effects on low-skill workers performing low-value tasks (Yilmaz, Naumovska, and Aggarwal 2023; Liu, Deng, and Monahan 2024). While generative AI may enable mediocre white-collar workers to undercut their highly skilled peers, potentially reducing within-occupation income inequality, the increased interchangeability of workers could suppress wages across entire occupations (Capraro et al. 2024; Frey and Osborne 2024).

Sixth, the model does not account for the effect of inequality on growth. Historical precedent suggests that digital technologies have fostered the rise of superstar firms, cities, and nations, exacerbating inequality. Workers and firms lacking adequate digital infrastructure, training, and access to generative AI tools may struggle to capitalize on productivity gains, widening the gap with better-resourced competitors or colleagues. If generative AI automates a broad spectrum of existing jobs without creating commensurate high-skill, well-paid new occupations, it may precipitate a downward shift in the labor market: skilled workers may be pushed into lower-paid, simpler tasks, while the lowest-skilled workers risk unemployment altogether (Acemoglu and D. Autor 2011). In a scenario where generative AI amplifies inequality and triggers social unrest, sustaining economic growth becomes increasingly challenging (Aghion, Caroli, and Garcia-Penalosa 1999).

Additionally, generative AI will affect individuals' incentives for acquiring education and skills. Traditionally, high-skill, well-paid jobs have demanded specialized expertise, with the promise of higher income and more fulfilling careers motivating individuals to invest in college degrees and advanced training. However, technological advancements continuously reshape the landscape of valuable skills, rendering some expertise obsolete while creating demand for new competencies.

The current competition for scarce generative AI talent exemplifies this shift, with annual compensation packages reaching a million dollars for top professionals[1]. Simultaneously, expertise in other fields is being devalued. If AI leads to a decline in the proportion of high-skill, well-paid jobs in the long term, individuals may be discouraged from investing in higher education due to diminished prospects of securing rewarding employment (Capraro et al. 2024).

Evidence suggests this trend is already underway. In the United States, the percentage of high school graduates immediately enrolling in college has decreased from 69% in 2018 to 62% in 2022[2]. Moreover, parents and students are increasingly questioning the value of a college degree, with approximately half of U.S. adults believing that a four-year degree is less important for obtaining a well-paying job today than it was two decades ago.[3]

This paper underscores risk of "premature de-professionalization" - the potential contraction of opportunities for well-paid jobs in high-skill services within developing countries. This could potentially lead to widespread underemployment, reduced social mobility, and disillusionment among younger generations. While economists have historically argued that technological advancements create more jobs than they eliminate, this optimism may not hold in the AI era. Acemoglu and Restrepo 2019 has documented an acceleration in automation coupled with a deceleration in the creation of new tasks. Digital technologies and AI have eliminated millions of middle-skill, middle-income routine jobs while generating low-barrier, poorly-paid, precarious positions in low-skill services and the gig economy. In developing countries, the current high employment shares in agriculture and low-skill services mask underemployment on a grand scale, as these sectors often serve as last resorts for those unable to secure more promising opportunities.

[1] The Fight for AI Talent: Pay Million-Dollar Packages and Buy Whole Teams. https://www.wsj.com/tech/ai/the-fight-for-ai-talent-pay-million-dollar-packages-and-buy-whole-teams-c370de2b

[2] Immediate College Enrollment Rate, https://nces.ed.gov/programs/coe/indicator/cpa

[3] Roughly half US adults say it's less important to have a four-year college degree today in order to get a well-paying job than it was 20 years ago. https://www.pewresearch.org/social-trends/2024/05/23/is-college-worth-it-2/

As automation and AI challenge the traditionally successful manufacturing-led development strategy, some developing nations are pivoting towards services-led growth. However, if AI advancements ultimately reduce the employment share in high-skill, tradable services as the model predicts, developing countries face a narrow window of opportunity. They must swiftly adopt AI to establish and entrench their comparative advantage in this sector, outpacing their peers. Late adopters will likely confront intensified competition, elevated automation risks, and a diminishing pool of high-skill service jobs. Consequently, these economies risk becoming trapped as commodity exporters, further widening the global economic and social divide.

6 Conclusion

This paper presents a multi-sector growth model that dissects the general equilibrium impact of AI on economic growth, structural transformation, and labor markets across various scenarios. The model propositions not only align with empirical evidence but also sound a stark warning: AI will shrink the space for countries to generate well-paid jobs in high-skill services.

The simulations deliver a sobering message: unless AI can be widely adopted across sectors and spark truly paradigm-shifting innovations that fundamentally alter consumer preferences, its growth benefits are likely to be limited. In contrast, its disruptive impact on labor markets threatens to be deep and far-reaching. This grim outlook is compounded by the well-documented premature de-industrialization plaguing developing countries. Now, even a services-led growth strategy is becoming increasingly elusive, thwarted by relentless technological progress and non-homothetic preferences that favor less-tradable, predominantly low-skill services.

The paper highlights the urgency for developing countries to embrace AI and cultivate a comparative advantage in more complex and growth-enhancing sectors. Currently the world is still in the nascent stages of AI development and deployment, creating a temporary expansion in demand for high-skill service jobs. Generative AI's ability to bridge language and cultural barriers promises to reduce trade costs and spark a new wave of services outsourcing and offshoring. However, this opportunity will not persist indefinitely.

The stakes for developing countries are immense. Those that fail to swiftly adopt AI risk being ensnared in a commodity exporter trap, condemning their youth to a future blighted by massive underemployment, dwindling social mobility, and potentially declining living standards.

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Appendix A: Corroborating the Model with Empirical Evidence

Appendix A employs multiple datasets to test the validity of key model propositions.

The Groningen Growth and Development Centre (GGDC) 10-sector database is the main dataset used. The GGDC 10-sector database provides internationally-comparable historical data on sectoral employment, output, and productivity performance in 42 countries around the world. Variables include value added, output deflators and employment data for 10 broad economic sectors from 1950 to 2014. The database is widely used in structural transformation studies (Timmer, Vries, and De Vries 2015).

In this analysis, the sectors are consolidated as follows:

1. Agriculture (A): Combines agriculture and mining
2. Manufacturing (M): Remains as defined in the database
3. High-skill services (Sh): Corresponds to Finance, insurance, real estate and business services
4. Low-skill services (Sl): Encompasses utilities, construction, trade, restaurants and hotels, transport, storage and communication, community, social, and personal services, and government services

Proposition 1 predicts a monotonous increase in the quantity of outputs in each sector as productivity and real income grow. This prediction is largely self-evident, as the quantity of outputs across all sectors has been growing in most countries experiencing positive productivity and real income growth. Technological advances have created an unprecedented abundance for people today, surpassing what was imaginable in the past.

Proposition 2 indicates that higher sectoral productivity growth will drive down prices. I use the simple regression below to test this proposition:

$$Pricegrowth_{it} = \beta 0 + \beta 1 lpgrowth_{it} + CountryFE + DecadeFE + \varepsilon_{it} \tag{31}$$

where $Pricegrowth_{it}$ represents the annual growth in sectoral price in country i, year t, $lpgrowth_{it}$ denotes annual labor productivity growth. The model also incorporates country and decade fixed effects to control for time-invariant country-specific factors and decade-specific trends. The regression is run separately for all four sectors using the GGDC 10-sector database.

Table A1 presents the regression results, which strongly support Proposition 4. Across all four sectors, higher labor productivity growth in a given country is associated with lower price growth. The coefficients are statistically significant in all cases, providing robust evidence for the inverse relationship between productivity growth and price increases.

Table A1: Labor productivity growth and price change

	(1)	(2)	(3)	(4)
Sector	A	M	Sh	Sl
	Dependent variable: Sectoral price growth			
Labprodg	-0.432***	-0.341*	-0.280**	-0.583***
	(0.0987)	(0.151)	(0.0886)	(0.156)
Country FE	Y	Y	Y	Y
Decade FE	Y	Y	Y	Y
Observations	1,937	1,937	1,937	1,937
R-squared	0.292	0.363	0.306	0.384

Note: Standard errors are clustered at the World Bank region level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Proposition 3 predicts an inexorable decline in the employment and nominal output share of agriculture sector, a continuous increase in the share of low-skill services, and a hump-shaped pattern for manufacturing and high-skill services. The following regression is used for $i \in \{A, Sl\}$:

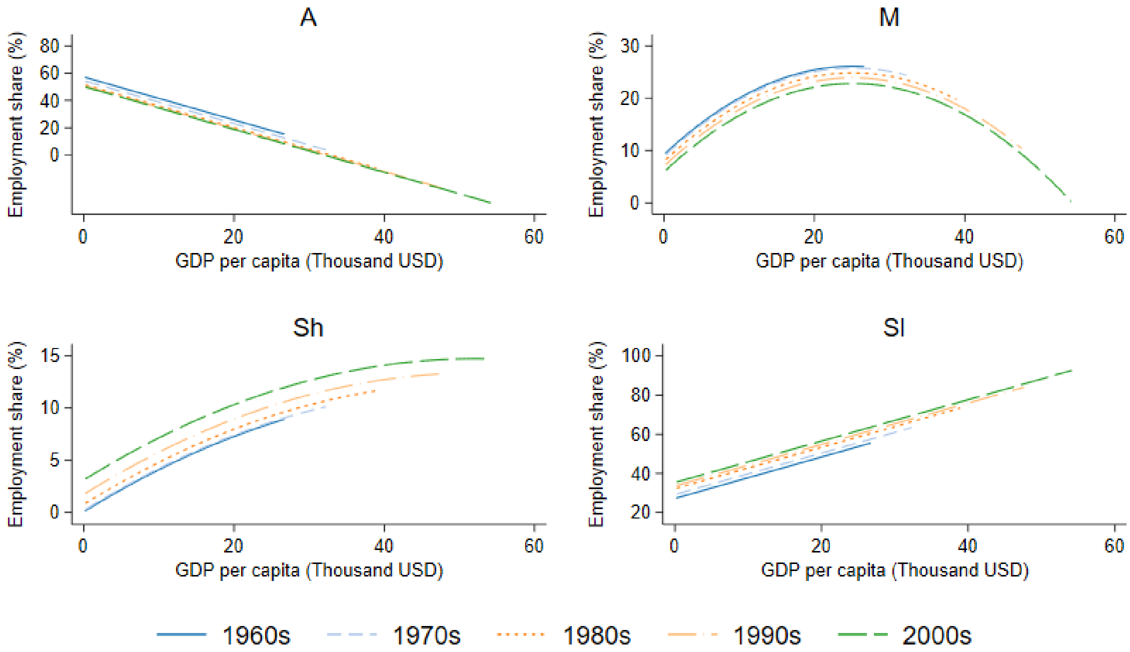
$$secs_{it} = \beta_0 + \beta_1 GDPpc_{it} + DecadeFE + \varepsilon_{it} \tag{32}$$

and the below for $i \in \{M, Sh\}$:

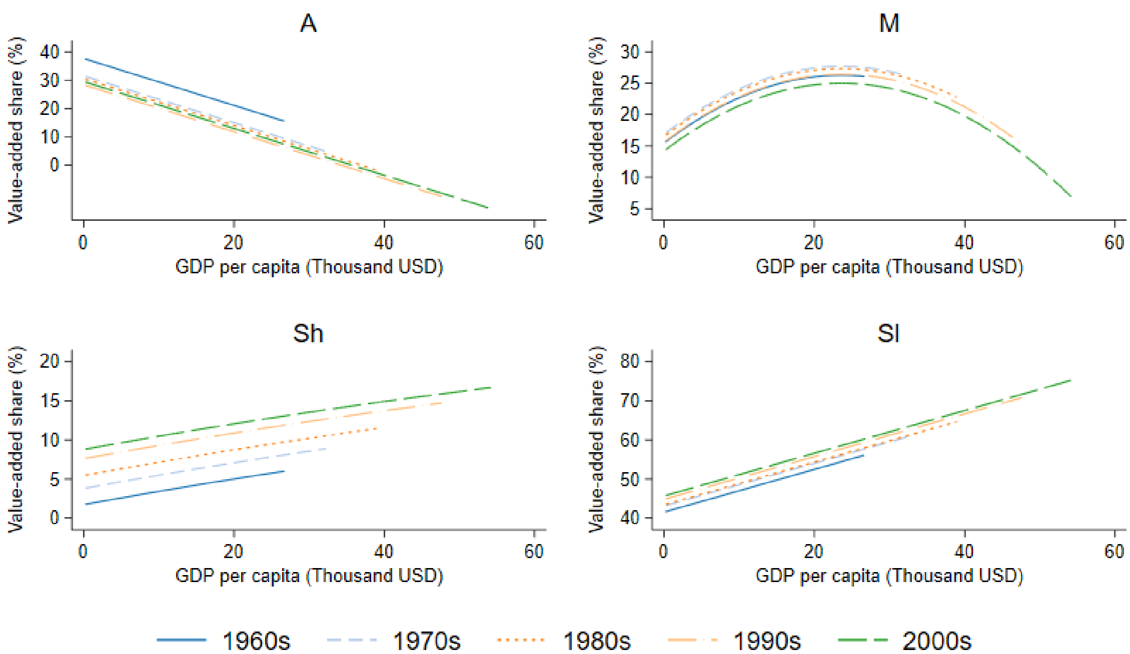
$$secs_{it} = \beta_0 + \beta_1 GDPpc_{it} + \beta_2 GDPpc_{it}^2 + DecadeFE + \varepsilon_{it} \tag{33}$$

where $secs_{it}$ represents either the sectoral employment share or nominal output share. $GDPpc_{it}$ and $GDPpc_{it}^2$ denote GDP per capita in constant 2015 US dollars and its quadratic term. Decade fixed effects are included to capture time-specific trends for the 1960s, 1970s, 1980s, 1990s, and 2000s.

Figure A1 shows how the employment and nominal output shares of each sector evolve with increasing GDP per capita. As predicted in proposition 3, agriculture share consistently declines as real income grows, low-skill services share increases steadily with real income growth. Both manufacturing and high-skill services shares exhibit a hump-shaped pattern when plotted against GDP per capita.



(a) Employment



(b) Nominal output

Figure A1: Predicted employment and value-added share over time

Proposition 3 also predicts that higher productivity in agriculture and low-skill services sectors will reduce their employment and nominal output shares at the same real income level. For manufacturing and high-skill services, higher productivity growth is expected to lead to a lower peak in sectoral employment and nominal output share at a lower real income level. Building on Rodrik 2016's documentation of premature de-industrialization in developing countries, this analysis extends the investigation to all four sectors using a similar specification:

$$secs_{it} = \beta_0 + \beta_1 lnpop_{it} + \beta 2(lnpop_{it})^2 + \beta 3lnGDPpc_{it} + \beta 4(lnGDPpc_{it})^2 + DecadeFE + \varepsilon_{it} \qquad (34)$$

Tables A2 and A3 present results on how population, real income, and time period affect sectoral shares. The focus is on decade dummies, which reflect general productivity improvements and common shocks across countries, with coefficients capturing effects relative to the 1960s. There is a clear downward trend in agriculture and manufacturing employment shares when controlling for population and real income, consistent with proposition 3. There is also an apparent upward trend in both high- and low-skill services sectors. Compared to the 1960s, countries in the 2000s at the same real income level show: 7.4 percentage points lower agriculture employment share, 6.3 percentage points lower manufacturing share, 10.1 percentage points higher low-skill services share. Similar trends in nominal output shares are observed, though not always statistically significant.

While some results may seem to contradict model predictions, they do not invalidate the model for several reasons: First, cross-country regressions cannot capture the true effect of productivity changes on sectoral shares for a single country under different productivity scenarios. Second, key technological advances in agriculture and manufacturing (e.g., mechanization, electrification) were already widely adopted during the sample period, while those relevant to services sectors (e.g., digital technologies) were not yet fully integrated, especially in developing countries. Computers were still rare in developing countries in the 2000s, and only around 1% of the population in these countries used the internet in early 2000s. Finally, the third industrial revolution and associated boom in high-skill services naturally led to an upward trend, which may not be sustainable long-term as digital technologies become more widely adopted and the pace of new product creation slows.

The GGDC 10-sector database ends in early 2010s, unable to reflect trends in the past 14 years. Sectoral employment data from the International Labor Organization (ILO) are used in later analysis to shed light on latest patterns.

Table A2: Sectoral employment share over time

	(1)	(2)	(3)	(4)
Sector	A	M	Sh	Sl
	Dependent variable: Sectoral employment share			
lnpop	10.02	-7.647	-0.197	-7.697
	(15.39)	(9.030)	(1.559)	(8.394)
lnpop_sq	-0.302	0.238	0.00637	0.216
	(0.431)	(0.252)	(0.0456)	(0.239)
lngdppc	-40.29***	14.88***	-5.765**	23.74***
	(8.201)	(3.984)	(2.245)	(5.665)
lngdppc_sq	1.372***	-0.643**	0.492***	-0.753**
	(0.482)	(0.242)	(0.142)	(0.340)
1970s	-2.720**	-0.572	0.220	2.883***
	(1.234)	(0.642)	(0.137)	(1.000)
1980s	-5.174***	-1.814*	0.809***	5.975***
	(1.691)	(0.937)	(0.195)	(1.403)
1990s	-6.596***	-3.426***	1.781***	7.985***
	(1.901)	(1.119)	(0.322)	(1.466)
2000s	-7.409***	-6.252***	3.066***	10.11***
	(2.200)	(1.290)	(0.506)	(1.630)
Observations	1,945	1,945	1,945	1,501
R-squared	0.900	0.601	0.785	0.908

Note: Standard errors are clustered at the economy level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A3: Sectoral value-added share over time

	(1)	(2)	(3)	(4)
Sector	A	M	Sh	Sl
Dependent variable: Sectoral nominal output share				
lnpop	8.833	-4.549	-8.140	1.283
	(13.08)	(9.525)	(7.053)	(9.850)
lnpop_sq	-0.264	0.195	0.249	-0.112
	(0.368)	(0.284)	(0.210)	(0.287)
lngdppc	-13.13	19.29***	-4.017	-7.075
	(13.66)	(5.776)	(8.648)	(9.170)
lngdppc_sq	0.248	-0.991***	0.322	0.727
	(0.793)	(0.351)	(0.532)	(0.542)
1970s	-3.450	0.871	1.985	1.096
	(2.071)	(0.793)	(2.971)	(1.039)
1980s	-4.357	-0.0678	3.621	2.010
	(2.843)	(1.073)	(4.130)	(1.256)
1990s	-6.619*	-1.904	5.716	4.050***
	(3.291)	(1.364)	(4.539)	(1.224)
2000s	-5.595	-4.994***	6.865	5.556***
	(3.383)	(1.579)	(4.539)	(1.615)
Observations	1,904	1,904	1,904	1,559
R-squared	0.609	0.442	0.110	0.611

Note: Standard errors are clustered at the economy level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Proposition 4 suggests that real income growth will decline as an economy transitions from high-productivity sectors to those with lower productivity growth. This phenomenon has been observed in many advanced countries. For instance, the United States experienced an annual growth rate of output per person of 2.41% during 1920-1970 when agriculture and manufacturing dominated employment. This rate decreased to 1.77% during 1970-2014 as the economy became more services-oriented Gordon 2017.

To test propositions 5 and 6, which posit that net exporters in a sector will have higher employment and output shares in that sector, the following regression model is employed:

$$emps_{it} = \beta_0 + \beta_1 lnpop_{it} + \beta 2(lnpop_{it})^2 + \beta 3 lnGDPpc_{it} + \beta 4(lnGDPpc_{it})^2 + \gamma Netexporter_i + \varepsilon_{it} \quad (35)$$

This analysis combines employment data from the ILO and trade data from the World Trade Organization (WTO), focusing on the period 2000-2023 to include more developing countries and minimize sectoral classification inconsistencies. The $Netexporter_i$ dummy variable identifies countries with a comparative advantage in each sector based on their average export-to-import ratio. Trade in the agriculture/primary sector (A) includes agriculture, mineral, and fuel products. Trade in manufacturing (M) includes all manufactured goods. Trade in high-skill services (Sh) encompasses all digitally-deliverable services, including ICT services, financial and insurance services, charges for the use of intellectual property, research and business services. Trade in low-skill services (Sl) include transport, travel, construction, personal, cultural, and recreational services.

I first calculate each country's export-to-import ratio in each sector and year $\frac{Exp_{ijt}}{Imp_{ijt}}$, and then obtain the average ratio for country j, sector i during the sample period. A country is considered a net exporter in sector i if it has the highest average export-to-import ratio in sector i than in other sectors.

The results, reported in Table A4, strongly support the propositions. Net exporters in the agriculture sector (A), manufacturing (M), and high-skill services (Sh) show significantly higher employment shares in their respective sectors compared to countries with similar population and GDP per capita but without such comparative advantages. Specifically: Agriculture sector net exporters have a 2.8 percentage point higher employment share. Manufacturing net exporters have a 4.4 percentage point higher employment share. High-skill services net exporters have a 1 percentage point higher employment share. The effect for low-skill services (Sl) is insignificant, likely due to their lower tradability and the small share of trade value in the sector's total value-added.

Table A4: Effect of trade on sectoral employment share

	(1)	(2)	(3)	(4)
Sector	A	M	Sh	Sl
	Dependent variable: sectoral employment share			
lnpop	-4.073	3.319	-0.113	3.340
	(3.650)	(2.285)	(0.774)	(6.203)
lnpop_sq	0.153	-0.0751	-0.00223	-0.158
	(0.117)	(0.0743)	(0.0225)	(0.204)
lngdppc	-48.42***	26.24***	-5.713***	33.63***
	(6.670)	(3.216)	(1.922)	(7.641)
lngdppc_sq	2.072***	-1.425***	0.498***	-1.485***
	(0.360)	(0.176)	(0.111)	(0.421)
netexp_d	2.837*	4.425***	1.021**	-1.988
	(1.657)	(1.234)	(0.459)	(1.613)
Observations	1,160	1,160	1,160	1,160
R-squared	0.758	0.402	0.741	0.576

Note: Standard errors are clustered at the economy level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

These findings demonstrate that the model predictions are largely consistent with observed reality. However, the model's long-term prognosis of stabilizing or declining employment and nominal output shares in high-skill services, particularly for developing countries, is yet to be fully realized. As the world is still in the early stages of digital transformation, many countries, especially net exporters, continue to see growth in high-skill services employment and output shares. The question of whether this growth will persist in the medium to long term remains open. Section 4 suggests that increasingly powerful AI is likely to eventually shrink the space to create quality jobs in high-skill services.

Appendix B: Additional Simulations

Appendix B presents additional simulations under different model settings and parameters. These results enrich the analysis and correspond to structural transformation patterns observed in different types of countries.

Derivative 1: Closed economy, exogenous growth, low productivity growth

In the closed economy baseline scenario, labor productivity growth is 8% in agriculture (A), 4% in manufacturing (M), 2% in high-skill services (Sh), and 1% in low-skill services (Sl). Alternatively, suppose in a low-growth case, labor productivity growth rate is 1.2% in A, 0.6% in M, 0.5% in Sh, 0.3% in Sl.

The simulation results are shown in Figure B1. Compared to the high-growth case in the baseline, agriculture share declines much more slowly and remains at 49% at t=100 (only 2% in the high-growth case). Manufacturing share and high-skill services share have yet to peak, reaching 16% and 5% respectively at t=100. Low-skill services share also grows more slowly. Real income only reaches 5.2 by the end of the simulation period, in contrast to 15 in the high-growth case. The low-growth case resembles the experience of some lower-income countries, where agriculture sector still accounts for a dominant share of employment, low-skill services employment share rises faster than manufacturing, and employment in high-skill services negligible.

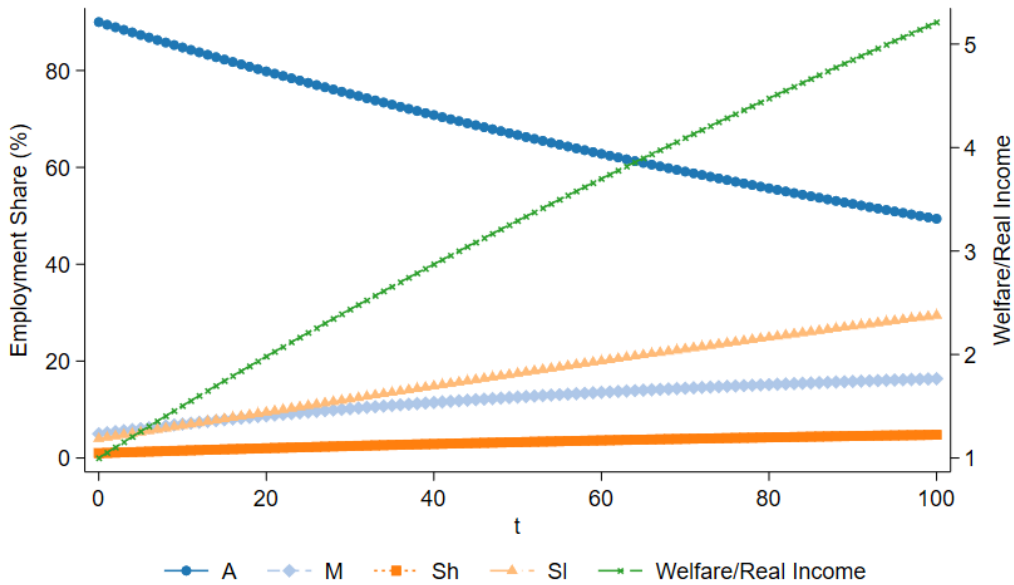


Figure B1: Closed economy, exogenous growth, low-growth

Derivative 2: Closed economy, endogenous productivity growth, no inter-sectoral productivity spillovers

Instead of constant labor productivity growth, now let sectoral labor productivity growth be proportional to its employment share. New model parameters are shown in Table B1, the elasticity of substitution, income elasticities, and sector constants remain the same as in Table 1.

Sectoral Endogenous Growth Multiplier			
$\eta_A = 0.1$	$\eta_M = 0.8$	$\eta_{Sh} = 1$	$\eta_{Sl} = 0.02$

Table B1: Parameters for closed economy with endogenous growth

Simulation results are shown in Figure B2. Compared to the closed economy baseline, agriculture share declines more slowly and reaches 16% at t=100. Manufacturing and high skill services employment shares peak earlier (at t=11 and t=25 respectively, compared to t=28 and t=60 respectively in the baseline) at a lower level (11.7% and 5% respectively, compared to 17% and 8% respectively in the baseline), the corresponding real income levels when they peak are also lower (4.1 and 6.6 respectively, compared to 7.4 and 11.4 respectively in the baseline). Employment share in low skill services initially grows faster than in the baseline model, then at a slower pace, ultimately reaching a lower level (77%) by the end of the simulation period. Real income growth reaches 14.9 at t=100, slightly lower than 15 in the baseline due to slower agriculture productivity growth.

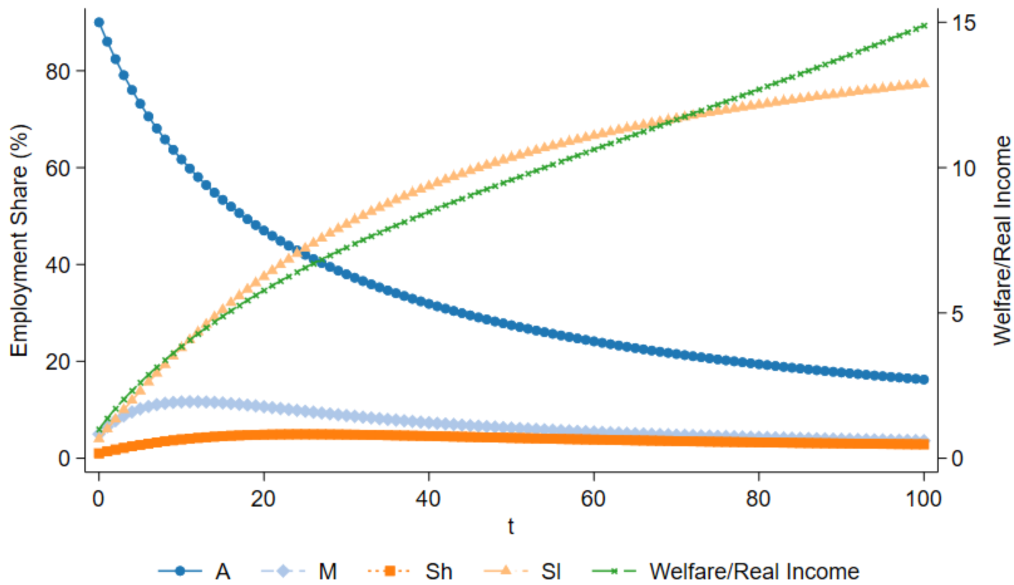


Figure B2: Closed economy, endogenous growth

Derivative 3: Closed economy, endogenous productivity growth, positive inter-sectoral productivity spillovers

Productivity spillovers across sectors can significantly impact economic development. For instance, advancements in manufacturing, such as improved fertilizers and agricultural machinery, have substantially boosted productivity growth in the agriculture sector. Similarly, technological progress in high-skill services can benefit all other sectors. This scenario incorporates these inter-sectoral productivity spillovers, assuming the following relationships for sectoral productivity growth:

$$\Delta logX_A = 0.1L_A + 0.2L_M + 0.05L_{Sh}$$
$$\Delta logX_M = 0.8L_M + 0.1L_{Sh}$$
$$\Delta logX_{Sh} = L_{Sh}$$
$$\Delta logX_{Sl} = 0.02L_{Sl} + 0.1L_{Sh}$$

Figure B3 illustrates the simulation results for this scenario. Agriculture employment share initially shrinks faster than in both the baseline and derivative 2. It then slows, maintaining a pace faster than derivative 2 but slower than the baseline. The value at t=100, 10%, falls between the baseline and derivative 2 levels. Manufacturing employment share will peak earlier both in terms of time and real income level (at t=11 when real income is 4.7) at a lower level (12.6%) than in the baseline model, but the peak is higher and reached at a higher real income level than in scenario 2. High-skill services share will also have a lower peak (5.6% at t=23, real income at 7.4) than in the baseline yet higher than in derivative 2. Low skill services share will be the highest in derivative 3, reaching 83.1% at t = 100. Real income growth will also be the highest in derivative 3, reaching 19 by the end of the simulation period.

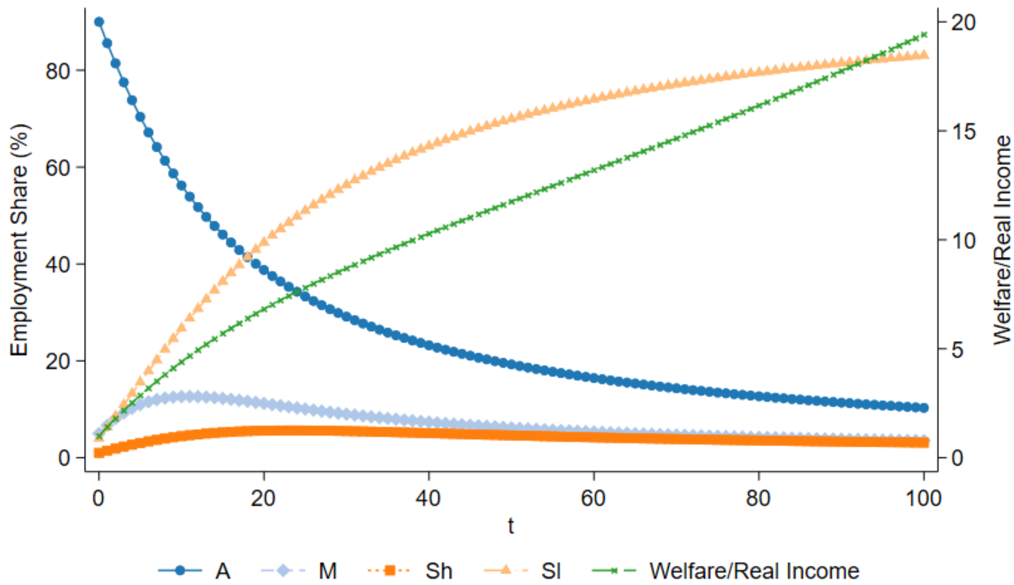


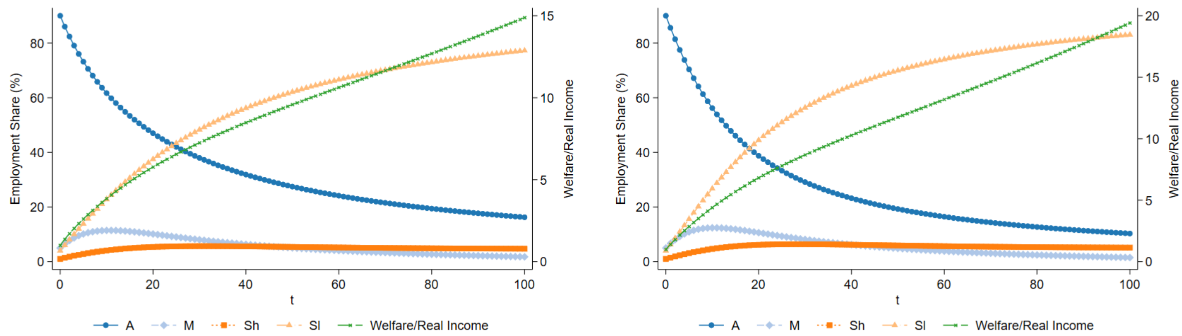
Figure B3: Closed economy, endogenous growth and inter-sectoral productivity spillovers

Derivative 4: Large open economy, endogenous productivity growth

Still consider the large open economy with a positive trade shock in high skill services sector in each period: $\Delta log\lambda_{Sht} = -0.005$ for all t. Using the parameters for endogenous productivity growth in derivative 2 and 3, the simulations for large open economy with endogenous growth with (derivative 4a) and without inter-sectoral productivity spillovers (derivative 4b) are shown in Figure **??**.

Compared to the large open economy baseline, agriculture employment share in derivatives 4a and 4b remains higher throughout the simulation. Manufacturing share peaks at 11% at t=11, real income 4.1 in scenario 4a, 12% at t=10, real income 4.4 in scenario 4b. Both peak earlier, lower, and at lower real income levels than in the large open economy baseline. High-skill services share peaks at 5.7% at t=31, real income 7.4 in scenario 4a, 6.4% at t=28, real income 8.3 in scenario 4b.

Scenario 4b achieves higher real income than in scenario 4a due to inter-sectoral spillovers, boosting demand across manufacturing, high-skill, and low-skill services. This exercise demonstrates that even as a net exporter of high-skill services, an economy cannot indefinitely sustain high employment share in this sector due to productivity-driven downward pressure on employment.



(a) Without inter-sectoral spillovers

(b) With inter-sectoral spillovers

Figure B4: Large open economy, endogenous growth, net exporter of high-skill services