ISSN: 2029-4913 / eISSN: 2029-4921

Article in press

TECHNOLOGICAL and ECONOMIC DEVELOPMENT of ECONOMY

https://doi.org/10.3846/tede.2026.25762

VERTICAL SPECIALIZATION AND THE MIDDLE-INCOME TRAP: AN EXPLANATION BASED ON GLOBAL VALUE CHAINS

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Article History:
- received 25 July 2024
- accepted 18 November 2025
- first published online 3 April 2026

Abstract. This paper aims to provide theoretical and empirical evidence to explain the middle-income trap from the perspective of Global value chains (GVCs). GVCs improve vertical specialization in two possible ways: (i) "economies of specialization", induced by market expansion among developed countries; and (ii) the inequity of factor prices between emerging markets and developed ones (comparative advantages). This paper clarifies the differences between the two channels with a model considering two kinds of labor – technological labor and regular labor – and shows how vertical specialization plays an important role in the so-called "middle-income trap". We argue that GVCs accelerate global market integration, which makes the labor wage in emerging markets to approach the middle-income level. Through vertical specialization, emerging markets lose their advantage of low labor costs, while the disadvantage in terms of technological production increases. We also explore the differences between vertical specialization patterns in empirical part to check whether the data can verify what we find in the theoretical part. We find that middle-income countries are at a more disadvantaged position than other countries in vertical specialization (they are locked in an unfavorable situation of international division of labor), which provides evidence for what are derived from the theoretical model.

Keywords: vertical specialization, technological monopoly, global value chains, middle-income trap, international division of labor.

JEL Classification: F14, F63, O11.

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1. Introduction

The concept of vertical specialization was first introduced to explain the extraordinary growth of global trade. Between 1950 and 2000, the proportion of global exports in GDP increased by 3.4 times, while tariffs decreased only by 11%, implying that the elasticity of trade volume to tariffs exceeded what classical trade theory predicts (Hummels et al., 2001). Vertical specialization, as the most important form of international production fragmentation, provides a more convincing explanation for this phenomenon than trade in final goods. Compared to final goods, trade in intermediates is more sensitive to transaction costs. The more complex the production process, the more likely intermediates cross borders multiple times, amplifying the impact of tariff reductions on trade volumes.

Most of the existing literature studies vertical specialization at a macro-level, finding that vertical specialization increases economic interdependence among countries. Participation in Global Value Chains (GVCs) leads to synchronized GDP growth across different countries (de Soyres & Gaillard, 2019). Moreover, macroeconomic policies of major economies can affect other countries through GVC linkages (Ahmed, 2020; Bräuning & Sheremirov, 2019; Georgiadis, 2016). At the industry or firm level, most studies on the vertical specialization focus on GVC positions or participation and their influences, and few pay attention on the patterns of vertical specialization. However, as a branch of international trade theory, vertical specialization should be studied on a more fundamental level, where GVC-related indicators can help explain the relationship between trade and economic development.

Classical trade theory suggests two possible patterns of vertical specialization: one driven by factor endowment differences and the other by economies of scale. These two patterns provide different paradigm for understanding the economic development. The contradiction between them provides us a framework to explain the "middle-income trap", which suggests that when a country steps into the "middle-income club", its endowment-based advantages diminish. If it fails to transition from an endowment-driven specialization pattern to one based on economies of scale, it is highly probable that the country falls into the middle-income trap. Despite its relevance, few studies have analyzed the middle-income trap from this perspective, leaving a critical gap in the literature.

This paper makes three key contributions. First, it offers a theoretical innovation by developing a model that incorporates two types of labor – technological and regular – to demonstrate how vertical specialization can impair the low-cost labor advantage of emerging economies while deepening their technological disadvantages. This provides a novel, GVC-based explanation for the middle-income trap. Second, it offers empirical evidence by using cross-country data to systematically compare different types of economies, which reveals strong support for the theoretical model's predictions. Third, the paper provides important policy implications by underscoring the need for a shift from endowment-driven to scale-driven specialization, offering practical insights for countries aiming to escape the middle-income trap.

The rest of this paper is organized as follows: Section 2 reviews the related literature. Section 3 describes the theoretical model. Section 4 analyzes the data to provide empirical evidence for what we find in Section 3. Section 5 provides a discussion on the main results. Section 6 concludes.

2. Literature review

The concept of the "middle-income trap" was proposed by the World Bank and Development Research Center of the State Council (2006) and is used to analyze the economic development of East Asian countries (Gill & Kharas, 2008). It has been empirically defined and tested in various ways (Felipe, 2012; Galor & Weil, 2000; Lin, 2017; Woo, 2012). For example, Hansen and Prescott (2002) present a neoclassical model that outlines three stages of economic development: the "Malthusian poverty trap," "post-Malthusian growth," and "modern growth equilibrium." However, the neoclassical model primarily focuses on the effects of exogenous factors on output while overlooking endogenous changes in production. In particular, it fails to account for how participation in Global Value Chains (GVCs) can reshape the division of labor, and consequently, change production patterns.

There are many studies on the impact of international trade on production efficiency. The new trade theory explains economic development through the interactions between production and trade, where trade affects the division of labor in production (Cheng et al., 2000; Sachs et al., 2000; Tombazos & Yang, 2006; Yang & Ng, 1993). Tombazos and Yang (2006) emphasize that endowment advantages are caused by specialization and are thus endogenous, and that comparative advantages are brought about by the division of labor. Hausmann et al. (2007) propose that specialization in certain sectors contributes more to economic development than specialization in other industries, and hence a country should be careful about what it exports. Export products with different levels of technological complexity differ significantly in their economic contribution. A typical example of this argument is the "natural resource curse" (Ding & Field, 2005; Sala-i-Martin et al., 2003).

Empirical analyses on the impact of GVC activities on production efficiency have yielded mixed results, especially when labor is taken into consideration. Recent evidence indicates that the effects of GVC participation on growth are nonlinear and vary across countries. A cross-country study of 62 economies (Ashraf & Umar, 2023) shows that GVC participation promotes growth in high-growth countries but may hinder it in lower-growth ones, particularly through forward linkages. Engel and Taglioni (2017) find that participating in GVCs is associated with the middle-income trap, and the upgrading of industry positions within GVCs plays a vital role in overcoming the middle-income trap. Ge et al. (2018) find that participating in GVCs enables manufacturing enterprises to experience dramatic improvement in productivity, and the effect is especially obvious for the capital-intensive and technology-intensive industries. Qu et al. (2020) show that driving up the positions within GVCs can significantly promote the green growth of manufacturing industry, and the effect varies significantly among different industries. As differences in factor intensities lead to the differences among industries, many studies on GVC participation focus on production factors. Dai et al. (2020) find that the gap between the GVC positions of China and the U.S. is widening[1], and this gap can be mainly attributed to the difference in industrial structure. Differences in the international division of labor result in the differences in GVC positions. Pan (2020) finds that GVCs have a positive impact on overall U.S. employment. However, the benefits stem only from the backward GVC linkages and medium-skilled labor, and the forward GVC linkages negatively affect the low-skilled labor. Chun et al. (2021) find that firms with manufacturing plants in foreign countries (especially those nearby) have changed their domestic employment structures to increase the number of service workers they employ. Similarly, CM et al. (2024) find that greater trade openness, FDI inflows, and high-technology exports accelerate the transition from middle- to high-income levels by enhancing innovation diffusion and structural transformation.

Recent studies also reflect concerns about premature deindustrialization, especially in middle-income and low-income countries. Rodrik (2016) highlights that countries are reaching peak industrialization at lower levels of income than early industrializers, and are deindustrializing sooner, often before fully capturing the growth benefits of manufacturing. The Latin American economies have been particularly severely affected, whereas their Asian exporting counterparts have demonstrated greater resilience. Moreover, Rodrik (2018)

[1] China is moving away from both end-users and primary factors, while the U.S. is moving towards both ends of the GVCs from 2000 to 2014.

argues that although GVCs and technological advancements facilitate market integration, they may simultaneously constrain broad-based skill and productivity development, particularly in labor-intensive industries. This restricts the productivity and employment gains developing countries can achieve from GVC participation. Recent empirical evidence also supports this argument. Hegerty and Weresa (2023) analyzes innovation capacity across Central and Eastern Europe, and found that external macroeconomic risks significantly hinder innovation outputs, while education exerts a stronger positive effect in less innovative economies.

Although some scholars argue that developing countries, such as Sub-Saharan Africa (SSA) have faced premature deindustrialization, which is marked by declining manufacturing value-added and employment at low-income levels (Rodrik, 2016), other evidence presents a more optimistic view. According to Abreha et al. (2021), SSA has not undergone premature deindustrialization in aggregate terms: while manufacturing value-added has remained relatively stagnant, manufacturing employment has grown substantially, particularly in conjunction with backward GVC linkages that support job creation. This view aligns with Lopes and Banaitienė (2024), who argue that sectoral dynamics, such as the stabilizing share of construction and manufacturing in GDP during the middle-income stage, reveal structural rigidity that may prevent economies from achieving sustained upgrading. This highlights that even in low-skill and resource-based industries, GVC integration may offer meaningful employment opportunities and a potential path for structural transformation.

To successfully transition beyond the middle-income trap, carefully designed industrial policies play a pivotal role. Yülek (2017) argues that sector-specific policies, combined with science, technology, and innovation strategies, can help developing countries identify and nurture strategic sectors capable for high value-added growth.

Vertical specialization provides a straightforward perspective for studying the division of labor caused by international trade, and the above-mentioned studies point out how GVCs are associated with the "middle-income trap" through division of labor. Lin (2017) defines the middle-income trap as a result of middle-income countries' failure to achieve faster labor productivity growth than high-income countries. This paper aims to further explore this issue by theoretically explaining how participation in GVCs affects production patterns and therefore economic growth, and by empirically investigating the differences in vertical specialization patterns of different income groups, which reveals the connection between vertical specialization and the middle-income trap.

3. Theoretical model

We adopt the analytical methodology from the inframarginal analysis framework (Cheng et al., 2000; Yang & Ng, 1993), and compare the production scenarios of self-production and specialization (i.e., autarky, partial specialization and complete specialization in inframarginal framework). In this paper, we consider technology, labor and capital as key factors of production. Technology is used to replace or augment human labor with machines to improve production efficiency and reduce costs (Qin et al., 2026). However, the substitutability between human beings and machines is limited. Compared with high-skilled workers, low-skilled ones are more easily substituted by machines, and one criterion that can be used to determine the complexity of a job is whether the type of labor can be effectively replaced by machines.

A similar phenomenon exists in the vertical specialization between developed and emerging countries, but developed countries take an opposite approach: to reduce costs, international companies transfer some of their production sectors to emerging markets and substitute machines with local labor. Such production processes generally involve limited technologies, and the core technologies are withheld from developing countries. In our theoretical model, to highlight the substitution between labor and machines while analyzing the impact of vertical specialization on labor income, we assume that capital is only utilized to hire labor engaged in low-tech production, which is defined as regular labor in this paper. Moreover, we define technology-intensive labor as technological labor. Production factors are thus classified into two types of labor: technological labor and regular labor.

The output is dependent on two kinds of labor inputs: technological labor L and regular labor R. Then the Cobb-Douglas production function is as following:

$$Y = R^{\alpha} L^{\beta}, \ \ \alpha, \beta \in (0,1), \alpha + \beta = 1. \tag{1}$$

The GVC-based production of technology-intensive products usually involves multiple production stages, and each with a different level of technological complexity. The value-added increases with the technology level. For the convenience of analysis, we introduce the concept of technology-added value, which captures the impact of technological differences on output. Furthermore, we assume that technology-added value is determined by a fixed learning cost (which is spent to acquire the technology) and hence is a function of the fixed cost. To further facilitate the analysis, this model takes only the existing technological conditions into consideration and does not consider technological innovations[2]; the producers know the fixed learning cost and choose the technological level of production according to their endowments. That is, the relationship between technology-added value and fixed learning costs is publicly known. We define the technology-added value v as a power function of the fixed learning cost F,

$$v = V(F) = F^{\theta}, \theta \in (0,1), \tag{2}$$

where $V'(F) > 0$ and $V''(F) < 0$.

With the above two Equations, the gross output value (G) can be expressed as:

$$G = v \cdot Y = v \cdot R^{\alpha} L^{\beta}. \tag{3}$$

There are two types of endowments: the technological endowments E owned by the producers and social capital E. The former can be used as either a technological or a regular input. The producers allocate their endowments between two types of production inputs: e_R and e_L, and the constraint on technological endowments is expressed as:

$$E = e_R + e_L. \tag{4}$$

Producers purchase labor in the labor market using social capital K. The capital market is assumed to be well developed, with sufficient capital available. Thus, the cost of capital is

[2] Technology innovation is more complexed than what we can analyze using this analysis framework. Thus, here we talk only about technological progress instead of technology innovation.

relatively negligible[3]. The labor acquired from market (represented by l) does not possess technological endowments and serves only as regular labor input. Assume that the wage rate per unit of labor in the market is w, then the relationship between the employment of labor and the available capital of producers can be expressed as follows:

$$K = wl. \tag{5}$$

By deducting the fixed cost from the technological endowments, we get the technological labor:

$$R = e_L - F. \tag{6}$$

Regular labor input is the sum of the producers' endowments and the labor purchased in the labor market:

$$L = e_L + l. \tag{7}$$

Profit can be obtained by subtracting the labor cost and the opportunity cost of producers' endowments from the total output, and thus, the optimization problem of producers is:

$$\max : \Pi = G - wl - wE \tag{8}$$
$$\text{s.t.} \begin{cases} K = wl \\ E = e_R + e_L \end{cases}.$$

Eq. (8) provides the conditions under which the producers decide whether to engage in technological production. The total output needs to cover both the producers' cost (wl) and the opportunity cost of their own endowments (wE). Since $K = wl$ always holds, and the fixed cost (F) is an exogenous variable in this model, the producers' ability to adopt technology depends on the technological endowments (E) and the opportunity cost (wage w). Then the profit function can be further simplified as $\Pi = \pi(E, w)$. In the following subsections we prove that the participation in GVCs changes the conditions for participating in technological production by influencing the two variables (E, w), which in turn affect production efficiency.

3.1. Without vertical specialization: a choice between technology level and output

When emerging markets are closed and there is no division of labor or external labor supply, firms in developed countries must rely on their own endowments and domestic labor for production. Under the constraint of limited endowments, the solution that maximizes the objective function is:

$$\begin{cases} e_R = \alpha E + (1-\alpha)F \\ R = e_R - F = \alpha(E - F) \\ L = e_L = \beta(E - F) \end{cases}. \tag{9}$$

The maximum output is:

$$\dot{G} = \alpha^{\alpha}\beta^{\beta}\left(EF^{\theta} - F^{\theta+1}\right). \tag{10}$$

[3] Capital is easier to obtain than technology. The higher the level of technology, the more favored it is than capital and the less it costs.

Based on their endowments, the producers select an appropriate technology level for production, allocate the fixed cost according to the first-order condition of maximizing output, and obtain the fixed cost as follows:

$$\dot{F} = \frac{\theta}{\theta+1}E. \tag{11}$$

The corresponding technology-added value is as following:

$$\dot{v} = \left(\frac{\theta}{\theta+1}E\right)^{\theta}. \tag{12}$$

By substituting the fixed cost $\dot{F}$ and the corresponding technology level into the maximum output, the output can be obtained as follows:

$$G = \left[\frac{\alpha^{\alpha}\beta^{\beta}\theta^{\theta}}{(\theta+1)^{\theta+1}}\right]E^{\theta+1}. \tag{13}$$

The producers can choose between using their endowments for production and selling their endowments. To make this decision, the producers have to compare the income generated from production with the income that could be earned by selling the endowments at the prevailing wage rate:

$$\Pi = \left[\frac{\alpha^{\alpha}\beta^{\beta}\theta^{\theta}}{(\theta+1)^{\theta+1}}\right]E^{\theta+1} - wE \geq 0. \tag{14}$$

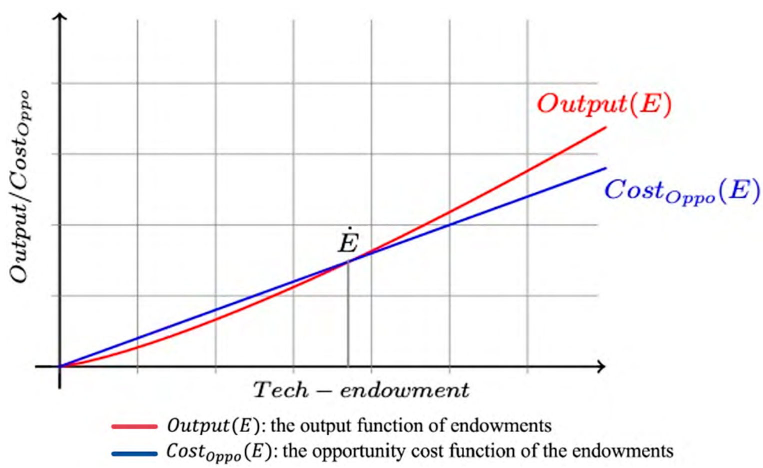

Figure 1. Participation in technological production requires endowment $\dot{E}$[4]

[4] Output (E) represents the output function of endowment, and $Cost_{oppo}$ (E) represents the opportunity cost function of the endowment.

According to this condition, the minimum amount of endowments required for producers to participate in technological production is:

$$\dot{E} = \left\{ \frac{w}{\frac{\alpha^{\alpha}\beta^{\beta}\theta^{\theta}}{(\theta+1)^{\theta+1}}} \right\}^{\frac{1}{\theta}} = \left\{ \left[\frac{(\theta+1)^{\theta+1}}{\alpha^{\alpha}\beta^{\beta}\theta^{\theta}} \right] \cdot w \right\}^{\frac{1}{\theta}}. \tag{15}$$

As shown in Figure 1, comparing the output with the opportunity cost, the likelihood of the producers engaging in technological production and the total output depends only on their technological endowments. In the case of limited endowments, although the producers fully understand that investing in learning and spending some fixed costs F can increase the technology-added value of production, they may not allocate much on improving technology because the profit may be negative if the output is not large enough. Therefore, in short-term production, there is a trade-off between two options: (i) to overcome technological barriers and improve their products' technology-added value, and (ii) to preserve most of their output and profit by avoiding investment. When there is no division of labor, choosing option (i) means that profit must be sacrificed for technology. Producers have to distribute their own endowments into two types of production based on regular and technological labor, which is a waste of their technological endowments. In this case, to improve the technology of the production, subsidies are needed to make up for the loss of profit due to reduced production.

3.2. With vertical specialization: the endogenous growth of technology

3.2.1. Open economies and vertical specialization

In the case of open economies, international companies in developed countries may transfer production that does not involve technology to emerging markets. This arrangement reflects a type of vertical specialization, in which producers in developed countries specialize in technology-related production; and the regular labor is purchased from outside (emerging markets) using capital K. Assume that the cost of financing is zero and the elasticity of labor supply is infinite, the optimal condition is achieved when the price per unit of effective labor w equals its marginal product MPl:

$$w = \beta v R^{\alpha} l^{\beta-1} = \beta\left[F^{\theta}(E-F)^{\alpha}\right] l^{\beta-1}. \tag{16}$$

The labor demanded is:

$$l = \left[\frac{w}{\beta v R^{\alpha}}\right]^{\left(\frac{-1}{1-\beta}\right)} = \left[F^{\theta}(E-F)^{\alpha}\right]^{\frac{1}{\alpha}} \left(\frac{\beta}{w}\right)^{\frac{1}{\alpha}}. \tag{17}$$

By substituting Eq. (15) into the production function, we obtain the total output value of the production function:

$$G = \left[F^{\theta}(E-F)^{\alpha}\right]^{\frac{1}{\alpha}} \left(\frac{\beta}{w}\right)^{\frac{\beta}{\alpha}}. \tag{18}$$

The producers choose the optimal production level based on their technological endowment. According to the first-order condition, the fixed cost is $\ddot{F} = \frac{\theta}{\theta+\alpha}E$, and the corresponding technology-added value is:

$$\ddot{v} = \left(\frac{\theta}{\theta+\alpha}E\right)^{\theta}. \tag{19}$$

The output constrained by the price of labor and the technological endowments of the producers is:

$$\ddot{G} = \left[\frac{\theta^{\theta}+\alpha^{\alpha}}{(\theta+\alpha)^{\theta+\alpha}}\right]^{\frac{1}{\alpha}}(E)^{1+\frac{\theta}{\alpha}}\left(\frac{\beta}{w}\right)^{\frac{\beta}{\alpha}}. \tag{20}$$

After deducting the capital used for purchasing labor from the total output, the income from technology-related production is αG. In this case, whether the producers choose to specialize in technological production depends on whether the earnings from vertical specialization overweigh those from selling their labor endowments, i.e., $\ddot{G}_R = \alpha\left[\frac{\theta^{\theta}+\alpha^{\alpha}}{(\theta+\alpha)^{\theta+\alpha}}\right]^{\frac{1}{\alpha}}(E)^{1+\frac{\theta}{\alpha}}\left(\frac{\beta}{w}\right)^{\frac{\beta}{\alpha}} \geq wE$. The minimum technological endowments required are:

$$\ddot{E} = \left\{\left[\frac{\beta^{\beta}(\theta+\alpha)^{\theta+\alpha}}{\alpha^{\alpha}(\theta^{\theta}+\alpha^{\alpha})}\right]\cdot w\right\}^{\frac{1}{\theta}}. \tag{21}$$

Comparing Eqs. (13)–(19) leads to the conclusion consistent with the economies of specialization (Cheng et al., 2000): the division of labor reduces the minimum endowment requirements for technological production and fosters endogenous growth of technology. The comparison is demonstrated in Figure 2.

3.2.2. Cost reduction and the endogenous growth of technological endowments

We have discussed the division of labor between developed and emerging markets in technological production, but the division of labor among developed countries is completely different: developed countries have a more complex division of labor with similar technological levels among each other, while developing countries or emerging economies do not. The vertical specialization of labor between countries is often driven by labor cost differences.

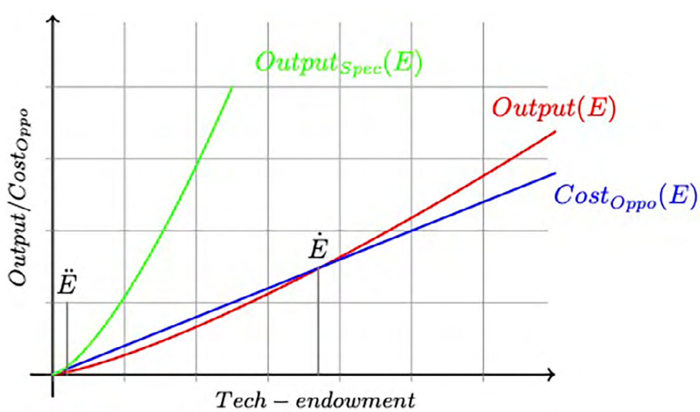

Figure 2. Division of labor reduces the endowment requirements for technological production

Labor cost increases with national income. In this subsection, we examine the impact of labor cost w on production. By adding $\dot{F} = \frac{\theta}{\theta+\alpha}E$ to Eq. (14), we derive that the wage rate for regular labor is determined by the technology level of production:

$$w = \beta\left[F^{\theta}\left(E-F\right)^{\alpha}\right]l^{\beta-1} = \beta\left[\frac{\theta^{\theta}+\alpha^{\alpha}}{\left(\theta+\alpha\right)^{\theta+\alpha}}\right]\left(E\right)^{\alpha+\theta} l^{\beta-1}. \tag{22}$$

Differences in technology levels and labor costs between developed countries and emerging ones determines their roles in the division of labor. The gap in labor cost stems from the difference in the technology level: a higher level of technology of developed countries enables a higher income and labor cost. Emerging economies engage in GVCs to improve income, but usually participate only in low value-added segments that require little technology. Wage growth has increased labor cost and the opportunity cost of engaging in technology-intensive production in these countries. Vertical specialization has opposite effects in developed markets: the profit from technological production increases with the reduction of labor cost, and then, with the original technological endowments, production can step up to the more technology-intensive stages. This lowers the endowment threshold for technological production, allowing more individuals to participate in such activities. Therefore, market integration leads to technological upgrading in developed countries, but may also cause regular labor to lose their jobs. In other words, it creates both opportunities and challenges. However, vertical specialization and global market integration generally pose greater challenges for emerging economies than for developed countries.

As shown in Figure 3, when labor cost is reduced, the income-endowment curve for technology rises from the orange curve to the red one. Meanwhile, the curve of opportunity cost shifts downward from the green curve to the blue one. These changes indicate that producers can obtain higher profit margins. Therefore, the endogenous growth of endowments leads to a mutually reinforcing dynamic: a reduction in the regular labor costs not only further promotes the division of labor, but also accelerates the endogenous growth of the producers' technological endowments.

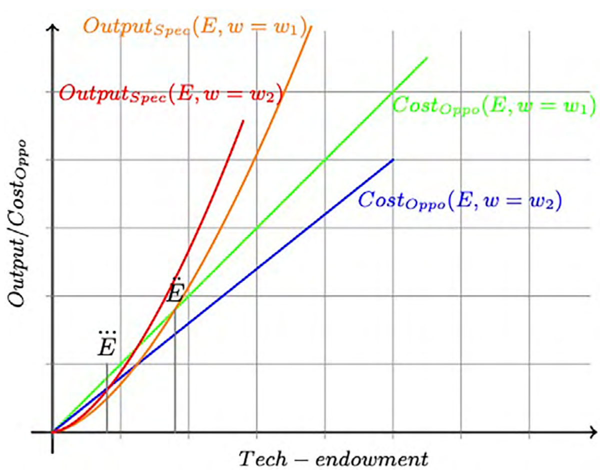

Figure 3. Reduction in regular labor cost further reduces technological endowment requirements

3.3. Monopoly of technological production and the middle-income trap

If producers have monopoly power in technological production, they can obtain excess profits. These profits allow further investment in R&D, which in turn enhances their technology level and leads to the growth of technological endowments. Assume that the technology endowment is priced at $\tilde{w}$, it is equal to their marginal product in an effective market:

$$\tilde{w} = \partial\ddot{G} \big/ \partial E = \left(1+\frac{\theta}{\alpha}\right)\left[\frac{\theta^{\theta}+\alpha^{\alpha}}{(\theta+\alpha)^{\theta+\alpha}}\right]^{\frac{1}{\alpha}}\left(\frac{\beta}{w}\right)^{\frac{\beta}{\alpha}}(E)^{\frac{\theta}{\alpha}}. \tag{23}$$

The average output of technological endowments is:

$$\bar{w} = \frac{\ddot{G}}{E} = \left[\frac{\theta^{\theta}+\alpha^{\alpha}}{(\theta+\alpha)^{\theta+\alpha}}\right]^{\frac{1}{\alpha}}\left(\frac{\beta}{w}\right)^{\frac{\beta}{\alpha}}(E)^{\frac{\theta}{\alpha}}. \tag{24}$$

For regular labor, the marginal product exhibits diminishing returns, and the average wage declines as the total labor input increases. In contrast, for technological labor, the marginal output of technological endowments consistently exceeds its average output, as shown in Figure 4. Therefore, the market fails to accurately reflect the value of technological endowments in the production process. As a result, in technological industries, technological development often has the nature of monopoly.

Given a certain technology level, the production cost of technology products comprises two parts: the fixed cost F mentioned before, which is used to acquire the technology, and the marginal cost of production. The marginal cost is much smaller than the fixed cost, i.e., the R&D cost of technology products is very large. In fact, the marginal cost mainly consists of the cost of labor. Notably, although technological production is often associated with market power, certain production stages, particularly with low entry barriers, may remain competitive. Only when the cost of technological production can effectively prevent other competitors from entering the technological stages and establish high technological entry barriers, can the producers dominate the entire value chain and obtain monopoly profits.

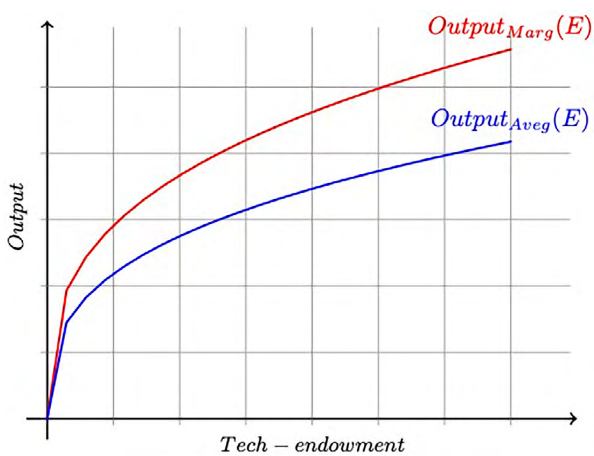

Figure 4. The marginal output of technology endowments is greater than the average output

The monopolistic nature of technological production hinders middle-income countries from shifting their pattern of vertical specialization from labor-driven to scale-driven. This provides an important explanation for their falling into the middle-income trap.

To enhance the connection between theory and empirical analysis, we now map the core elements of the theoretical model to the empirical variables used in Section 4. In particular, technological endowments (E) in the model relate to proxies of human capital, while labor costs (w) correspond to income levels and comparative advantage is reflected by the New Revealed Comparative Advantage (NRCA), which are variables of interest in the regressions in Section 4. The theoretical model's implications regarding constraints and opportunities for technological upgrading are tested by examining how vertical specialization indicators (GVC participation, GVC position, Upstreamness, downstreamness, VS, and VS1) vary across income groups.

4. Empirical analysis

Building on the theoretical model presented in Section 3, the empirical analysis in this section aims to test whether the predicted constraints on technological upgrading (which arise from insufficient endowments and rising labor costs in middle-income countries) can be observed in real-world GVC data. To this end, we construct empirical proxies for key theoretical concepts, including technological endowments, labor inputs, and specialization patterns, based on available macroeconomic indicators and trade data.

In particular, we use human capital indicators as proxies for technological endowments, and GDP per capita as proxies for labor costs. The GVC position index and NRCA are adopted to capture each country's specialization pattern within the global production network, and to distinguish upstream, technology-intensive segments from downstream, assembly-focused stages. These mappings allow us to empirically test whether the theoretical mechanisms, such as barriers to upgrading due to endowment thresholds, are consistent with observed international trade patterns.

Currently, it is difficult to directly investigate the relationship between the middle-income trap and vertical specialization patterns due to lack of data or widely recognized methods. Thus, this paper examines the relationship indirectly by two steps. First, we add the trade value as an independent variable into the economic growth model of Mankiw et al. (1992) to identify the middle-income trap. This allows us to assess whether international trade helps countries sustain growth or whether its benefits diminish as countries reach middle-income levels, which is the key feature of the trap. Second, we investigate the differences in vertical specialization patterns across the different income levels. This grouping reflects the theoretical concern that different stages of development entail distinct constraints and opportunities, and helps us observe whether middle-income countries, in particular, show the predicted structural rigidity in specialization. In this way, we can testify whether the data is consistent with our theoretical prediction.

In both steps, we group our data based on the average value of GDP per capita over the analysis period. Our classification differs from the World Bank's income classification, which is based on Gross National Income (GNI) per capita measured in current U.S. dollars using the Atlas Method. We adopt the average GDP per capita in constant prices during the period under analysis to reflect countries' long-term income levels and smooth out short-term fluctuations or shocks. This method ensures the stability and internal consistency of income groupings across the panel dataset, and is particularly suitable for analyzing structural development patterns such as the middle-income trap.

4.1. Empirical strategy and data

4.1.1. Step 1: identifying the middle-income trap

Since Mankiw et al. (1992), the growth convergence model has been widely applied to study cross-country differences in economic growth. Aiyar et al. (2018) analyze the middle-income trap in terms of growth slowdowns. They identify it by sudden, sustained deviations from conditional convergence paths. Following these studies, we investigate the impact of trade on growth convergence. We include trade volume as an additional explanatory variable. The convergence recognition model is set as following:

$$g_{i,t} = \ln\left(\frac{Rgdp_{i,t}}{Rgdp_{i.t-1}}\right) = \beta \times \ln Rgdp_{i,t-1} + \gamma \times Value_{i,t-1} + X_{i,t-1}^{T}\delta + \mu_i + \omega_i + \varepsilon_{i,t}, \tag{25}$$

where $Rgdp_{i,t}$ represents the per capita GDP of country i in year t; $g_{i,t}$ is the growth rate of country i's per capita GDP; β is the convergence coefficient, which is expected to be negative, since the growth is expected to slow down with the increase of GDP per capita. $Value_{i,t-1}$ represents trade flows of country i, the coefficient of which (γ) is expected to be positive, as the international trade can help sustain economic growth; and X represents the control variables, including the capital stock (*Cap*) and human capital (*HC*) that are key determinants of economics growth, and the coefficients of them are both expected to be positive. μ_i and ω_i represent country-specific and year-fixed effects, respectively.

The data on GDP, population, fixed capital, and human capital are obtained from the Penn World Table (PWT) Groningen Growth and Development Centre (n.d.-a) and the per capita GDP and capital of each country is measured in constant 2017 price using data calculated[5] based on the PWT, measured in purchasing power parity (PPP), ensuring comparability across countries. For the main explanatory variables, we use the trade value obtained from the UN Comtrade Database (n.d.). Our panel data contains 3683 observations covering 173 countries[6] from 1988 to 2019. Summary statistics are shown in Table 1.

Table 1. Summary statistics of variables for step 1

VARIABLE	Obs	Mean	SD	Min	Median	Max
Growth	3,828	0.023	0.042	–0.46	0.02	0.46
RGDP	3,828	11.235	2.206	4.12	11.21	16.80
HC	3,288	0.872	0.302	0.04	0.94	1.38
Cap	3,806	12.527	2.258	6.37	12.40	18.24
Value	3,570	8.836	2.717	–0.33	8.97	14.67

[5] The total real GDP of the year divided by the country's population.

[6] Among the countries and regions included in PWT 10.01, some were excluded due to the lack of complete trade flow data in the UN Comtrade Database (which we use to obtain trade value data), making it impossible to effectively match with the GDP and other data from PWT 10.01 used in this paper. The excluded countries or regions include: D.R. of the Congo, Curaçao, Cayman Islands, Equatorial Guinea, Guyana, Liberia, Sint Maarten (Dutch part), Chad, Taiwan, British Virgin Islands.

4.1.2. Step 2: vertical specialization patterns across income groups

According to the definitions proposed by Hummels et al. (2001), Yi (2003) constructs an indicator of vertical specialization, *VS*, which represents the share of imported intermediate inputs in a country's exports. Koopman et al. (2010) construct another indicator *VS1*, which is the value of a country's exports that are used as imported inputs to produce other countries' exports. These two indicators can be calculated as follows:

$$VS_i = \left(\frac{imported\ intermediates}{gross\ output}\right) \cdot exports; \tag{26}$$

$$VS1_i = \sum_{j=1}^{n} exported\ intermediates_{ji} \left(\frac{exports_{ji}}{gross\ output_{ji}}\right). \tag{27}$$

Koopman et al. (2014) develop indicators of GVC participation and GVC position on the basis of *VS* and *VS1*. The indicators are calculated as follows:

$$GVC\ Participation_i = \frac{IV_i}{E_i} + \frac{FV_i}{E_i}; \tag{28}$$

$$GVC\ Position_i = \ln\left(1+\frac{IV_i}{E_i}\right) - \ln\left(1+\frac{FV_i}{E_i}\right), \tag{29}$$

where IV_i represents forward participation, i.e., domestic value added in country *i*'s intermediate exports used by other countries to produce their exports, FV_i represents backward participation, i.e., foreign value added embodied in country *i*'s own exports. E_i represents the gross exports of country *i*. The GVC participation index measures the extent to which a country is involved in global value chains, capturing both forward and backward linkages in production fragmentation. In contrast, the GVC position index reflects a country's relative location within the value chains: whether it is more upstream (providing intermediate inputs) or downstream (engaged in final-stage assembly). These two indicators offer a sophisticated analytical framework for examining economies' integration patterns within global production networks. Their relevance to the middle-income trap lies in the fact that countries heavily reliant on low-value-added, downstream tasks may struggle to upgrade technologically and move up the value chains, thus becoming stuck in a pattern of specialization that limits income growth.

In addition to GVC participation and position, previous literature has provided the calculation of upstreamness and downstreamness in GVCs (Antràs et al., 2012; Antràs & Chor, 2017; Fally, 2012; Johnson, 2018). Based on the distance between an industry's total output and final consumption, Antràs et al. (2012) define the upstreamness as follows:

$$Up_{1i} = 1 \cdot \frac{f_i}{y_i} + 2 \cdot \frac{\sum_j a_{ij} f_j}{y_i} + 3 \cdot \frac{\sum_j \sum_k a_{ik} a_{kj} f_j}{y_i} \ldots, \tag{30}$$

where Up_{1i} represents the upstreamness of industry *i*, f_i represents final demand for the output of industry *i*, y_i represents total output of industry *i*. a_{ij} is an input coefficient, and indicates the share of output of industry *i* used in industry *j*.

Similarly, Antràs and Chor (2018) define the downstreamness of the industry[7] as the value added from the total output, weighted by the distance between the industry and consumers:

$$Down_{1i} = 1 \cdot \frac{v_i}{y_i} + 2 \cdot \frac{\sum_j v_j a_{ij}}{y_i} + 3 \cdot \frac{\sum_j \sum_k v_j a_{ik} a_{kj}}{y_i} \ldots, \tag{31}$$

where $Down_{1i}$[8] represents the downstreamness of industry i, v_i represents value added by industry j in final demand. The upstreamness and downstreamness in GVCs further distinguish the structural position of industries based on the distance to final consumption, thereby complementing the GVC position from a production network perspective.

With the indicators described in Eqs. (28)–(31), we can examine how patterns of vertical specialization differ across countries at different income levels. To do so, we regress RCA on GVC-related indicators, where the estimated coefficients reflect the characteristics of vertical specialization patterns.

Using the aforementioned equations of indicators, we calculate GVC participation, GVC position indicators, GVC upstreamness and downstreamness, and NRCA based on two sets of international input-output tables (covering 1995–2011 and 2000–2014, respectively) provided by the World Input-output Database (WIOD) (Groningen Growth and Development Centre, n.d.-b)[9]. We match each country's annual GDP per capita by country code and merge this information into the national-industry-level unbalanced panel data covering 1995 to 2014. Summary statistics are given in Table 2.

Table 2. Summary statistics of variables for step 2

Variable	Obs	Mean	Std. Dev.	Min	MAX
NRCA	41,930	1.104	1.713	–0.985	71.657
Position	41,930	–0.0004	0.019	–0.350	0.596
Participation	41,930	0.012	0.027	–0.002	0.815
Down	41,930	2.058	0.500	1.000	9.493
Up	41,930	2.221	2.045	1.000	222.650
VS1	41,930	0.006	0.018	–0.002	0.815
VS	41,930	0.006	0.017	–0.002	0.513
GDP	41,930	25467.800	21384.470	370.101	119225.400
Country	41,930	21.377	12.260	1.000	44.000
Industry	41,930	26.835	15.834	1.000	56.000

[7] Johnson (2018) called this industry length.

[8] Fally (2012) defines $Up_{2i} = 1 + \sum_j b_{ij} U_{2j}$, $Down_{2i} = 1 + \sum_j a_{ij} D_{2j}$. Antràs and Chor (2018), Miller and Temurshoev (2017) proved that U_{p1} equals U_{p2} and $Down_1$ equals $Down_2$.

[9] World Input-output Database input-output table for 1995–2011 contains data on 40 countries and 35 industries; the international input-output table for 2000–2014 contains 43 countries and 56 industries.

4.2. Empirical results and interpretation

4.2.1. Growth slowdown and trade

First, we examine whether it is appropriate to incorporate trade flows into the standard growth convergence model. Column (1) of Table 3 shows the regression results based on the original PWT data, without including trade values (8155 observations). After matching the PWT data with the trade values from UN Comtrade Database, the number of observations is reduced to 3683. Column (2) reports the regression results without using trade values as an independent variable, while columns (3)–(4) include them. The growth rate of per capita GDP is sensitive to per capita GDP even with trade value controlled, and an increasing per capita GDP significantly lowers the growth rate of itself. Notably, when considering the impact of trade, the per capita GDP level has a greater impact on the convergence of growth for sampled countries. In other words, when considering the impact of trade, the growth of per capita GDP is more likely to converge when it is affected by the level of per capita GDP.

Table 3. Regression results of growth convergence model

VARIABLE	(1)	(2)	(3)	(4)
Value			0.004	0.006*
			(1.47)	(1.83)
RGDP	–0.015**	–0.025**	–0.033***	–0.040***
	(–2.33)	(–2.495)	(–2.87)	(–3.30)
HC	0.049***	0.108***	0.073**	0.035
	(3.01)	(3.23)	(2.39)	(1.20)
Cap	–0.000	–0.007	–0.001	–0.001
	(–0.03)	(–1.07)	(–0.14)	(–0.12)
Constant	0.156***	0.318***	0.319***	0.424***
	(4.77)	(5.02)	(5.01)	(4.61)
Country fixed effects	YES	YES	YES	YES
Year fixed effects	NO	NO	NO	YES
Observations	8,443	3,266	3,059	3,059

Note: T-values are in parentheses; *, **, and ***, respectively represent significance at the 10%, 5%, and 1% levels.

After confirming the validity of the growth convergence model with trade, we examine the convergence dynamics across different income groups, classified by per capita GDP. This also allows us to test the robustness of our results.

Columns (1)–(5) of Table 4 present the regression results grouped by GDP per capita percentiles: 0–20% (35 countries), 21–40% (35 countries), 41–60% (35 countries), 61–80% (35 countries), 81–100% (33 countries), respectively. The results suggest that in the lowest-income countries, economic growth can be improved by capital[10], while it is decreased by GDP per

[10] When using the updated dataset (PWT 10.01), the coefficient for capital is positive and close to conventional significance levels (t = 1.49), although not statistically significant at the 10% threshold. To assess robustness, we also re-run the analysis using the previous version of the data (PWT 9.1), where the result is statistically significant (results are available upon request). The consistency in coefficient signs suggests a persistent underlying positive relationship between capital and economic growth for low-income countries, though sensitivity to data version highlights the need for cautious interpretation.

capita. This aligns with Solow Growth Model (Solow, 1956), which emphasizes that capital accumulation is crucial in the early stages of economic development.

For middle-income countries (columns (2)–(4), corresponding to the 21–40%, 41–60%, 61–80% GDP per capita percentiles), capital generally appear ineffective in improving economic growth. On the contrary, the human capital is important to improve growth in the middle-low-income and middle-high-income countries (column (2) and column (4)). The inefficacy of capital and human capital in the 41–60% percentile economies suggests deeper structural constraints. For example, institutional weaknesses (such as low-quality governance, financial market inefficiencies, or misallocation of resources) may hinder the effective deployment of production factors (Acemoglu & Robinson, 2012; North, 1990). Moreover, middle-income countries often face technology adoption challenges: they may lack the absorptive capacity to assimilate advanced technologies, while simultaneously losing their competitive edge in low-cost labor (Cohen & Levinthal, 1990; Howitt & Mayer-Foulkes, 2002). As economies progress to the middle-high-income stage and achieve institutional advancement and enhanced technological absorption capabilities, human capital becomes a significant driver of economic growth.

Table 4. The impact of trade on the convergence of economic growth

VARIABLE	(1)	(2)	(3)	(4)	(5)
Value	0.01	–0.008	0.013	0.002	0.023***
	(1.02)	(–0.66)	(1.34)	(0.26)	(3.39)
RGDP	–0.117**	–0.049*	–0.001	–0.053	–0.064***
	(–2.54)	(–1.98)	(–0.02)	(–1.58)	(–2.75)
HC	–0.091	0.401***	–0.218*	0.129**	0.027
	(–0.88)	(2.87)	(–1.99)	(2.58)	(0.92)
Cap	0.042	–0.032	–0.035	–0.011	0.013
	(1.49)	(–1.43)	(–0.80)	(–0.51)	(0.95)
Constant	0.670***	0.627**	0.578**	0.705**	0.421**
	(2.75)	(2.05)	(2.25)	(2.39)	(2.04)
Country fixed effects	YES	YES	YES	YES	YES
Year fixed effects	YES	YES	YES	YES	YES
Observations	356	619	633	713	738

Note: T-values are in parentheses; *, **, and *** respectively represent significance at the 10%, 5%, and 1% levels.

Most interestingly, the GDP per capita hinders the growth rate of high-income countries as well. However, these countries can benefit from trade. According to the extended convergence model proposed by Barro and Sala-i-Martin (2004), as high-income countries approach the technological frontier, capital deepening intensifies the effect of diminishing returns, making it more difficult to sustain rapid growth for countries with higher initial GDP per capita. Nonetheless, trade partially offsets this diminishing returns.

These regressions reveal the differences in access to and utilization of production factors across different income-level groups. For low-income group, a key approach to achieve development is obtaining capital through trade. However, for middle-income countries (column (3) with GDP per capita of 41–60% percentiles), neither trade nor other factors (such as human capital, etc.) can contribute to improve production. Based on our theoretical analysis, this outcome is not coincidental. This happens because trade does not help in enhancing production specialization in middle-income countries, and the marginal output of production factors is nearly zero, both of which results in the so called "middle-income trap". In contrast, for high-income countries, trade facilitates greater specialization, thereby ensuring that increased input of production factors remains effective in driving growth.

The results of our empirical analysis are consistent with the theoretical explanation of middle-income trap from the GVCs perspective. However, they do not offer sufficient details to explain the middle-income trap from an industry-level perspective. In the following subsection, we incorporate patterns of vertical specialization and explore the relationships between Revealed Comparative Advantage (RCA) and GVC-related indicators.

4.2.2. Vertical specialization and comparative advantage

According to GDP per capita, the data are divided into four groups: low-income, middle-low-income, middle-high-income, and high-income. The regression results are given in Table 5. The relationship between NRCA and GVC-related indicators varies significantly across income groups. First, GVC participation is positively associated with the NRCA, and the relationship between GVC downstreamness and NRCA is negative in all groups. Second, the relationships among the GVC position, GVC upstreamness and NRCA vary across income levels, which indicates that there are significant differences among vertical specialization patterns. Third, the relationship between GVC position and NRCA changes from negative to positive as the income rises, which indicates that in low- and middle-income countries, competitive advantages and GVC positions tend to lock them in an unfavorable situation in international division of labor, for these two are negatively correlated with each other. Forth, for high-income countries, the relationship between GVC position and the NRCA is insignificant. However, for middle-high to high-income countries, the positive correlation between GVC upstreamness and NRCA becomes stronger and more significant. This indicates that GVC upstreamness plays a more decisive role than GVC position in shaping comparative advantage at higher income levels. These patterns can be partially explained by institutional and technological factors: countries with better contract enforcement and intellectual property protection tend to capture more value from GVC participation, while technological gaps may hinder middle-income countries from effectively upgrading their positions.

Therefore, the results strongly support our hypotheses regarding the link between vertical specialization patterns and the middle-income trap. First, the analysis reveals distinct differences in the relationship between GVC indicators and comparative advantage across different income groups. This confirms the hypothesis that countries at different stages of development participate in GVCs in structurally different ways. Specifically, the positive effect of GVC participation on NRCA suggests that deeper involvement in GVCs can enhance competitiveness across all income levels. However, the consistently negative relationship between GVC downstreamness and NRCA indicates that being locked in low-value-added, downstream tasks can weaken comparative advantage, especially for low- and middle-income countries.

Table 5. The relationship between GVC related indicators and NRCA

VARIABLE	(1)	(2)	(3)	(4)
	Low	Middle-low	Middle-high	High
Position	–5.246**	–11.800*	18.110**	7.407
	(–2.095)	(–1.686)	(2.118)	(1.022)
Participation	10.590***	17.330***	40.110***	15.080***
	(4.795)	(3.043)	(4.647)	(2.797)
Up	0.099	–0.002	0.003**	0.285***
	(1.537)	(–1.340)	(2.467)	(4.338)
Down	–0.483***	–0.634***	–0.306**	–0.467***
	(–5.634)	(–4.073)	(–2.125)	(–6.031)
Constant	1.715***	2.329***	1.301***	1.225***
	(9.618)	(7.414)	(3.934)	(6.721)
Observations	10,444	10,507	10,486	10,493
Country fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes

Note: T-values are in parentheses; *, **, and *** respectively represent significance at the 10%, 5%, and 1% levels.

Second, the finding that the relationship between GVC position and NRCA becomes positive as income increases supports the hypothesis that middle-income countries face structural constraints in moving up the value chains. This suggests that their current specialization patterns may inhibit further development. Moreover, the result that GVC upstreamness has a stronger and increasingly positive association with NRCA for higher-income countries demonstrates that comparative advantage is increasingly concentrated in upstream, knowledge-intensive segments of GVCs, reinforcing the hypothesis that vertical specialization can both enable and constrain development, depending on a country's institutional and technological capacity.

4.3. Robustness tests

First, we test the robustness of our results by regressing on two groups: those with a per capita GDP greater than or equal to USD 7000, and those with less than USD 7000, following a threshold commonly used in previous literature (e.g., Eichengreen et al., 2012; Felipe et al., 2012) to approximate the transition from middle-income to high-income levels. The results are reported in Table 6. For the group with per capita GDP below USD 7000, there is a negative relationship between the GVC position and NRCA, consistent with the results for low- and middle-low-income countries reported in Table 5.

For a further robustness check, we incorporate two vertical specialization indicators (*VS* or *VS1*) into the regressions. Since *VS* and *VS1* are negatively correlated, they cannot be included in the model simultaneously. The results with *VS* in the regressions are shown in Table 7. The main conclusions remain robust: the pattern of vertical specialization varies across income levels. For low- and middle-low-income countries, deeper vertical specialization is associated with a weaker NRCA. In contrast, for middle-high- and high-income countries, vertical specialization does not harm NRCA. For low- or middle-low-income countries, participation in GVCs hampers their NRCA, while a better GVC position enhances it. For Middle-high- and high-income countries, neither GVC participation nor position has a significant impact on NRCA. However, the degree of upstreamness plays a critical role in improving NRCA. Notably, being located in the downstream segments of GVCs has a consistently negative impact on NRCA across all income groups.

Table 6. The relationship between GVC related indicators and NRCA (Robustness tests)

VARIABLE	GDP < 7000	GDP > 7000
Position	–4.603*	1.484
	(–1.749)	(0.299)
Participation	10.130***	14.120***
	(4.310)	(3.530)
Up	0.086	0.0005
	(1.498)	(0.548)
Down	–0.445***	–0.396***
	(–5.369)	(–4.133)
Constant	1.644***	1.807***
	(9.986)	(8.535)
Observations	8,785	33,145
Country fixed effects	Yes	Yes
Year fixed effects	Yes	Yes

Note: T-values are in parentheses; * and *** respectively represent significance at the 10% and 1% levels.

Table 7. The relationship between GVC related indicators and NRCA

VARIABLE	Low	Middle-low	Middle-high	High
Position	62.360**	139.400***	162.100	40.820
	(–2.454)	(–4.579)	(–0.710)	(–0.961)
Participation	–47.860**	–84.270***	–96.280	–15.480
	(–2.286)	(–4.698)	(–0.430)	(–0.338)
Up	0.093	–0.002	0.003**	0.276***
	(–1.532)	(–1.528)	(–2.395)	(–4.531)
Down	–0.480***	–0.509***	–0.290**	–0.448***
	(–5.620)	(–3.395)	(–2.084)	(–6.634)
VS	120.600***	238.000***	273.900	60.650
	(–2.715)	(–4.856)	(–0.622)	(–0.714)
Constant	1.701***	1.909***	1.258***	1.209***
	(–9.682)	(–6.213)	(–4.068)	(–6.927)
Observations	10,444	10,507	10,486	10,493
Country fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes

Note: T-values are in parentheses; *, ** and *** respectively represent significance at the 10%, 5%, and 1% levels.

Then we replace *VS* with *VS1*. The results are shown in Table 8. A comparison between Table 8 and Table 7 indicates that with either *VS* or *VS1* in the regressions, the GVC position or participation does not influence the NRCA for countries at the middle-high- or high-income levels.

Table 8. The relationship between GVC related indicators and NRCA

VARIABLES	Low	Middle-low	Middle-high	High
Position	94.790***	139.400***	162.100	40.820
	(–5.473)	(–4.579)	(–0.710)	(–0.961)
Participation	99.310***	153.700***	177.600	45.160
	(–6.074)	(–4.887)	(–0.820)	(–1.141)
Up	4.14E-05	–0.002	0.003**	0.276***
	(–0.050)	(–1.528)	(–2.395)	(–4.531)
Down	–0.333***	–0.509***	–0.290**	–0.448***
	(–3.625)	(–3.395)	(–2.084)	(–6.634)
VS1	–157.300***	–238.000***	–273.900	–60.650
	(–5.758)	(–4.856)	(–0.622)	(–0.714)
Constant	1.604***	1.909***	1.258***	1.209***
	(–8.115)	(–6.213)	(–4.068)	(–6.927)
Observations	33,145	10,507	10,486	10,493
Country fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes

Note: T-values are in parentheses; *, ** and *** respectively represent significance at the 10%, 5%, and 1% levels.

5. Discussion

This study contributes to the growing literature on the middle-income trap and global value chains by providing both a theoretical model and empirical evidence that links patterns of vertical specialization to development outcomes. In particular, our findings provide insights about how differences in technological endowments and labor costs shape countries' positions in GVCs, and how these positions, in turn, affect productivity and comparative advantage across income levels.

Our theoretical model builds upon the inframarginal analysis framework (Cheng et al., 2000; Yang & Ng, 1993) and specifies the conditions under which producers engage in technological production. We show that vertical specialization reduces the minimum endowment required for technological upgrading. Therefore, it allows developed countries to achieve endogenous growth in technological endowments. However, this process is asymmetric: while developed economies benefit from cost-reducing global labor markets, emerging economies often remain confined to low-value-added segments due to limited technological capabilities and high opportunity costs of learning.

These insights are consistent with Rodrik (2016), who argues that many developing countries are experiencing premature deindustrialization, which is a process in which the manufacturing sector declines at lower income levels than observed historically in industrialized countries. In a follow-up study, Rodrik (2018) further notes that although GVCs and new technologies help integrate developing countries into global production networks, they may limit the ability to move up the value chains.

Empirically, our results complement these arguments by showing that for middle-income countries, vertical specialization tends to be associated with a negative relationship between GVC position and comparative advantage (NRCA). This implies that these countries may become “stuck” in downstream, low-tech roles, which is in line with previous literature (e.g., Gereffi, 2019; Taglioni & Winkler, 2016). By contrast, for high-income countries, upstreamness in GVCs correlates positively with comparative advantage, reflecting their dominance in knowledge-intensive production stages.

These differentiated outcomes point to the critical role of industrial policy, particularly for middle-income countries seeking to escape the trap of stagnant productivity. Yülek (2017) emphasizes that countries must adopt sector-specific strategies that combine industrial development with science and technology policy to identify and support strategic sectors capable of producing higher value-added. This policy perspective is in line with our model’s implication that technology adoption is constrained by both institutional capacity and opportunity cost, and that deliberate interventions are needed to shift production toward more technology-intensive activities.

6. Conclusions

Classic trade theories suggest that there are two patterns of vertical specialization in GVCs. One stems from the comparative advantage of production factors and causes exogenous technological progress, and the other stems from the “economies of scale” and brings about the endogenous progress of technology. In an open economy, stepping into the middle-income level means the disappearance of the comparative advantage of labor for developing countries. During this process, the pattern of vertical specialization should be changed from one driven by resource endowments to one based on economies of scale. However, the challenges associated with this transformation often prevent these countries from sustaining high growth at the middle-income level. This provides a new perspective for understanding the middle-income trap.

To highlight the separation between technological and non-technological components of production, this paper employs a Cobb-Douglas production function to develop its theoretical framework. A key distinction of this study from previous literature lies in comparing the threshold conditions for engaging in technological production under different patterns of vertical specialization, and evaluating their respective impacts on technological progress. We find that: (i) developing countries’ role in the international division of labor is different from that of the developed countries; (ii) developing countries participating in GVCs face a dilemma between increasing income and maintaining their comparative advantage; and (iii) the interactions between market scale and the division of labor have significant effects on both economic and technological growth.

The empirical analysis proceeds in two steps. The first step verifies the existence of the “middle-income trap”, and the second step examines the relationship between vertical specialization and income (particularly differences across income groups), as emphasized in the theoretical model. Due to the limitations of method and data, this paper cannot directly establish a causal relationship between vertical specialization and the “middle-income trap.” This limitation highlights a promising direction for future research.

Our findings have important policy implications. For developing countries which seek to avoid the middle-income trap, it is crucial to shift from relying on low-cost labor and resource-based advantages to fostering scale-driven industrial upgrading. This requires not only investment in infrastructure and education, but also institutional reforms that improve innovation capacity, support firm-level upgrading, and facilitate deeper integration into the high-value segments of GVCs. Policymakers should also strategically foster domestic market expansion and facilitate firms’ realization of scale economies, as these are fundamental prerequisites for transitioning toward innovation-driven growth.

Although it is not easy for developing countries to overcome the middle-income trap, the successful practices of certain industries in some countries can serve as valuable references for us. For example, South Korea achieved the transition from contract manufacturing to independent innovation in its electronics industry. This process was facilitated by government-led “Five-Year Science and Technology Development Plans,” a “symbiotic value chain” model that fostered collaboration between large conglomerates and small-to-medium enterprises, and the establishment of top-tier engineering institutions like Korea Advanced Institute of Science and Technology (KAIST) to cultivate specialized talents.

Funding

This work was supported by the National Social Science Fund of China under Grant [number 23BGJ027].

Author contributions

Lina Yu proposed the idea, derived the hypothesis using mathematical formulas, and conceptualized the empirical model framework. Jinlu Liu worked for the mathematical part with Lina Yu, performed the regression analysis and interpreted the results using empirical data. Xinran Liu verified the empirical section, and drafted the manuscript. Ziqi Wei conducted the additional regressions during the major revision. Tao Wang verified the section of theoretical model.

Disclosure statement

The authors declare that they have no conflict of interest.

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