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The impact of information and communication technologies on export diversification: Evidence from developing countries

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ABSTRACT
As economies increasingly rely on digitalization, information and communication technologies (ICT) have become critical in shaping global economic transformations. This study explores the impact of ICT on export concentration and diversification in emerging markets and developing countries. Using a panel data set of 110 countries from 2000 to 2019, the Generalized Method of Moments (GMM) estimator has been employed to assess the short- and long-term effects of ICT on these economies. To summarize information on various ICT channels, an ICT index has been constructed through principal component analysis (PCA). Additionally, the study examines the combined influence of ICT and human capital on export concentration. Findings indicate that ICT development significantly accelerates export diversification in developing countries, aligning their export structures with global standards. The interaction between ICT and human capital positively impacts export concentration, suggesting that higher levels of human capital enhance ICT's effects. Overall, ICT not only boosts human capital but also equips developing countries with the skills needed to enter new markets, develop high-value products, and compete globally. Consequently, governments in developing countries should prioritize investments in ICT infrastructure to lower trade costs, diversify exports, and promote sustainable economic growth.

KEYWORDS ICT; export concentration; export diversification; system GMM; developing countries

JEL CLASSIFICATIONS O1, C23, F10, F14, F43

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1. Introduction

Export diversification is a key factor that developing countries focus on when seeking sustainable and inclusive economic growth (Mania and Rieber 2019). Diversifying exports across products and geographic markets has three main benefits: it improves the country's terms of trade in the long run, ensures macroeconomic stability, and promotes the economy's structural transformation (Mania and Rieber 2019).

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The volatility in prices of primary products leads to income instability affecting commodity-exporting countries (Bleaney and Greenaway 2001); thus, export diversification helps stabilize exports' long-term earnings (Al-Marhubi 2000). Diversification involves increasing the number of exported commodity items and high-value-added manufactured goods to reduce exports' dependence on world market conditions. The United Nations Conference on Trade and Development (UNCTAD) highlighted that diversifying exports beyond raw materials is a strategic way to mitigate global commodity price volatility (UNCTAD, 2018). The dependence on a limited range of exports could potentially lead to foreign debt accumulation or reserve depletion, which can negatively affect the economy's position, leading to the depreciation of the national currency and a price level increase. However, if the national currency's devaluation rate is less than the inflation rate, the real exchange rate will increase but decrease the country's export levels. Diversifying export structures affects the economy's growth level, fosters sustainable economic growth, and mitigates weaknesses.

Export diversification can be a key strategy for an economy's structural transformation (Pageorgiou et al. 2014). This transformation involves investments in physical, human, and institutional capital (Hausmann and Klinger 2006). Additionally, firms' export activities can positively impact the economy by producing and exporting new goods and entering new markets, which involves sharing knowledge, skills, and information with other firms and industries (Herzer and Nowak-Lehnmann 2006). Chang et al. (2024) emphasize the significance of diversifying the export basket, particularly through creative products. They argue that such diversification reduces reliance on a limited range of products and accelerates economic growth by accessing global markets. Zhang et al. (2023) examine the factors influencing the export diversification of creative products, identifying key elements such as economic policies, market access, and the inherent productive capabilities of the economy. Effective policies enhance and develop productive capabilities, while diverse skills across sectors facilitate the production of a wide range of creative products. Ranjbar, Saboori, and Gholipour (2023) highlight that tourism development can drive export product diversification by increasing demand for various local products and services. Tailoring products to tourists, such as crafts, supports this diversification, while effective tourism development necessitates capabilities in services like hospitality, transportation, and cultural services. Ranjbar and Rassekh (2022) note that economies with higher complexity, marked by sophisticated and diversified productive capabilities, can better leverage FDI to further diversify and grow. Thus, building and enhancing productive capabilities are crucial for economies aiming to diversify their export baskets.

Information and communications technologies (ICTs) play a vital role in productive capabilities, encompassing the skills, infrastructure, and systems necessary for leveraging digital technologies. ICT facilitates innovation by providing tools and platforms for developing new products and services, enhancing efficiency and productivity, and enabling firms to compete globally (Qiang, Clarke, and Halewood 2006). Moreover, ICT supports knowledge sharing and collaboration, which are essential for fostering creativity and technological advancements (Bresnahan and Trajtenberg 1995). Access to reliable and high-speed internet, digital literacy, and robust ICT infrastructure are fundamental for economies seeking to diversify exports and achieve sustainable growth (Gnangnon 2020). The Global Alliance for Trade Facilitation (2022) emphasizes that technology, particularly ICT, is crucial for improving customs processes and trade efficiency. The report highlights key outcomes such as reduced trade delays, enhanced transparency, and cost efficiency, advocating for policies that promote technology adoption to foster economic growth and improve competitiveness, especially in developing countries. Gnangnon's (2020) study on the effect of the Internet on services export diversification provides valuable insights into this relationship. Utilizing a panel dataset of 100 developing countries from 2000 to 2017, Gnangnon employs econometric techniques to analyze how Internet penetration influences the diversification of services exports. The findings indicate that higher Internet penetration significantly enhances services export diversification by reducing information asymmetries, lowering transaction costs, and facilitating access to international markets. Additionally, the study highlights the importance of supportive policy environments and infrastructure development in maximizing the benefits of Internet usage for export diversification. This work underscores the transformative potential of digital technologies in reshaping export structures in developing economies, thus providing a critical foundation for understanding the broader impact of ICT on export diversification.

Recent developments show that ICT significantly contributes to economic growth and social development, improving living standards (ITU 2017). ICT enhances export diversification by allowing businesses to enter new markets, boost industry competitiveness, and expand product ranges (Rao 2001). Businesses utilizing ICT tools gain a competitive edge through in-depth market research, better understanding of consumer preferences, market trends, and identification of new opportunities, thereby promoting export diversification (Mariani and Wamba 2020).

E-commerce platforms are a starting point for businesses to enter new markets, present their products, and diversify their export destinations (Dethine, Enjolras, and Monticolo 2020). By building an online presence, businesses can connect with customers, expand their customer base, and set targeted marketing strategies to enter foreign markets (Borges, Hoppen, and Luce 2009; Mathews and Healy 2008). Communication and collaboration tools help foster partnerships between companies, drive innovation, and lead to the development of new export-worthy products and services (Dethine, Enjolras, and Monticolo 2020). Also, for businesses to broaden their product range, they must optimize supply chains with ICTs to reduce costs and delivery times (Cassetta et al. 2020). By embracing the power of ICTs, businesses can take advantage of more export opportunities and create a diversified global marketplace.

This paper aims to investigate the ICT index's short- and long-term impact on the Herfindahl-Hirschmann index of export product concentration. This research contributes to the existing literature by first examining the long-run impact of ICT on export diversification in emerging markets and developing countries. Second, the ICT index can be constructed using the principal component analysis method (PCA) and tested on its impact on developing countries' export concentration and diversification indices in the short and long term. Last, identifying the potential mechanism that links ICT and export diversification, analyzing the impact of the interaction between ICT and human capital on the degree of export concentration in developing countries.

The rest of the paper is organized as follows: Section 2 presents the literature review on the main determinants of export diversification and the role of ICT in this process. Section 3 describes the theoretical framework explaining the key channels through which ICT accelerates export diversification. Section 4 outlines the research methodology and describes the data used. Section 5 presents and discusses the empirical findings. Section 6 interprets and explains the results of different robustness tests. Finally, Section

7 concludes the paper with practical policy implications and recommendations for future research.

2. Literature review

2.1. Research on determinants of export diversification

The macroeconomic indicators, the geographic location of the economy (distance to major world markets), the quality of human capital (average number of years of schooling), size (GDP or population), infrastructure development (density of railways, paved roads, and telephone lines), the quality of institutions (quality of governance), foreign trade policy, endowment with natural resources, and the characteristics of firms are all factors that greatly influence export diversification. These factors play a crucial role in determining the success of export activity.

A study conducted by Imbs and Wacziarg (2003) explores the relationship between the concentration of employment or value added in individual production sectors and the level of per capita income. By employing sectoral data from the International Labor Office (ILO 1997) and United Nations Industrial Development Organization (UNIDO 1997) for a wide range of countries, the results show that as per capita income increases to a certain level ($9,000), production and employment structure diversify, but eventually, at around $9,000, production reconcentration occurs.

Naudé and Rossouw (2011) examined the relationship between GDPs per capita and export diversification; the results revealed a strong relationship between the two variables in South Africa, a weaker relationship in India, and a linear relationship in Brazil. The AGE simulation models were used to clearly understand the impact of export specialization versus export diversification on economic development. The results concluded that Brazil, China, and India favor export specialization, while export diversification significantly impacts South Africa's economic development.

A study by Chang et al. (2024) calculated the diversification level of creative products' export baskets since creative industries are emerging and affecting the export basket's composition and the growth of nations. By gathering data from 2002-2020, the results of Chang et al.'s (2024) study shows that the diversification level of creative products' basket in the US, France, Switzerland, and China decreased over the years, while the level increased in the Netherlands and Germany. In other countries, the indexes do not exhibit significant fluctuations. By estimating a Barro-type growth regression model and conducting a panel Granger non-causality test, the study found that diversification of creative products serves as a pro-growth factor in these nations.

The influence of different factors on export diversification indices to identify the most significant determinants of the intensive or extensive margin of export diversification in developing countries is a topic extensively analyzed in the literature. On the one hand, the intensive margin is the even distribution of the total value of exports among traditionally exported commodity items without including new goods in the export structure. On the other hand, extensive margin refers to the increase in the number of active commodity items in exports (Dennis and Shepherd 2011).

Parteka and Tamberi (2011) conducted a study identifying the main factors affecting the degree of export diversification. These include economic size, geographical location, trade freedom index, and participation in regional trade agreements. The study's results confirm that economies of scale are crucial to developing international trade. Similarly, the study by Cadot et al. (2011a) confirms that the size of the economy and the preferential market access positively impact export diversification, while a geographic gap negatively affects export diversification. Other factors explored by Cadot et al. (2011b) include infrastructure development, improvements in the quality of human capital, and increases in the quality of institutions. Although the net inflow of foreign direct investment leads to the concentration of exports, Cadot et al. (2011b) explain that this is due to multinational corporations (MNCs) specializing in producing specific goods in large volumes.

Analyzing the topic on a larger scale, Agosin, Alvarez, and Bravo-Ortega (2012) gathered data from 79 countries from 1962 to 2000 using the GMM estimator method. The results indicate that while the accumulation of human capital positively impacts export diversification, the increase in a country's GDP-weighted average distance from its trading partners has a negative impact. Agosin, Alvarez, and Bravo-Ortega (2012) touch upon other factors that negatively impact export diversification, such as the real exchange rate volatility and the improvement in trade for countries with low-quality human capital. Likewise, Jetter and Ramírez Hassan (2015) emphasized the importance of human capital quality as a variable affecting export diversification. Jetter and Ramírez Hassan (2015) also highlighted that the total rent from natural resources negatively affects export diversification. Giri, Quayyum, and Yin (2019) explained the relationship through the 'resource curse' phenomenon, which is when the abundance of natural resources and high income from exports hinder the development of other industries' production and exports (Sachs and Warner 2001). Giri, Quayyum, and Yin (2019) find that developing human capital and reducing trade barriers are necessary to enhance export diversification in developing countries.

A study by Vogel (2022) analyzed data from 36 African countries and 123 trading partners from 1995 to 2018. The study followed the Bayesian averaging method and found that regional trade agreements accelerate the diversification of exports of developing countries. However, the total rent from natural resources, tariffs imposed on intermediate goods by African exporters, and high bilateral tariffs negatively affect the degree of export diversification. Vogel (2022) also highlighted the importance of improving the quality of institutions to enhance the educational system.

Ranjbar and Rassekh (2022) conducted research to examine the relationship between economic complexity and the effectiveness of inward foreign direct investment (FDI). The study is framed within a theoretical context that links economic growth to both the inflow and stock of FDI, while accounting for the complexity of the economy, measured by the Economic Complexity Index (ECI). This index reflects the capabilities embedded within a nation's productive structure. Their empirical analysis reveals that economic complexity significantly affects how FDI influences growth in host countries. Specifically, nations with higher economic complexity experience positive benefits from FDI, whereas those with very low complexity may face negative repercussions. This finding underscores the importance of economic structure in maximizing the advantages of foreign investments.

In another study, Ranjbar, Saboori, and Gholipour (2023) explored the impact of tourism development on export product diversification (EPD). Utilizing data from 150 countries and applying a system generalized method of moments (GMM) estimator, the researchers assessed how tourism development influences EPD and its two dimensions: the extensive and intensive margins. The findings were analyzed by categorizing countries based on different income levels. The results indicate that an increase in international tourist arrivals and tourism receipts significantly boosts EPD. Interestingly, the research also reveals that tourism development has a more pronounced pro-diversification effect in low-income economies compared to high-income economies. Furthermore, when examining the sub-dimensions of EPD, it was found that the influence of tourism development is more substantial on the extensive margin than on the intensive margin. These insights provide valuable guidance for policymakers aiming to enhance export diversification through tourism.

Zhang et al. (2023) focused on measuring the export diversification of creative products across 109 countries from 2000 to 2018, employing Theil inequality and Herfindahl–Hirschman concentration indexes. The study further identifies the drivers of export diversification by specifying a dynamic panel data model and utilizing system-GMM and quasi-maximum likelihood estimators. The results reveal that accumulated productive capabilities, financial development, and structural changes positively impact the diversification of creative products. Conversely, factors such as economic growth, trade openness, and FDI tend to lead to greater specialization within a country. This research emphasizes the necessity for nations to enhance their institutional quality, allocate resources to support creative industries, and develop robust infrastructures to promote the diversification of creative exports.

Lectard and Rougier (2018) conducted a study to analyze the relationship between vertical FDI and export diversification in developing countries. The results indicate that shifting away from comparative advantage promotes export diversification for middle-income countries. This is due to the size of accumulated FDI and the country's specialization in producing low-value-added goods within global value chains. However, Lectard and Rougier (2018) explain that attracting FDI will have a negative long-term impact. An increase in exports of manufactured goods will decrease the manufacturing industry's added value, which limits the further transformation of an economy's production structure and consolidates its specialization in assembly industries.

Dennis (2007) revealed that reducing transaction costs in exports accelerates diversification in developing countries. The study emphasizes the significance of enhancing trade logistics, infrastructure, and customs efficiency to boost trade flows and promote economic integration, both within the region and on a global scale. Dennis and Shepherd (2011) explained that export costs, international transport costs, and domestic market access costs significantly negatively impact export diversification in developing countries. However, simplified customs procedures significantly positively affect export diversification, creating an equal incentive for all market participants and stimulating enterprises' export activities.

Shepherd (2010) assessed the influence of factors such as developing countries' geography by analyzing data from 117 developing countries in 2005. The results show that a one-standard-deviation reduction in international transport costs, tariffs, and export transaction costs increases a country's export markets by 4%, 3.5%, and 12%, respectively. Also, Shepherd's (2010) study revealed that trade facilitation policies at unilateral, regional, and multilateral levels positively and significantly impact export diversification. Beverelli, Neumueller, and Teh (2015) explained that implementing the World Trade Organization (WTO) Trade Facilitation Agreement rules would positively impact the extensive margin of export diversification of developing countries, recommending that developing countries prioritize the implementation of the Agreement within their trade policies.

Regarding the impact of exchange rates on export diversification, Sekkat (2016) gathered data on 55 low- and middle-income countries and found an insignificant relationship between currency overvaluation and export diversification within manufacturing industries. However, Bahmani-Oskooee and Jamilov (2014) conducted a study on Azerbaijan and concluded the presence of the S-curve. The study also supports using currency depreciation as an instrument for export diversification in resource-rich countries.

Gul et al.'s (2024) study used gravity models to assess how the World Bank's Logistic Performance Index (LPI) affects Pakistan's exports. Gul et al.'s (2024) results show that the quality of logistics services, such as reasonably priced shipments, the ability to track and trace shipments, and trade and logistical transit standards, are all essential determinants of international trade and can positively impact the increasing levels of exports.

2.2. Research on the impact of ICT on the development and diversification of exports

Multiple papers in the literature illustrate that ICT positively impacts production, economic growth, and export diversification. For instance, Rao (2001) analyzes the ICT revolution's impact on the internationalization of technological activities, particularly in emerging economies, and its implications for global marketing. The study, using a transaction cost framework, suggests that ICT tools – such as email and videoconferencing – have reduced market failures that previously justified vertical integration. This shift enables multinational enterprises (MNEs) to internationalize their R&D and fosters technology alliances. Consequently, product development strategies are influenced, with trends toward modular designs and platform strategies. Hybrid governance structures, like alliances, are expected to grow, enhancing product differentiation in global markets. For emerging economies, the ICT revolution improves global information exchange, reducing risks in product development. Countries like India and China, with strong ICT capabilities, are poised to become key players in this space.

In addition, Oumbé, Djeunankan, and Ndzana (2023) study took a sample of 112 countries from 1986 to 2017, and the results reveal that in the long run, the quality and quantity of ICT positively and significantly impact a country's economic complexity index. Oumbé, Djeunankan, and Ndzana (2023) recommend executing certain measures that boost ICT quality and quantity to increase economies' sophistication. Using the gravity model and looking at 122 countries from 1995 to 2008, Abeliansky and Hilbert's (2017) results show a significant positive impact between the data transfer rate per subscription and the data subscriptions per capita of ICT on volumes of bilateral trade in goods. Abeliansky and Hilbert's (2017) results reveal that while the quality of ICT is of greater importance in developing countries, the quantity of ICT is more important in developed countries.

Gnangnon's (2020) study examines the impact of Internet penetration on services export diversification in 100 developing countries from 2000 to 2017. The research reveals that increased Internet access significantly boosts the diversification of services exports, particularly in countries starting with lower levels of diversification. The study also finds that this positive effect is stronger in nations with higher institutional quality, indicating that effective institutions enable firms to better utilize the Internet for diversifying their export portfolios. These findings suggest that expanding Internet access and improving institutional frameworks are crucial for enhancing export diversification, thereby supporting more robust and sustainable economic growth in developing countries.

Also, a study prepared by Ma, Shen, and Chao (2024) evaluated the impact of data flow provisions on trade in goods and services. The study shows that signing provisions on the free flow of data can encourage the growth of goods traded by reducing distance restrictions. As for the trade-in services, the study suggests that signing data free flow provisions varies depending on the country's degree of Internet access.

Nham and Bao (2023) conducted a study on 23 European countries with data from 2015 to 2020 and concluded that digitalization positively impacts export development by reducing costs and time for export procedures and improving the quality of logistics services and transport infrastructure. The results also reveal that the relationship between digitalization and export diversification is non-linear. Takpara, Djiogap, and Sawadogo (2022) suggest that trade facilitation measures like physical infrastructure and ICT development positively and significantly impact export diversification in sub-Saharan Africa. Another study conducted by Ouedraogo and Mineyama (2023), looking at panel data from 151 countries from 1980 to 2014, shows that the quality of transport infrastructure, ICT infrastructure, and electricity supply are essential factors in export diversification.

To provide a comprehensive overview of the factors influencing export diversification and the role of ICT, the following Table 1 summarizes key research studies sorted by their publication year. This table organizes the studies based on their geographical focus and the main determinants analyzed, offering a structured view of how research has evolved over time. By examining these studies, we can better understand the diverse factors impacting export diversification and the contribution of ICT to this process. The subsequent sections will delve deeper into specific findings and their implications for economic policy and development strategies.

2.3. Literature gaps

Despite these insights, there are notable gaps in the literature above. Regional studies, particularly in Latin America, Southeast Asia, and Central Asia, are limited, leaving a gap in understanding the regional nuances of export diversification. Additionally, much research relies on data from earlier decades, which may not fully reflect recent trends and technological advancements. There is also a need for more comprehensive indices to capture various aspects of ICT development and a deeper exploration of the mechanisms through which ICT impacts export diversification. Addressing these gaps will provide a more detailed understanding of how ICT and other factors influence export strategies, offering valuable insights for policymakers and researchers aiming to enhance economic development.

3. Theoretical framework

ICT plays a vital role in accelerating export product diversification through several key channels. ICT enhances market access, improves competitiveness, and facilitates better market research, all of which support the expansion of export activities (Beverelli, Neumueller, and Teh 2015). It streamlines trade facilitation by reducing transaction costs and improving logistics, thereby fostering a more dynamic export sector. Additionally,

Table 1. Key research studies on the determinants of export diversification.

Study	Year	Geographical focus	Key factors analyzed
Imbs and Wacziarg	2003	Global	Per capita income levels, production diversification
Cadot et al.	2011a	156 countries	Trade and income per capita
Cadot et al.	2011b	Global	Economy size, preferential market access, infrastructure
Naudé and Rossouw	2011	South Africa, India, Brazil	GDP per capita, export diversification
Parteka and Tamberi	2011	Global	Economic size, geographical location, trade freedom, regional trade agreements
Dennis	2007	Developing countries	Transaction costs, export diversification
Bahmai-Oskooee and Jamilov	2014	Azerbaijan	Currency depreciation, export diversification
Jetter and Ramírez Hassan	2015	Global	Human capital quality, natural resource rents
Sekkat	2016	55 low – and middle-income countries	Currency overvaluation, export diversification
Abeliansky and Hilbert	2017	122 countries	ICT data transfer rate, bilateral trade volumes
Lectard and Rougier	2018	Developing countries	Vertical FDI, export diversification
Gnangnon	2020	Developing countries	Internet penetration, service export diversification
Roa	2021	Emerging economies	ICT applications, internationalization of technological activities, implications on marketing
Ranjbar and Rassekh	2022	Sample 1: 79 countries Sample 2: 105 countries	Economic complexity, FDI, human capital
Takpara et al.	2022	Sub-Saharan Africa	ICT development, export diversification
Vogel	2022	36 African countries	Regional trade agreements, natural resource rents
Gul et al.	2023	Pakistan	Logistics quality, export levels
Ma et al.	2023		Data flow provisions, trade growth
Nham and Bao	2023	23 European countries	Digitalization, export development
Oumbé et al.	2023	112 countries	ICT quality, economic complexity
Ranjbar, Saboori, and Gholipour	2023	150 countries	Export product diversification (EPD), productive capacity index, real GDP per capita (and its square term), domestic credit to the private sector by banks (as a percentage of GDP), value added in the manufacturing and service sectors (as a percentage of GDP), net inward FDI flow (as a percentage of GDP), and total foreign trade (as a percentage of GDP)
Zhang et al.	2023	109 countries	Theil inequality and Herfindahl – Hirschman concentration indexes
Chang et al.	2024	Top ten exporters including China, the US, France, Italy, the UK, Germany, India, Switzerland, Singapore, and the Netherlands.	Real GDP per capita, HH, Gini index, Theil index, gross capital information, population growth rate, human capital, inflation rate, government consumption expenditure, volatility in GDP per capita growth rate.

Source: Authors.

ICT contributes to human capital development by providing online education and training, which helps build a skilled workforce capable of managing diverse export activities (Nham and Bao 2023). Moreover, ICT improves the quality of institutions by promoting transparency, reducing corruption, and automating administrative procedures, creating a more favorable business environment (Vogel 2022). These channels collectively enhance the capacity of economies to diversify their export products (Oumbé, Djeunankan, and Ndzana 2023).

In this section below, we will discuss the literature review for each trade facilitation channel, human capital channel, and institutional quality channel.

3.1. Trade facilitation channel

ICT improves trade facilitation by streamlining customs procedures, enhancing transparency, and reducing transaction costs. This efficiency supports the expansion of export activities and product diversification. The World Trade Organization (WTO) Trade Facilitation Agreement, as discussed by Beverelli, Neumueller, and Teh (2015), highlights that implementing ICT-related trade facilitation measures positively impacts export diversification (Beverelli, Neumueller, and Teh 2015). Billon and Rodriguez-Crespo (2020) applied a gravity model. They found that mobile phone subscriptions significantly positively affect exporters, broadband subscriptions positively affect both trading partners, and internet use favors importers. Digital technologies play an essential role in boosting global trade through the development of e-commerce and increasing trade and border efficiency. Since ICTs provide accessibility and transparency of information on export, import, and transit requirements, implementing them can positively affect international trade by increasing operating efficiency, lowering costs, and promoting the implementation of the Trade Facilitation Agreement (TFA) (UN.ESCAP 2016). Automation of customs procedures reduces customs clearance time and costs and increases customs bodies' effectiveness and transparency. Thus, ICTs help decrease transaction costs in global trade by simplifying and modernizing export and import procedures.

In addition, trade facilitation plays an essential role in export diversification. A study by Zaki (2014), following the computable general equilibrium model, found that reducing administrative barriers improves export diversification in the most time-sensitive industries, such as food, electronics, and textiles. Also, another study conducted by Dennis and Shepherd (2011) gathered data from 118 developing countries and found that export costs and market entry expenditures adversely influence the export diversification of developing countries. Thus, setting and implementing trade facilitation measures and improving customs procedures are vital for export diversification.

H1: ICT development helps decrease the concentration levels of export portfolios in developing countries.

3.2. Human capital channel

ICT development can facilitate human capital accumulation by easing access to education through online libraries, educational platforms, and other learning resources. Oluwatobi, Olurinola, and Taiwo (2016) conducted a study on 32 economies in Sub-Saharan Africa (SSA) and found that ICT significantly facilitated school attendance at secondary and tertiary levels. Modern educational methods and interactive learning techniques based on ICT instruments can improve students' educational achievements (Comi et al. 2017). Fernández-Gutiérrez, Gimenez, and Calero (2020) also found a positive influence of ICT usage at school on science PISA scores. The study's results show that the impact of ICT on learning outcomes varies depending on the course and the type of technology used.

Education is a substantial factor in export diversification. The studies of Jetter and Hassan (2015) and Giri, Quayyum, and Yin (2019) provide evidence for the importance of primary and secondary education in accelerating export diversification. Thus, improving the quantity and quality of education are recommended to diversify the export basket of nations.

ICT can also advance the quality of human capital by facilitating investments in professional training. The results of the Batalla-Busquets and Myrthianos (2015) study show that the level of Internet usage is one of the factors determining the probability of companies' investments in training for employees in the Spanish industry. Another advantage of ICT is increased labor productivity in industrial sectors due to human capital development; for instance, Shahiduzzaman, Layton, and Alam (2015) discovered substantial proof of the beneficial impact of investments in ICT on marginal labor productivity in Australia using time-series and panel data analysis.

Product diversification requires knowledge accumulation and diffusion among industries, sectors, and countries. This knowledge dissemination is key to the development of technological and innovation capabilities, which are crucial for creating new export goods and services (Ali 2017). Agosin, Alvarez, and Bravo-Ortega (2012) have found evidence that human capital accumulation positively contributes to export diversification. The accumulation of human capital enables countries to produce more sophisticated, knowledge-intensive goods, thereby shifting their specialization from commodities to high-value-added manufacturing goods and services. The high quality of human capital is a vital factor in research and development (R&D), which leads to the creation of new products for exports. Therefore, by enhancing the quality of human capital, ICT provides a favorable ground for export diversification.

H2: Human capital development is a crucial pathway through which ICT positively influences export product diversification in developing countries.

3.3. *Institution quality channel*

ICT significantly enhances the quality of institutions, which is crucial for fostering export diversification. By enabling better governance, transparency, and public service delivery, ICT helps create a stable and favorable environment for businesses to expand their export activities. Vogel (2022) highlights that improved institutional quality, supported by ICT, accelerates export diversification by creating a more conducive business environment.

Empirical literature supports the role of ICT in improving institutional quality. Ali (2020) found that ICT promotes democracy and reduces corruption, though the effects vary between developed and developing countries. The usage of the Internet and mobile technologies has been shown to increase democratic engagement. Additionally, Bhattacherjee and Shrivastava (2018) observed that ICT's capability to track, document, analyze, and transmit large volumes of information aids in identifying and prosecuting corrupt activities, thereby discouraging future corruption. Furthermore, ICT enhances institutional quality by automating administrative procedures, reducing bureaucracy, and increasing the transparency of government operations (Oumbé, Djeunankan, and Ndzana 2023).

Scholars emphasize the importance of institutional quality in promoting export diversification. For instance, Parteka and Tamberi (2013) found that higher-quality institutions positively impact export diversification. This perspective is reinforced by Cadot et al. (2011b), Giri, Quayyum, and Yin (2019), and Vogel (2022), who underline that improvements in institutional quality, facilitated by ICT, play a critical role in supporting and accelerating export diversification. Thus, ICT contributes positively to export diversification by enhancing the quality of institutions.

H3: ICT development promotes the alignment of developing countries' export structure with global export patterns.

4. Research methodology and data description

4.1. Model construction

The impact of ICT development on the export concentration index is estimated using the following equation:

$$Y_{it} = \varphi Y_{it-1} + \beta ict\_index_{it} + \gamma X'_{it} + d_t + \varepsilon_{it} \tag{1}$$

where Y_{it} is the export concentration index for country i in year t;

Y_{it-1} – lagged value of the export concentration index of country i in year t–1;

ict_index_{it} – the value of the ICT index of country i in year t;

X'_{it}– vector of control variables;

d_t – dummy time variable;

ε_{it} – error term;

φ, β, γ – estimated coefficients.

To dynamically analyze panel data using equation (1), the GMM estimation method that was proposed by Arellano and Bover (1995) and improved by Blundell and Bond (1998) has been used in this paper. This method is utilized to analyze panel data in which the number of observed objects (N) is greater than the number of periods (T) (N > T). The assumptions on the data generation process under the system GMM assessment are the following (Roodman 2009):

- the process can be dynamic, and the previous value of the dependent variable can affect its current value;
- randomly distributed individual fixed effects may be observed;
- some predictors may be endogenous;
- idiosyncratic residuals (separate from fixed effects) may have individual-specific properties of heteroskedasticity and autocorrelation;
- idiosyncratic residuals are not correlated across individuals (countries);

Additional model assumptions include (Roodman 2009):

- some regressors may be predetermined but are not strictly exogenous (for example, a lagged dependent variable);
- the number of time periods may not be large (small T, large N);
- external instrumental variables may be incorporated in the model.

The general dynamic GMM estimation model is as follows:

$$y_{it} = \alpha y_{i,t-1} + x'_{it}\beta + \varepsilon_{it} \tag{2}$$
$$\varepsilon_{it} = \mu_i + v_{it}$$
$$E(\mu_i) = E(v_{it}) = E(\mu_i v_{it}) = 0$$

where $y_{i,t-1}$ are predefined regressors, which may contain lagged values of y, and endogenous regressors, all of which can be correlated with ε_{it}; x' – vector of exogenous regressors.

In equation (2), the residual term consists of two orthogonal components: fixed effects μ_i and idiosyncratic shocks v_{it}. Equation (2) can be rearranged as follows:

$$\Delta y_{it} = (\alpha - 1)y_{i,t-1} + x'_{it}\beta + \varepsilon_{it} \tag{3}$$

Accordingly, the model can be equally considered for current values y and increases of y. A system of two equations (one equation per period) is built by the system GMM estimator. This method allows the introduction of different instrumental variables that apply to each equation. To obtain the transformed form of the equation, instead of subtracting the previous observation from the current one, orthogonal deviations are used – subtracting the average value of all future available observations of the variable from the current value, which minimizes data loss if there are gaps in the sample (Arellano and Bover 1995). Due to gaps in the collected database, orthogonal deviations are used in the transformed equation. The robust option is used to obtain standard errors that are robust to heteroskedasticity and autocorrelation.

The system GMM technique has some advantages over other panel data methods. First, the system GMM effectively addresses endogeneity issues that arise from unobserved heterogeneity and measurement error as it uses internal instruments derived from the lagged values of the outcome and explanatory variables (Arellano and Bover 1995). Second, it is beneficial for estimating models where past values of the dependent variable influence its current value, allowing for a more accurate representation of dynamic relationships. Third, the system GMM is exceptionally reliable in short panels where the number of periods is limited relative to the number of cross-sectional units (Roodman 2009).

After conducting a system GMM assessment, the Arellano and Bond (1991) test is used for serial correlation of an idiosyncratic residual v_{it}. Failure to reject the null hypothesis of insignificance of the residuals AR (2) indicates the absence of serial correlation of the residual term. The instruments' overall validity is tested using the Hansen test of over-identifying restrictions (Hansen's test 1982). Failure to reject the null hypothesis specifies the correct choice of instrumental variables.

To estimate equation (1), one- and two-step versions of the system GMM estimation are used. In comparison to the difference GMM estimator, the system GMM estimator offers several benefits. The system GMM estimator surpasses the difference GMM estimator in unbalanced panels (Roodman 2009). The system GMM estimator enhances accuracy and minimizes finite sample bias in the first-difference GMM estimator, according to Blundell and Bond (1998). Furthermore, some recent studies in the literature (e.g. Agosin, Alvarez, and Bravo-Ortega 2012; Cadot et al. 2011a; Lectard and Rougier 2018; Ranjbar, Saboori, and Gholipour 2023; Shepherd 2010; Zhang et al. 2023) support the use of the system GMM technique in investigating the determinants of export diversification.

4.2. Variable measures and data sources

The export concentration index, available on the UNCTAD statistics database, is chosen as the dependent variable to analyze the impact of ICT on the degree of export diversification of selected developing countries.

This indicator is a normalized Herfindahl-Hirschmann index of the product concentration of the country's merchandise exports. The formula for calculating this index is the following:

$$H_j = \frac{\sqrt{\sum_{i=1}^{N}\left(\frac{x_{ij}}{X_j}\right)^2} - \sqrt{\frac{1}{N}}}{1 - \sqrt{\frac{1}{N}}}; X_j = \sum_{i=1}^{N} x_{ij} \tag{4}$$

Here, H_j is the export product concentration index for country j, x_{ij} is the value of exports of product i by country j, X_j is the total value of exports of country j, and N is the number of products exported at the three-digit level of the SITC Revision 3. The index ranges from zero to one, with a larger value indicating a higher concentration of merchandise exports structure. The index value close to zero denotes the high level of export diversification, i.e. the county's exports are equally distributed among all products (UNCTADStat 2019).

The second variable of interest is the ICT index, which was constructed in accordance with the methodology of the International Telecommunication Union (ITU) for calculating the ICT Development Index – the composite index combined with eleven indicators reflecting the ICT infrastructure, ICT usage, and ICT skills (ITU 2009). The following indicators were chosen for creating the ICT index implemented in our study: (1) fixed-telephone subscriptions per 100 inhabitants; (2) percentage of individuals using the Internet; (3) fixed-broadband subscriptions per 100 inhabitants; (4) mobile-cellular telephone subscriptions per 100 inhabitants. The data for these indicators come from the World Development Indicators (WDI) database. The value of all indicators was standardized, and the ICT index was calculated using the Principal component analysis (PCA) method, a statistical method for multivariate data reduction (Jackson 2005). After predicting the ICT index, its values were recalculated to obtain the numbers between zero and one (See Appendix 1 for more information on the results of PCA).

Control variables were chosen according to the main determinants of export diversification indicated in the literature. Control variables are grouped into macroeconomic indicators (GDP per capita (in constant 2015 US dollars), population (number of people), total rents from natural resources (% of GDP), domestic credit to the private sector (% of GDP), foreign trade turnover (% of GDP), foreign direct investment, net inflow (% of GDP)); infrastructure development indicators (access to electricity (% of population)); human capital development indicators (primary school enrollment (% gross), preprimary school enrollment (% gross)). The data for these indicators were taken from the 2022 World Development Indicators (World Bank 2022). Some of the empirical studies that justify the inclusion of these variables in the analysis are (Dennis and Shepherd 2011; Giri, Quayyum, and Yin 2019; Jetter and Ramírez Hassan 2015; Lectard and Rougier 2018; Parteka and Tamberi 2011; Shepherd 2010; Vogel (2022). The definitions of the selected variables given in the data sources are shown in Table 2.

For an econometric analysis, statistical data are selected for 110 emerging market and developing countries (according to IMF classification) for 2000–2019. Various cutoffs

Table 2. Definitions and sources of the selected variables.

Variable name	Description	Source
Export concentration index	Normalized Herfindahl-Hirschmann index of the product concentration of the country's merchandise exports.	UNCTAD Stat (2022)
Export diversification index	Index measuring the absolute deviation of a country's export structure from the world export structure.	UNCTAD Stat (2022)
GDP per capita (constant 2015 US$)	Gross domestic product divided by midyear population.	World Bank (2022). World development indicators
Population, total (people)	Total population is based on the de facto definition of population, which counts all residents regardless of legal status or citizenship. The values shown are midyear estimates.	World Bank (2022). World development indicators
Total natural resources rents (% of GDP)	Total natural resources rents are the sum of oil rents, natural gas rents, coal rents (hard and soft), mineral rents, and forest rents.	World Bank (2022). World development indicators.
Domestic credit to private sector (% of GDP)	Domestic credit to private sector refers to financial resources provided to the private sector by financial corporations, such as through loans, purchases of nonequity securities, and trade credits and other accounts receivable, that establish a claim for repayment.	World Bank (2022). World development indicators
Trade (% of GDP)	Trade is the sum of exports and imports of goods and services measured as a share of gross domestic product.	World Bank (2022). World development indicators
Foreign direct investment, net inflow (% of GDP)	Net inflows (new investment inflows less disinvestment) in the reporting economy from foreign investors divided by GDP.	World Bank (2022). World development indicators
Access to electricity (% of population)	The percentage of population with access to electricity.	World Bank (2022). World development indicators
Subscription to broadband Internet access (per 100 people)	Fixed subscriptions to high-speed access to the public Internet (a TCP/IP connection), at downstream speeds equal to, or greater than, 256 Kbit/s.	World Bank (2022). World development indicators
Individuals using the Internet (% of population)	Internet users are individuals who have used the Internet (from any location) in the last 3 months. The Internet can be used via a computer, mobile phone, personal digital assistant, games machine, digital TV etc.	World Bank (2022). World development indicators
Fixed telephone subscriptions (per 100 people)	The sum of active number of analogue fixed telephone lines, voice-over-IP (VoIP) subscriptions, fixed wireless local loop (WLL) subscriptions, ISDN voice-channel equivalents and fixed public payphones.	World Bank (2022). World development indicators
School enrollment, primary (% gross)	Total enrollment in primary education, regardless of age, expressed as a percentage of the population of official primary education age.	World Bank (2022). World development indicators
School enrollment, preprimary (% gross)	Total enrollment in pre-primary education, regardless of age, expressed as a percentage of the total population of official pre-primary education age.	World Bank (2022). World development indicators

Source: Authors.

Table 3. Descriptive statistics of the selected variables.

Variables	Obs.	Mean	Std. Dev.	Min	Max
Concentration index	2200	0.357	0.210	0.063	0.976
Diversification index	2200	0.710	0.122	0.353	0.935
GDP per capita	2179	5268.934	8208.136	255.100	73493.269
Population (mln people)	2200	51.8	173.7	0.265	1410
Total natural resources rents	2194	9.473	11.096	0.002	65.318
Domestic credit to private sector	1879	34.298	28.871	0.002	165.39
ICT Index	1662	0.2692	0.2044	0	1
School enrollment, primary	1913	103.159	14.822	32.356	150.786
School enrollment, preprimary	1635	46.346	31.466	0.577	160.081

Obs. refers to number of observations; Std. Dev. refers to standard deviation.
Source: Authors.

were considered for removing countries from the sample, for example, only considering economies with all observations for the export concentration and diversification indices and excluding countries that frequently lack data across regressors (the list of countries in the sample is presented in Appendix 2).

Table 3 demonstrates the descriptive statistics of selected variables. The minimum value of the export concentration index in the specified sample of countries is 0.063, and the maximum is 0.976. The values of the export diversification index for a sample of countries for 2000–2019 are in the range of 0.353-0.935. A higher value of both indices characterizes a higher degree of export concentration and a lower degree of export diversification. The statistics indicate that developing countries in the sample recorded a mean export concentration index of 0.357, which is relatively low. At the same time, the mean of the export diversification index for developing countries in the sample is 0.710, which is relatively high. The minimum value of the ICT index is zero, and the maximum is one, with a mean of 0.269. A higher ICT index value means a more developed ICT infrastructure. A more advanced ICT sector fosters digital transformation that can increase economic growth through new technologies, significantly reduce transaction costs, and facilitate international trade.

5. Empirical findings and discussions

5.1. Preliminary analysis

We conducted preliminary tests before applying the system GMM estimation in our empirical investigation. To be precise, the Fisher-type unit root test (Dickey-Fuller and Phillips-Perron category tests) was employed to find the presence of unit roots (Choi 2001). One of the benefits of this test is that it does not require a balanced panel, unlike the Im-Pesaran-Shin test (Maddala and Wu 1999). Fisher-type tests incorporate the *p*-values from individual unit root tests for each cross-section to derive an overall test statistic (Choi 2001). This flexible approach allows the tests to be conducted even when some cross-sections have missing data, as long as there are enough observations across the panel. The null hypothesis of the Fisher-type test is that all panels contain a unit root, and the alternative hypothesis is that at least one panel is stationary. The null hypothesis is rejected if the *p*-value of the inverse chi-squared is below 0.1, 0.05, and 0.01. The unit root test results displayed in Table 4 show that all variables are stationary at the I(0) order of integration. We proceeded to the regression analysis using the system GMM estimator. A maximum of two lags of dependent and independent variables were used as

Table 4. Fisher Unit root test results (Inverse chi-squared).

Variables	I(0)
Concentration index	455.40***
Diversification index	383.90***
ICT Index	405.47***
GDP per capita	401.26***
Population	879.28***
Total natural resources rents	301.73***
Domestic credit to private sector	319.06***
School enrollment, primary	281.57***
School enrollment, preprimary	279.93***

***refer to statistical significance at the 1% level.
Source: Authors.

Table 5. Results of correlation checks.

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
(1) Concentration index	1.000							
(2) Lag of concentration index	0.973	1.000						
(3) GDP per capita	0.011	0.012	1.000					
(4) Population	−0.186	−0.185	−0.050	1.000				
(5) Total natural resources rents	0.665	0.657	0.229	−0.083	1.000			
(6) Domestic credit to private sector	−0.429	−0.427	0.290	0.285	−0.255	1.000		
(7) ICT Index	−0.221	−0.223	0.496	−0.024	−0.103	0.491	1.000	
(8) School enrollment, primary	−0.155	−0.146	0.046	−0.023	−0.059	0.073	−0.078	1.000

Source: Authors.

instruments in the model because of the concern over too many instruments (Roodman 2009).

A correlation matrix of variables has been constructed to examine the presence and nature of the relationship between the response and predictors, as shown in Table 5. A relatively strong (compared to other variables in the model) positive relationship has been found between the export concentration index and total natural resources rents (0.665), a relatively moderate negative relationship between the outcome variable and domestic credit to the private sector (−0.429), as well as the ICT index (−0.221), a relatively weak negative correlation between export concentration index and population (−0.186), as well as primary school enrollment (−0.155), and extremely weak positive correlation between the dependent variable and GDP per capita (0.011). There is no high correlation ($>$ 0.7) found between the regressors, which could lead to a multicollinearity problem. The obtained signs of correlation coefficients coincide with the expected signs, meaning that countries obtaining high natural resource rent tend to have a more concentrated structure of exports, while the countries with more developed financial and ICT sectors are more likely to have a more diversified export portfolio.

The scatterplot, which shows the ICT index on the x-axis and the export concentration index on the y-axis, also indicates relatively moderate feedback between the variables. In other words, the development of ICT in developing countries is associated with a decline in the degree of concentration of their export basket (Figure 1).

5.2. Benchmark estimates

A dynamic panel data analysis has been conducted using the one-step and two-step system GMM estimation method to discover the relationship between ICT development

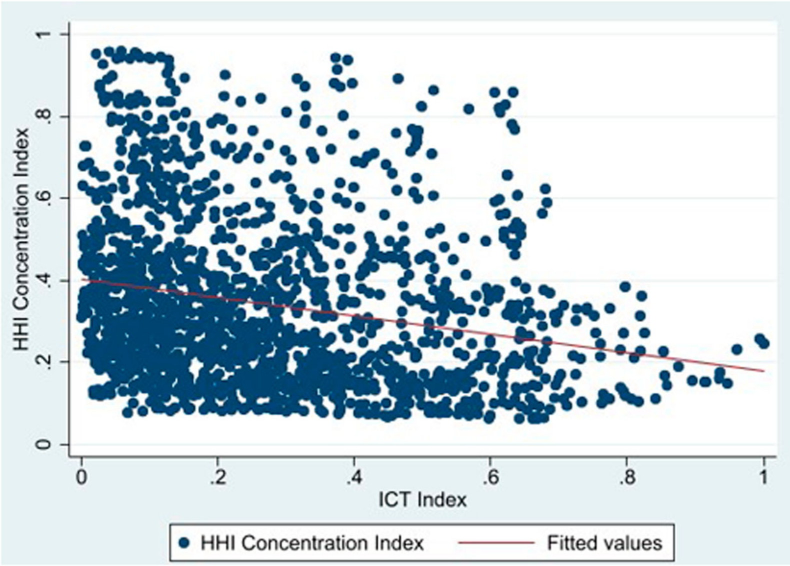

Figure 1. Scatterplot of export concentration index and ICT index.
Source: Authors.

and the degree of export concentration. The variables used to explain changes in the dependent variable are the one-year lagged export concentration index, GDP per capita, population, ICT index, total natural resources rents, domestic credit to the private sector, and primary school enrollment. In addition to the indicated regressors, the model included trade (as a percentage of GDP), net FDI inflow (as a percentage of GDP), and access to electricity (as a percentage of population) as instrumental variables.

Table 6 presents the results of one- and two-step system GMM regression for this study. The outcomes of the analysis indicate that a decrease in the export concentration index of developing countries is associated with the development of ICT. In the two-step GMM estimation model, the coefficient of the ICT index is significantly negative at the 5% significance level. All other things being equal, an increase in the ICT index by one unit relates to a decrease in the export concentration index by 0.0339. This result is consistent with the Takpara, Djiogap, and Sawadogo (2022) study, where the authors found that a 1% increase in the accessibility of ICT and its usage in production is connected with a 0.378-point rise in export diversification in SSA. As for the controlling variables, in the dynamic two-step GMM estimation model, the significant factor that has a reverse impact on the export concentration index is domestic credit to the private sector, which is consistent with the effect revealed in Giri, Quayyum, and Yin (2019). We find that the one-year lagged export concentration index coefficient is positive and statistically significant at the 1% level in both models. If the country had a more concentrated export structure in the previous year, it tends to have a similar export structure in the next year. Substantial changes in the export structure occur in the long term by adding new products and moving from shipping primary commodities to the exports of high-value-added goods. In a one-year period, the changes in the export concentration index are usually not considerable. The total rent from natural resources also has

Table 6. One-step and two-step system GMM estimation results on the effect of ICT index on export concentration index.

Variables	(1) One-step system GMM estimation Concentration index	(2) Two-step system GMM estimation Concentration index
Lag of concentration index	0.7900***	0.7928***
	(0.0646)	(0.0837)
GDP per capita (thousand US dollars)	0.000003	0.000007
	(0.0002)	(0.0002)
Population (mln people)	−0.00002**	−0.00002
	(0.00001)	(0.00001)
ICT Index	−0.0473***	−0.0339**
	(0.0142)	(0.0161)
Total natural resources rents	0.0022***	0.0021**
	(0.0007)	(0.0008)
Domestic credit to private sector	−0.0002**	−0.0002*
	(0.0001)	(0.0001)
School enrollment, primary	−0.0004**	−0.0002
	(0.0002)	(0.0002)
Constant	0.1215***	0.1028**
	(0.0348)	(0.0473)
Number of observations	1208	1208
Number of countries	102	102
Year fixed effects	Yes	Yes
Hansen *p*-value	0.173	0.173
AR(1) *p*-value	0.000	0.000
AR(2) *p*-value	0.842	0.877

∗∗∗, ∗∗, and ∗ Refer to statistical significance at the 1%, 5%, and 10% levels, respectively; the values in parentheses indicate the robust standard errors.
Source: Authors.

a significant positive impact on the export concentration index. This result aligns with Vogel (2022), who also found a significant favorable influence of total natural resources rents on the export concentration of African countries.

5.3. Assessment of the impact of the interaction between the ICT index and school enrollment on export diversification

As mentioned in the theoretical framework, ICT can influence export diversification through human capital channels, making education more accessible, improving educational outcomes, and facilitating investments in professional training. We created a new interaction variable by multiplying the ICT index and primary school enrollment variables to examine this mechanism in the nexus between ICT development and export diversification. We included GDP per capita, population, total natural resource rents, and domestic credit to the private sector in a vector of control variables. In addition to the indicated regressors, the model included trade (as a percentage of GDP), net FDI inflow (as a percentage of GDP), and access to electricity (as a percentage of population) as instrumental variables.

Table 7 presents the results of one- and two-step system GMM regression with the interaction term. The coefficients of the ICT index and primary school enrollment (a proxy for human capital) are significantly negative. This result suggests that higher ICT and human capital levels are associated with lower export concentration. However, the coefficient of the interaction between the ICT index and school enrollment

Table 7. One-step and two-step system GMM estimation results on interaction of ICT index and school enrollment effect on export concentration index.

Variables	(1) One-step system GMM estimation Concentration index	(2) Two-step system GMM estimation Concentration index
Lag of concentration index	0.8051***	0.8171***
	(0.0617)	(0.0346)
GDP per capita (thousand US dollars)	−0.00002	−0.00005
	(0.0002)	(0.0001)
Population (mln people)	−0.00002**	−0.00001
	(0.000009)	(0.000008)
ICT index	−0.1291*	−0.1834***
	(0.0696)	(0.0528)
Interaction of ICT and school enrollment	0.0008	0.0015***
	(0.0007)	(0.0005)
School enrollment, primary	−0.0004**	−0.0004***
	(0.0002)	(0.0001)
Total natural resources rents	0.0021***	0.0019***
	(0.0007)	(0.0004)
Domestic credit to private sector	−0.0002**	−0.0002***
	(0.00009)	(0.00007)
Constant	0.1243***	0.1125***
	(0.0363)	(0.0256)
Number of observations	1208	1208
Number of countries	102	102
Year fixed effects	Yes	Yes
Hansen *p*-value	0.142	0.142
AR(1) *p*-value	0.000	0.000
AR(2) *p*-value	0.846	0.885

***, **, and * Refer to statistical significance at the 1%, 5%, and 10% levels, respectively; the values in parentheses indicate the robust standard errors.
Source: Authors.

is significantly positive. This result implies that the level of human capital influences the relationship between ICT and export concentration. More specifically, it means that with higher school enrollment rates, the adverse effect of the ICT index on the export concentration index becomes less pronounced or even reversed. At low levels of school enrollment, both ICT and school enrollment negatively impact export concentration, implying that without sufficient education and skills in the labor force, increasing ICT may not promote export diversification but instead enhance concentration. As the school enrollment rate increases, the negative impact of ICT on export concentration diminishes. In other words, firms with a skilled workforce can better leverage ICT to diversify their exports. Thus, at high levels of human capital, increased ICT may contribute to a more diverse export portfolio. The pattern of influence of the main controlling variables does not change: the level of domestic credit to the private sector is associated with a decrease in the export concentration index. In contrast, an increase in total natural resource rents is associated with an increase in the export concentration index.

6. Robustness check

To check the results' reliability, the ICT index's impact on the export diversification index is assessed based on equation (1).

Table 8. Results of correlation checks.

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
(1) Diversification index	1.000							
(2) Lag of the diversification index	0.967	1.000						
(3) GDP per capita	−0.178	−0.178	1.000					
(4) Population	−0.318	−0.315	−0.050	1.000				
(5) Total natural resources rents	0.313	0.322	0.229	−0.083	1.000			
(6) Domestic credit to private sector	−0.518	−0.517	0.289	0.285	−0.254	1.000		
(7) ICT Index	−0.398	−0.412	0.496	−0.024	−0.103	0.491	1.000	
(8) School enrollment	−0.408	−0.410	0.298	0.074	−0.211	0.406	0.557	1.000

Source: Authors.

The export diversification index is calculated by evaluating the absolute deviation of a country's export portfolio from the world export composition (UNCTAD Stat).

$$S_j = \frac{\sum_i |h_{ij} - h_i|}{2} \tag{5}$$

where h_{ij} – share of product i in total exports of country j;

h_i – share of product i in total world exports.

The export diversification index ranges between zero and one. A value closer to one signifies a greater deviation from the global trend.

Correlation analysis of the variables presented in Table 8 demonstrates a relatively strong (compared to other variables in the model) negative relationship (−0.518) between the dependent variable and the domestic credit to the private sector. A relatively strong inverse relationship is also observed between the export diversification index and school enrollment (−0.408), along with the ICT index (−0.398). A moderate negative correlation exists between the dependent variable and population (−0.318). The relationship between the export diversification index and total natural resources rents is weakly positive (0.313). The correlation between the explained variable and GDP per capita is relatively weak and negative (−0.178).

Figure 2 shows a negative relationship between export diversification and ICT indexes. As the ICT index's value increases, the export diversification index's value decreases. Precisely, this reveals that the export composition of developing countries is approaching the structure of world exports.

The presence of a negative association between the ICT index and the export diversification index is assessed using a one-step and two-step system GMM method. In addition to the ICT index, the model included as explanatory variables the one-year lagged value of the dependent variable, GDP per capita and population, total rent from natural resources, domestic credit to the private sector, and school enrollment. In addition to the indicated regressors, trade (as a percentage of GDP) and net FDI inflow (as a percentage of GDP) are also used as instrumental variables.

Table 9 presents the results of one- and two-step system GMM regression with export diversification index as a dependent variable. The results of the econometric analysis reveal that the ICT index has a significant negative impact on the export diversification index. All other things being equal, a one-unit increase in the ICT index is associated with a decrease in the export diversification index by 0.0968. Among the controlling variables, population negatively affects the export diversification index. The lagged value of the dependent variable and the total rents from natural resources positively affect

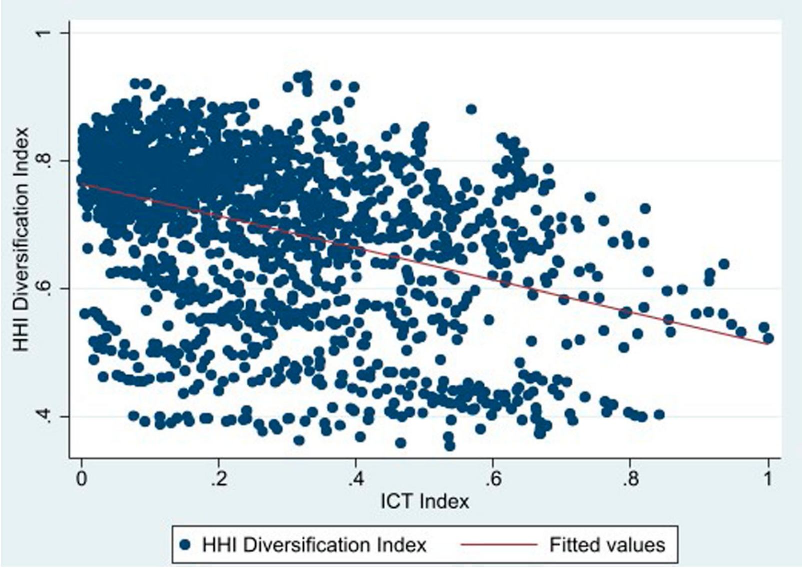

Figure 2. Scatterplot of export diversification index and ICT index.
Source: Authors.

the export diversification index. Our findings are consistent with recent studies on the main determinants of export diversification. For instance, Parteka and Tamberi (2011) also found a statistically significant negative relationship between the population and the degree of export specialization. Jetter and Ramírez Hassan (2015); and Lectard and Rougier (2018) found that total natural resources rents positively affect export specialization in developing countries.

To check the robustness of the results obtained in the benchmark estimation, we incorporated the index for ICT in UNCTAD's Productive Capacities Index database into equation (1) instead of our ICT index. ICT assesses the availability and incorporation of communication systems among the population. This encompasses users of fixed-line and mobile phones, internet access, and server security (UNCTAD 2024). This index is constructed by the PCA method using fixed broadband subscriptions (per 100 people), fixed telephone subscriptions (per 100 people), individuals using the Internet (% of the population), mobile cellular subscriptions (per 100 people), and secure Internet servers (per 1 million people) indicators. Data for the first three measurements is derived from the ITU World Telecommunication/ICT Indicators Database. Data for the last indicator is obtained from Netcraft (netcraft.com) and World Bank (UNCTAD 2023). The ICT index in our sample ranges from 1 to 81.23, with a mean of 28.48. A higher value indicates a more developed ICT sector in the economy. As the structure of UNCTAD's ICT index is almost identical to ours, it provides a reliable basis for the robustness check.

We have used the same control variables as in the benchmark estimate to explain changes in the export concentration index. These include the one-year lagged export concentration index, GDP per capita, population, total natural resources rents, domestic credit to the private sector, and primary school enrollment. In addition to these, our

Table 9. One-step and two-step system GMM estimation results on the effect of ICT index on export diversification index.

Variables	(1) One-step system GMM estimation Diversification Index	(2) Two-step system GMM estimation Diversification Index
Lag of diversification index	0.7361***	0.7172***
	(0.0624)	(0.0645)
GDP per capita (thousand US dollars)	0.0003	0.0004
	(0.0003)	(0.0003)
Population (mln people)	−0.00004**	−0.00004**
	(0.00002)	(0.00002)
ICT Index	−0.0908***	−0.0968***
	(0.0259)	(0.0289)
Total natural resources rents	0.0006**	0.0007**
	(0.0003)	(0.0003)
Domestic credit to private sector	−0.0001	−0.0002
	(0.0001)	(0.0002)
School enrollment	0.00008	0.00001
	(0.00009)	(0.0001)
Constant	0.2277***	0.2403***
	(0.0528)	(0.0540)
Number of observations	1052	1052
Number of countries	100	100
Year fixed effects	Yes	Yes
Hansen *p*-value	0.347	0.347
AR(1) *p*-value	0.000	0.000
AR(2) *p*-value	0.105	0.114

***, **, and * Refer to statistical significance at the 1%, 5%, and 10% levels, respectively; the values in parentheses indicate the robust standard errors.
Source: Authors.

model incorporates trade (as a percentage of GDP), net FDI inflow (as a percentage of GDP), and access to electricity (as a percentage of population) as instrumental variables.

Table 10 presents the results of one- and two-step system GMM regression with UNCTAD's ICT index. In the two-step GMM estimation model, the coefficient of the ICT index is significantly negative at the 5% significance level. All other things being equal, an increase in the ICT index by one unit relates to a decrease in the export concentration index by 0.0011. As for the controlling variables, in the dynamic two-step GMM estimation model, the decrease in the export concentration index is associated with the increase in population and domestic credit to the private sector. The one-year lagged export concentration index coefficient is positive and statistically significant at the 1% level in both models. The total rent from natural resources also has a significant positive impact on the export concentration index. The obtained results demonstrate the robustness of the benchmark estimate outcomes.

We continued the robustness check by dividing the countries in the sample into two groups according to the World Bank country classification by income level and following the method of Ranjbar, Saboori, and Gholipour (2023). The group of high-income economies includes the countries with high- and upper-middle levels of GNI per capita. The group of low-income economies consists of countries with low- and lower-middle levels of GNI per capita. We estimated equation (1) for different groups of countries using the export product concentration index and export diversification index as dependent variables and the constructed ICT index as a key explanatory variable. The findings for the two income groups are presented in Table 11. The results show that the ICT

Table 10. One-step and two-step system GMM estimation results on the effect of UNCTAD's ICT index on export concentration index.

Variables	(1) One-step system GMM estimation Concentration index	(2) Two-step system GMM estimation Concentration index
Lag of concentration index	0.6653***	0.6710***
	(0.0940)	(0.0987)
GDP per capita (thousand US dollars)	0.0005	0.0002
	(0.0004)	(0.0004)
Population (mln people)	−0.00004**	−0.00003**
	(0.00001)	(0.00001)
ICT	−0.0012***	−0.0011**
	(0.0005)	(0.0004)
Total natural resources rents	0.0033***	0.0035***
	(0.0011)	(0.0013)
Domestic credit to private sector	−0.0002*	−0.0003*
	(0.0002)	(0.0002)
School enrollment, primary	−0.0004	−0.0004
	(0.0003)	(0.0003)
Constant	0.1941***	0.1936**
	(0.0550)	(0.0584)
Number of observations	1484	1484
Number of countries	106	106
Year fixed effects	Yes	Yes
Hansen *p*-value	0.187	0.187
AR(1) *p*-value	0.000	0.000
AR(2) *p*-value	0.198	0.223

***, **, and * Refer to statistical significance at the 1%, 5%, and 10% levels, respectively; the values in parentheses indicate the robust standard errors.
Source: Authors.

index negatively influences export concentration and diversification indexes in both income groups. The coefficients of the ICT index are higher for low-income countries, reflecting a more substantial magnitude of the ICT development's impact on accelerating export diversification in low- and lower-middle-income countries than in high- and upper-middle-income economies. These findings suggest that ICT development can play a significant role in promoting export diversification, particularly in low-income countries, thereby contributing to their economic development.

For further analysis, we employed the two-way fixed effects method as the alternative estimator for our model to check the reliability of the study's results. This model controls for both unit-fixed effects and time-fixed effects (Imai and Kim 2021). The model helps reduce estimates' bias by accounting for unobserved heterogeneity (Halder and Malikov 2020). It also focuses on changes within entities over time, which can provide more precise insights into causal relationships. The general form of a two-way fixed effects model can be expressed as follows:

$$Y_{it} = \alpha + \beta X_{it} + \mu_i + \lambda_t + \varepsilon_{it} \tag{6}$$

where: Y_{it} is the dependent variable for entity i at time t;

X_{it} represents the vector of independent variables;

μ_i captures the entity-specific effects;

λ_t captures the time-specific effects;

ε_{it} is the error term.

Table 11. Two-step system GMM estimation results on the effects of ICT index on export product concentration and export diversification indexes in high-income and low-income countries.

	(1) High-income countries		(2) Low-income countries	
Explanatory variables	Concentration index	Diversification index	Concentration index	Diversification index
ICT Index	−0.0204**	−0.0591**	−0.1550**	−0.1090**
	(0.0098)	(0.0257)	(0.0770)	(0.0514)
Control variables	Yes	Yes	Yes	Yes
Number of observations	644	554	584	522
Number of countries	45	50	51	50
Year fixed effects	Yes	Yes	Yes	Yes
Hansen p-value	0.293	0.312	0.147	0.444
AR(1) p-value	0.000	0.000	0.000	0.000
AR(2) p-value	0.254	0.117	0.971	0.092

***, **, and * Refer to statistical significance at the 1%, 5%, and 10% levels, respectively; the values in parentheses indicate the robust standard errors.
Source: Authors.

Table 12. Two-way fixed effects estimation results on the effect of ICT index on export diversification index.

Variables	(1) Two-way fixed effects estimation Diversification Index
Lag of diversification index	0.5802***
	(0.0328)
GDP per capita (thousand US dollars)	−0.0005
	(0.0006)
Population (mln people)	−0.00016***
	(0.00005)
ICT Index	−0.0393**
	(0.0165)
Total natural resources rents	−0.0003
	(0.0002)
Trade	−0.0001
	(0.0001)
Constant	0.3166***
	(0.0317)
Number of observations	1551
Number of countries	102
Year fixed effects	Yes
R-squared (within)	0.4332
R-squared (between)	0.9019
R-squared (overall)	0.8560
Rho	0.7265

***, **, and * Refer to statistical significance at the 1%, 5%, and 10% levels, respectively; the values in parentheses indicate the robust standard errors.
Source: Authors.

Using the two-way fixed effects model, we checked the inverse relationship between the export diversification and ICT indexes. GDP per capita, population, total natural resources rents, and trade to GDP ratio were included as control variables in the model. The option robust was used to obtain heteroskedasticity-robust standard errors. The estimation results presented in Table 12 reveal that the ICT index significantly negatively affects the export diversification index. All other things being equal, a one-unit increase in the ICT index is associated with a decrease in the export diversification index by

Table 13. Two-step system GMM estimation results on the interaction of UNCTAD's ICT index and school enrollment effect on export concentration index.

Variables	Two-step system GMM estimation Concentration index
Lag of concentration index	0.7128***
	(0.0540)
GDP per capita (thousand US dollars)	−0.00002
	(0.0002)
Population (mln people)	−0.00003***
	(0.00001)
ICT index	−0.0026***
	(0.0007)
Interaction of ICT and school enrollment	0.00002***
	(0.000006)
School enrollment, primary	−0.0008***
	(0.0002)
Total natural resources rents	0.0031***
	(0.0006)
Domestic credit to private sector	−0.0003***
	(0.00008)
Constant	0.2039***
	(0.0372)
Number of observations	1403
Number of countries	106
Year fixed effects	Yes
Hansen *p*-value	0.550
AR(1) *p*-value	0.000
AR(2) *p*-value	0.210

***, **, and * Refer to statistical significance at the 1%, 5%, and 10% levels, respectively; the values in parentheses indicate the robust standard errors.
Source: Authors.

0.0393. Among the controlling variables, population negatively affects the export diversification index. The lagged value of the dependent variable has a positive impact on the export diversification index. The signs and values of the obtained coefficients of the significant variables closely align with those acquired by the two-step GMM method, confirming the robustness of our findings.

To check the robustness of the ICT index and primary school enrollment interaction's effect on the export concentration index, we generated the new interaction term by multiplying UNCTAD's ICT index with the primary school enrollment rate. We have incorporated the same control variables as in the model with the constructed ICT index and school enrollment interaction. These include the one-year lagged export concentration index, GDP per capita, population, total natural resource rents, and domestic credit to the private sector. In addition, the model included trade (as a percentage of GDP), net FDI inflow (as a percentage of GDP), access to electricity (as a percentage of population), and index of democratization as instrumental variables.

Table 13 presents the two-step system GMM regression results with the interaction of UNCTAD's ICT index and primary school enrollment variable. The results are consistent with those demonstrated in Table 7. The ICT index and school enrollment rate have adverse effects on export concentration, while the interaction term significantly positively impacts the export concentration index. These findings imply that the ICT index's effect on export diversification depends on the level of human capital development. In

Table 14. Coefficients of significant variables in the equations of indexes of concentration and diversification of exports in the long term.

Export concentration index			Export diversification index		
Variable	Coefficient	*p*-value	Variable	Coefficient	*p*-value
ICT Index	−0.1638	0.006	ICT Index	−0.3424	0.000
Total natural resources rents	0.0102	0.000	Population	−0.00015	0.004
Domestic credit to private sector	−0.0012	0.001	Total natural resources rents	0.0025	0.007

Source: Authors.

the same way, the relationship between human capital and export diversification is influenced by the level of ICT development. Higher human capital development can enhance the potential benefits of ICT, leading to higher levels of export diversification.

Finally, the coefficients of the significant variables in the resulting equations in the long term are calculated. The results are presented in Table 14. In equations with the export concentration index as the dependent variable, all relevant regressors are significant at the 1% significance level. The coefficient of the ICT index in the long term is about 5 times higher than the coefficient in the short term. All other things being equal, an increase in the ICT index by one unit is associated with a decrease in the export concentration index by 0.1638, which is a noticeable effect in the long term. Similarly, the ICT index has a more pronounced effect on reducing the export diversification index in the long term. All other things being equal, an increase in the ICT index by one unit decreases the export diversification index by 0.3424 in the long term. Among the controlling variables, the export concentration and diversification indexes are more influenced by total natural resources rents. This result is accordant with the findings of Jetter and Ramírez Hassan (2015), where the authors found a significant negative impact of the share of natural resources in GDP on export diversification in the long run, using the instrumental variable BMA method. The coefficients of the remaining control variables do not differ significantly in various specifications of the equations.

7. Conclusions and policy implications

7.1. Concluding remarks

This study explored the dynamic relationship between ICT development and export diversification by analyzing panel data from 110 countries from 1995 to 2019; after estimating the results using the one- and two-step GMM models, the findings have some policy implications.

Firstly, the advancement of ICTs in developing countries has significantly contributed to the diversification of exports and brought their structure closer to the global structure. The results are reliable since the study used both the constructed ICT index and UNCTAD's ICT index, and similar positive effects of ICT development on export diversification were obtained. This paper's results are consistent with Dahmani, Mabrouki, and Ben Youssef (2022) study, which confirms that ICT has positively affected value-added and increased economic growth in Tunisia.

Secondly, the level of human capital development influences the relationship between ICT and export concentration. Similarly, the level of ICT development influences the relationship between human capital and export diversification. Studies reveal that the development of ICT infrastructure positively affects human capital, which increases and enables school attendance, improves educational outcomes, and increases labor productivity (Batalla-Busquets and Myrthianos 2015; Fernández-Gutiérrez, Gimenez, and Calero 2020; Oluwatobi, Olurinola, and Taiwo 2016). Cadot et al. (2011b) emphasize the importance of human capital for export diversification. This paper investigated this factor by incorporating the interaction term of the ICT index and primary school enrollment in the estimation. The results indicate that interaction term positively and significantly influences developing countries' export concentration, implying that at high levels of human capital, increased ICT contributes to a more diverse export portfolio. Therefore, investments in both ICT and human capital are essential for accelerating export diversification. Overall, ICT development enhances human capital, which leads to a more skilled, knowledgeable, and adaptable workforce. This empowers developing countries to enter new export markets, develop higher-value products, and compete effectively globally, which leads to more sustainable and diversified export growth.

Lastly, the results suggest that the volume of domestic credit to the private sector (as a % of GDP) reduces the degree of export concentration in developing countries. In contrast, an increase in the value of total rents from natural resources leads to a rise in the export concentration of developing countries.

7.2. Policy implications

Recently, developing countries have taken necessary steps toward export diversification to increase and stabilize export earnings and ensure economic growth in the long run (Agosin 2008). Since this paper's results suggest that ICT positively impacts export diversification, several recommendations can be made. First, governments of developing economies should ensure adequate provision of ICT quantity and quality by investing in ICT infrastructure and improving access to internet and telecommunication services for individuals. Second, policymakers should promote digitalization and the comprehensive application of ICTs in different sectors of the economy. To boost international trade, governments should actively adopt digital technologies in customs body activities to increase their effectiveness and transparency. Third, firms in developing countries should be supported in building an online presence to participate in e-commerce, connect with customers, and optimize supply chains. Last, governments of developing countries should promote greater literacy rates in terms of ICT instrument utilization and human capital development to enhance export diversification.

Developing countries must prioritize strategic investments in infrastructure, digital literacy programs, and policies encouraging digitalization to take advantage of ICT's full potential for export diversification and sustainable growth. This targeted approach will empower nations to navigate the unique challenges and maximize the opportunities digital transformation presents.

7.3. Future recommendations

While there are some research limitations and gaps, this study can contribute significantly to the literature examining the relationship between ICT and export diversification. Some recommendations to further enhance this research include conducting an in-depth analysis of the other channels through which ICT expansion influences export diversification in developing nations and how they can adopt various strategies for boosting export diversification to ensure economic growth. Also, it is recommended that indicators reflecting the quality of ICT services and infrastructure be included in the model to assess their impact on developing countries' export diversification.

Disclosure statement

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References

Abeliansky, A. L., and M. Hilbert. 2017. "Digital Technology and International Trade: Is it the Quantity of Subscriptions or the Quality of Data Speed That Matters?" *Telecommunications Policy* 41 (1): 35–48. https://doi.org/10.1016/j.telpol.2016.11.001.

Agosin, M. R. 2008. *Export Diversification and Growth in Emerging Economies*. Santiago, Chile: Cepal Review. https://repositorio.cepal.org/handle/11362/11322.

Agosin, M. R., R. Alvarez, and C. Bravo-Ortega. 2012. "Determinants of Export Diversification Around the World: 1962–2000." *The World Economy* 35 (3): 295–315. https://doi.org/10.1111/j.1467-9701.2011.01395.x.

Al-Marhubi, F. 2000. "Export Diversification and Growth: An Empirical Investigation." *Applied Economics Letters* 7 (9): 559–562. https://doi.org/10.1080/13504850050059005.

Ali, M. 2017. "Determinants of Related and Unrelated Export Diversification." *Economies* 5 (4): 50. https://doi.org/10.3390/economies5040050.

Ali, M. S. B. 2020. "Does ICT Promote Democracy Similarily in Developed and Developing Countries? A Linear and Nonlinear Panel Threshold Framework." *Telematics and Informatics* 50:101382. https://doi.org/10.1016/j.tele.2020.101382.

Arellano, M., and S. Bond. 1991. "Some Tests of Specification for Panel Data: Monte Carlo Evidence and an Application to Employment Equations." *The Review of Economic Studies* 58 (2): 277–297. https://doi.org/10.2307/2297968.

Arellano, M., and O. Bover. 1995. "Another Look at the Instrumental Variable Estimation of Error-Components Models." *Journal of Econometrics* 68 (1): 29–51. https://doi.org/10.1016/0304-4076(94)01642-D.

Bahmani-Oskooee, M., and R. Jamilov. 2014. "Export Diversification and the S-Curve Effect in a Resource-Rich State: Evidence from Azerbaijan." *Economic Change and Restructuring* 47 (2): 135–154. https://doi.org/10.1007/s10644-013-9145-8.

Batalla-Busquets, J. M., and V. Myrthianos. 2015. "The Impact of Innovation and the use of ICTs on Human Capital Development in Spanish Industry." *Intangible Capital* 11 (2): 249–269. https://doi.org/10.3926/ic.423.

Beverelli, C., S. Neumueller, and R. Teh. 2015. "Export Diversification Effects of the WTO Trade Facilitation Agreement." *World Development* 76:293–310. https://doi.org/10.1016/j.worlddev.2015.07.009.

Bhattacherjee, A., and U. Shrivastava. 2018. "The Effects of ICT use and ICT Laws on Corruption: A General Deterrence Theory Perspective." *Government Information Quarterly* 35 (4): 703–712. https://doi.org/10.1016/j.giq.2018.07.006.

Billon, M., and E. Rodriguez-Crespo. 2020. "ICT use and Trade Facilitation: Impacts on Bilateral Trade of Sub-Saharan Countries." *Studies of Applied Economics* 38 (2): 1–12. https://doi.org/10.25115/eea.v38i2.3238.

Bleaney, M., and D. Greenaway. 2001. "The Impact of Terms of Trade and Real Exchange Rate Volatility on Investment and Growth in sub-Saharan Africa." *Journal of Development Economics* 65 (2): 491–500. https://doi.org/10.1016/S0304-3878(01)00147-X.

Blundell, R., and S. Bond. 1998. "Initial Conditions and Moment Restrictions in Dynamic Panel Data Models." *Journal of Econometrics* 87 (1): 115–143. https://doi.org/10.1016/S0304-4076(98)00009-8.

Borges, M., N. Hoppen, and F. B. Luce. 2009. "Information Technology Impact on Market Orientation in e-Business." *Journal of Business Research* 62 (9): 883–890. https://doi.org/10.1016/j.jbusres.2008.10.010.

Bresnahan, T. F., and M. Trajtenberg. 1995. "General Purpose Technologies 'Engines of Growth'?" *Journal of Econometrics* 65 (1): 83–108. https://doi.org/10.1016/0304-4076(94)01598-T.

Cadot, O., C. Carrère, and V. Strauss-Kahn. 2011a. "Export Diversification: What's Behind the Hump?" *Review of Economics and Statistics* 93 (2): 590–605. https://doi.org/10.1162/REST_a_00078.

Cadot, O., C. Carrère, and V. Strauss-Kahn. 2011b. “Trade Diversification: Drivers and Impacts. Trade and Employment: From Myths to Facts, 253–305.” https://www.ilo.org/wcmsp5/groups/public/@ed_emp/documents/publication/wcms_162297.pdf.

Cassetta, E., U. Monarca, I. Dileo, C. Di Berardino, and M. Pini. 2020. “The Relationship Between Digital Technologies and Internationalisation. Evidence from Italian SMEs.” *Industry and Innovation* 27 (4): 311–339. https://doi.org/10.1080/13662716.2019.1696182.

Chang, T., Y. Lyu, T. Chang, O. Ranjbar, and B. Saboori. 2024. “Diversifying the Export Basket of Creative Products and Accelerating Economic Growth.” *The Journal of International Trade & Economic Development*, 1–20. https://doi.org/10.1080/09638199.2024.2323047.

Choi, I. 2001. “Unit Root Tests for Panel Data.” *Journal of International Money and Finance* 20 (2): 249–272. https://doi.org/10.1016/S0261-5606(00)00048-6.

Comi, S. L., G. Argentin, M. Gui, F. Origo, and L. Pagani. 2017. “Is it the way They use it? Teachers, ICT and Student Achievement.” *Economics of Education Review* 56:24–39. https://doi.org/10.1016/j.econedurev.2016.11.007.

Dahmani, M., M. Mabrouki, and A. Ben Youssef. 2022. “ICT, Trade Openness and Economic Growth in Tunisia: What is Going Wrong?” *Economic Change and Restructuring* 55 (4): 2317–2336. https://doi.org/10.1007/s10644-022-09388-2.

Dennis, A. 2007. “The Impact of Regional Trade Agreements and Trade Facilitation in the Middle East and North Africa region.” World Bank Policy Research Working Paper No. 3837. World Bank.

Dennis, A., and B. Shepherd. 2011. “Trade Facilitation and Export Diversification.” *The World Economy* 34 (1): 101–122. https://doi.org/10.1111/j.1467-9701.2010.01303.x.

Dethine, B., M. Enjolras, and D. Monticolo. 2020. “Digitalization and SMEs’ Export Management: Impacts on Resources and Capabilities.” *Technology Innovation Management Review* 10 (4): 18–34. https://doi.org/10.22215/timreview/1344.

Fernández-Gutiérrez, M., G. Gimenez, and J. Calero. 2020. “Is the use of ICT in Education Leading to Higher Student Outcomes? Analysis from the Spanish Autonomous Communities.” *Computers & Education* 157:103969. https://doi.org/10.1016/j.compedu.2020.103969.

Giri, R., M. S. N. Quayyum, and R. Yin. 2019. *Understanding Export Diversification: Key Drivers and Policy Implications*. Washington, DC: International Monetary Fund.

Global Alliance for Trade Facilitation. 2022. *ITC, Faster Customs, Faster Trade: Using Technology for Trade Facilitation*. Paris: Global Alliance for Trade Facilitation. https://www.tradefacilitation.org/what-we-have-learned/itc-faster-customs-faster-trade-using-technology-trade-facilitation/.

Gnangnon, S. 2020. “Effect of the Internet on Services Export Diversification.” *Journal of Economic Integration* 35 (3): 519–558. https://doi.org/10.11130/jei.2020.35.3.519.

Gul, N., J. Iqbal, M. Nosheen, and M. E. Wohar. 2024. “Untapping the Role of Trade Facilitation Indicators, Logistics and Information Technology in Export Expansion and Diversification.” *The Journal of International Trade & Economic Development* 33 (3): 369–389. https://doi.org/10.1080/09638199.2023.2182606.

Halder, S. C., and E. Malikov. 2020. “Smoothed LSDV Estimation of Functional-Coefficient Panel Data Models with two-way Fixed Effects.” *Economics Letters* 192:109239. https://doi.org/10.1016/j.econlet.2020.109239.

Hansen, L. P. 1982. “Large Sample Properties of Generalized Method of Moments Estimators.” *Econometrica* 50 (4): 1029–1054. https://doi.org/10.2307/1912775.

Hausmann, R., and B. Klinger. 2006. “Structural Transformation and Patterns of Comparative Advantage in the Product Space.” Working Paper Series rwp06-041. Harvard University, John F. Kennedy School of Government, Cambridge, MA.

Herzer, D., and D. F. Nowak-Lehmann. 2006. “What Does Export Diversification do for Growth? An Econometric Analysis.” *Applied Economics* 38 (15): 1825–1838. https://doi.org/10.1080/00036840500426983.

Imai, K., and I. S. Kim. 2021. “On the Use of Two-way Fixed Effects Regression Models for Causal Inference with Panel Data.” *Political Analysis* 29 (3): 405–415. https://doi.org/10.1017/pan.2020.33.

Imbs, J., and R. Wacziarg. 2003. “Stages of Diversification.” *American Economic Review* 93 (1): 63–86. https://doi.org/10.1257/000282803321455160.

International Labour Organization. 1997. *Yearbook of Labour Statistics: Sources and Methods*. 56th ed. Vol. 8. Geneva: International Labour Office.

International Telecommunication Union. 2009. *Measuring the Information Society – The ICT Development Index*. Geneva: ITU. https://www.itu.int/en/ITU-D/Statistics/Documents/publications/mis2009/MIS2009_w5.pdf.

International Telecommunication Union. 2017. *The ICT Development Index (IDI): Conceptual Framework and Methodology*. Geneva: ITU. https://www.itu.int/en/ITU-D/Statistics/Pages/publications/mis2017/methodology.aspx.

Jackson, J. E. 2005. *A User's Guide to Principal Components*. Canada: Wiley.

Jetter, M., and A. Ramírez Hassan. 2015. "Want Export Diversification? Educate the Kids First." *Economic Inquiry* 53 (4): 1765–1782. https://doi.org/10.1111/ecin.12213.

Lectard, P., and E. Rougier. 2018. "Can Developing Countries Gain from Defying Comparative Advantage? Distance to Comparative Advantage, Export Diversification and Sophistication, and the Dynamics of Specialization." *World Development* 102:90–110. https://doi.org/10.1016/j.worlddev.2017.09.012.

Ma, S., Y. Shen, and F. Chao. 2024. "Can Data Flow Provisions Facilitate Trade in Goods and Services? Analysis based on the TAPED Database." *The Journal of International Trade & Economic Development* 33 (3): 343–368. https://doi.org/10.1080/09638199.2023.2179860.

Maddala, G. S., and S. Wu. 1999. "A Comparative Study of Unit Root Tests with Panel Data and a new Simple Test." *Oxford Bulletin of Economics and Statistics* 61 (S1): 631–652. https://doi.org/10.1111/1468-0084.0610s1631.

Mania, E., and A. Rieber. 2019. "Product Export Diversification and Sustainable Economic Growth in Developing Countries." *Structural Change and Economic Dynamics* 51:138–151. https://doi.org/10.1016/j.strueco.2019.08.006.

Mariani, M. M., and S. F. Wamba. 2020. "Exploring how Consumer Goods Companies Innovate in the Digital age: The Role of big Data Analytics Companies." *Journal of Business Research* 121:338–352. https://doi.org/10.1016/j.jbusres.2020.09.012.

Mathews, S., and M. Healy. 2008. "From Garage to Global': The Internet and International Market Growth, an SME Perspective." *International Journal of Internet Marketing and Advertising* 4 (2/3): 179–196. https://doi.org/10.1504/IJIMA.2008.017021.

Naudé, W., and R. Rossouw. 2011. "Export Diversification and Economic Performance: Evidence from Brazil, China, India and South Africa." *Economic Change and Restructuring* 44 (1–2): 99–134. https://doi.org/10.1007/s10644-010-9089-1.

Nham, N. T. H., and N. K. Q. Bao. 2023. "Nonlinear Effects of Digitalization on Export Activities: An Empirical Investigation in European Countries." *Technological and Economic Development of Economy* 29 (3): 1041–1079. https://doi.org/10.3846/tede.2023.17061.

Oluwatobi, S. O., I. O. Olurinola, and O. Taiwo. 2016. "Human Capital Development in sub-Saharan Africa: The Role of ICT." *Journal of Economic Studies and Research* 2016:d1–11.

Ouedraogo, R., and T. Mineyama. 2023. "Fostering Export Diversification in Niger. IMF eLibrary." https://www.elibrary.imf.org/view/journals/018/2023/010/article-A001-en.xml.

Oumbé, H. T., R. Djeunankan, and A. M. Ndzana. 2023. "Does Information and Communication Technologies Affect Economic Complexity?" *SN Business & Economics* 3 (4): 92. https://doi.org/10.1007/s43546-023-00467-8.

Pageorgiou, C., S. Jahan, G. Ho, K. Wang, L. Kolovich, C. Minoiu, … N. Spatafora. 2014. "Sustaining Long-run Growth and Macroeconomic Stability in Low Income Countries – The Role of Structural Transformation and Diversification." IMF. https://www.elibrary.imf.org/view/journals/007/2014/039/article-A001-en.xml.

Parteka, A., and M. Tamberi. 2011. "Export Diversification and Development – Empirical Assessment." *SSRN Electronic Journal*, 359: 1–38. https://doi.org/10.2139/ssrn.1890767.

Parteka, A., and M. Tamberi. 2013. "What Determines Export Diversification in the Development Process? Empirical Assessment." *The World Economy* 36 (6): 807–826. https://doi.org/10.1111/twec.12064.

Productive capacities index: 2nd generation. UNCTAD. 2023. https://unctad.org/publication/productive-capacities-index-2nd-generation.

Productive capacities index. UNCTAD. 2024. https://unctad.org/topic/least-developed-countries/productive-capacities-index.

Qiang, C. Z. W., G. R. Clarke, and N. Halewood. 2006. "The Role of ICT in Doing Business." *Global Trends and Policies* 57: 57–85.

Ranjbar, O., and F. Rassekh. 2022. “Does Economic Complexity Influence the Efficacy of Foreign Direct Investment? An Empirical Inquiry.” *The Journal of International Trade & Economic Development* 31 (6): 894–910. https://doi.org/10.1080/09638199.2022.2036792.
Ranjbar, O., B. Saboori, and H. F. Gholipour. 2023. “Does Tourism Development Spur Export Product Diversification?” *Current Issues in Tourism*, 1–15. https://doi.org/10.1080/13683500.2023.2284784.
Rao, P. M. 2001. “The ICT Revolution, Internationalization of Technological Activity, and the Emerging Economies: Implications for Global Marketing.” *International Business Review* 10 (5): 571–596. https://doi.org/10.1016/S0969-5931(01)00033-6.
Roodman, D. 2009. “How to do xtabond2: An Introduction to Difference and System GMM in Stata.” *The Stata Journal: Promoting Communications on Statistics and Stata* 9 (1): 86–136. https://doi.org/10.1177/1536867X0900900106.
Sachs, J. D., and A. M. Warner. 2001. “The Curse of Natural Resources.” *European Economic Review* 45 (4–6): 827–838. https://doi.org/10.1016/S0014-2921(01)00125-8.
Sekkat, K. 2016. “Exchange Rate Misalignment and Export Diversification in Developing Countries.” *The Quarterly Review of Economics and Finance* 59:1–14. https://doi.org/10.1016/j.qref.2015.08.001.
Shahiduzzaman, M., A. Layton, and K. Alam. 2015. “On the Contribution of Information and Communication Technology to Productivity Growth in Australia.” *Economic Change and Restructuring* 48 (3–4): 281–304. https://doi.org/10.1007/s10644-015-9171-9.
Shepherd, B. 2010. “Geographical Diversification of Developing Country Exports.” *World Development* 38 (9): 1217–1228. https://doi.org/10.1016/j.worlddev.2010.02.005.
Takpara, M. M., C. F. Djiogap, and B. Sawadogo. 2022. “Trade Facilitation and Export Diversification in Sub-Saharan Africa: Role of Hard and Soft Infrastructure.” *Research Square*. https://doi.org/10.21203/rs.3.rs-1967800/v1.
UNCTAD. 2018. “Trade and Development Report 2018.” https://unctad.org/system/files/official-document/tdr2018_en.pdf.
UNCTADSTAT. 2019. “Indicators Explained #1: Export Product Concentration Index.” https://unctadstat.unctad.org/EN/IndicatorsExplained/statie2019d1_en.pdf.
UNCTAD Stat. 2022. “UNCTADSTAT Data Centre.” https://unctadstat.unctad.org/datacentre/.
UN.ESCAP 2016. “The Role of ICT in Implementation of the WTO Trade Facilitation Agreement: Some Preliminary Reflections.” https://hdl.handle.net/20.500.12870/489.
United Nations Industrial Development Organization. 1997. *Industrial Statistics Database, 3-Digit Level of ISIC Code*. Vienna: United Nations Industrial Development Organization Press.
Vogel, T. 2022. “Structural and Policy Determinants of Export Diversification in Africa: A Bilateral Panel Approach using Bayesian Model Averaging.” UNCTAD. https://unctad.org/system/files/non-official-document/aldcafrica2022_background01_vogel_en.pdf.
World Bank. 2022. “World Development Indicators.” https://databank.worldbank.org/source/world-development-indicators.
Zaki, C. 2014. “An Empirical Assessment of the Trade Facilitation Initiative: Econometric Evidence and Global Economic Effects.” *World Trade Review* 13 (1): 103–130. https://doi.org/10.1017/S1474745613000256.
Zhang, L. X., M. T. Lai, T. Chang, O. Ranjbar, and B. Saboori. 2023. “Measuring the Export Diversification of Creative Products’ Basket and Identifying its Drivers: Cross-Country Evidence.” *Applied Economics Letters*, 1–5. https://doi.org/10.1080/13504851.2023.2219883.

Appendices

Appendix 1

The principal component analysis (PCA) is typically considered a data reduction statistical approach. It lessens the number of variables in an analysis by describing a set of uncorrelated linear combinations of the variables that interpret the majority of the variance. Aside from data reduction, the eigenvectors of a PCA are frequently examined to understand more about the underlying structure of the data. PCA is implemented in the case of substantial correlation among the original variables.

PCA aims to find components $z = [z_1, z_2, \dots, z_p]$ which are a linear combination $u = [u_1, u_2, \dots, u_p]'$ of the original variables $x = [x_1, x_2, \dots, x_p]$ that accomplish greatest variance. The first component, z_1, is given by a linear combination of original variables x and accounts for maximum possible variance. The second component that is not correlated with the first component captures information

Table A1. Pairwise correlations of the variables used for the construction of ICT index.

Variables	(1)	(2)	(3)	(4)
(1) fixed-broadband subscriptions	1.000			
(2) individuals using the Internet	0.818*	1.000		
(3) fixed-telephone subscriptions	0.614*	0.519*	1.000	
(4) mobile-cellular telephone subscriptions	0.593*	0.807*	0.356*	1.000

Note: The results of correlation analysis indicate relatively strong correlations between all variables (above 0.5) except the correlation between mobile-cellular telephone subscriptions and fixed-telephone subscriptions (0.356).
$*p < 0.1$.

Table A2. Principal components, eigenvalues, and proportion of variance explained.

Component	Eigenvalue	Difference	Proportion	Cumulative
Comp1	2.7134	2.0121	0.7099	0.7099
Comp2	0.7013	0.4242	0.1835	0.8934
Comp3	0.2771	0.1466	0.0725	0.9659
Comp4	0.1305		0.0341	1.0000

Note: The first component has an eigenvalue above one and explains 72% variation.

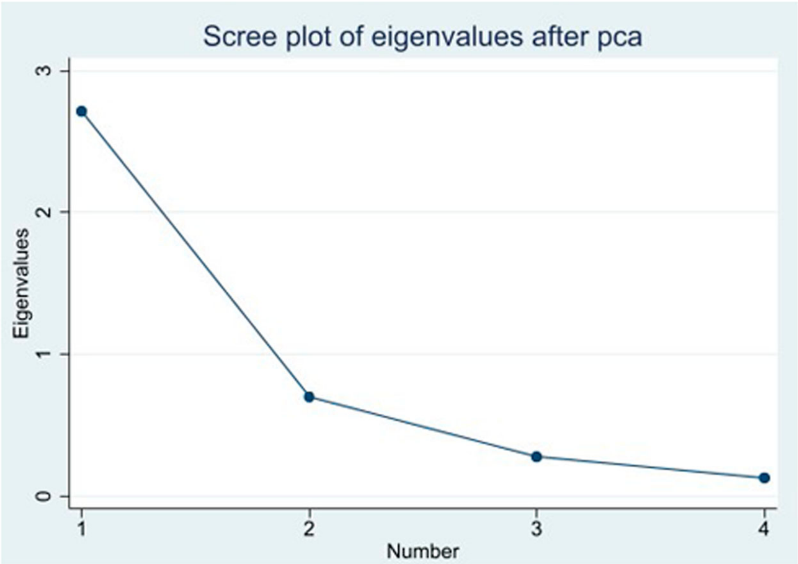

Figure A3. Scree plot of eigenvalues after PCA. The first component has an eigenvalue above one, i.e. this component explains at least as much of the variation as the original variables.

not captured by the first component. The last principal component has the smallest variance among all unit-length linear combinations of the variables. PCA maximizes the variance of elements of $z = xy$, such that $u'u = 1$.

In the equation $(R - \lambda \mathrm{I})*u = 0$, R is the sample correlation matrix of the original variables x, λ is eigenvalue (variances of associated components z), and u is eigenvector. Factor loadings are the correlations between the original variables x and the components z, represented as $F = \mathrm{cor}\,(x, z) = u\mathrm{D}^{1/2}$. The Kaiser–Meyer–Olkin (KMO) measure of sampling adequacy assigns values between 0 and 1, with small values suggesting that the variables have little in common to support a PCA and values above 0.5 indicating that the variables have enough in common to warrant a PCA.

Table A3. Component loadings.

	Comp1
Fixed-broadband subscriptions	0.5395
Individuals using the Internet	0.5747
Fixed-telephone subscriptions	0.4298
Mobile-cellular telephone subscriptions	0.4404

Note: The first component loadings (correlation between original variables and the components) are above 0.3.

Table A4. Principal components (eigenvectors).

	Comp1	Unexplained variation
Fixed-broadband subscriptions	0.5395	0.1591
Individuals using the Internet	0.5747	0.1318
Fixed-telephone subscriptions	0.4298	0.5021
Mobile-cellular telephone subscriptions	0.4404	0.3159

Note: The unexplained variation of fixed-telephone subscriptions and mobile-cellular telephone subscriptions is 0.50 and 0.31, respectively.

Table A5. Kaiser-Meyer-Olkin (KMO) measure of sampling adequacy.

Variable	KMO
Fixed-broadband subscriptions	0.7093
Individuals using the Internet	0.6516
Fixed-telephone subscriptions	0.8007
Mobile-cellular telephone subscriptions	0.6897
Overall	0.6974

Note: The values of KMO are more than 0.5, which is considered satisfactory for a principal component analysis.

Appendix 2

Table B1. List of countries in the sample.

1. Albania	56. Liberia
2. Algeria	57. Madagascar
3. Angola	58. Malaysia
4. Azerbaijan	59. Maldives
5. Argentina	60. Mali
6. Bahrain	61. Mauritania
7. Bangladesh	62. Mauritius
8. Armenia	63. Mexico
9. Barbados	64. Mongolia
10. Bhutan	65. Moldova (the Republic of)
11. Bolivia (Plurinational State of)	66. Morocco
12. Botswana	67. Mozambique
13. Brazil	68. Oman
14. Bulgaria	69. Namibia
15. Myanmar	70. Nepal
16. Burundi	71. Nicaragua
17. Belarus	72. Niger (the)
18. Cambodia	73. Nigeria
19. Cameroon	74. Pakistan
20. Central African Republic (the)	75. Panama
21. Sri Lanka	76. Paraguay
22. Chad	77. Peru
23. Chile	78. Philippines (the)
24. China	79. Poland
25. Colombia	80. Guinea-Bissau
26. Congo (the)	81. Qatar
27. Congo (the Democratic Republic of the)	82. Romania
28. Costa Rica	83. Russian Federation (the)
29. Benin	84. Rwanda
30. Dominican Republic (the)	85. Saudi Arabia
31. Ecuador	86. Senegal
32. El Salvador	87. Sierra Leone
33. Ethiopia	88. Viet Nam
34. Fiji	89. South Africa
35. Gabon	90. Suriname
36. Georgia	91. Eswatini
37. Gambia (the)	92. Syrian Arab Republic (the)
38. Ghana	93. Tajikistan
39. Guatemala	94. Thailand
40. Guinea	95. Togo
41. Guyana	96. Trinidad and Tobago
42. Honduras	97. United Arab Emirates (the)
43. Hungary	98. Tunisia
44. India	99. Turkey
45. Indonesia	100. Uganda
46. Iran (Islamic Republic of)	101. Ukraine
47. Iraq	102. North Macedonia
48. Côte d'Ivoire	103. Egypt
49. Jamaica	104. Tanzania, the United Republic of
50. Kazakhstan	105. Burkina Faso
51. Jordan	106. Uruguay
52. Kenya	107. Uzbekistan
53. Kyrgyzstan	108. Venezuela (Bolivarian Republic of)
54. Lao People's Democratic Republic (the)	109. Yemen
55. Lesotho	110. Zambia