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EXPORT COMPETITIVENESS AND TECHNOLOGICAL GAPS: AN EVOLUTIONARY ANALYSIS OF MARKET SHARE DYNAMICS, 1995–2021

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ABSTRACT

Over the past 25 years, a series of economic changes have led to the rise and consolidation of new East Asian countries in global technological development. This study aims to examine the extent to which narrowing the technological gap between countries can explain gains in export competitiveness. To achieve this, a series of dynamic models were employed to analyze the path dependence of export shares in the international market, carefully accounting for technological differences across sectors using a classification derived from Pavitt (1984). The technological gap was measured through patent registration data, foreign direct investment (FDI) stock, productive capacity, and a range of UNCTAD data related to the technological frontier, covering up to 164 countries between 1995 and 2021. The findings indicate that market share in low-tech sectors cannot be meaningfully explained by variables related to the technological gap. In contrast, reductions in the technological gap – specifically in patents and improvements in workforce skills – are positively associated with increased market share in total exports and technology-intensive sectors.

Keywords: export, competitiveness and technological *gap*.
Classificação JEL: F14 L60 O14

Introduction

In the neo-Schumpeterian evolutionary theory firms are the central drivers of innovation and technological development (DOSI, 1988; AMSDEN, 2001). This view of innovation as a continuous process is linked to its cumulative nature, which becomes evident at the national level and creates a technological gap between countries – comparable to Adam Smith's concept of absolute advantage (DOSI et al., 1990). Another implication of understanding technological development as a process is its self-perpetuating nature, meaning there is no inherent tendency for it to diminish (FREEMAN, 1974). Recent empirical studies also suggest that commodity specialization is not associated with technological development, productivity growth, or structural change (NUVOLARI and RUSSO, 2019; UNCTAD, 2021b).

Recent advancements in empirical research have benefited from new, more granular data across a broader range of countries. However, there remains a shortage of studies examining the relationship between the technological gap and market share in international trade. Much of this challenge stems from the complex and multidimensional nature of technology, which limits the variables that can serve as a common denominator for explaining development. A critical issue in this area of research is endogeneity, which frequently affects measures derived from GDP, GDP *per capita*, or technology-intensive exports – key indicators used to explain income differences between countries.

This article seeks to explore the relationship between technological gap indicators and market share in technology-intensive exports. Specifically, it investigates whether narrowing the technological gap affects market share in technology-intensive exports. If the factors influencing

export market share vary by technological intensity, industrial policies can be more effectively tailored to target specific dimensions of the technological gap and identify sectors most responsive to these changes.

Market share is estimated using trade flow data, categorized by technological intensity and grounded in the neo-Schumpeterian evolutionary framework initially proposed by Pavitt (1984). To quantify the technological gap, the analysis uses data on patents, foreign direct investment stock, capital stock, and information from a UNCTAD (2021a) database, which provides disaggregated technological data for 164 countries. The underlying hypothesis is that reducing the technological gap enhances export competitiveness and, in turn, market share – but primarily within the most technology-intensive sectors.

Beyond this introduction, the article is structured into four main sections. The first section provides a concise literature review discussing the determinants and implications of technological gaps for economic development. The second section details the data sources and methodological framework employed in the analysis. The third section presents the computation of export competitiveness, highlighting the importance of incorporating technological intensity, given the relevance of sectoral analysis for understanding international trade dynamics over the period 1995-2021. This section also classifies countries to elucidate distinct export patterns. The fourth section develops dynamic models to examine the relationship between market share and indicators of technological gaps. Finally, the concluding section synthesizes the main findings and outlines potential avenues for future research.

1 – Review of theoretical and empirical literature on technology gaps and economic development

In the Neo-Schumpeterian evolutionary framework, firms play a central role in driving technological development, with significant implications for prices and profits that diverge from the traditional profit-maximization assumption. This section provides a concise overview of the theoretical and empirical literature, focusing on the Neo-Schumpeterian perspective while also considering alternative approaches with similar outcomes despite differing theoretical foundations.

Dosi (1988) argues that successful innovation allows firms to lower prices, enhancing their competitiveness and reshaping industry dynamics. Firms that fail to innovate or offer alternatives risk being driven out of the market. Amsden (2001) emphasizes that the manufacturing sector is not just a repository of knowledge but a critical driver of national economic success. Historical accumulation and institutional evolution are essential for countries to compete with established powers. An example is Toyota's sale of a loom patent to a British company before World War II, illustrating how firm size and structure support industrial diversification and economic growth.

Dosi et al. (1990) extend this argument by suggesting that the unique characteristics of countries, sectors, and firms drive patterns of trade convergence or divergence. These technological differences resemble Adam Smith's concept of absolute advantage. Countries that specialize in sectors with allocative efficiency, technological dynamism, and rising global demand experience virtuous growth cycles. The authors argue that a country's position relative to the technological frontier shapes its long-term innovation potential, making static resource allocation a poor predictor of future innovation opportunities.

Fagerberg (1987) provides evidence that countries like Japan, South Korea, and Finland achieved rapid development through fast-paced imitation, innovation, and economic growth. Freeman and Soete (1997) highlight that while technology gap and product cycle models acknowledge innovation's monopoly power, they fail to fully capture the innovation process. They note that, according to the Neo-Schumpeterian model, innovation occurs at the firm level but does not always lead to technological or income convergence due to barriers in technology diffusion.

Cimoli (2014) analyzes technological convergence and divergence through the Neo-Schumpeterian lens, emphasizing the interaction between macroeconomic systems, national innovation capabilities, and economic performance. He argues that productivity-enhancing policies can create a virtuous cycle of improved exports and productivity growth, but these mechanisms

must align with global consumption patterns. Even advanced economies may face weak growth if firms prioritize macroeconomic volatility over long-term innovation and technology diffusion.

Empirical studies support these theoretical perspectives. Fagerberg (2000) identifies a shift after 1973 with the emergence of information and telecommunications technology, where productivity gains increasingly occurred within sectors rather than through labor shifts between sectors. He also finds that market power differs across industries, contradicting the neoclassical trade model. Countries that expanded their share in technologically advanced sectors – like electrical machinery – saw the highest productivity gains, exemplified by South Korea, Taiwan, Singapore, and Japan. Fagerberg, Srholec and Knell (2007) demonstrated the relevance of technology, capacity, and demand competitiveness for growth and development.

Dosi et al. (2022) empirically validate the hypothesis that growth depends on allocative, technological, and demand efficiency. Their findings show that trade specialization in areas of comparative advantage reduces growth resilience, while focusing on products with high demand elasticity and dynamic technological production fosters longer growth periods.

These findings align with Fajnzyber's (1990) thesis that Latin America's failure to *open the black box* of technical progress is the main reason for its stagnant growth and income inequality. He advocates for an import-substitution strategy focused on high-technology sectors to overcome underdevelopment.

Ocampo and Parra (2006) describe the period from 1980 to 2005 as "dual divergence," marked by frequent growth collapses and fewer successful development cases. They argue that advanced economies thrive in high-tech manufacturing, while successful developing countries rely on resource-intensive sectors. Growth in East Asian economies, such as China and South Korea, was largely driven by shifting exports from labor-intensive to technology-intensive products.

Kohn and Tretvoll (2018) highlight how emerging economies became vulnerable to terms-of-trade shocks after China's WTO accession in 2001. While benefiting from commodity export surpluses, these economies faced increased business cycle volatility, experiencing rapid growth during commodity *booms* and stagnation during downturns.

Nuvolari and Russo (2019) stress that productivity gains occur in sectors aligned with a country's technological stage. While knowledge-intensive activities boost productivity in all economies, rapid convergence can also result from substantial productivity gains in mass-production sectors, as seen in China.

Aghion et al. (2021) challenge the notion of a trade-off between income inequality and sustainable growth. They argue that economic dynamism – characterized by sophisticated industrial exports, innovation, and competitive markets – can achieve both high growth and low inequality. They advocate for industrial policies promoting innovation and technological diffusion while encouraging market reforms to prevent corporate capture of government support.

UNCTAD (2021b) conducted an econometric study of 206 countries between 1995 and 2008, finding that commodity specialization restricts opportunities for diversification and technological advancement. They recommend active government policies to strengthen industrial capabilities, support technological development, and promote innovation. Counter-cyclical fiscal policies can help reallocate resources from the commodity sector to other industries during commodity *booms*.

Recent studies on Brazil underscore the impact of a commodity-focused export structure on economic growth. Lélis et al. (2019) estimate that one-third of Brazil's post-2014 economic contraction was due to falling commodity prices. Magacho and Rocha (2022) attribute 34% of Brazil's GDP decline after 2013 to reduced commodity prices, with further impacts from lower infrastructure investment and household consumption. They suggest revitalizing domestic demand through infrastructure investment.

Neo-Schumpeterian and structuralist approaches agree that specializing in low-tech sectors weakens economic dynamism. While a large domestic market may sustain technology-intensive firms under protectionist policies, sustained economic growth requires dynamic domestic firms that

expand market share abroad, particularly in high-quality-demanding markets. Exporting low-tech, price-sensitive commodities is not a viable long-term development strategy.

2 – Data sources and methodological choices

The data used in the empirical analyses in the following sections include foreign trade statistics, patent applications, GDP per capita, and various technological indicators used to calculate the technology gap. Further details are available in Table A.1 in the Appendix.

Trade flow data came from UN COMTRADE, obtained via BACI/CEPII. Gaulier and Zignago (2010) describe the adjustments made to the raw data, which result in some differences from the original source. First, the authors evaluate the reliability of the trade flow data reported by each country. In cases where reliability is low, they apply the *mirror data* approach – using import data from trade partners to estimate the export flows of the reporting country. This method accounts for the difference in value, because import data are reported on a CIF basis (cost, insurance, and freight), while export data are reported on a FOB basis (free on board), which excludes transportation costs.

To facilitate the analysis, we aggregated the original HS6-level data according to Pavitt's (1984) taxonomy. Its original version classifies the agricultural sector as supplier-dominated. In contrast, in this study, we categorize sectors outside the manufacturing industry (such as agriculture, livestock, and extractive industries) as primary sectors. The food processing industry, however, remains classified as supplier-dominated.

One limitation of this study is the lack of trade flow data based on value added. As Marcatto, Baltar, and Sarti (2019) point out, the main advantage of using value-added data is that it avoids double counting in trade flows (such as imports used to produce exported goods), allowing for a clearer understanding of each country's specialization pattern. However, value-added measures also have their limitations, including limited detail for more granular analyses, reliance on certain assumptions, and significant time lags in data availability.

Regarding the independent variable, several important considerations must be taken into account. The technological gap is closely linked to GDP *per capita*, which is often used as a proxy in the literature[1]. However, this study does not use income *per capita* differences for two primary reasons: first, GDP reflects total income, regardless of the underlying technology. For instance, in oil-exporting countries, *per capita* income is highly sensitive to commodity price fluctuations, which may not correspond to actual technological progress in the short term. Second, endogeneity is also a concern because exports are a component of GDP, requiring specific adjustments if this measure were used. This endogeneity also complicates the measurement of the technological gap through the difference in technology-intensive exports relative to the leading country.

A common methodological approach is to use a specific benchmark country, typically the United States, as the technological frontier. However, this assumption can be problematic since any country can surpass others technologically over time or in specific fields. To mitigate this, the study tests four different measures of the technological gap, each calculated relative to the leading country in a given domain. For the leading country itself, the technological gap is measured against the second most advanced nation under each criterion[2].

The first variable tested is the technological gap, measured by the number of patents registered by each country[3]. Figure 1 illustrates a positive relationship between the total patent gap

[1] For example, as Magacho (2015), based in turn on Hausmann et al. (2007).

[2] This point also has implications for the econometric model. When a country is used as the benchmark the technology gap measure will remain constant at one for the technological leader. This could affect the evaluation of how changes in the leader's market share are assessed.

[3] The details of this and other data used are presented in Table A.2 in the Appendix. The World Bank provides not only the aggregate series of total patents registered in the country but also disaggregated data, distinguishing between patents filed by resident and non-resident companies. Using patents filed by residents may offer a more accurate measure of the country's technological development, even accounting for filings by subsidiaries of multinational corporations. This approach could be more reflective of domestic innovation than total patent filings, which may be influenced by the

and the share of R&D expenditure in GDP. China became the world leader in total patent registrations in 2011, surpassing Japan, following a consistent increase in R&D spending as a percentage of GDP – rising from 0.5% in 1995 to 2.5% in 2021. Another significant trend in China's economy was the increase in the share of patents filed by domestic residents, which grew from 54% to 90% over the same period.

Figure 1 - Patent Gap and R&D Share in GDP

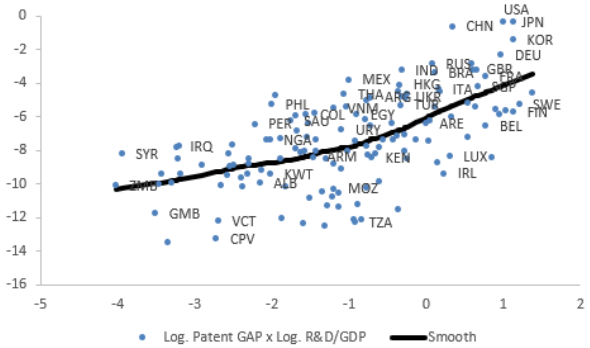
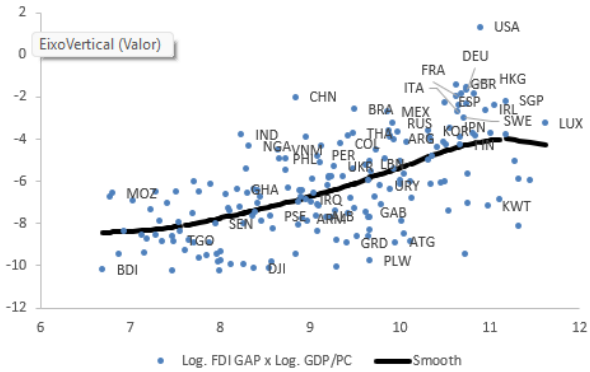


Figure 2 - Foreign Direct Investment Stock Gap and GDP *per capita*



Prepared by the authors, on the basis of data from WORLD BANK (2024) and UNCTAD (2024a).

Three additional variables are also tested: foreign direct investment (FDI) stock gaps, productive capacity indicators, and technological frontier indicators, both sourced from UNCTAD. Figure 2 reveals that the FDI stock gap narrows as GDP *per capita* increases, although there is a maximum point beyond which the relationship between these variables ceases to be positive. Between 1995 and 2021, the United States maintained its position as the leading country in FDI stock and is projected to retain this dominance due to a substantial lead over other nations, including China, which became the second-largest in 2021.

Figure 3 displays the productive capacity indicator, available for the period 2000 to 2022. This indicator assesses productive capacity across multiple dimensions: human capital, natural capital, energy, transportation, information and communication technology (ICT), institutions, the private sector, and structural transformation. Throughout the observed period, Australia and Denmark alternated as the leading countries in the aggregate productive capacity indicator.

Figure 3 - Production Capacity Gap and GDP *per capita*

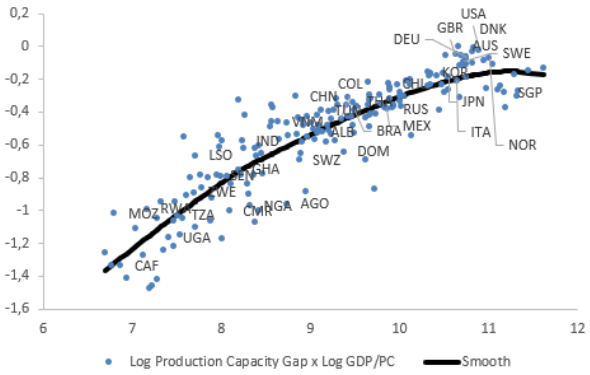
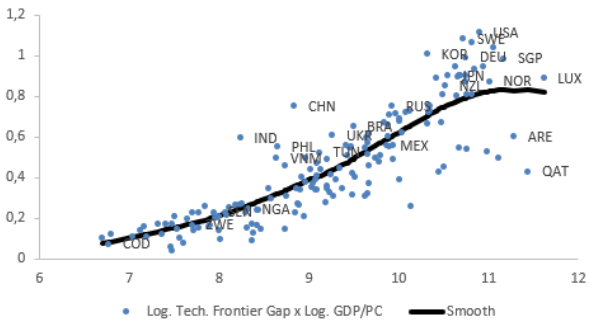


Figure 4 - Technological Frontier Gap and GDP *per capita*



Prepared by the authors, on the basis of data from WORLD BANK (2024) and UNCTAD (2024b; 2024c).

The technological frontier indicator is available only for the period between 2008 and 2021. According to UNCTAD (2021a) and UNCTAD (2023), this indicator is based on five key criteria:

commercial interests of foreign companies. Both total patent registrations and those filed exclusively by residents will be tested.

information and communication technology (ICT) infrastructure, human skills, research and development (R&D) activity, industrial activity, and access to financing. Each criterion is scored on a scale from zero to one with decimal increments, resulting in the data distribution shown in Figure 4. Although this indicator differs from the others, it also shows a positive correlation with GDP *per capita*. In 2020 and 2021, Singapore, Sweden, and the United States led the rankings for the aggregate technological frontier indicator.

3 – Market share and export competitiveness

This section provides a concise overview of the evolution of the "Constant-Market-Share" (CMS) methodology for measuring export competitiveness and presents the results for the period between 1995 and 2021. The core idea behind this method (also known as first-level analysis) is to assess a country's competitiveness by examining changes in its market share. An increase in market share reflects export growth that outpaces the average growth of imports in a given destination.

Table 1 presents export data for the world's leading exporters. The most striking development during this time was China's rapid ascent to become the world's leading exporter in 2005. China more than tripled its market share, reaching 15.9% in 2021 – greater than the combined share of the United States and Germany. Notably, China's 12-percentage-point increase in market share matched the combined loss experienced by the three leading exporters in 1995: the United States, Germany, and Japan.

Table 1 – Top global export countries and their respective market shares

Country	Exports (US$ bi.)		Rank		CAGR (%)	Market Share (%)			Cluster
	1995	2021	1995	2021		1995	2021	Change	
China	193.6	3,362.2	7º	1º	11.6	3.9	15.9	12.0	4
Unites States	589.2	1,660.6	1º	2º	4.1	11.8	7.8	-3.9	5
Germany	498.4	1,571.5	2º	3º	4.5	10.0	7.4	-2.5	5
Japan	448.8	756.1	3º	4º	2.0	9.0	3.6	-5.4	5
South Korea	128.0	659.1	11º	5º	6.5	2.6	3.1	0.6	2
Netherlands	176.7	620.6	9º	6º	4.9	3.5	2.9	-0.6	5
Italy	231.6	601.9	6º	7º	3.7	4.6	2.8	-1.8	5
France	277.3	581.2	4º	8º	2.9	5.5	2.7	-2.8	5
Mexico	82.1	505.7	16º	9º	7.2	1.6	2.4	0.7	2
Canada	188.0	485.5	8º	10º	3.7	3.8	2.3	-1.5	3
Others	2,087	9,619			6.1	41.7	45.4	3.7	
Total	5,004	21,199			5.7	100	100	0.0	

Prepared by the authors, on the basis of data from CEPII (2023).

Table 1 also presents a grouping of countries based on their market share data in 2021 and the changes between 1995 and 2021, categorized by Pavitt's (1984) taxonomy, discussed in the previous section. It also includes each country's *per capita* GDP for 2021 and its variation over the same period. Cluster analysis, an exploratory data technique, was used to group countries according to their similarities, measured by the distance between them. The Two-Step clustering method was applied, with five clusters discretionarily defined[4].

Table 2 provides key statistics for each cluster. China stands out as a separate group due to its exceptional performance, far surpassing other countries. The country recorded significant gains in market share in the manufacturing sector, increasing by +18.5 percentage points in specialized supplier industries and +19 percentage points in science-intensive industries. Countries that lost market share in science-intensive sectors are grouped in Cluster 5. In addition to the six countries

[4] In the two-step method, a pre-clustering is first performed — a preliminary grouping of the data using a non-hierarchical approach, such as the K-means method, for example. Subsequently, a hierarchical analysis is applied. The distance measure utilized was log-likehood. About cluster methodology see Everitt et al. (2001).

listed in Table 1, this cluster also includes Belgium and the United Kingdom, as shown in Figure A.1 in the Appendix.

Table 2 – Summary of country grouping by technological intensity (Means)

Cluster (# Countries)	GDP PPP *per capita*[1]		Share Primary Product		Share Supplier-Dominated		Share Scale-intensive		Share Specialized-suppliers		Share Science-based	
	2021	Median CAGR 95-21	2021	Chg.[2]	2021	Chg.[2]	2021	Chg.[2]	2021	Chg.[2]	2021	Chg.[2]
1 (108)	9,472	1.7	0.2	0.0	0.1	0.0	0.1	0.0	0.0	0.0	0.0	0.0
2 (43)	42,830	2.1	0.4	-0.1	0.8	0.0	0.8	0.3	0.7	0.2	0.8	0.1
3 (8)	41,514	1.1	5.4	2.0	0.9	0.1	1.5	-0.1	0.5	-0.1	0.5	0.0
4 (1)	17,658	8.0	1.2	-0.9	21.8	12.3	8.9	7.2	21.1	18.5	21.9	19.0
5 (8)	50,081	1.2	2.0	-1.2	3.3	-1.8	4.3	-2.7	5.2	-3.2	4.0	-3.4

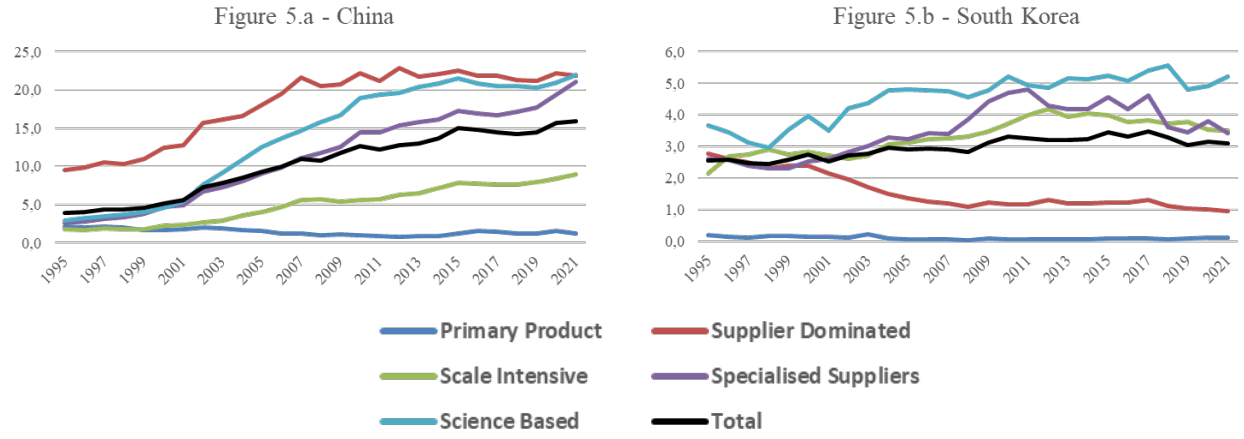
Prepared by the authors, on the basis of data from CEPII (2023) and WORLD BANK (2024). Notes: (1) in 2017 values; (2) Average change in percentage points between 1995 and 2021.

Cluster 3 includes countries with a significant share of primary product exports that, on average, gained market share between 1995 and 2021. However, this diverse group – which includes Canada, Russia, Brazil, Australia, the United Arab Emirates, Saudi Arabia, Norway, and Iraq – also experienced relatively slower growth in *per capita* GDP.

Clusters 1 and 2 are the largest and most heterogeneous. Cluster 1 comprises 108 countries with lower incomes and slower average growth compared to Cluster 2. Notable members of Cluster 1 include South Africa, Argentina, the Philippines, and Kazakhstan. Cluster 2 features countries characterized by higher average *per capita* GDP – partly due to the presence of small-population economies like Singapore, Ireland, Switzerland, Bermuda, and Hong Kong – a lower reliance on primary product exports, and a declining trend in these exports between 1995 and 2021. This cluster also includes countries such as India, Poland, South Korea, Mexico, Spain, and Vietnam.

Figure 5 illustrates the evolution of market share by Pavitt's (1984) taxonomy for selected countries that increased their share of global exports between 1995 and 2021, mainly in the science-based sectors. In Figure 5.a, China's market share grew rapidly across several sectors – including supplier-dominated, labor-intensive manufacturing, science-based industries, and specialized suppliers (such as machinery and equipment production) – particularly after its accession to the World Trade Organization (WTO) in 2001. Figure 5.b highlights South Korea's increasing specialization in technology-intensive sectors. Notably, its share of global science-based exports rose from 3.7% in 1995 to 5.2% in 2021.

Figure 5 – Export share in the world market by Pavitt taxonomy, in %



Prepared by the authors, on the basis of data from CEPII (2023)

The first-level analysis of market share changes, supported by cluster analysis, provides a clear understanding of the dynamics of global exports between 1995 and 2021. However, research on the "Constant-Market-Share" (CMS) method gained momentum following Tyszynski's (1951) proposal to calculate the commodity composition effect (second-level analysis). This approach aims to quantify the portion of competitiveness gains driven by increased demand in sectors where the exporting country holds a larger share.

A significant advancement came from Leamer and Stern (1970) introducing the concept of market distribution (third-level analysis). This method further breaks down competitiveness gains by evaluating whether a country's exports are concentrated in regions experiencing above-average growth. A positive effect indicates that the country's exports are focused on faster-growing markets. Richardson (1971) criticized this CMS methodology, emphasizing that the order in which the commodity composition and market distribution effects are calculated can influence the final results. Despite this, empirical studies generally follow Leamer and Stern's (1970) approach of calculating the commodity composition effect first, followed by the market distribution effect, while adjusting for the average growth of each sector in the destination markets.

The CMS methodology has been widely applied across various countries. Notable examples include Simonis (2000) for Belgium, Mahmood and Akhtar (1996) for Pakistan, Lohrmann (2000) for Turkey, and Memedovic and Lapadre (2009) for multiple countries. For Brazil, key studies include Batista and Azevedo (2002), Batista and Santos (2007) Batista (2008), Pinheiro and Bonelli (2007), and Lima et al. (2015). Fligenspan et al. (2015) applied the CMS analysis to Brazil's labor-intensive exports during the 2000s, comparing its performance with other countries. Their findings revealed a significant loss of global market share, primarily due to the increased competitiveness of East Asian products.

Fagerberg and Sollie (1987) proposed an alternative approach to measuring competitiveness, which decomposes the change in a country's market share (ΔM) at an aggregate level across regions (k):

$$\Delta M^k = \Delta M_m^k + \Delta M_c^k + \Delta M_{mc}^k \quad (1)$$

Therefore, changes in market share are attributed to three main factors: the competitiveness effect (2), the market composition effect (3), and the market adaptation effect (4):

$$\Delta M_m^k = \left(m_t^k - m_0^k\right)c_0 \quad (2)$$

$$\Delta M_c^k = m_0^k(c_t - c_0) \quad (3)$$

$$\Delta M_{mc}^k = \left(m_t^k - m_0^k\right)(c_t - c_0) \quad (4)$$

Where:

m represents the share of the country's exports in the global imports of region k.

c denotes the share of region k's imports in total world trade.

0 indicates the initial period, and t represents the final period.

Competitiveness (2), in turn, can be further decomposed according to the export composition within each region, *k*:

$$\Delta M_m^k = \Delta M_a^k + \Delta M_b^k + \Delta M_{ab}^k \quad (5)$$

In other words, the gain in competitiveness (2) can be divided into the market share effect (6), the product composition effect (7), and finally, the product adaptation effect (equation 8):

$$\Delta M_a^k = \left\{\sum_t \left(a_t^{k\prime} - a_0^{k\prime}\right)b_0'\right\}c_0' \quad (6)$$

$$\Delta M_b^k = \left\{\sum_t a_0^{k\prime}\left(b_t^{k\prime} - b_0^{k\prime}\right)\right\}c_0' \quad (7)$$

$$\Delta M_{ab}^k = \left\{\sum_t \left(a_t^{k\prime} - a_0^{k\prime}\right)\left(b_t^{k\prime} - b_0^{k\prime}\right)\right\}c_0' \quad (8)$$

Where:

a^{k}' represents the share of the country's exports in the world's imports for region k, by sector (´);

b^{k}' represents the share of region k's imports in global trade, by sector (´);

c' represents the share of imports by region in global trade, by sector (´).

It is important to note that the calculation structure of equations (6), (7), and (8) closely mirrors that of equations (2), (3), and (4), respectively. The primary difference lies in the summation of the products exported to each region ($\sum_t$) and their weighting by that market's share (c').

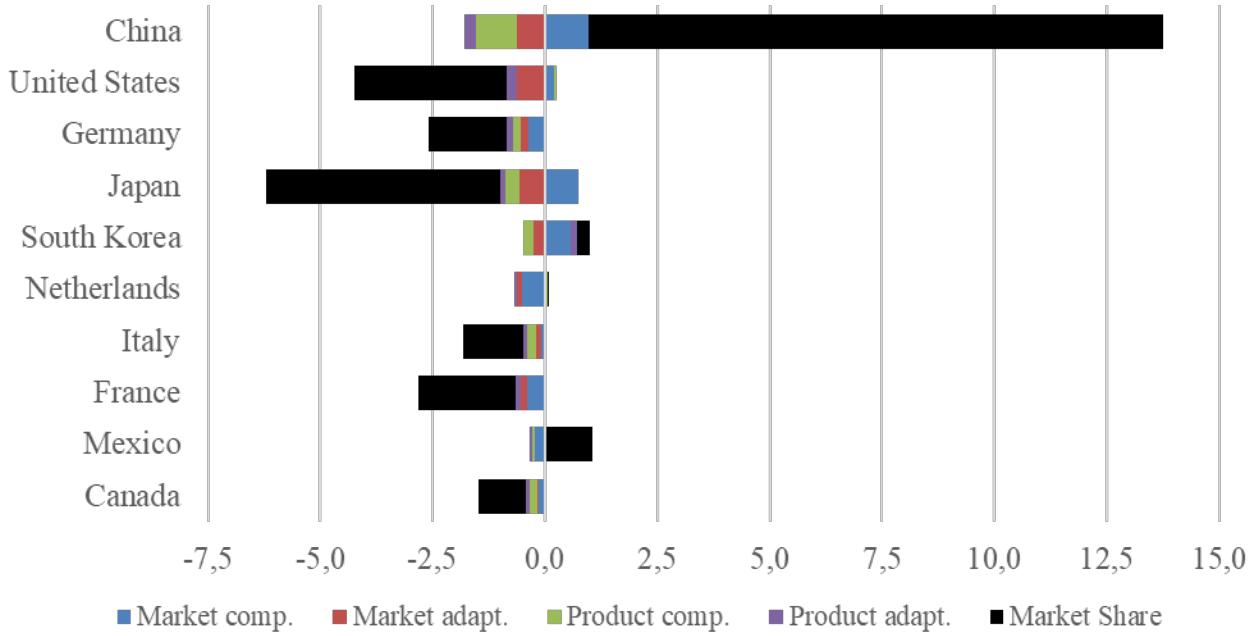
In summary, the interpretation of each component is as follows:

- **Competitiveness** (equation 2): evaluates export performance relative to the global trade structure at the initial period. A country's competitiveness increases when it gains market share in key destinations. This can be further broken down into the market share effect (6), product composition effect (7), and product adaptation effect (8).
- **Market composition effect** (equation 3): assesses whether the regions where a country exported during the initial period increased or decreased their share in global trade.
- **Market adaptation effect** (equation 4): examines the interaction between changes in a country's export destinations and the changing importance of those destinations in global trade. A positive effect occurs when a country increases its share in markets that are growing in relevance or reduces its share in markets that are declining in importance.
- **Market share effect** (equation 6): indicates the extent to which a country gains market share for its key products in each region.
- **Product composition effect** (equation 7): reflects whether the most significant export products have increased their share in each destination.
- **Product adaptation effect** (equation 8): gauges whether a country has successfully expanded its share in products that have become more critical in each destination.

A notable critique of the CMS method, raised by Richardson (1971), is the index number problem – distortions caused by the arbitrary selection of the initial period as the reference point for market share variation. To mitigate this issue, Jepma (1986, cited in Ahmadi-Esfahani, 2006) proposes using a moving base rather than a fixed base. Following this approach, the decomposition was conducted annually from 1995 to 2021 to minimize any discretionary effects on the competitiveness measurement.

Figure 6 illustrates the decomposition of market share variation between 1995 and 2021, based on the methodology introduced by Fagerberg and Sollie (1987). The selected countries are the same as those in Table 1, i.e., the main exporters in 2021. The market share effect – which captures the measure of competitiveness while controlling for market share changes (Equation 6) – was the dominant factor for almost all major countries, with the exceptions of South Korea and the Netherlands.

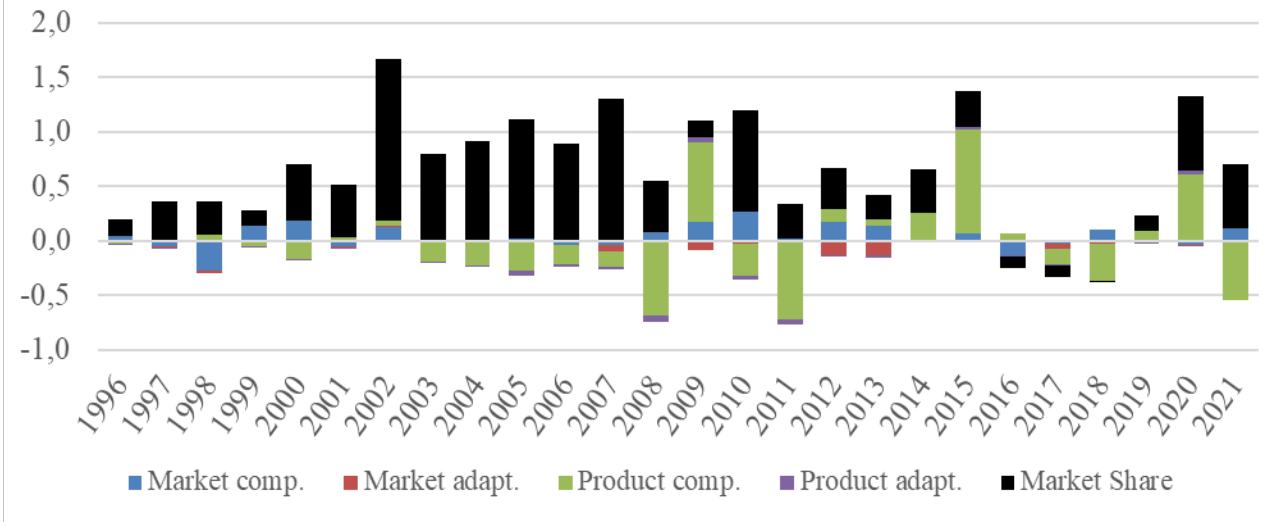
Figure 6 – Decomposition of Change in Market Share – 1995-2021



Prepared by the authors, on the basis of data from CEPII (2023).

The market share growth decomposition confirms the insights from Table 1. Figure 7 shows the year-by-year results for China from 1995 to 2021. Notably, market share gains were most significant between 2001 and 2008, reflecting export growth far exceeding the growth of destination markets, with the United States being the main market where China expanded its share.

Figure 7 – Decomposition of China's Market Share Variation – 1995-2021



Prepared by the authors, on the basis of data from CEPII (2023).

A significant portion of South Korea's market share growth—and a factor that mitigated Japan's declining share—was driven by the market composition effect, primarily due to the expansion of its export markets, especially China. However, this advantage was concentrated between 2008 and 2012, in the aftermath of the U.S. subprime crisis.

According to the chosen aggregation method, market share gains were the main driver of competitiveness improvements between 1995 and 2021. This suggests that sustained competitiveness gains lead to a consistent increase in a country's export market share.

China emerged as an outlier during the 1995–2021 period, not only due to its rapid economic growth but also because of its significant increase in global market share in specialized supplier and science-intensive sectors. The market share gains achieved by economies at the

technological frontier may reflect China's progress in closing the technology gap – a topic that will be explored in the next section.

4 – The relationship between export participation and technological gap

This section aims to examine the relationship between global export market share and technological gaps, a task that presents two key challenges. First, market share operates as a zero-sum game, meaning one country's gain directly corresponds to another's loss. Second, accurately measuring technological gaps is complex due to the dynamic and multidimensional nature of technology, whose effects on both competitiveness and market share may not be immediately clear.

One of the defining characteristics of market share is its path dependence – a country's position in global trade tends to shift gradually, except in exceptional circumstances such as wars, pandemics, or environmental disasters. Given the long-term persistence of these effects, the application of dynamic models is well-supported, as argued by Baltagi (2008).

With this in mind, the objective is to explain variations in global export market share (ΔMS) as a function of changes in the technological gap (Δgap_tec) through a dynamic model (GMM-dif, following Rodman, 2009), as expressed in the following formulation:

$$\Delta MS_{jit} = \beta_1 \Delta MS_{jit-1} + \beta_N \Delta gap_tec_{it} + \Delta v_{jit} \quad (9)$$

In this formulation, subscript *j* indicates the technological intensity of exports, which can refer to the total or be disaggregated based on Pavitt's (1984) taxonomy: primary-intensive, supplier-dominated, scale-intensive, specialized suppliers, or science-based sectors. That is, the effect of technological gap variables is tested across different levels of technological intensity. Subscripts *i* and t represent countries and time, respectively.

By applying differencing, equation (9) eliminates the constant and the fixed effects, but endogeneity may still arise due to the correlation between MS_{jit-1} and v_{jit-1}. To address this, the instrumental variables approach proposed by Arellano and Bond (1991) is used. Additionally, due to the limitations of this method in handling endogeneity in unbalanced panels – where some variables have missing data – the sample balance will also be tested[5].

Table 3 provides a statistical summary of the variables used in the econometric models. The market share metrics for each of Pavitt's classifications include nearly 6,000 observations, covering the period from 1995 to 2021. However, data availability is more limited for the explanatory variables, especially for the patent gap and the technological frontier gap (Gap_tf_ind), which have 3,337 and 2,303 observations, respectively. Notably, the minimum value for most variables is zero, except for the productive capacity gap (Gap_pc_ind). As a result, the variables were not converted to logarithmic form – a transformation that would have simplified result interpretation but would have treated zero values as missing data.

Table 3 – Statistical summary of variables used, 1995-2021

Variable	# Cases	Mean	Standard-Deviation	Min.	Max.
Share_Total	5,996	0.450	1.355	0.000	15.863
Share_Primary	5,985	0.451	1.176	0.000	14.122
Share_Supplier	5,992	0.451	1.548	0.000	22.895
Share_Scale	5,993	0.451	1.369	0.000	13.488
Share_Specialized	5,993	0.451	1.791	0.000	21.057
Share_Science	5,990	0.451	1.676	0.000	21.928
Gap_patent_total	3,337	0.029	0.168	0.000	2.681
Gap_tf_ind	2,303	0.451	0.274	0.000	1.111

[5] The Blundell and Bond (1998) methodology was also tested, but as there was no significant improvement, the results will not be analyzed in this work.

Gap_pc_ind	4,221	0.620	0.191	0.142	1.019
Gap_fdi_stock	5,038	0.038	0.283	0.000	5.910

Prepared by the authors, on the basis of data from research, see Table A.1.

Table 4 shows the results of the econometric analysis using the full dataset from 1995 to 2021. The dynamic model demonstrates a good fit when the explanatory variable is the overall export market share and the share of technology-intensive sectors. Specifically, the tests for the models explaining the total export market share, scale-intensive sectors, specialized suppliers, and science-based sectors indicate that the estimates are robust and consistent[6].

Table 4 – Dynamic Model for the period 1995-2021 – Unbalanced Panel

Dependent Variable	MS Total	MS Primary	MS Supplier	MS Especialized	MS Scale	MS Science
MS_def_1	0.476***	0.239***	-0.095	0.824***	0.423**	0.693***
	(0.128)	(0.068)	(0.193)	(0.109)	(0.185)	(0.038)
Gap_patent_total	0.929***	0.259	0.585***	0.614	0.632**	0.626***
	(0.183)	(0.874)	(0.115)	(0.594)	(0.306)	(0.172)
Gap_tf_ind	0.087**	0.135**	0.064	0.004	0.076*	0.035
	(0.042)	(0.067)	(0.058)	(0.049)	(0.044)	(0.036)
Gap_pc_ind	0.340	-0.054	0.095	0.302	0.158	0.051
	(0.339)	(0.383)	(0.083)	(0.344)	(0.204)	(0.104)
Gap_fdi_stock	0.504***	0.165	0.018	-0.301	0.013	0.444*
	(0.157)	(0.699)	(0.26)	(0.245)	(0.139)	(0.241)
# Cases	1516	1516	1516	1516	1516	1516
# Countries	145	145	145	145	145	145
# Instruments	29	29	29	29	29	29
AR(1)	-2.207	-1.177	-0.776	-2.578	-1.976	-3.121
[p-value]	[0.027]	[0.239]	[0.438]	[0.010]	[0.048]	[0.002]
AR(2)	-0.419	0.793	1.197	0.627	-0.891	0.730
[p-value]	[0.675]	[0.428]	[0.231]	[0.531]	[0.373]	[0.465]
Hansen Test	40.896	29.113	27.479	39.512	30.549	31.12
[p-value]	[0.017]	[0.216]	[0.283]	[0.024]	[0.167]	[0.150]

Prepared by the authors, on the basis of data from research, see Table A.1. Note: Standard deviation in parentheses. P-value in brackets or * for <10%, ** <5% and *** <1%.

Since the explanatory variables are expressed as gaps relative to the technological frontier for each criterion, the estimated coefficients reflect the difference in export market share for each technological classification in percentage points[7]. For example, the model estimates a 0.93 percentage point (p.p.) difference in total export market share (MS Total) between a country at the technological frontier for total patent registrations and a country with no registered patents. For the FDI stock gap, the estimated difference is 0.5 p.p., while for the technological frontier indicator, it is just 0.09 p.p. Meanwhile, the productive capacity gap does not show a significant effect on either the total export market share or any technological intensity category[8].

[6] The consistency of the estimates relies on the validity of the instruments and the absence of second-order serial correlation in the error term. The first assessment is the Hansen (1982) test for overidentifying restrictions, where the null hypothesis states that the model is correctly specified and the instruments are valid. The second is the Arellano-Bond AR(2) test, which checks for second-order serial correlation in the error term. While it allows for first-order correlation (AR(1)), it assumes no correlation at higher orders.

[7] The logarithmic transformation was not applied because the variables are continuous and bounded. Moreover, the results obtained using the logarithmic transformation were not significant.

[8] The high correlation between the production capacity gap and GDP per capita (0.89) may indicate endogeneity in this variable. However, it was decided not to control for it in this model, as the main objective was to address the endogeneity of market share.

In the model controlling for the market share of technology-intensive exports (MS scale-intensive, MS specialized suppliers, and MS science-based), the total patent gap has an estimated coefficient of approximately 0.6 p.p., although it is not significant for the specialized supplier sector (MS Especial). Significant effects are also observed for the technological frontier gap in scale-intensive sectors and for the FDI stock gap in science-based sectors.

As previously mentioned, the dynamic model methodology may be affected by missing data, and one approach to address this issue is to balance the sample. By limiting the sample to the years between 2008 and 2021 – when UNCTAD's technological frontier data is fully available – there is a noticeable reduction in observations, as shown in Table A.3 in the Appendix compared to Table 3. However, despite restricting the dataset to 164 countries, the expectation is that this approach will yield more robust and meaningful results.

Initially, equation (9) was estimated similarly to Table 4 but using the disaggregated components of the technological frontier indicator – namely ICT, skills, R&D, industrial activity, and finance – as shown in Table A.4 in the Appendix. Among these components, the labor skills gap (Gap_Skills) is the only one to display a significant effect across the various models, making it a viable alternative to the aggregated technological frontier gap indicator[9].

Accordingly, Table 5 presents the dynamic model for total export market share and the Pavitt classification, using the restricted sample from 2008 to 2021, during which the technological frontier gap indicator data is available. Care must be taken when analyzing these results, because using different explanatory variables prevents comparisons across the different levels of technological intensity.

Table 5 – Dynamic Model for the period 2008-2021

Dependent Variable	MS Total	MS Primary	MS Supplier	MS Especialized	MS Scale	MS Science
MS_def_1	0.573***	-0.063	-0.063	0.955***	0.636***	0.609***
	(0.169)	(0.152)	(0.150)	(0.291)	(0.189)	(0.104)
Gap_patent_total	0.451*					0.339**
	(0.272)					(0.145)
Gap_Skills_tf	0.114*	0.088	0.051**	0.094*	0.126	0.123**
	(0.062)	(0.090)	(0.023)	(0.048)	(0.081)	(0.056)
Gap_pc_ind	0.225	0.188	0.140**		0.127*	0.216**
	(0.143)	(0.146)	(0.064)		(0.072)	(0.108)
Gap_fdi_stock	0.374	0.332**	0.183**			0.170
	(0.259)	(0.167)	(0.088)			(0.161)
Gap_patent_res					0.154	
					(0.219)	
Gap_rnd_tf					0.106	
					(0.067)	
Gap_ict_tf						-0.041
						(0.035)
# Cases	1407	1938	1938	1968	1417	1407
# Countries	144	163	163	164	145	144
# Instruments	16	15	15	13	16	17
AR(1)	-2.281	-0.65	-1.024	-1.977	-2.362	-2.924
[p-value]	[0.023]	[0.516]	[0.306]	[0.048]	[0.018]	[0.003]
AR(2)	0.555	-0.295	1.099	0.605	-0.547	0.831
[p-value]	[0.579]	[0.768]	[0.272]	[0.545]	[0.584]	[0.406]
Hansen Test	14.816	17.858	8.187	10.958	15.724	11.023

[9] GDP per capita, population, and their respective squared terms were also included as explanatory variables to capture the effect of domestic market size on global market share. Since these variables were relevant only for total market share and scale-intensive sectors, they were not included in the other models.

[p-value]	[0.191]	[0.085]	[0.696]	[0.447]	[0.152]	[0.441]

Prepared by the authors, on the basis of data from research, see Table A.1. Note: Standard deviation in parentheses. P-value in brackets or * for <10%, ** <5% and *** <1%.

In the total market share model (MS Total), the variables remain largely the same as in previous models, with one key change: the technological frontier gap is replaced by the labor skills gap (Gap_Skills_tf), which is statistically significant. Additionally, the coefficient for the total patent gap decreases to 0.45 percentage points (p.p.), while the foreign direct investment (FDI) stock gap is no longer significant. For *specialized suppliers* (MS Specialized), only the skills gap indicator was significant, contrary to expectations of a positive association with other technological variables. However, the value close to one for the lagged dependent variable indicates that time persistence remains an issue with this specification.

The results presented in Table 5 are consistent with those in Table 4, indicating that the dynamic model did not provide an adequate fit for market shares in primary and labor-intensive products. This is likely due to the limited explanatory power of technology-related variables in capturing market share changes in these sectors, which are probably influenced by each country's static comparative advantages. A more detailed analysis of these sectors falls outside the scope of this study.

For the period from 2008 to 2021, the results for scale-intensive sectors did not show significant improvement compared to the full period, despite the relatively good fit of the dynamic model. The total registered patents variable was excluded, and domestic patent registrations were not statistically significant. Notably, the labor skills gap variable (Gap_Skills_tf) showed a positive and significant coefficient.

In the model estimating the market share of science-intensive sectors from 2008 to 2021, the estimated coefficient for the total patent gap decreased. However, the coefficients for the labor skills gap and productive capacity gap remained significant. Hypothetically, a country at the technological frontier in these three significant variables would have an estimated market share in science-intensive sectors 0.68 percentage points higher than a country lagging in these areas. In contrast, the technological gap measured by the FDI stock was not significant in this restricted sample.

The findings of this study align with existing literature. Country groupings indicate that increasing market share in primary products correlates with a relatively lower growth rate. These results are consistent with Dosi et al. (2022), who show that gaining market share in labor-intensive (supplier-dominated) sectors increases the risk of growth interruptions, while expanding market share in technology-intensive sectors – such as science-based industries – reduces this risk.

Measuring the technological frontier is a complex task, but the analysis in this section provides some valuable insights. The best model fit was observed in the technology-intensive sectors. The total patent gap was a significant factor in increasing market share in science-intensive exports, both for the full sample (1995 to 2021) and the restricted sample (2008 to 2021), as demonstrated by the example of China, which became a leader in this area. Other variables did not perform as consistently, such as the FDI stock gap, which was only significant in the full sample for total exports and science-intensive sectors.

This nonlinearity observed in the results for technology-intensive sectors, across different gap measures, may actually signal the relevance of Pavitt's (1984) taxonomy. The difficulty in identifying an appropriate specification for the specialized-suppliers sector may be linked to its distinctive characteristics, as these firms are often the source of many innovations adopted by other sectors. Typically, companies in this category are small, highly specialized (with limited economies of scope), and exhibit low vertical integration. They also tend to benefit from external economies arising from regional production agglomeration, along with substantial learning gains generated through customer-supplier interactions.

5 – Final remarks

Specializing in low-technology sectors leads to limited economic dynamism. The process of cumulative causation for economic development requires active domestic companies, which can only be confirmed if they successfully increase their market share abroad, particularly in high-quality and competitive markets. Export specialization in low-technology sectors – often price-takers in international markets, such as commodities – is not regarded as a sustainable path for development, either in the literature or based on the empirical analysis in this study.

The analyzed data show that countries specializing in primary goods experienced relatively lower economic growth compared to other groups, along with weaker performance in technology-intensive sectors. Dynamic models assessing the relationship between market share in resource and labor-intensive sectors and technological gap measures did not exhibit a significant fit, whether for the full or the restricted sample. Conversely, in technology-intensive sectors, the dynamic models demonstrated a better fit, with technological gap measures explaining export market share. The gap associated with total patent registrations had the most significant effect, while the labor skills gap also showed a positive and significant – albeit smaller – impact, consistently across models using the restricted sample from 2008 to 2021.

Although measuring the technological frontier is complex, further research is needed to deepen the understanding of this topic, including the influence of macroeconomic variables on domestic technological development. Methodological enhancements, such as a more detailed decomposition analysis of market share changes considering sector-specific price dynamics, could be interesting. Additionally, expanding the dataset on technological gaps – both in terms of variety and the number of countries – could provide more robust insights. Future studies should also examine the determinants of patent growth in leading countries, improvements in labor skills, productive capacities, and how foreign investments can effectively boost higher value-added exports. In addition, a greater level of data disaggregation could be conducted to enable a more in-depth analysis of the effects of patents on specific products.

The findings of this study require further robustness testing. One potential approach is to restrict the analysis period to post-2010 due to data limitations and the potential effects of the 2008 financial crisis. Another improvement would be to transform the current variables, such as adjusting patent counts by population and FDI by GDP, while incorporating additional control variables. More precise patent data could also help clarify the relationship between patent growth and increased international market share.

Understanding the dynamics of variables that genuinely impact the competitive performance of technology-intensive exports is essential for shaping industrial policies in a rapidly evolving environment. Continuous evaluation of laws and institutions promoting industrial activity is crucial, especially as national industrial policies regain prominence. Some R&D incentive programs are overly focused on tax benefits, which may obscure actual spending while failing to reinforce the true drivers of innovation. Patents and investments in human capital should grow in conjunction with a productive structure capable of absorbing and utilizing these resources, which largely depends on the sectors in which these investments are made. The institutions that comprise the national innovation system require ongoing oversight to prevent policies from becoming entrenched in bureaucratic routines or being captured by rent seekers that contribute little to advancing high-technology exports.

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Appendix

Table A.1 – Source and details of data used

Reference	Name of Data Base	Data (Unit)	Sector Clas. / Sample / Period	Site:
CEPII (2023)	BACI/UN COMTRADE	- Exports (current US$, in FOB or *mirror data*)	SH6 /200 countries / 1995-2021	http://www.cepii.fr/
GGDC (2023)	Maddison Project Database	- PIB per capita a preços de 2011 - População	143-166 países /1950-2022	https://www.rug.nl/ggdc/historicaldevelopment/maddison/
WORLD BANK (2024)	World Development Indicators	- Patent application, residents	69 to 138 countries /1980-2021	https://databank.worldbank.org/
		- GDP *per capita*, in PPP (prices of 2017 US$)	207 to 242 countries /1990-2022	
		- R&D expenditure in GDP	68 to 130 countries /1996-2021	
UNCTAD (2024a)	Foreign direct investment	- Stock of Foreign Direct Investment	151 to 199 countries /1990-2022	https://unctadstat.unctad.org/datacentre/
UNCTAD (2024b)	Productive capacities index	- Productive Capacity Index	190 to 193 countries /2000-2022	
UNCTAD (2024c)	Frontier technology readiness	- Technological Frontier Index	164 and 165 countries /2008-2021	

Prepared by the authors, on the data base from research.

Table A.2 – International Standard Industrial Classification (ISIC) and revised Pavitt taxonomy

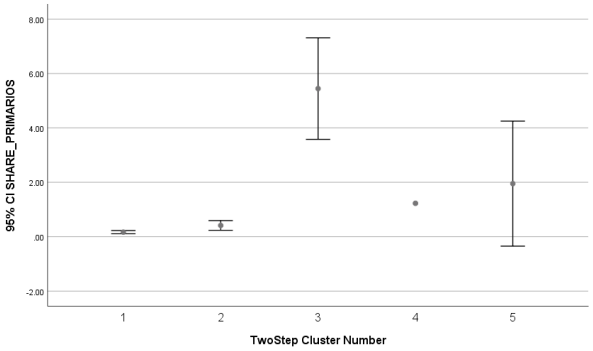
ISIC	Description ISIC 2 digit.	Pavitt Taxonomy
<=14	Several	Primary Product
15	Food and beverages	Supplier Dominated
16	Tobacco products	Supplier Dominated
17	Textiles	Supplier Dominated
18	Wearing apparel, fur	Supplier Dominated
19	Leather, leather products and footwear	Supplier Dominated
20	Wood products (excl. furniture)	Supplier Dominated
21	Paper and paper products	Scale Intensive
22	Printing and publishing	Scale Intensive
23	Coke,refined petroleum products,nuclear fuel	Scale Intensive
24	Chemicals and chemical products	Science Based
25	Rubber and plastics products	Scale Intensive
26	Non-metallic mineral products	Scale Intensive
27	Basic metals	Scale Intensive
28	Fabricated metal products	Supplier Dominated
29	Machinery and equipment n.e.c.	Specialised Suppliers
30	Office, accounting and computing machinery	Science Based

31	Electrical machinery and apparatus	Specialised Suppliers
32	Radio,television and communication equipment	Science Based
33	Medical, precision and optical instruments	Science Based
34	Motor vehicles, trailers, semi-trailers	Scale Intensive
35	Other transport equipment	Specialised Suppliers
36	Furniture; manufacturing n.e.c.	Supplier Dominated

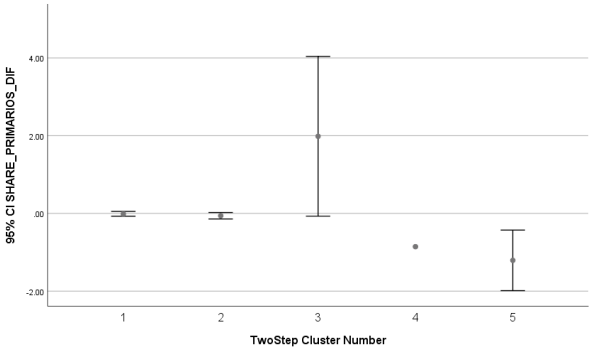
Prepared by the authors, based on Pavitt (1984), Dosi, Riccio and Virgillito (2021).

Figure A.1 – 95% Confidence Interval of Cases by Country Cluster

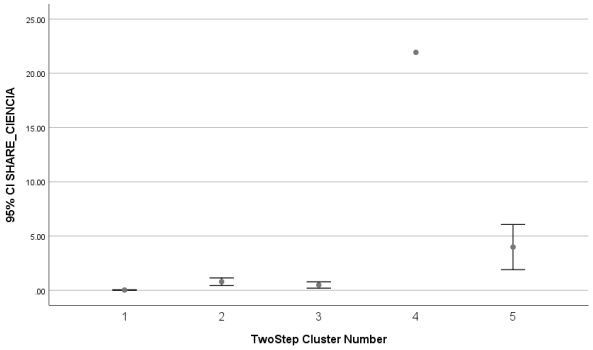
Market Share Primaries-products



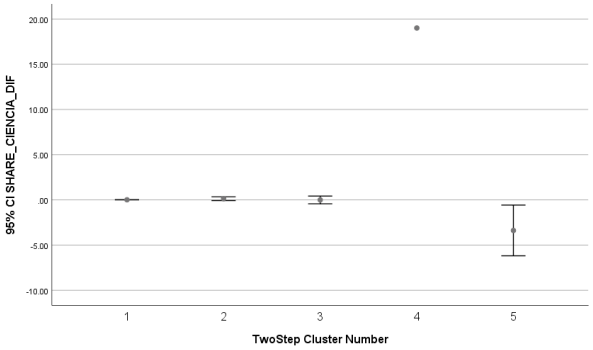
Change of Market Share Primaries-products



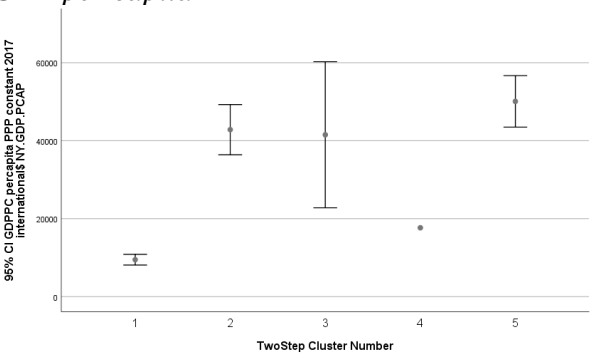
Market Share Science-based



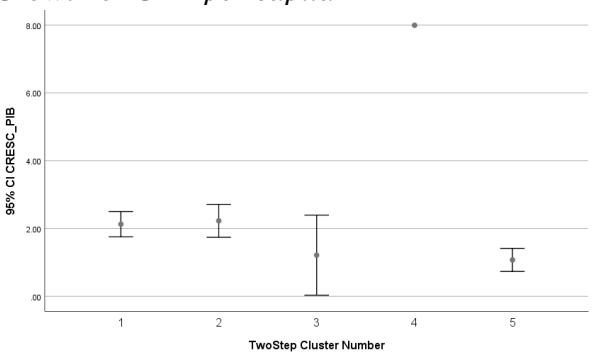
Change of Market Share Science-based



GDP *per capita*



Growth of GDP *per capita*



Prepared by the authors, on the basis of data from research, see Table A.1.

Table A.3 – Statistical summary of variables used, 2008-2021

Variable	# Cases	Mean	Standard-Deviation	Min.	Max.
Share_Total	2,296	0.576	1.525	0.000	15.863
Share_Primaries	2,296	0.597	1.351	0.000	14.122
Share_Supplier	2,296	0.580	1.909	0.000	22.895
Share_Scale	2,296	0.568	1.997	0.000	21.057
Share_Specialized	2,296	0.582	1.428	0.000	11.315
Share_Science	2,296	0.562	1.963	0.000	21.928
Gdp_pc	2.263	20,342	20,728	711	118,510
Pop	2.100	18,385	20,039	579	160,051
Population	2.100	46,581	154,973	160	1,402,537
Gap_patent_total	1,742	0.029	0.184	0.000	2.681
Gap_pc_ind	2,296	0.646	0.179	0.185	1.019
Gap_fdi_stock	2,262	0.044	0.275	0.000	4.158
Gap_tf_ind	2,296	0.453	0.273	0.000	1.111
Gap_ict	2,296	0.428	0.272	0.000	1.250
Gap_Skills	2,296	0.456	0.242	0.000	1.111
Gap_rnd	2,296	0.241	0.244	0.000	1.250
Gap_ind_activity_ind	2,296	0.553	0.195	0.000	1.111
Gap_Finances	2,296	0.662	0.178	0.000	1.111

Prepared by the authors, on the basis of data from research, see Table A.1.

Table A.4 – Dynamic Model of the Components of the UNCTAD Technological Frontier Indicator – 2008 and 2021 – Balanced Panel

Dependent Variable	MS Total	MS Primary	MS Supplier	MS Especialized	MS Scale	MS Science
MS_def_1	0,649***	0,026	-0,106	0,900***	0,699***	0,592***
	(0,139)	(0,108)	(0,136)	(0,34)	(0,247)	(0,108)
Gdp_pc	-0,690**	-1,89	0,221	-0,140	-0,899**	-0,150
	(0,299)	(1,300)	(0,241)	(0,839)	(0,425)	(0,484)
Gdp_pc_2	0,047***	0,133*	-0,009	0,01	0,054**	0,011
	(0,017)	(0,079)	(0,013)	(0,054)	(0,025)	(0,03)
Pop	0,02	0,435	-0,343	0,155	-0,043	-0,002
	(0,249)	(0,961)	(0,385)	(0,339)	(0,252)	(0,211)
Pop_2	-0,004	-0,03	0,017	-0,01	0,001	0,000
	(0,013)	(0,056)	(0,022)	(0,018)	(0,015)	(0,011)
Gap_ict	-0,01	-0,055	-0,012	-0,007	-0,054	-0,047
	(0,03)	(0,078)	(0,015)	(0,034)	(0,055)	(0,029)
Gap_Skills	0,120**	0,067	0,059*	0,104	0,163***	0,112***
	(0,059)	(0,105)	(0,031)	(0,076)	(0,062)	(0,038)
Gap_rnd	0,045	0,075	0,027	-0,034	0,097	0,023
	(0,03)	(0,062)	(0,023)	(0,105)	(0,061)	(0,031)
Gap_activity_ind	0,017	0,078	0,012	0,001	0,008	0,007
	(0,028)	(0,075)	(0,016)	(0,022)	(0,049)	(0,021)
Gap_Finances	0,021	-0,031	0,019	-0,049	-0,012	-0,013
	(0,041)	(0,072)	(0,024)	(0,057)	(0,046)	(0,032)
# Cases	1800	1800	1800	1800	1800	1800
# Countries	150	150	150	150	150	150
# Instruments	21	21	21	21	21	21

AR(1)	-2,417	-1,271	-0,001	-2,111	-1,81	-2,671
[p-value]	[0,016]	[0,204]	[0,342]	[0,035]	[0,07]	[0,008]
AR(2)	0,982	0,603	1092	-0,408	0,626	0,897
[p-value]	[0,326]	[0,547]	[0,275]	[0,683]	[0,531]	[0,370]
Hansen Test	11,094	15,635	9,903	14,113	13,858	5,439
[p-value]	[0,435]	[0,155]	[0,539]	[0,227]	[0,241]	[0,908]

Prepared by the authors, on the basis of data from research, see Table A.1. Note: Standard deviation in parentheses. P-value in brackets or * for <10%, ** <5% and *** <1%.

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