경제학박사 학위논문

Dynamic Comparative Advantage and its Effect on Economic Growth

비교우위의 동태적 변화와 경제성장 간의

관계에 대한 실증분석 연구

2023 년 2 월

서울대학교 대학원

경제학부 경제학전공

이 보 람

Dynamic Comparative Advantage and its Effect on Economic Growth

지도 교수 이 근

이 논문을 경제학박사 학위논문으로 제출함

2022 년 12 월

서울대학교 대학원

경제학부 경제학전공

이 보 람

이보람의 경제학박사 학위논문을 인준함

2022 년 12 월

위 원 장 김 재 영

부위원장 이 근

위 원 최 보 영

위 원 신 호 철

위 원 한 준 희

Abstract

Dynamic Comparative Advantage and its Effect on Economic Growth

Boram Lee
Department of Economics
The Graduate School
Seoul National University

This thesis measures the dynamic comparative advantage (DCA) and empirically analyzes its effects on economic growth in the long run. In the context of economic development, determining a better trade strategy between diversification and specialization has been a topic of interest. Literature on export diversification highlights the growth effects of the overall degree of specialization, while literature on export specialization points out the importance of the quality of the specialization pattern.

The successful export-led development experiences in East Asia—Korea and Taiwan—share some common features of export patterns. First, exports are concentrated on a relatively few top export products over the course of time. Second, the composition of top exports continuously changes. Third, change in the composition of top exports is associated with technological upgrading from low-to high-technological sectors. Theoretical literature on DCA and growth are in line with the shift in export specialization patterns of East Asia which highlight the role of DCA on long-run economic growth. This finding suggests that the emergence of new top exports which reflect a shift in comparative advantage can be an important source of drivers for sustainable growth.

One of the main contributions of the study is the new measurement which captures the dynamic properties of comparative advantage. This study proposes that the emergence of new top exports captures the generation of new comparative advantage based on traditional trade theories arguing that under an opened economy, countries specialize in and trade products on the bases of their own comparative advantage. To empirically investigate the effects of DCA on economic growth, the system generalized methods of moments (GMM) approach and the cross-sectionally augmented distributed lag (CS-DL) approach are used. Notably, the CS-DL approach directly estimates the long-run effects in large dynamic heterogeneous panel data models and accounts for cross-country heterogeneity and cross-sectionally dependent errors (Chudik et al., 2016). Growth regressions consistently confirm the significant and positive impacts of change in comparative advantage on economic growth. The results are robust to a wide range of control variables, including the economic complexity index (ECI); whereas the ECI loses significance in the CS-DL estimations.

Confirming the significant growth effects of the DCA, the second major contribution of this paper is related to an important feature of the DCA index. Given that the emergence of new export specialization leads to export diversification, the DCA index generally represents both aspects of export diversification and export specialization. This finding shows that export diversification and specialization are not opposite concepts but are actually related.

Finally, another contribution relies on verifying the effects of the level of technology embedded in the new comparative advantage on economic growth. This thesis closely examines the DCA index through the lenses of the OECD industrial classification on technological intensity. Contrary to the findings of the literature on specialization which advocates the growth effects of specialization patterns with higher productivity, evidence is insufficient to support that new comparative advantage in higher

or lower technological sectors over the course of time enhances per capita income in the long run. The CS-DL estimation results indicate that for non-developed economies, a gradual approach on creating new comparative advantage in higher technological sectors in the long run can be a viable alternative development strategy.

Keywords: Dynamic comparative advantage, Economic growth, Export diversification, Export specialization, Export strategy, Large dynamic heterogeneous panel data model
Student Number: 2015-30062

Table of Contents

List of Tables

List of Figures

Chapter 1. Introduction

Determining a better strategy for sustainable, long-term economic development is a common goal for world economies. Accordingly, the successful export-led development experiences of East Asian countries—Korea and Taiwan—in recent decades provide a desired growth model for many non-developed economies. In search for drivers of continuous and sustainable economic development, a recent strand of economic literature continues to debate on whether export diversification or specialization is a better growth strategy.

Literature on export diversification concentrates on the overall level of distribution of exports and finds mixed results on the effect of diversification on growth. Some studies find empirical evidence of a positive growth effect on various export products (De Benedictis, Gallegati, & Tamberi, 2009; Nomaler & Verspagen, 2021). Other studies argue that the growth effect of diversification differs across the stage of development on the basis of finding an inversed U-shape relationship between per capita income and diversification. The findings indicate that low-income countries benefit from diversifying export products, while high-income countries benefit more from concentrating exports within a certain range of products (Cadot, Carrere, & Strauss-Kahn, 2011; Hesse, 2008).

Literature on export specialization focuses more on the quality of the composition of exports and finds evidence of different growth effects across industries, implying that "not all specialization paths are equally desirable" (Dosi, Riccio, & Virgillito, 2022, p. 3). More recently, the literature introduces new measurements to estimate the embedded production capacity from the composition of exports and investigates its effect on growth. Hidalgo and Hausmann (2009) measure the complexity of an economic system using export data at country-product level and find evidence that the new measurement has a positive and significant effect on economic growth (Hausmann et al., 2013).

Meanwhile, some aspects of export specialization in East Asia—Korea and Taiwan—have not gained much attention in the literature on export diversification, specialization, and growth. First, a few top export products continue to account for a large share of total exports over the course of time. Second, top export products continue to change dynamically. Third, changes in the composition of top exports are associated with gradual industrial upgrading from labor (or resource)-intensive to more capital-intensive processes, along the lines of economic development. This finding implies that the emergence of new top exports, which have the economic weight to have an impact on the economy, can be an important source of drivers to achieve continued, long-run economic growth. Change in export specialization also reveals change in comparative advantage. Based on the traditional trade theories, countries specialize in and trade goods on the bases of their own comparative advantage under an open economy. The experience of dynamic change in comparative advantage revealed by changes in top exports of East Asian countries in the process of economic growth supports the arguments of the theoretical literature on dynamic comparative advantage (DCA) (Krugman, 1987; Reddings, 1999; Lin, 2010) or the emergence of new sectors (Saviotti & Pyka, 2011) on long-run economic development.

Based on the theoretical framework on DCA, this thesis empirically verifies the effect of changes in comparative advantage on economic development in the long run. The first part of the study proposes a new measurement which captures the dynamic properties of export specialization and comparative advantage and verifies its effect on long-run economic growth. The proposed measurement in this study, namely, the DCA index, captures change in comparative advantage by the ratios of new top exports.

The index has distinct features from the existing indices frequently used in the literature on export diversification, specialization, and growth. First, the DCA index captures the revealed changes in comparative advantage of countries by focusing on change in top exports. Second, the DCA index considers both aspects of export diversification and export specialization, as the emergence of new specialization generally leads to diversification. Third, the DCA index considers the export specialization pattern in two different points of time, while many existing indices capture static instances of the evolving export pattern.

While existing literature frequently applies the cross-sectional dynamic panel estimation, namely, the fixed effects and the GMM methodologies, this study additionally applies the large heterogeneous panel approach, namely, the cross-sectional augmented distributed lag (CS-DL) methodology which estimates the long-run effects (Chudik et al., 2016) and checks for endogeneity issues. The findings from both cross-sectional panel analyses and large heterogeneous panel analysis consistently show that DCA has a positive and significant effect on economic growth in the long run.

Meanwhile, the DCA index introduced in the first part of the study is limited to measuring the quantitative changes in comparative advantage because the index does not distinguish the different levels of technology embedded across export products. Literature on export specialization highlights the importance of the nature of specialization pattern on economic growth.

In this aspect, the second part of the study investigates the growth effect of DCA, considering the different levels of technology across industries. The cross-sectional dynamic panel estimation results suggest empirical evidence that new comparative advantage in lower technological sectors promotes the growth prospects for non-developed countries. However, the CS-DL estimation results show insufficient evidence to support that change in comparative advantage within lower technological sectors promotes economic development in the long run. Instead, the CS-DL estimation results provide the possibility of long-run growth effects of change in comparative advantage associated with technological upgrading for non-developed countries, which is in line with the argument by Lin (2010).

The rest of the paper is organized as follows. Chapter 2 discusses the related literature on diversification, specialization, DCA, and economic growth and derives the hypothesis for the study. Chapter 3 introduces the econometric methodologies used in the study. Chapter 4 proposes the DCA indices and verifies its effects on long-term economic development. Chapter 5 considers different technological contents across export products when measuring the DCA and evaluates its effects on long-run growth. Chapter 6 concludes.

Chapter 2.
Literature on diversification, specialization, DCA, and economic growth

2.1. Export diversification and economic growth

Literature on export diversification emphasizes the important role of various export products in economic growth. Nomaler and Verspagen (2021) find the theoretical framework linking diversification and growth from technology gap theory which helps explain that non-developed countries can catch up due to international knowledge spillover. In this process, the authors expect lower-income countries to diversify in products which require stronger technological capabilities along the development path. The economic complexity index (ECI) proposed by Hidalgo and Hausmann (2009) is also based on the idea that countries diversify by achieving higher production capacity. The literature finds the rationale for the growth effects of diversification from risk dispersion from economic shocks (Hesse, 2008), increase in production capacity to produce a wider range of products (Hausmann et al., 2013), and shift in comparative advantage to higher value-added sectors due to slow adjustment across diversification cones (Schott, 2003).

The empirical findings of the relationship between export diversification and growth present mixed results. Some studies find a non-linear, inversed U-shape relationship between diversification of export products and country income: lower income countries, which generally have a narrow range of export products, diversify concomitant with the rise in income and re-concentrate after reaching a certain level of high income (Cadot, Carrere, & Strauss-Kahn, 2011; Hesse, 2008; Aditya & Acharyya, 2013; Di Salvo & Pelkmans-Balaoing, 2015; Bahar, 2016). A cross-sectional dynamic panel regression is generally applied adding measures of export concentration indices, namely, the Hirschman and Herfindahl index (HHI), the Theil (entropy) index, and the Gini index, to the basic growth equation. Cadot, Carrere, and Strauss-Kahn (2011) show the turning point for countries that the switch from diversification to specialization occurred at nearly US$25,000 per capita at PPP. Hesse (2008) finds a nonlinear relationship between diversification and growth arguing that diversification assists low-income countries, which generally specialize in primary products, in overcoming export instability.

Other research finds a positive linear correlation between export diversification and economic growth (De Benedictis, Gallegati, & Tamberi, 2009; Parteka, 2010; Nomaler & Verspagen, 2021). The literature uses indices based on the revealed comparative advantage (RCA) or the number of export products which is a comparative advantage of a country. De Benedictis et al. (2009) measure the overall diversification based on Balassa's RCA and show that countries continue to diversify along the development path. Nomaler and Verspagen (2021) focus on the heteroscedasticity in the high-income countries' composition of exports and argue that few resource-rich countries may have caused the inversed U-shape relationship between export diversification and growth. Nomaler and Verspagen (2021; p. 309) point out that "countries tend to diversify all across the product space, not in a limited to part of the product space."

Some literature presents the negative effect of export diversification and economic growth on a country-basis analysis. Amin and Thrift (2000) find a negative relationship between export diversification and economic growth in Columbia. Similarly, Abdelhadi et al. (2019) find a positive effect of export instability on economic growth in the case of Saudi Arabia and Algeria in the long run. The underlying argument is that uncertainty in export revenue may lead to a fall in consumption expenditure which can result in further savings, investment, and thus growth (Sarin et al., 2020).

The mixed empirical findings in the literature on export diversification and growth which depend on the measurements used to proxy diversification or methodology applied suggest room for further study. In addition, whether specialization in a particular industry or diversification in a variety of products is a better strategy for economic growth remains controversial.

Meanwhile, export patterns of each country are observed to be continuously concentrated in a number of products. The median share for the top 10 goods is 76% in world exports. Considering the dynamic perspective of diversification, this study proposes a new measurement that captures the dynamic aspects of patterns of specialization which may result in diversification.

2.2. Export specialization and economic growth

International trade theories predict that economic liberalization encourages countries to specialize in goods which are a comparative advantage of those countries. Ricardo's theory sees that the pattern of export specialization is determined by relative productivity differences and shows that all countries, including the countries which have no absolute advantage, benefit from trade. The Heckscher-Ohlin model finds the differences in factor endowments as a determinant of the pattern of trade specialization. Afterwards, the Krugman (1979; 1981) model finds that economies of scale and monopolistic competition determine the specialization pattern of export.

While traditional trade theories contend that irrespective of one's specialization patterns, all trading countries gain from trade than under autarky, a large volume of empirical literature finds empirical evidence of different growth prospects across different specialization patterns in exports. A strand of literature finds that specializing in specific sectors, which is a comparative advantage of high-income countries, promotes growth. Plumper and Graff (2001) present empirical evidence that export specialization in high-tech sectors enhances economic growth potential. Lee (2010) finds that countries that have increased its competitiveness in products with high technological content typically experienced more rapid growth, whereas countries that have increased its competitiveness in products with low technological contents have fallen behind. Fosu (1990) shows that developing countries specializing in manufacturing achieved higher growth than those specializing in primary sector exports. However, we observe that Korea in the 1970s changed its specialization pattern to lower technological sectors, and the higher technological products gradually emerged in the top exports from the 1970s to 2010s. The cases of Korea and Taiwan suggest that targeting industries which is the specialization of high-income countries without considering national characteristics may not promise the expected, positive growth effects. Meanwhile, other literature shows that optimal specialization which enhances the growth prospects is different at the level of income. Using survival analysis, Dosi, Riccio, and Virgillito (2022) empirically show that specialization structure, which enhances the growth potential, differs across different stages of development; changing patterns of specialization to scale intensive (lower technological contents) is economically beneficial for developing countries, while changing specialization patterns to specialized suppliers (lower technological contents) promotes the growth prospects for developed countries. However, it should be noted that economic development is a dynamic process and evolves from one stage of development to the next. In this aspect, this study focuses on determining a better strategy for economic growth in the long run from a lower-income to a higher-income stage of development.

Another strand of literature proposes indicators measuring the quality of products in terms of production capacity and knowledge using export data. Based on a simple assumption that high-income countries have higher production capacity, Hausmann, Hwang, and Rodrik (2007) introduce an export sophistication index, namely, the EXPY to measure the quality of a country's export basket and find evidence that EXPY is broadly correlated with growth (Jarreau & Poncet, 2012). Hidalgo and Hausmann (2009) propose the Economic Complexity Index (ECI) based on the idea that high-income countries export more diverse and less ubiquitous products. Hausmann et al. (2013) point out that the ECI “captures the knowledge and capacity embedded in the economic structure” and finds empirical evidence that the ECI successfully predicts economic growth. Meanwhile, the ECI and EXPY imply that countries can enhance their growth prospects by targeting industries referring to the economic structure of high-income countries. However, as aforementioned, Korea and Taiwan gradually started changing their comparative advantage in higher technological products in the transition of the 1980s and 1990s instead of restricting their economy from the world to promote industries which are the comparative advantage of high-income countries. Lee and Lee (2020) question the robustness of ECI and point out that the indicator and the implications assume the endogenous path-dependent nature of economic growth moving through the product space to complex export baskets and do not consider idiosyncratic shocks (Fidrmuc, 2004; Toya & Skidmore, 2007) nor technological breakthroughs which may result in a sudden change in a nation's trajectory (Palmer & Richards, 1999).

2.3. Theoretical framework for the research: DCA

The theoretical literature on trade and growth points out that comparative advantage is dynamic and evolves endogenously over time (Krugman, 1987; Redding, 1999). Redding (1999) proposes to define DCA as concerned with the rate of growth in relative levels of opportunity costs of production in low- or high-tech sector, while static comparative advantage concerns relative levels of opportunity costs of production. The theoretical literature points out factor endowment change (Redding, 2002), accumulation of technological capabilities (Grossman & Helpman, 1991; Redding, 1999; Dosi & Matteo, 2019), and cumulative production experience (Krugman, 1987) as determinants of the evolution of comparative advantage. Redding (2002) finds that country-specific changes in factor endowments become relatively more influential for specialization dynamics over longer time horizons of 10 years and above, while it could not explain specialization dynamics over shorter time horizons. The study also shows that over time horizons of 5 years, change in specialization patterns is largely explained by common changes in technical efficiency. Krugman (1987) emphasizes the effects of cumulative production experience on comparative advantage via dynamics of learning. Similarly, Redding (1999) argues that comparative advantage is endogenously determined by past technological change, and shapes current rates of learning by doing.

Theoretical literature on structural economics emphasizes the role of DCA on the long run, sustainable economic development, which provides the theoretical framework for this study. Lin (2010) utilizes the determinants of comparative advantage pointed out by previous literature (e.g., Redding 1999; Redding 2002) and suggests a long-run development strategy for non-developed economies. First, the author highlights that economic development is a continuous process of increase in per capita income and not a dichotomy between developed and developing income groups. This point emphasizes the importance of estimating the long-run effects of DCA on economic growth. Second, the author argues that non-developed countries should alter the given pattern of comparative advantage by achieving technological upgrading over the course of time and not to fall in economic stagnation as predicted by Solow's neoclassical growth model (Krugman, 1987; Redding, 1999). Third, during the initial periods, conforming to endowment-based comparative advantage provides the opportunity to “benefit from advantages of backwardness in technology and industrial innovation, and to upgrade their endowments” (pp. 20–21). Dosi and Matteo (2019) point out that the economic benefits from gaining absolute advantage in the technological base through the accumulation of technology can dominate over the short-term efficiency gains from the endowment-based comparative advantage.

Another theoretical literature by Saviotti and Pyka (2011) which points out the importance of introducing new sectors to the economy on growth also motivates this study. Saviotti and Pyka (2004) introduce a model of economic development determined by the creation of new sectors. The supporting argument is that when the demand growth of existing sectors reaches saturation due to increasing intensity of competition, it leads to inefficient, surplus use of resources. The authors also note that the resources required to search for new sectors come from the increase in productivity in existing sectors, which is in line with Krugman (1987) and Redding (1999). Saviotti and Pyka (2011) extend the closed economy model of Saviotti and Pyka (2004) to a North-South model by adding the concept of generalized barriers to entry to the model which encompasses a wide range of resources, including institutions, which increase over time. Considering the growing barriers to entry, the model shows the growing delay in the emergence of new sectors in non-developed economies, which enter the market later than the developed countries and further face declining growth rates of economic outcomes from the new sectors. The implications of Saviotti and Pyka (2011) can be extended to the discussion on the emergence of new top exports and growth. Countries which overcome the increasing barriers to entry and succeed in creating comparative advantage in new sectors would succeed in achieving sustainable, long-run economic growth.

2.4. Derivation of research hypothesis

This study attempts to empirically verify the implications from the theoretical literature on DCA which highlights the role of dynamic changes in comparative advantage on sustainable, long-run economic growth. The theory of DCA is supported by the changing patterns of export specialization in Korea and Taiwan which achieved continuous economic development from low- to high-income economy. Figure 2.1 exhibits the top 10 export products of Korea and Taiwan in every 10 years from 1962 to 2010. The high rates of mobility in the top exports are observed in both countries. Korea showed complete transformation of top 10 exports starting from the 1980s compared with the composition of exports in the early 1960s, while Taiwan showed complete transformation of top 10 exports in the early 2000s. This finding leads to the first research question: can the ability of creating new top exports be the source of economic development? Saviotti and Pyka (2011) argue that the ability of creating new sectors is an important determinant of sustainable economic development based on a growth model determined by the emergence of new sectors. In this aspect, this study verifies the hypothesis as follows:

Hypothesis 1: Changes in top exports which reflect change in comparative advantage have a significant, positive effect on long-run economic growth.

As the DCA concept is motivated by observing that dwelling in the current comparative advantage in low-tech sectors has limited growth effect for non-developed economies, the growth effect of DCA in non-developed economies will be investigated.

Figure 2.1.A.Importance of changes in top exports: The case of Korea

	1962–1965	1971–1975	1981–1985	1991–1995	2000–2005	2006–2010
1	Wood, plywood (634.0)	Clothing accessories (847.0)	Ships (793.0)	Thermionic, cold cathode (776.0)	Thermionic, cold cathode (776.0)	Thermionic, cold cathode (776.0)
2	Iron ore (281.0)	Wood, plywood (634.0)	Footwear (851.0)	Ships (793.0)	ICT equipment (764.0)	ICT equipment (764.0)
3	Crustaceans (036.0)	Thermionic, cold cathode (776.0)	Thermionic, cold cathode (776.0)	Passenger vehicle (781.0)	Passenger vehicle (781.0)	Passenger vehicle (781.0)
4	Cotton fabrics (652.1)	Footwear (851.0)	Leather accessories (848.0)	Fabrics (653.1)	Ships (793.0)	Ships (793.0)
5	Raw silk (261.3)	Textile yarn (651.0)	Toys, games (894.0)	ICT equipment (764.0)	Refined petroleum (334.0)	Refined petroleum (334.0)
6	Ores of non-ferrous metal (287.9)	Other manufactures (899.0)	Clothing accessories (847.0)	Footwear (851.0)	Units, computers (752.5)	Optical instrument (871.0)
7	Vegetable origin, n.e.s. (292.9)	Leather accessories (848.0)	ICT equipment (764.0)	Units, computers (752.5)	Parts, machines (759.9)	Parts, vehicles (784.0)
8	Animal origin n.e.s. (291.9)	Textile fabrics (654.0)	Textile yarn (651.0)	Parts, machines (759.9)	Optical instrument (871.0)	Parts, machines (759.9)
9	Coal, lignite (322.0)	Crustaceans (036.0)	Radio receivers (762.0)	Refined petroleum (334.0)	Parts, vehicles (784.0)	Hydrocarbon (511.0)
10	Clothing accessories (847.0)	Raw silk (261.3)	Travel goods (831.0)	TV receivers (761.1)	Other elec. machinery (778.8)	Civil engineering (723.0)

Source: Author’s calculation
Note1: Figures in parentheses are SITC code numbers
Note2: SITC rev.2 776.0 includes electronic integrated circuits
Note3: Products in shade indicate new top 10 export products compared with the top 10

exports in the early 1960s.

Figure 2.1.B. Importance of changes in top exports: The case of Taiwan

	1962–1965	1971–1975	1981–1985	1991–1995	2000–2005	2006–2010
1	Sugars (061.1)	Clothing accessories (847.0)	Footwear (851.0)	Thermionic, cold cathode (776.0)	Thermionic, cold cathode (776.0)	Thermionic, cold cathode (776.0)
2	Crude petroleum (333.0)	Footwear (851.0)	Toys, games (894.0)	Parts, machines (759.9)	Parts, machines (759.9)	ICT equipment (764.0)
3	Fruits, nuts (057.0)	Textile yarn (651.0)	ICT equipment (764.0)	Units, computers (752.5)	ICT equipment (764.0)	Optical instrument (871.0)
4	Rice (042.0)	Vegetables, prepared (056.5)	Travel goods (831.0)	Toys, games (894.0)	Computers (752.2)	Parts, machines (759.9)
5	Refined sugar (061.2)	Reconstituted wood (634.0)	Thermionic, cold cathode (776.0)	ICT equipment (764.0)	Unit, computers (752.5)	Printed circuits (772.2)
6	Reconstituted wood (634.0)	Sugars (061.1)	Radio receivers (762.0)	Motorcycles (785.0)	Other elec. machinery (778.8)	Motorcycles (785.0)
7	Refined petroleum (334.0)	Radio receivers (762.0)	Textile yarn (651.0)	Other machinery (728.0)	Printed circuits (772.2)	Other elec. machinery (778.8)
8	Vegetables, prepared (056.5)	Toys, games (894.0)	Other manufactures (899.0)	Textile yarn (651.0)	Optical instrument (871.0)	Machine (736.0)
9	Textile yarn (651.0)	Cotton fabrics (652.1)	Jerseys, pull (845.1)	Articles of plastics (893.9)	Phonograph records (898.0)	Nails, screws (694.0)
10	Construction materials (661.0)	ICT equipment (764.0)	Clothing accessories (847.0)	Base metal manufactures (699.0)	Motorcycles (785.0)	Polystyrene (583.3)

Source: Author's calculation
Note1: Figures in parentheses are SITC code numbers
Note2: SITC rev.2 776.0 includes electronic integrated circuits
Note3: Products in shade indicate new top 10 export products compared with the top 10 exports in the early 1960s.

Another important feature from the changing pattern of export specialization in Korea and Taiwan is the gradual industrial upgrading. After tracking the technological contents of top export products based on the OECD classification of technological intensity (Hatzichronoglou, 1997), both countries were found to have experienced gradual industrial upgrading in its changing comparative advantage from low- to high-technological sectors. As shown in Figure 2.2, low-tech sectors accounted for a larger share in the top 10 exports in Korea and Taiwan up until the early 1980s. The share of high-tech sectors in top 10 exports in Korea and Taiwan gradually increases over the course of time and eventually accounted for a majority of share in the top 10 exports from the 1990s.

Figure 2.2.A. Industrial upgrading in the changing top exports: Korea

	1962–1965	1971–1975	1981–1985	1991–1995	2000–2005	2006–2010
1	Wood, plywood (634.0)	Clothing accessories (847.0)	Ships (793.0)	Thermionic, cold cathode (776.0)	Thermionic, cold cathode (776.0)	Thermionic, cold cathode (776.0)
2	Iron ore (281.0)	Wood, plywood (634.0)	Footwear (851.0)	Ships (793.0)	ICT equipment (764.0)	ICT equipment (764.0)
3	Crustaceans (036.0)	Thermionic, cold cathode (776.0)	Thermionic, cold cathode (776.0)	Passenger vehicle (781.0)	Passenger vehicle (781.0)	Passenger vehicle (781.0)
4	Cotton fabrics (652.1)	Footwear (851.0)	Leather accessories (848.0)	Fabrics (653.1)	Ships (793.0)	Ships (793.0)
5	Raw silk (261.3)	Textile yarn (651.0)	Toys, games (894.0)	ICT equipment (764.0)	Refined petroleum (334.0)	Refined petroleum (334.0)
6	Ores of non-ferrous metal (287.9)	Other manufactures (899.0)	Clothing accessories (847.0)	Footwear (851.0)	Units, computers (752.5)	Optical instrument (871.0)
7	Vegetable origin, n.e.s. (292.9)	Leather accessories (848.0)	ICT equipment (764.0)	Units, computers (752.5)	Parts, machines (759.9)	Parts, vehicles (784.0)
8	Animal origin n.e.s. (291.9)	Textile fabrics (654.0)	Textile yarn (651.0)	Parts, machines (759.9)	Optical instrument (871.0)	Parts, machines (759.9)
9	Coal, lignite (322.0)	Crustaceans (036.0)	Radio receivers (762.0)	Refined petroleum (334.0)	Parts, vehicles (784.0)	Hydrocarbon (511.0)
10	Clothing accessories (847.0)	Raw silk (261.3)	Travel goods (831.0)	TV receivers (761.1)	Other elec. machinery (778.8)	Civil engineering (723.0)
Share of top 10 exports in high- or low-sectors						
HT	13.2	11.5	23.3	65.2	83.4	76.7
LT	47.3	79.0	76.6	34.8	16.6	23.3

Source: Author's calculation
Note1: Figures in parentheses are SITC code numbers
Note2: SITC rev.2 776.0 includes electronic integrated circuits
Note3: Products in blue shade indicate new top 10 exports in low-tech sectors compared with the top 10 exports in the early 1960s, and products in orange shade indicate new top 10 exports in high-tech sectors.

Figure 2.2.B. Industrial upgrading in the changing top exports: Taiwan

	1962–1965	1971–1975	1981–1985	1991–1995	2000–2005	2006–2010
1	Sugars (061.1)	Clothing accessories (847.0)	Footwear (851.0)	Thermionic, cold cathode (776.0)	Thermionic, cold cathode (776.0)	Thermionic, cold cathode (776.0)
2	Crude petroleum (333.0)	Footwear (851.0)	Toys, games (894.0)	Parts, machines (759.9)	Parts, machines (759.9)	ICT equipment (764.0)
3	Fruits, nuts (057.0)	Textile yarn (651.0)	ICT equipment (764.0)	Units, computers (752.5)	ICT equipment (764.0)	Optical instrument (871.0)
4	Rice (042.0)	Vegetables, prepared (056.5)	Travel goods (831.0)	Toys, games (894.0)	Computers (752.2)	Parts, machines (759.9)
5	Refined sugar (061.2)	Reconstituted wood (634.0)	Thermionic, cold cathode (776.0)	ICT equipment (764.0)	Unit, computers (752.5)	Printed circuits (772.2)
6	Reconstituted wood (634.0)	Sugars (061.1)	Radio receivers (762.0)	Motorcycles (785.0)	Other elec. machinery (778.8)	Motorcycles (785.0)
7	Refined petroleum (334.0)	Radio receivers (762.0)	Textile yarn (651.0)	Other machinery (728.0)	Printed circuits (772.2)	Other elec. machinery (778.8)
8	Vegetables, prepared (056.5)	Toys, games (894.0)	Other manufactures (899.0)	Textile yarn (651.0)	Optical instrument (871.0)	Machine (736.0)
9	Textile yarn (651.0)	Cotton fabrics (652.1)	Jerseys, pull (845.1)	Articles of plastics (893.9)	Phonograph records (898.0)	Nails, screws (694.0)
10	Construction materials (661.0)	ICT equipment (764.0)	Clothing accessories (847.0)	Base metal manufactures (699.0)	Motorcycles (785.0)	Polystyrene (583.3)
Share of top 10 exports in high- or low-sectors						
HT	0	14.3	28.5	71.7	96.3	97.4
LT	63.8	85.7	71.5	28.3	3.7	2.6

Source: Author's calculation
Note1: Figures in parentheses are SITC code numbers
Note2: SITC rev.2 776.0 includes electronic integrated circuits
Note3: Products in blue shade indicate new top 10 exports in low-tech sectors compared with the top 10 exports in the early 1960s, and products in orange shade indicate new top 10 exports in high-tech sectors.

The observation from the changing technological composition of top exports in Korea and Taiwan presents a different implication from the literature on specialization (Hausmann et al., 2007; Hausmann et al., 2013). The literatures generally imply that specializing in sectors which are the comparative advantage of high-income countries enhances growth potential irrespective of one's endowment structure. In this aspect, this study verifies the hypothesis as follows:

Hypothesis 2: Changes in comparative advantage to specific level of technological sectors, including the industries that are a comparative advantage of high-income countries, do not promote continuous long-run development.

The third hypothesis of the study is derived from the new structural economic framework as well as observations from Korea and Taiwan which exhibit gradual industrial upgrading from low- to high-technology sectors. Lin (2010) points out that economic development has "a wide spectrum from a low-income to high income" (p. 3) and argues that having a comparative advantage based on the given endowment structure promotes higher growth potential in the short run, while continuous economic development requires industrial upgrading from resource- and labor-intensive to more capital intensive in comparative advantage. This finding leads to the third hypothesis of the study as follows.

Hypothesis 3: Changes in top exports associated with technological upgrading in the long run promote economic development for non-developed economies which initially have general comparative advantage in the low-tech sectors.

Chapter 4 presents an analysis verifying the first hypothesis of the study, and Chapter 5 presents the analysis verifying the second and third hypotheses.

Chapter 3. Econometric methods

3.1. Generalized method of moments (GMM) approach

A dynamic homogeneous panel model is widely applied in the literature on export diversification, export specialization and growth (Hesse, 2008; Aditya & Acharyya, 2011; Cadot et al., 2011; Hausmann et al., 2013). The fixed-effects (FE) and system GMM approaches check for the biases generated by the unobserved, individual effects. However, the consistency of the FE estimator depends on the assumption of strict exogeneity of the explanatory variable (Pesaran 2015). It is important to note that the growth regression includes lagged dependent variable as explanatory variable, and the issues of endogeneity need to be addressed when analyzing the growth regression (Lee & Kim, 2009).

The system GMM approach addresses the problems of endogeneity by using an instrumental variable which is correlated with the endogenous variable but not related to the error-term.[1] Arellano and Bond (1991) introduce the difference GMM approach.

Consider the model,

$$y_{it} = \gamma_t + \lambda y_{i,t-1} + \boldsymbol{\beta}'\mathbf{x}_{it} + \varepsilon_{it} \tag{3.1}$$

where $\varepsilon_i = \alpha_i + u_{it}$

The time-invariant, individual effects, α_i, can be eliminated by taking first differences.

$$\Delta y_{it} = \Delta\gamma_t + \lambda\Delta y_{i,t-1} + \boldsymbol{\beta}'\Delta\mathbf{x}_{it} + \Delta u_{it} \tag{3.2}$$

Meanwhile, the first-differenced model (3.2) gives the transformed error, Δu_{it}, correlated with the differenced lagged dependent variable, $\Delta y_{i,t-1}$ which results in inconsistent estimates. As Anderson and Hsiao (1981) proposed, $y_{i,t-2}$ can be a valid

[1] This part of the chapter refers to Cavalcanti et al. (2015) and Pesaran (2015).

instrument since $E(y_{i,t-2}, \Delta u_{it}) = 0$, assuming that ε_{it} is not serially correlated. Assuming that ε_{it} are serially uncorrelated and that the explanatory variables $\mathbf{x}_{it}$ are weakly exogenous, the difference GMM estimator uses the following moment conditions:

$$E(y_{i,t-s}, \Delta u_{it}) = 0 \ \text{ for s } \geq 2 \ \text{ and } t = 3, 4, \dots, T \tag{3.3}$$

$$E(\mathbf{x}_{i,t-s}, \Delta u_{it}) = 0 \ \text{ for s } \geq 2 \ \text{ and } t = 3, 4, \dots, T \tag{3.4}$$

However, when explanatory variables are persistent over time (λ is close to 1), the lagged levels are often weak instruments for the first differenced variables. In this regard, Arellano and Bover (1995) and Blundell and Bond (1998) introduce the system GMM estimator which adds additional moment conditions for the model in levels.

$$E(\Delta y_{i,t-1}, \varepsilon_{it}) = 0 \tag{3.5}$$

$$E(\Delta \mathbf{x}_{i,t-1}, \varepsilon_{it}) = 0 \tag{3.6}$$

To test the validity of the instruments and consistency of the GMM estimator, a Hansen test of over-identifying restriction, which tests the overall validity of the instruments, and the second-order correlation of error term verifying the hypothesis that the differenced error term is not serially correlated in second-order are checked.

Meanwhile, the FE and system GMM estimations have some limitations. First, the estimations assume a homogeneous slope coefficient across countries and independent errors across countries (Pesaran & Smith, 1995). These restrictions do not seem to reflect reality considering the diverse institutions, geography, and factor endowments across countries. Furthermore, the growing interdependence across countries, of which by means of trade and finance, suggests the presence of error cross-sectional dependence. The endogenously determined variables of the growth regression are another concern which leads to the issue of reverse causality (Durlauf, 2009).[2]

[2] As Caselli et al. (1996) points out, most macroeconomic variables are interdependent.

3.2. Cross-sectionally augmented distributed lag (CS-DL) approach

The cross-sectionally augmented distributed lag (CS-DL) approach estimates the long-run effects in large dynamic heterogeneous panel data models with cross-sectionally dependent errors (Chudik et al., 2016). The CS-DL estimator may help overcome the limitations of the dynamic homogeneous panel data models as it allows for heterogeneous slope coefficients across countries by applying the mean-group (MG) approach and checks for the issue of cross-country error dependency by applying the common correlated effect (CCE) approach. Furthermore, the CS-DL approach is based on the panel auto-regression distributed lag (ARDL) model, proposed by Pesaran and Smith (1995), which is robust to the feedback effects from lagged dependent variable to the regressors. Other advantages of the ARDL approach includes "its ability to long-run equilibrium" (Ardiansyah et al. 2021, p. 2) and the coefficient is consistent regardless of whether the variables are integrated of order one, $I(1)$, or integrated of order zero, $I(0)$.

The ARDL model is derived from the VAR model which assumes that variables are jointly determined.

Consider the following vector autoregression of order 1, VAR(1),

$$\begin{bmatrix} y_t \\ x_t \end{bmatrix} = \begin{bmatrix} \emptyset_{11} & \emptyset_{12} \\ \emptyset_{21} & \emptyset_{22} \end{bmatrix} \begin{bmatrix} y_{t-1} \\ x_{t-1} \end{bmatrix} + \begin{bmatrix} e_t^y \\ e_t^x \end{bmatrix} \quad (3.7)$$

where y_t is the dependent variable, x_t is the explanatory variable, and t is the time period. In growth regression which includes endogenously determined explanatory variable, the correlation between the error terms e_t^y and e_t^x is expected which causes the endogeneity issue when estimating the effect of y_t on x_t by least square methods. Denoting the covariance of e_t^y and e_t^x by $\omega VAR(e_t^x)$, the error terms can be written as follows:

$$e_t^y = E\left(e_t^y \middle| e_t^x\right) + u_t = \omega e_t^x + u_t \tag{3.8}$$

where $\omega = cov(e_t^y, e_t^x)/var(e_t^x)$.

Substituting e_t^y from (3.8) to the equation for $\mathrm{y_t}$ on (3.7), one can obtain,

$$y_t = \emptyset_{11} y_{t-1} + \emptyset_{12} x_{t-1} + \omega e_t^x + u_t \tag{3.9}$$

Substituting e_t^x from the equation (3.7) in (3.9), a simple ARDL(1,1) model is obtained.

$$y_t = \varphi y_{t-1} + \beta_0 x_t + \beta_1 x_{t-1} + u_t \tag{3.10}$$

where $\varphi = \emptyset_{11} - \omega\emptyset_{21}, \beta_0 = \omega, \beta_1 = \emptyset_{12} - \omega\emptyset_{22}$.

The error term u_t in equation (3.10) is uncorrelated with x_t and its lags by construction (see equation 3.8). This means that φ, β_0, and $\beta_1$can be directly estimated by least square method.

The model can also be written as the level relationship.

$$y_t = \theta x_t + \alpha(L)\Delta x_t + \tilde{u}_t \tag{3.11}$$

where L is the lag operator, $\tilde{u}_t = (1 - \varphi L)^{-1} u_t$, $\alpha(L) = \sum_{l=0}^{\infty} \alpha_t L^l$, $\alpha_l = \sum_{s=l+1}^{\infty} \delta_s$ for $l = 0,1,2, \ldots$ and $\delta(L) = \sum_l^{\infty} \delta_l L^l = (1 - \varphi L)^{-1}(\beta_0 + \beta_1 L)$.

The level coefficient θ in equation (3.11) represents the long-run effects, and is defined by $\theta = (\beta_0 + \beta_1)/(1 - \varphi)$. It is notable to mention that the level coefficient θ is consistent regardless of whether the variables are integrated of order one or integrated of order zero (I(1) or I(0)).

Equations (3.10) and (3.11) can be extended to estimation of panel data regression as the following ARDL(p_{yi}, p_{xi}) model.

$$y_{it} = \sum_{l=1}^{p_{yi}} \varphi_i y_{i,t-l} + \sum_{l=0}^{p_{xi}} \beta_{li} x_{i,t-l} + u_{it} \tag{3.12}$$

for i = 1, 2, ..., N and t = 1, 2, ..., T, where i is the county.

The level relationship equation of the model can be written as

$$y_{it} = \boldsymbol{\theta}_i \mathbf{x}_{it} + \boldsymbol{\alpha}_i'(L)\Delta\mathbf{x}_{it} + \tilde{u}_{it} \tag{3.13}$$

where the vector of long-run coefficient of each panel unit i is defined by $\theta_i = \sum_{l=0}^{p_{xi}} \beta_{il} / (1 - \sum_{l=1}^{p_{yi}} \varphi_{il})$. The mean group estimator of the long-run coefficients θ_i is given by $\hat{\theta}_{MG} = N^{-1} \sum_{i=1}^{N} \hat{\theta}_i$.

Applying the ARDL(p_{yi}, p_{xi}) model and level relationship equation to panel data regression, however, result in correlation between the error terms, u_{it}, across i countries which makes the estimates of parameter θ_i inconsistent. Pesaran (2006) addresses the cross sectional dependency issue by introducing a CCE approach which includes the cross-section averages of the dependent and explanatory variables and its lags to the regression as proxy for the omitted common cross-sectional factors correlated across panel units.

$$u_{it} = \boldsymbol{\gamma}_t' \mathbf{f}_t + \varepsilon_{it} \tag{3.14}$$

for i = 1,2, …, N and t = 1, 2, …, T, where $\mathbf{f}_t$ is an m x 1 vector of the unobserved common factors. The CCE approach allows for heterogeneity in the effects of common factors across countries ($\boldsymbol{\gamma}_t$).

Chudik, Mohaddes, Pesaran, and Raissi (2016) propose the CS-DL approach which directly estimates the long-run coefficients, θ_i, with the level relationship equation (3.13) with common correlated effects mean-group (CCEMG) estimator. The CS-DL approach adds $\sqrt[3]{T}$ lags of the cross sectional averages of explanatory variables and the cross sectional averages of the dependent variable as proxy for the omitted common cross-sectional factors.

The equation for the CS-DL approach is derived as follows:

$$y_{it} = c_{yi} + \boldsymbol{\theta}_i' \mathbf{x}_{it} + \sum_{l=0}^{p-1} \delta_{i,l} \Delta x_{it} + \sum_{l=0}^{p_{\bar{y}}} \omega_{il} \bar{y}_{t-l} + \sum_{l=0}^{p_{\bar{x}}} \boldsymbol{\tau}'_{il} \bar{\mathbf{x}}_{t-l} + e_{it} \tag{3.15}$$

where $\bar{\mathbf{x}}_t = N^{-1}\sum_{i=1}^{N}\mathbf{x}_{it}$, $\bar{y}_t = N^{-1}\sum_{i=1}^{N} y_{it}$, $p = p_{\bar{x}} = \left[\sqrt[3]{T}\right]$, and $p_{\bar{y}} = 0$. After estimating independent coefficients, $\hat{\theta}_i$, for each panel unit i, the mean-group estimator is derived by averaging the individual coefficients. The CS-DL mean-group estimator of the long-run coefficients is defined by $\hat{\theta}_{CS-DL} = N^{-1}\sum_{i=1}^{N}\hat{\theta}_i$.

The CS-DL approach has the following merits and drawback compared to the cross-sectionally augmented autoregressive distributed lag (CS-ARDL) approach[3] which is another ARDL based model estimating long-run effects. First, the CS-DL approach is robust to small sample performance, and often exhibits better performance compared to the CS-ARDL estimator when the time dimension for the panel data (*T*) is not very large and lies in the range of 30 to 50. Moreover, the CS-DL approach is robust to misspecification of lag-order and thus, does not require specifying individual lag orders but only a truncation lag order. In addition, the CS-DL estimator allows for residual serial correlation and/or breaks in errors. The main drawback of the CS-DL estimator is that in the presence of the feedback effects from lagged values of dependent variable to the regressors, the CS-DL estimator may not be consistent. However, Chudik et al. (2016) note that "the bias due to feedback effects seems to be quite small; between -0.02 and 0.06, and the CS-DL estimators tend to outperform the CS-ARDL estimators when $T \leq 50$" (p. 116). Pesaran (2015) notes that "CS-ARDL approach seems to dominate CS-DL approach only if the time dimension is sufficiently large and the underlying ARDL model is correctly specified" (p. 783).

---

[3] The CS-ARDL approach, proposed by Chudik and Pesaran (2015), estimates the ARDL model with dynamic CCEMG estimator. The CS-ARDL model estimates the individual short-run coefficients $\{\varphi_{il}\}$ and $\{\beta_{il}\}$ using the following equation:

$$y_{it} = c_{yi}^{*} + \sum_{l=1}^{p_y}\varphi_i y_{i,t-l} + \sum_{l=0}^{p_x}\boldsymbol{\beta}'_{il}\mathbf{x}_{i,t-l} + \sum_{l=0}^{p_{\bar{z}}}\boldsymbol{\beta}'_{il}\bar{\mathbf{z}}_{t-l} + e_{it}^{*},$$

where $\bar{\mathbf{z}}_t = (\bar{\mathbf{z}}_t, \bar{\mathbf{x}}'_t)'$, $p_{\bar{z}} = \left[T^{\frac{1}{3}}\right]$.

The estimates of long-run effects are derived by computing the estimated individual short-run coefficients as follows: $\theta_i = \sum_{l=0}^{p_{xi}}\beta_{il}/(1-\sum_{l=1}^{p_{yi}}\varphi_{il})$.

To test the consistency of the CS-DL estimator, the cross-sectional dependence (CD) test is checked which verifies the hypothesis that the adjustment is able to eliminate cross-sectional dependence.

Chapter 4.
Growth effect of DCA

4.1. Introduction

This chapter empirically analyzes the effects of DCA on economic growth in the long run. The analysis finds its theoretical framework from the literature on DCA (i.e., Lin, 2010; Saviotti & Pyka, 2011; Krugman, 1987). Existing literature on export diversification, specialization, and growth highlights the overall degree and nature of specialization pattern at a point in time (i.e., ECI, Herfindahl-Hirschman index). Meanwhile, theoretical literature on trade and growth points out that comparative advantage endogenously evolves over time and emphasizes the role of change in comparative advantage on economic growth. In particular, Saviotti and Pyka (2011) argue that the ability of creating new sectors is an important determinant of sustainable development.

Motivated by the theoretical discussions on DCA and the high transformation rate of top exports in East Asia, this chapter aims at answering the following research question: can the ability of creating new top exports be the source of economic development? Accordingly, this chapter introduces a new measurement which captures changes in comparative advantage by focusing on the emergence of new top exports. Accordingly, this chapter investigates the following hypothesis: change in top exports which captures the change in comparative advantage has a significant and positive effect on economic growth in the long run.

4.2. Measuring changes in comparative advantage

4.2.1. Data

To measure the dynamic changes in comparative advantage, the export data of SITC rev.2, 4-digit classification is used considering its long time dimension and a high level of data disaggregation. The continuity of product code is key issue to measure the changes in the composition of top exports. The discontinuity of dataset is highly caused by the introduction of a new classification for compiling trade statistics in 1984, namely, the SITC rev.2. Export data from 1962 to 1983 were compiled by the SITC rev.1, and the data afterwards used the SITC rev.2. Whenever the conversion between rev.1 and rev.2 is unequivocal, products are reported at the 3-digit level with zero added in the end. To avoid any product code discontinuity problem and minimize loss of information, partial data aggregation process is conducted following the work of Dosi, Riccio, and Virgillito (2022). Product codes which have discontinuity issue at 4-digit level in 1983 are aggregated to 3-digit level, and a consistent 486 product categories are constructed.

4.2.2. Generating DCA index

The changes in comparative advantage is quantified by calculating the emergence of new top 25 exports. The top 25 export products consist of 5% of the total number of world export products. However, the top 25 export products play a crucial role in each economy as its median share in total exports accounts for 82% for a total of 95 countries. In particular, this study compares the changes in the top 25 exports between year *t* and the top 25 exports from the first three-year averages of exports from 1962 to 1964. We name the index as the DCA index. Measuring the changes in the top 25 exports can be done in two ways. First, the equally weighted DCA index captures changes in the numbers of top exports and can be defined as the following equation.

$$EW - DCA_{it} = \frac{1}{N}\sum_{k=1}^{N} \delta_{ikt} \tag{4.1}$$

where k is product, i is country, t denotes year, and N denotes the numbers of top exports which in this study is fixed to 25 and

$$\delta_{ikt} = \begin{cases} 1 \text{ if product } k \text{ is newly emerged top exports in country } i \text{ in year } t \\ 0 \text{ otherwise} \end{cases}$$

Second, the weighted DCA index measures the changes in the share of top exports and is calculated as follows:

$$W - DCA_{it} = \frac{\sum_{k=1}^{N} \delta_{ikt} E_{ikt}}{\sum_{k=1}^{N} E_{ikt}} \tag{4.2}$$

where E_{ikt} is the value of export product k in country i in year t. Other abbreviations are the same with the equally weighted DCA index.

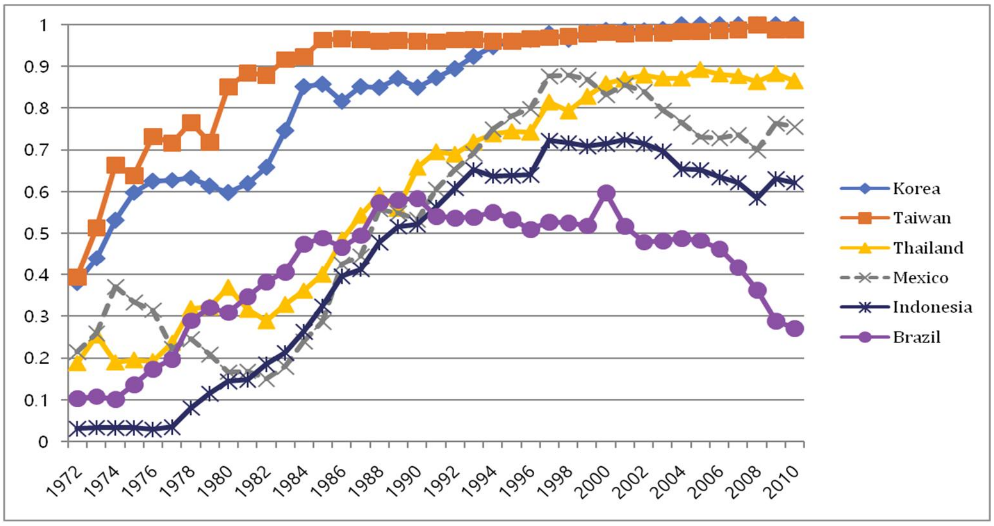
Some distinct features of the DCA index are found from the existing measures used in the literature in export diversification, specialization, and growth. First, the existing measures of export diversification and specialization capture static instances of the composition of exports, even when the implication from the measurements is considered a dynamic concept. The DCA index considers the past composition of top exports, apart from the current composition of top exports, which enables the index to capture the changes in the composition of top exports in its evolving pattern. Second, the DCA index captures both aspects of diversification and specialization which enables the index to link between the literature on export diversification and export specialization. Third, the DCA index captures the revealed changes in comparative advantage of countries from the changes in specialization based on traditional trade theories. Under an opened economy, specialization pattern is determined by the current comparative advantage.

The DCA index applies a fixed initial period of specialization, an average of 1962 to

1964 to calculate the change in comparative advantage. Applying fixed comparison year in the index computation instead of comparison of specialization pattern over a 10-year period helps avoid measurement error of capturing reversion to former comparative advantage as a generation of new comparative advantage (refer to the case of Brazil shown in Figure 4.1). However, the downside of this computation method is its failure to capture the change in comparative advantage during the intermediate periods. Nonetheless, the DCA index notably implies that sustained new comparative advantage can be an important source of growth. Capturing cumulative change in comparative advantage is in line with the theoretical literature which finds the determinant of DCA from the associated change in factor endowments, including capital and infrastructure (Lin, 2010) or relative productivity change determined by cumulative past production and technology (Krugman, 1987; Redding, 1999).

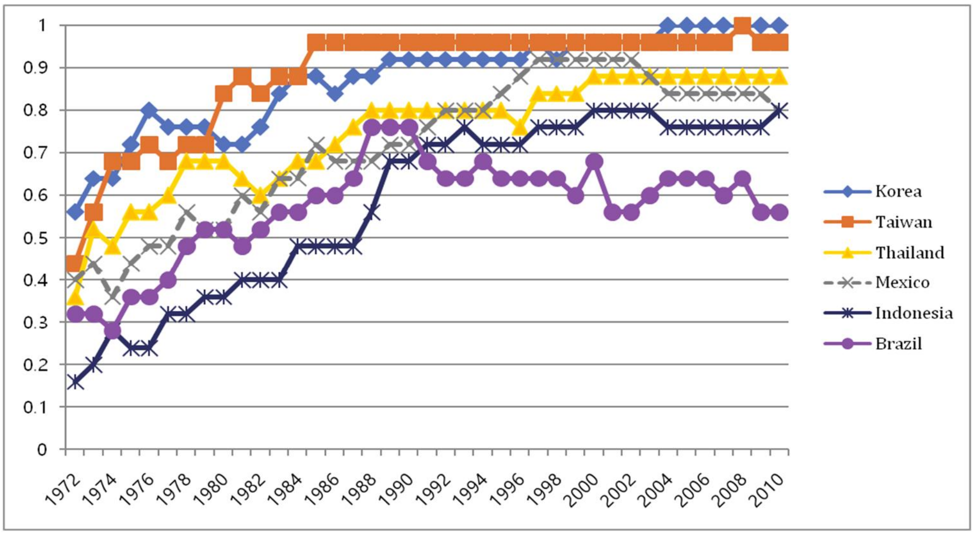
Figures 4.1 and 4.2 respectively exhibit the weighted and the equally weighted DCA index for selected countries of East Asia and Latin America from 1972 to 2010. The two indices show similarities in terms of country ranking, whereas the value of the weighted DCA index shows a distinct difference between countries compared with that of equally weighted DCA index. The successful export-led developed countries—Taiwan and Korea—consistently show high values of both indices throughout the whole period which indicates that the two countries experienced sustained changes in comparative advantage along the process of development from low- to high-income. More specifically, the composition of top exports of Taiwan and Korea nearly changed completely compared with the top exports in the initial period of the early 1960s. Thailand also started exhibiting dynamic changes in comparative advantage during the latter half of the period but not to the extent compared with those of Korea and Taiwan. Other countries, including Indonesia, Mexico, and Brazil show a relatively stable trend in the value of the weighted DCA index which indicates that the comparative advantages of the countries in the early 1960s continue to have an important position in the economy. In particular, it is observed that Brazil reverted to the comparative advantage it once possessed in the early 1960s.

Figure 4.1. Dynamic changes in the share of top 25 exports in selected economies



Source: Author's calculation
Note: The figure presents the trend of the weighted DCA index.

Figure 4.2. Dynamic changes in the number of top 25 exports in selected economies



Source: Author's calculation
Note: The figure presents the trend of the equally weighted DCA index.

4.3. Models and key variables

4.3.1. Analysis using a homogeneous dynamic panel data model

The baseline model specification for estimating the effects of changes in comparative advantage on per capital GDP follows the growth equation from Mankiw, Romer, and Weil (1992) which empirically examines the Solow growth model by including factors related to savings and population growth as determinants of income per capita. The system GMM approach is applied using five-year-average panel data. Following the literature on growth using system GMM estimation (Islam, 1995; Hesse, 2008; Lee & Kim, 2009; Lee & Lee, 2020), a non-overlapping eight five-yearly observations per country panel data is constructed for system GMM estimation from 1972–1976, 1977–1981, ... , 2002–2006, and 2007–2010. The sample consists of 95 countries which include 24 developed and 71 non-developed countries with the time period from 1972 to 2010. Developed countries are defined as countries having a per capita GDP exceeding the first quartile of the wealthiest per capita GDP in year 1972 and 2010. Appendix 1 provides a detailed list of developed and non-developed countries.

The baseline model specification for estimating the effects of DCA proxied by the DCA index on per capita GDP follows the following growth equation:

$$y_{it} = \gamma_t + \alpha y_{it-1} + \mathbf{x}'_{it}\boldsymbol{\beta} + \gamma z_{it} + \eta_i + \varepsilon_{it} \tag{4.3}$$

for $i = 1, 2, \dots, N$ and $t = 1, 2, \dots, T$, where i is the country, and t is the time period. The dependent variable y_{it} denotes the real GDP per capita in log, y_{it-1} is the logarithm of initial GDP per capita in each period, γ_t captures the time effects, η_i captures the unobserved, individual fixed effects, and ε_{it} is the error term. $\mathbf{x}_{it}$ is a vector of potential determinants of growth used as control variables. Growth regression based on the Solow model commonly includes the log of initial income of each period which captures the convergence term, savings rate, and population growth variables for baseline control variables. Following Mankiw et al. (1992), the difference in the logs of average investment share of real GDP over each five-year period and the logs of the sum of the population growth variable is included as baseline control variable for all models (averaged over each five-year period) and 0.05 (log [investment ratio]- log [population growth rate] + 0.05). The literature verifying the Solow growth regression, including Mankiw, Romer, and Weil (1992) and Hoeffler (2002) assumes that a constant rate of technological process and depreciation rate across countries sum to 0.05.[4] Data for the aforementioned variables were obtained from the Penn World Table version 10.0.

z_{it} is the variable of interest which includes the weighted and equally weighted DCA index introduced in Chapter 4.2. Another variable of interest is the ECI proposed by Hidalgo and Hausmann (2009) discussed in Chapter 2. The ECI data were obtained from the observatory of economic complexity website downloaded on April 19, 2020 (oec.world).

Other control variables include trade openness which is a commonly included variable in literature on trade and growth, human capital which is an important determinant on growth argued by Mankiw et al. (1992), government expenditure, increase in exports, and increase in primary exports within each period. In particular, the variable related to increase in exports and resource exports is included to capture the effect on growth caused by an increase in income that comes from exports or resource exports not related to changes in comparative advantage following Hausmann et al. (2013). Appendix Table 2 provides a data dictionary.

4.3.2. Analysis using a large heterogeneous panel data model

This study applies the cross-sectionally augmented distributed lag (CS-DL)

[4] *0.05 = technical progress(g) + depreciation of capital(δ)

methodology on annual data from 1973 to 2010, apart from the system GMM approach which is frequently used in the literature on growth. The system GMM estimation is based on strong homogeneity restrictions, assumes no feedback effects from dependent variable to regressor, and is independent of cross-country error terms. Meanwhile, the CS-DL approach allows for cross sectional heterogeneity and cross country error dependencies that are likely to be present in growth regression. The estimation method also checks the endogeneity issue by allowing for feedback effects of dependent variable as well as between explanatory variables. Given that the control variables added in the growth regression are the main components of per capita income and are interdependent with each other (Caselli et al., 1996; Hesse, 2008), allowing for feedback effect should help consider the limitations from the GMM estimation.

The following equation for the CS-DL model regression is estimated:

$$y_{it} = c_{yi} + \boldsymbol{\theta}_i' \mathbf{x}_{it} + \sum_{l=0}^{p-1} \delta_{il} \, \Delta \mathbf{x}_{it} + \omega_{il} \bar{y}_{it} + \sum_{l=0}^{p_x} \boldsymbol{\tau}'_{il} \bar{\mathbf{x}}_{i,t-l} + e_{it} \quad (4.4)$$

where $p = p_x = \left[\sqrt[3]{T}\right]$

for $i = 1, 2, \ldots, \mathrm{N}$ and $t = 1, 2, \ldots, T$. y_{it} denotes the real GDP per capita for country *i* and year *t*. x_{it} is a vector of explanatory variables, including the variable of interest and the conventional control variable frequently used in growth regression based on the Solow growth model (Mankiw et al., 1992; Hoeffler, 2002). The variable of interest includes the DCA index and the ECI. In the CS-DL estimation, the past three-year averages of the DCA index are applied to average out changes in export structure not caused by changes in comparative advantage such as idiosyncratic shocks caused by political reasons and price variations. The baseline control variable includes the variable constructed with the difference in the logs of investment share of real GDP and the logs of the sum of the population growth variable and 0.05 following Mankiw et al. (1992). To test the robustness of results, other control variables added to the model include trade openness, government burden, and increase in exports. Human capital-related variable is excluded in the CS-DL estimation due to limitation of annual datasets. $\bar{y}_{it}$ and $\bar{\mathbf{x}}_{it}$ denote the cross section averages of y_{it} and $\mathbf{x}_{it}$ in year t. As discussed in subchapter 3.2., $\left[\sqrt[3]{T}\right]$ lags of cross-sectional averages of explanatory variables and those of the lags of dependent variable are included following the CCE approach. Accordingly, given that our sample data have a total of 38 observations from 1973 to 2010 per country, three lags of the cross-sectional averages of the explanatory variables are added to the regression to check for cross-country dependencies which may arise from omitted common factors.

4.4. Empirical Results: from DCA to economic growth

Table 4.1 shows the results from fixed effect and system GMM estimations with baseline control variables, including initial income level, investment, and population growth-related factors along with trade openness. The coefficients of the weighted DCA index all came out positive and statistically significant at the 5% significance level in fixed effect estimation and 1% significance level in system GMM estimation. The coefficients of the equally weighted DCA index came out positive and significant only in the case of system GMM estimation in the non-developed countries sample. Other coefficients came out positive but statistically insignificant, which questions the robustness of the results. The results show that the weighted DCA index better captures the growth effects of change in comparative advantage than the equally weighted DCA index. To further verify the robustness of the results concerning the weighted DCA index, additional explanatory variables are considered including human capital, government burden, and increase in exports (see Tables 4.2 and 4.3).

The robustness pattern of the positive effects of weighted DCA index on per capita income is repeated with additional control variables at the 5% significance level. The coefficients of the weighted DCA index are observed to cluster around 0.1.

Another variable of interest is the ECI developed by Hidalgo and Hausmann (2009), an index also calculated from export data in SITC rev.2, 4-digits. In Table 4.4, the coefficients of the ECI came out significant in the case for system GMM estimation in all models. Meanwhile, the coefficients of the FE estimation came out insignificant, which questions the robustness of the results. The effects of dynamic changes in comparative advantage on growth captured by the weighted DCA index continue to be significantly positive in both FE and system GMM estimation, even after the ECI is controlled for.

Table 4.1. Growth effect of DCA: Fixed-effects and system GMM regression results

Dependent Variable	per Capita GDP, real in log							
	All countries				Non-developed countries			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
VARIABLES	FE	GMM	FE	GMM	FE	GMM	FE	GMM
Log(1+initial DCA index)	0.151**	0.205***			0.145**	0.195***		
- Weighted	(0.0648)	(0.038)			(0.0619)	(0.049)		
Log(1+initial DCA index)			0.0919	0.116			0.156	0.203**
- Equally weighted			(0.106)	(0.073)			(0.105)	(0.081)
Initial GDP per capita, log	0.753***	0.952***	0.761***	0.958***	0.758***	0.965***	0.763***	0.969***
	(0.0405)	(0.014)	(0.0398)	(0.014)	(0.0476)	(0.017)	(0.0469)	(0.016)
log(I/GDP) - log(η+0.05)	0.0870***	0.057**	0.0943***	0.089***	0.0706**	0.070***	0.0760***	0.092***
	(0.0245)	(0.025)	(0.0228)	(0.023)	(0.0276)	(0.022)	(0.0267)	(0.024)
Trade Openness, log	0.0377***	0.046**	0.0383***	0.028*	0.0356**	0.031	0.0359***	0.019
	(0.0132)	(0.020)	(0.0124)	(0.016)	(0.0140)	(0.019)	(0.0135)	(0.021)
	2.178***	0.472***	2.093***	0.360***	2.056***	0.329**	1.985***	0.217*
	(0.348)	(0.134)	(0.330)	(0.125)	(0.383)	(0.134)	(0.367)	(0.128)
Observations	760	760	760	760	568	568	568	568
Number of country	95	95	95	95	71	71	71	71
Year FE	YES	YES	YES	YES	YES	YES	YES	YES
AR(2)		-0.316		-0.389		-1.546		-1.485
[p-value]		0.752		0.697		0.122		0.137
Hansen test		87.46		84.45		67.41		64.90
[p-value]		0.104		0.150		0.163		0.221

Note1: *** p<0.01, ** p<0.05, and * p<0.1.

Table 4.2. Results of fixed-effects estimations: Robust check for weighted DCA index

	All countries				Non-developed countries			
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Log(1+initial DCA index)	0.128**	0.146**	0.153**	0.150**	0.124**	0.144**	0.148**	0.134**
- Weighted	(0.0579)	(0.0639)	(0.0638)	(0.0635)	(0.0533)	(0.0615)	(0.0616)	(0.0590)
Initial GDP per capita, log	0.786***	0.758***	0.757***	0.752***	0.796***	0.761***	0.761***	0.751***
	(0.0225)	(0.0402)	(0.0403)	(0.0408)	(0.0253)	(0.0475)	(0.0476)	(0.0499)
log(I/GDP) - log(η+0.05)	0.108***	0.0890***	0.0886***	0.0890***	0.0915***	0.0723**	0.0720**	0.0796***
	(0.0251)	(0.0242)	(0.0244)	(0.0235)	(0.0293)	(0.0273)	(0.0276)	(0.0287)
Trade Openness, log	0.0308**	0.0347***	0.0370***	0.0358***	0.0288**	0.0338**	0.0352**	0.0305**
	(0.0132)	(0.0132)	(0.0132)	(0.0128)	(0.0142)	(0.0140)	(0.0141)	(0.0131)
Initial Human Capital	0.000373				0.000312			
	(0.000791)				(0.00128)			
Increase in exports/GDP		0.00224				0.00145*		
		(0.00142)				(0.000775)		
Increase in primary exports/GDP			0.00194				0.00113**	
			(0.00123)				(0.000464)	
Government consumption, log				0.0155				0.0372
				(0.0195)				(0.0247)
Constant	1.883***	2.121***	2.135***	2.212***	1.735***	2.027***	2.033***	2.166***
	(0.201)	(0.346)	(0.346)	(0.365)	(0.210)	(0.382)	(0.383)	(0.424)
Observations	704	760	760	760	512	568	568	568
Number of country	88	95	95	95	64	71	71	71
Year FE	YES	YES	YES	YES	YES	YES	YES	YES

Note1: *** p<0.01, ** p<0.05, and * p<0.1.

Table 4.3. Results of system GMM estimations: Robust check for weighted DCA index

	All countries				Non-developed countries			
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Log(1+initial DCA index)	0.163***	0.183***	0.188***	0.174***	0.180***	0.131**	0.143**	0.134**
- Weighted	(0.045)	(0.047)	(0.043)	(0.044)	(0.048)	(0.062)	(0.064)	(0.060)
Initial GDP per capita, log	0.094***	0.064**	0.059**	0.057**	0.111***	0.064***	0.079***	0.081***
	(0.025)	(0.026)	(0.027)	(0.027)	(0.030)	(0.023)	(0.025)	(0.024)
log(I/GDP) - log(η+0.05)	0.027*	0.029**	0.033**	0.039**	0.004	-0.008	0.009	0.007
	(0.016)	(0.014)	(0.015)	(0.016)	(0.010)	(0.011)	(0.023)	(0.020)
Trade Openness, log	0.942***	0.962***	0.964***	0.962***	0.963***	1.002***	0.976***	0.974***
	(0.015)	(0.013)	(0.014)	(0.014)	(0.019)	(0.019)	(0.020)	(0.018)
Initial Human Capital	0.001*				0.000			
	(0.001)				(0.001)			
Increase in exports/GDP		0.002				0.000**		
		(0.001)				(0.000)		
Increase in primary exports			0.001				0.001**	
			(0.001)				(0.000)	
Government consumption, log				-0.014				-0.003
				(0.013)				(0.018)
Observations	704	760	760	760	512	568	568	568
Number of country	88	95	95	95	64	71	71	71
Year FE	YES	YES	YES	YES	YES	YES	YES	YES
AR(2)	0.325	-0.330	-0.341	-0.332	-1.067	-1.548	-1.534	-1.543
[p-value]	0.745	0.741	0.733	0.740	0.286	0.122	0.125	0.123
Hansen test	78.86	88.38	87.87	86.06	57.22	63.42	62.64	61.88
[p-value]	0.483	0.220	0.232	0.275	0.255	0.291	0.315	0.339

Note1: *** p<0.01, ** p<0.05, and * p<0.1.

Note2: Constant term is included in the analysis but omitted in this table.

Table 4.4. Results of FE and system GMM estimations: growth effects of weighted DCA index and ECI

Econometric Method:	Cross-sectional dynamic panel Estimation: Fixed effect and System GMM							
Dependent Variable	per Capita GDP, real in log							
	All countries				Non-developed countries			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
VARIABLES	FE	Sys. GMM	FE	Sys. GMM	FE	Sys. GMM	FE	Sys. GMM
Log(1+initial DCA index)			0.155**	0.139***			0.149**	0.110*
- Weighted			(0.0663)	(0.046)			(0.0668)	(0.057)
Initial ECI	0.0221	0.054***	0.0156	0.027**	0.0223	0.042**	0.0138	0.044**
	(0.0147)	(0.015)	(0.0155)	(0.013)	(0.0182)	(0.017)	(0.0198)	(0.018)
Initial GDP per capita, log	0.745***	0.924***	0.731***	0.939***	0.742***	0.959***	0.732***	0.926***
	(0.0402)	(0.017)	(0.0430)	(0.019)	(0.0511)	(0.028)	(0.0534)	(0.027)
log(I/GDP) - log(η+0.05)	0.0947***	0.079***	0.0859***	0.060**	0.0797***	0.053*	0.0711**	0.083***
	(0.0218)	(0.024)	(0.0237)	(0.027)	(0.0269)	(0.028)	(0.0280)	(0.022)
Trade Openness	0.0439***	0.024	0.0427***	0.043*	0.0417***	0.029*	0.0404***	0.039**
	(0.0131)	(0.018)	(0.0140)	(0.022)	(0.0139)	(0.017)	(0.0148)	(0.017)
Constant	2.270***	0.693***	2.373***	0.587***	2.214***	0.438*	2.280***	0.685***
	(0.345)	(0.158)	(0.369)	(0.175)	(0.415)	(0.233)	(0.432)	(0.224)
Observations	750	750	750	750	558	558	558	558
Number of country	94	94	94	94	70	70	70	70
Year FE	YES	YES	YES	YES	YES	YES	YES	YES
AR (2)		-0.207		-0.235		-1.415		-1.481
[p-value]		0.836		0.814		0.157		0.139
Hansen test		87.15		85.50		59.85		64.38
[p-value]		0.248		0.132		0.304		0.234

Note1: *** p<0.01, ** p<0.05, and * p<0.1.

Tables 4.5 to 4.9 show the results for the CS-DL estimations which are developed to estimate the long-run effects. Each table includes the cross-sectional dependence (CD) statistics and the p-value in the last two rows which tests for cross-sectional independence of residuals. In most cases, the CD statistics rejects the null hypothesis of no cross-sectional dependence. This finding indicates that the adjustment by adding three lags of cross-sectional averages of explanatory variables and those of dependent variable is able to eliminate cross-sectional dependence. Before reporting the results of the variables of interest, the investment rate adjusted by population growth, which is included as the baseline control variable, remarkably came out to have a positive and significant effect on per capital income level in the long-run at a 1% significance level in all models which is in line with the Solow growth model.

Looking into the estimation results for the variables of interest, the coefficients of the weighted DCA index consistently came out positive and statistically significant with the baseline control variable, whereas the coefficients of the equally weighted DCA index came out statistically insignificant in Table 4.5. The results are consistent with the results of the cross-sectional dynamic panel models in Table 4.1.

To check the robustness of the weighted DCA index, other control variables are added to the model including trade openness, and Table 4.6 presents the results.[5] The latter consistently supports the positive and significant effects of DCA weighted by export ratio on per capita income in the long run. One exception is when government expenditure is additionally controlled for where the coefficient for the weighted DCA index loses significance in case of all countries sample in column (4). Another variable of interest is the ECI which measures the amount of productive capabilities that each country processes from

[5]Additional robustness test includes modification of DCA index by (1) changing the number of top exports, (2) changing the aggregation level of dataset from 4 digits to 3 digits, (3) changing the initial year from average of 1962–1964 to 1965, and (4) changing dataset to HS 6digits and the initial year to 2000. Appendix 5 reports the results.

export data. Table 4.7 shows the results with the variable of ECI added. Different from previous studies which show that ECI has a positive effect on economic growth (Hausmann et al., 2013), the coefficients of the ECI came out insignificant in the CS-DL estimation when investment rate adjusted by population growth is controlled for. Lee and Lee (2020) also questioned the robustness of the ECI after including the variable of terms of trade or government consumption. Even more, the sign of the coefficient of the ECI in the case of non-developed countries sample came out negative. Meanwhile, the long-run effects of changes in comparative advantage weighted by export share on development are not undermined by the inclusion of the ECI.

Another robustness test is conducted by applying different choices of dynamic specifications (lag length, p), and Table 4.8 presents the results. The number of lags added for the cross-sectional correction is fixed to 3 ($p_{\mathrm{x}} = \left[\sqrt[3]{T}\right] = 3$) following Lombardi et al. (2017). Specifically, columns (1) and (4) report the estimates when p= 2, columns (2) and (5) report the estimates when p =$\left[\sqrt[3]{T}\right]$ = 3, and columns (3) and (6) apply p= 4. The coefficient estimates for the weighted DCA index all came out positive and statistically significant in all models. The coefficients of the weighted DCA index notably came out larger with the inclusion of longer lag lengths of the weighted DCA index, ranging from 0.6 to 0.8 for all countries sample and from 0.5 to 0.6 for non-developed countries sample. The theoretical literature points out that cumulative past production (Krugman, 1987) or cumulative past technology (Redding, 1999) determines the current comparative advantage. The results from Table 4.8 support the arguments of the theoretical literature and emphasize the dynamic effect of shift in comparative advantage on the level of income.

The coefficients of the weighted DCA index from the CS-DL model ranges from 0.7 to 1.3 in the case for all countries sample and from 0.5 to 0.9 in the case for non-developed countries sample. The coefficients from the CS-DL estimation consistently came out larger than the coefficients from the system GMM estimation. For comparison, Table 4.9 shows the estimation results using a lagged variable of DCA index instead of the past three-year averages of the DCA index. The size of the statistically significant coefficients of the DCA index is around 0.5, while the coefficients from the cross-sectional dynamic panel models are around 0.15. The results indicate that the CS-DL approach better captures the dynamic effects of change in comparative advantage on economic growth compared with the system GMM approach.

The results of the additional control variables are consistent with existing literature. Variables related to increase in exports and increase in primary exports show positive and significant effects on long-run growth which is in line with Hausmann et al. (2013) who include the increase in primary exports as baseline control variable estimating the effects of ECI on growth.

Overall, the estimation results from both cross-sectional dynamic panel model and panel time-series model support the hypothesis of the positive effects of DCA on per capita income in the long run which is in line with Saviotti and Pyka (2011). The mixed results between the weighted DCA index and the equally weighted DCA index imply that the weighted DCA index better captures the growth effects of changes in comparative advantage than the equally weighted DCA index. Notably, the existing measures of comparative advantage (Balassa, 1965; Vollrath & Vo, 1988; Laursen, 1998) commonly refer to the values of trade. In addition, the creation of new sectors or products needs sufficient economic weight to have an important impact on the economy.

Table 4.5. Growth effect of DCA: CS-DL regression results

Dependent Variable	GDP per capita, real in logs					
	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	All countries			Non-developed countries		
Compared with early 1960s						
Log(1+DCA Index*)		0.737***			0.648**	
- Weighted by export ratio		(0.255)			(0.313)	
Log(1+DCA Index*)			0.286			0.210
- Equally Weighted			(0.228)			(0.234)
Control variables						
log(I/GDP) - log$(\eta+g+\delta)$	0.171***	0.161***	0.153***	0.222***	0.186***	0.172***
	(0.032)	(0.028)	(0.028)	(0.032)	(0.032)	(0.030)
Constant	-0.218	0.087	0.869	-0.198	-0.317	0.692
	(1.115)	(1.414)	(1.092)	(1.351)	(1.096)	(0.982)
Observations	3,315	3,315	3,315	2,481	2,481	2,481
Number of countries	95	95	95	71	71	71
CD stats.	2.867	0.879	0.521	-2.003**	0.996	-2.138
CD stats.[p-value]	0.004	0.379	0.603	0.045	0.319	0.033

Note1: *** p<0.01, ** p<0.05, and * p<0.1.
Note2: DCA index* indicates the past three-year averages of the DCA index.

Table 4.6. CS-DL regression results: Robust check for weighted DCA index

Dependent Variable	Per Capita GDP, Real in logs							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
VARIABLES	All countries				Non-developed countries			
Compared to early 1960s								
Log(1+DCA Index*)	1.346**	0.907***	0.812***	0.542	0.953***	0.599**	0.628**	0.570*
- Weighted by export ratio	(0.527)	(0.334)	(0.265)	(0.449)	(0.318)	(0.248)	(0.263)	(0.337)
Control variables								
log(I/GDP) - log(η+0.05)	0.119***	0.159***	0.149***	0.148***	0.153***	0.145***	0.183***	0.194***
	(0.037)	(0.032)	(0.034)	(0.034)	(0.037)	(0.035)	(0.035)	(0.041)
Trade Openness, log	0.031				0.024			
	(0.047)				(0.044)			
Increase in exports/GDP		0.038***				0.039***		
		(0.010)				(0.013)		
Increase in primary EX/GDP			0.193***				0.154**	
			(0.069)				(0.075)	
Government consumption, log				-0.081*				-0.007
				(0.047)				(0.048)
Constant	0.504	1.571	-0.274	1.680	-0.643	1.263	0.390	0.659
	(1.842)	(1.405)	(1.590)	(1.611)	(1.312)	(1.302)	(1.414)	(2.397)
Observations	3,315	3,311	3,311	3,315	2,481	2,481	2,481	2,481
Number of countries	95	95	95	95	71	71	71	71
CD stats.	0.678	1.397	0.793	-0.208	1.586	0.611	0.675	0.121
CD stats [p-value]	0.498	0.163	0.428	0.835	0.113	0.541	0.499	0.904

Note1: *** p<0.01, ** p<0.05, and * p<0.1.
Note2: DCA index* indicates the past three-year averages of the DCA index.

Table 4.7. CS-DL regression results: comparison between weighted DCA index and ECI

Dependent variables	GDP per capita, real in logs			
	(1)	(2)	(3)	(4)
VARIABLES	All countries		Non-developed countries	
Compared to early 1960s list				
Log(1+DCA Index*)		0.961***		0.611*
- Weighted by export ratio		(0.372)		(0.367)
ECI	0.035	-0.050	-0.010	-0.076
	(0.047)	(0.048)	(0.058)	(0.062)
Control variables				
log(I/GDP) - log(η+0.05)	0.151***	0.165***	0.227***	0.210***
	(0.033)	(0.026)	(0.033)	(0.041)
Constant	-0.120	1.862	0.939	1.327
	(1.212)	(1.546)	(1.007)	(1.537)
Observations	3,245	3,245	2,411	2,411
Number of countries	93	93	69	69
CD stats.	7.479	0.105	-0.441	1.008
CD stats [p-value]	0	0.917	0.659	0.314

Note1: *** $p<0.01$, ** $p<0.05$, and * $p<0.1$

Note2: DCA index* indicates the past three-year averages of DCA index

Table 4.8. CS-DL regression results: Robust check with different lag of orders ($p_x = 3$)

Dependent Variable	per Capita GDP, real in log					
	All countries			Non-developed countries		
lag of orders	p=2	p=3	p=4	p=2	p=3	p=4
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
Weighted index						
Log(1+ DCA index*)	0.454**	0.737***	0.891***	0.440*	0.648**	0.703**
	(0.190)	(0.255)	(0.283)	(0.256)	(0.313)	(0.332)
log(I/GDP) - log(η+0.05)	0.176***	0.161***	0.168***	0.197***	0.186***	0.163***
	(0.024)	(0.028)	(0.031)	(0.028)	(0.032)	(0.043)
Constant	-0.068	0.087	1.336	-0.048	-0.317	0.139
	(1.290)	(1.414)	(1.440)	(1.016)	(1.096)	(1.386)
Observations	3,412	3,315	3,218	2,553	2,481	2,409
Number of countries	95	95	95	71	71	71
CD stats	1.121	0.879	0.624	-0.616	0.996	1.588
CD stats [p-value]	0.262	0.379	0.532	0.538	0.319	0.112

Note1: *** $p<0.01$, ** $p<0.05$, and * $p<0.1$.

Note2: DCA index* indicates the past three-year averages of the DCA index.

Table 4.9. CS-DL regression results: Robust test with lag DCA index

Dependent variables	GDP per capita, real in logs			
	(1)	(2)	(3)	(4)
VARIABLES	All countries		Non-developed countries	
Compared with early 1960s list				
Log(1+lag DCA Index)	0.595***		0.474**	
- Weighted by export ratio	(0.191)		(0.233)	
Log(1+lag DCA Index)		0.184		0.160
- Equally weighted		(0.131)		(0.141)
Control variables				
log(I/GDP) - log(η+0.05)	0.163***	0.148***	0.192***	0.178***
	(0.028)	(0.027)	(0.032)	(0.029)
Constant	0.207	0.570	-0.251	0.575
	(1.188)	(0.993)	(0.955)	(0.896)
Observations	3,311	3,311	2,481	2,481
Number of groups	95	95	71	71
CD stats.	3.078	2.162	1.280	-1.497
CD stats. [p-value]	0.00208	0.0306	0.200	0.134

Note1: *** p<0.01, ** p<0.05, and * p<0.1.

4.5. Concluding remarks and limitations of the study

The study introduces an index which measures the DCA and examines its impact on economic growth. The growth regressions from fixed effect (FE), system GMM, and CS-DL estimations consistently confirm the positive and significant impacts of the weighted DCA index on long-run economic growth. The robustness of the weighted DCA index is observed with additional controls including the ECI, but ECI loses significance in the CS-DL estimations. The results follow the literature on DCA on growth which argues that countries which overcome the increasing barriers to entry and succeed in creating new comparative advantage may achieve economic growth by reallocating underutilized resources to a growing market (Saviotti & Pyka, 2004). Similarly, Lin (2010) notes that economies that attempt to grow simply by adding more and more resources to the existing industries eventually run into diminishing returns.

The implications from the results can be summarized as follows. First, export diversification and specialization are not opposite concepts but related as pointed out by Nomaler and Verspagen (2021). This finding comes from the distinct feature of the DCA index which captures both aspects of diversification and specialization because if the newly emerged top exports are incomplete substitutes for the existing ones, adding new top exports should lead to diversification. Second, the findings suggest that the weighted DCA index measured by the changes in the share of top exports better captures the effects of DCA on economic growth in the long run than the index which calculates the change in the numbers of top exports. Third, the regression results indicate that the CS-DL approach better captures the dynamic effects of new comparative advantage on per capita income than the system GMM approach by consistently showing larger coefficients which are in line with the theoretical literature on DCA and economic growth (Krugman, 1987; Redding, 1999).

Meanwhile, the DCA index overlooks the changes in the nature and the composition of comparative advantage, while economic development requires both quantitative and qualitative changes in the economic system. Literature on specialization highlights that the composition of exports has an important influence on growth. As Lin (2010) puts it, economic development requires continuous technological innovation and industrial upgrading. Saviotti and Pyka (2008) define qualitative change as "changes in composition at much lower levels of aggregation" (p. 324) from the emergence of low-technological, labor-intensive sectors to higher technological, capital-intensive sectors.

The next chapter verifies the growth effects of the qualitative aspects of change in comparative advantage by tracking the different technological contents across sectors through the lenses of the OECD classification of technological intensity.

Chapter 5.

Growth effect of DCA tracking technological contents

5.1. Introduction

This chapter considers the different levels of technology embedded in each sector when measuring the DCA and verifies the effects of the nature of changes in comparative advantage on long-run economic growth. Empirical findings of the literature on specialization show that products which are generally a comparative advantage of high-income countries (e.g., high technological, manufacturing products) generate higher growth potential. The findings generally imply that irrespective of a country's endowment structure, targeting a higher level of technological industries enhances the growth potential. A different perspective is given by the empirical work of Dosi et al. (2022) which finds that scale intensive exports (can be classified as lower technology) are economically beneficial for developing countries, and specialized supplier exports (higher technology) are beneficial for developed countries. Meanwhile, using survival analysis, Dosi et al. (2022) do not focus on verifying the effects of composition of exports on economic growth in the long run.

The theoretical discussions on the new structural economics (Lin, 2010) and Korea and Taiwan's changes in comparative advantage within lower-technological sectors up until the early 1980s indicate a different argument from the literature on specialization. Lin (2010) points out that economic structure is competitive when it follows the comparative advantage determined by factor endowments including capital, labor, land, and infrastructure. This finding implies that for non-developed countries which generally have relative abundance in labor than capital may obtain the opportunity to accumulate capital needed to gain competitiveness in higher technological sectors from initially specializing in lower-technological sectors and gradually adopting new specialization in higher-technological sectors.

Accordingly, the first and second hypotheses to be verified in this chapter are related to defying comparative advantage:

Hypothesis 1: New comparative advantage in higher level of technology does not guarantee higher growth potential in the long run.

Hypothesis 2: New comparative advantage in lower level of technology does not enhance the growth potential in the long run.

The third hypothesis is based on the theoretical work of Lin (2010) which argues that apart from the need for countries to follow their comparative advantage determined by endowments, sustainable economic development requires the upgrading of existing industries from labor-intensive industries to new, more capital-intensive industries. Accordingly, it is more focused on non-developed countries under the assumption that non-developed countries initially have relative abundance in labor than capital.

Hypothesis 3: For non-developed countries, new comparative advantage associated with industrial upgrading over the course of time promotes economic growth in the long run.

5.2. Generating a DCA index considering technological heterogeneity

This study further investigates the emergence of new top exports with the lenses of the OECD classifications of technological intensity. The OECD classifies industries into four groups on the basis of the level of technology specific to the sector measured by the ratio of R&D expenditure to value added and the technology embodied in purchases of intermediate and capital goods. This study aggregates the four groups into two classes: lower technology which includes the low and medium-low technology and higher technology which includes medium-high and high technology (see Appendix 4 for the products in each of the two sectors). Accordingly, this study generates three additional weighted DCA indices which consider the different levels of technological contents across export products.[6]

---

[6] Results from Chapter 4 showed that the weighted DCA index better captures the economic effects of DCA than the equally weighted DCA index. This chapter, therefore, utilizes the weighted DCA index.

First, to verify the first and second hypotheses of the study, the weighted DCA index in higher technological class and the weighted DCA index in lower technological class are calculated and defined as the following equations:

$$DCA\_HT_{it} = \frac{\sum_{i=1}^{N} \delta_{ikt}^{H} E_{ikt}}{\sum_{i=1}^{N} E_{ikt}} \tag{5.1}$$

$$DCA\_LT_{it} = \frac{\sum_{i=1}^{N} \delta_{ikt}^{L} E_{ikt}}{\sum_{i=1}^{N} E_{ikt}} \tag{5.2}$$

where E_{ikt} is the export value of product *k* in country *i* in year *t*, *N* is the numbers of top products which in this study is fixed to 25 which is 5% of the total 486 world exports, and

$$\delta_{ikt}^{H} = \begin{cases} 1 \text{ if } k \text{ is new top 25 exports in higher technology,} \\ 0 \text{ otherwise} \end{cases}$$

$$\delta_{ikt}^{L} = \begin{cases} 1 \text{ if } k \text{ is new top 25 exports in lower technology.} \\ 0 \text{ otherwise} \end{cases}$$

Second, the weighted industrial upgrading DCA index is constructed to verify the third hypothesis of the study: for non-developed countries, new comparative advantage associated with technological upgrading promotes growth in the long run. Industrial upgrading can be defined as gaining new comparative advantage in sectors from lower to higher technology. Lin (2010) argues that a gradual, pragmatic approach is a viable development strategy for non-developed countries, and initial specialization in lower-technological sectors provides the opportunity to benefit from the advantages of backwardness in technology and to upgrade the endowments. The author also highlights the need to “upgrade its existing industries from labor-intensive to more capital-intensive industries over the course of time; otherwise, per capita income will stagnate as predicted by Solow’s neoclassical growth model” (Lin, 2010; p. 14).

Considering the above statement, the industrial upgrading DCA index is constructed by dividing the time span of the dataset into two periods based on the observations in Korea and Taiwan. The first half of the period (e.g., from 1972 to 1991) accounts for the export share of the new top exports in lower technology, and the second half of the period (e.g., from 1992 to 2010) accounts for the export share of new top exports in higher technology. The index is calculated with the following equation:

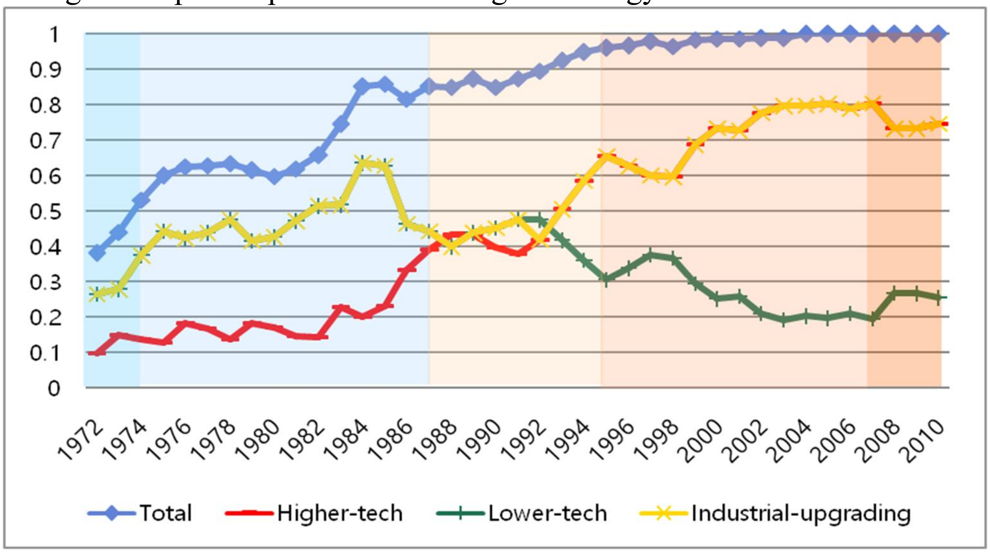
$$DCA\_upgrade_{it} = \frac{\sum_{i=1}^{N} \delta_{ikt}^{L\rightarrow H} E_{ikt}}{\sum_{i=1}^{N} E_{ikt}} \tag{5.3}$$

where $\delta_{ikt}^{L\rightarrow H} = \begin{cases} \delta_{ikt}^{L}, 1972 \leq t \leq 1991 \\ \delta_{ikt}^{H}, 1992 \leq t \leq 2010 \end{cases}$.

Abbreviations are the same with the weighted DCA index in higher (lower) technology.

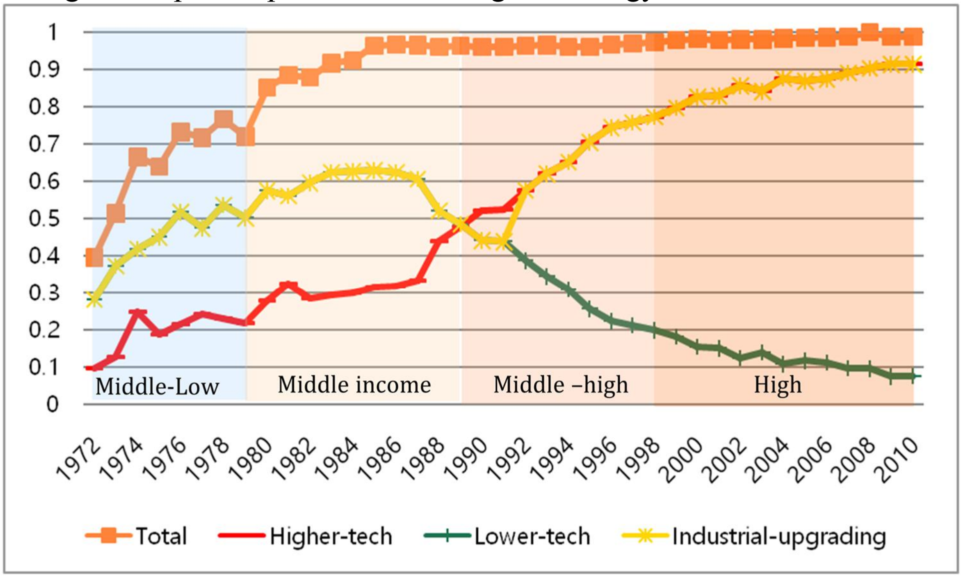
Figures 5.1 to 5.4 exhibit the weighted DCA index in total, higher technology, lower-technology, and industrial upgrading for selected countries in East Asia and Latin America. The successful export-led developed countries—Korea and Taiwan—show that its dynamic changes in comparative advantage are associated with industrial upgrading from lower to higher technological sectors. Both countries first specialized in the lower technological sectors, showing that the emergence of new top exports mostly consisted of lower technological sectors until the late 1980s. Products in higher technology gradually increased in terms of its share in top exports and outweighed the share of lower-technological products in top exports only after 1986.

Figure 5.1.
Changes in top 25 export share tracking technology contents: Korea



Source: Author's calculation
Note1: The Total presents the trend of the weighted DCA index introduced in chapter 4; Higher-tech presents the DCA_HT index; Lower-tech presents the DCA_LT index; and Industrial upgrading presents the DCA_upgrade index.
Note2: Income group is categorized based on GDP per capita relative to the United States Im & Rosenblatt (2013)

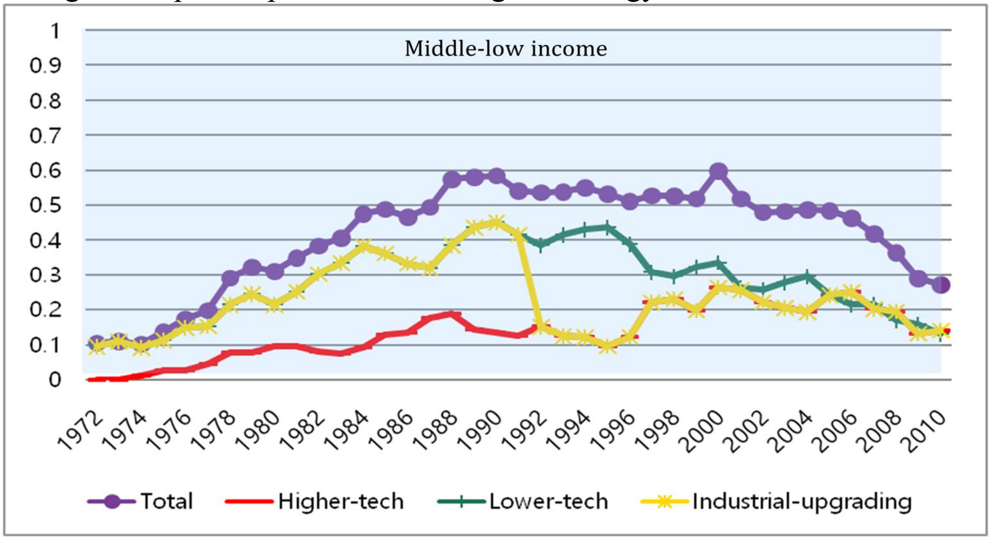
Figure 5.2.
Changes in top 25 export share tracking technology contents: Taiwan



Source: Author's calculation
Note: The Total presents the trend of the weighted DCA index; Higher-tech presents the DCA_HT index; Lower-tech presents the DCA_LT index; and Industrial upgrading presents the DCA_upgrade index.
Note2: Income group is categorized based on GDP per capita relative to the United States, following Im & Rosenblatt (2013)

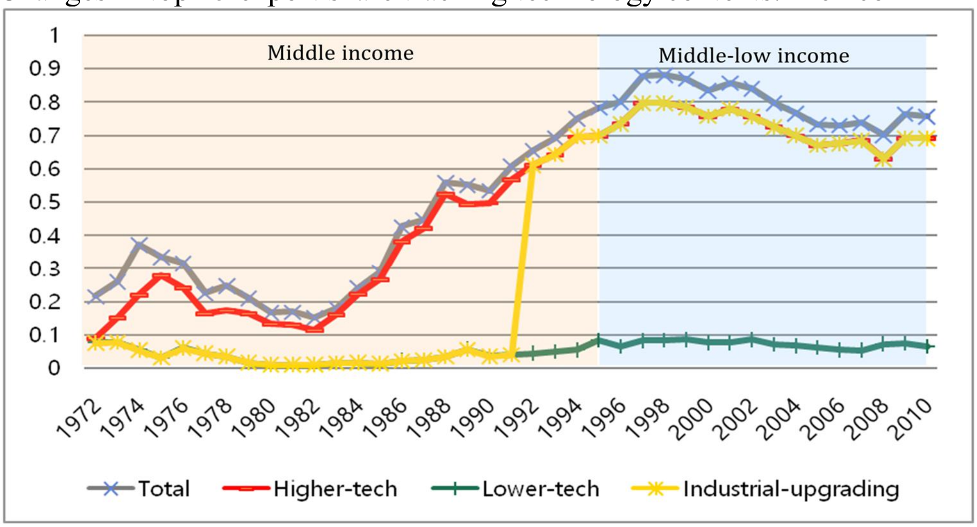
In the cases of selected Latin American countries, the industrial upgrading from lower to higher technological sectors was not observed (see Figures 5.3 and 5.4). In the case of Brazil, whereas the country shows limited transformation rate of comparative advantage, new comparative advantage took place within lower technological sectors. Solow's neoclassical growth model predicts that the per capita income of countries maintaining its specialization in lower technological sectors will stagnate. In the case of Mexico, the emergence of top exports is continuously concentrated in higher technological sectors over the course of time. The newly emerged top exports in Mexico include ICT equipments and motor vehicle-related products.

Figure 5.3.
Changes in top 25 export share tracking technology contents: Brazil



Source: Author's calculation
Note1: The Total presents the trend of the weighted DCA index; Higher-tech presents the DCA_HT index; Lower-tech presents the DCA_LT index; and Industrial upgrading presents the DCA_upgrade index.
Note2: Income group is categorized based on GDP per capita relative to the United States, following Im & Rosenblatt (2013)

Figure 5.4.
Changes in top 25 export share tracking technology contents: Mexico



Source: Author's calculation
Note1: The Total presents the trend of the weighted DCA index; Higher-tech presents the DCA_HT index; Lower-tech presents the DCA_LT index; and Industrial upgrading presents the DCA_upgrade index.

Note2: Income group is categorized based on GDP per capita relative to the United States, following Im & Rosenblatt (2013)

Several limitations need to be pointed out regarding the DCA index in higher technology, lower technology, and industrial upgrading. First, this study applies the OECD industrial classification to distinguish the different levels of technologies across products which overlook the different levels of technologies within products. For instance, Tulip production is considered a lower technological product based on the OECD classification; nonetheless, the Netherlands is known to apply high technology in the Tulip production process. Another example is the case in Korea. The level of technology used in producing TV in Korea in the early 1970s is unlikely to be the same between the TV productions in the 2000s. Indices used in previous studies including ECI and EXPY also share the same limitations (e.g., Hausmann et al., 2007; Hausmann et al., 2013; Lee, 2010; Dosi et al., 2022). This finding suggests the need for further research in the subject.

The second limitation is related to the industrial upgrading DCA index and the universal and arbitrary selection for the dividing year to reflect the industrial upgrading over the course of time. The universal selection of the dividing year may overlook the heterogeneous country characteristics (e.g., endowments) at a given year. However, compared with the DCA index in higher (lower) technology, the index is expected to capture the technological change in specialization over the course of time which is another important determinant of current productivity pointed out by the literature (Krugman, 1987; Redding, 1999) apart from the endowment structure (Redding, 2002; Lin, 2010). The drawbacks of the industrial upgrading DCA index suggest caution in interpretation and address the need for future work to improve the index to reflect the heterogeneous country characteristics and the gradual transition process of countries.

5.3. Empirical results: from DCA, industrial upgrading, to economic growth

This study empirically tests three hypotheses using the indices introduced in subchapter 5.2. The baseline model specification for estimating the effects of new comparative advantage across different levels of technology on per capita income follows the growth equations introduced in subchapter 4.2.

Tables 5.1 and 5.2 respectively exhibit the fixed-effects and system GMM estimation results following the Equation (4.3). After verifying the effects of new comparative advantage in lower technology or in higher technology in Table 5.1, the coefficients of the DCA index in lower technology are found to be consistently positive and significant in all models. The size of the coefficients is slightly larger when the regression is conducted with non-developed countries sample. Meanwhile, the coefficient of the DCA index in higher technology is only significant in the system

GMM estimation for all countries sample, but the index loses significance in other models. The results somewhat follow the work of Dosi et al. (2022), which shows that a change in scale intensive (lower technology) exports is economically beneficial for developing countries.

Meanwhile, the FE and the system GMM estimations results in Table 5.2 reveal that DCA associated with industrial upgrading has no significant effects on income per capital.[7] The results indicate that there is limited evidence to support that new comparative advantage associated with industrial upgrading promotes economic growth.

[7] Changing the dividing year to reflect the industrial upgrading from 1992 to 1987, mixed results are obtained. The FE estimation results reveal that DCA associated with industrial upgrading has no significant effects, but the system GMM results show that industrial upgrading DCA index is significantly positive for both all countries and non-developed countries sample. Overall, the results find limited evidence to support that industrial upgrading in change in comparative advantage promotes growth.

Table 5.1. FE and system GMM results for growth effect of DCA index in higher/lower technology

	Per capita, GDP in logs							
	All countries				Non-developed countries			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
VARIABLES	FE	Sys.gmm	FE	Sys.gmm	FE	Sys.gmm	FE	Sys.gmm
Log(1+initial DCA index)	0.114	0.122**			0.0889	0.056		
- higher technology	(0.0741)	(0.054)			(0.0866)	(0.057)		
Log(1+initial DCA index)			0.103*	0.187***			0.138**	0.193***
- lower technology			(0.0596)	(0.046)			(0.0598)	(0.044)
Initial GDP per capita, log	0.750***	0.942***	0.768***	0.967***	0.757***	0.972***	0.772***	0.982***
	(0.0426)	(0.015)	(0.0378)	(0.017)	(0.0514)	(0.020)	(0.0455)	(0.015)
log(I/GDP) - log(η+0.05)	0.0976***	0.095***	0.0878***	0.060**	0.0815***	0.101***	0.0676**	0.070***
	(0.0225)	(0.023)	(0.0248)	(0.030)	(0.0274)	(0.026)	(0.0280)	(0.025)
Trade Openness	0.0379***	0.027*	0.0363***	0.043**	0.0359**	0.006	0.0335***	0.036*
	(0.0131)	(0.016)	(0.0120)	(0.019)	(0.0136)	(0.019)	(0.0126)	(0.020)
Constant	2.209***	0.518***	2.058***	0.354***	2.078***	0.233	1.949***	0.204*
	(0.365)	(0.134)	(0.325)	(0.134)	(0.413)	(0.147)	(0.366)	(0.112)
Observations	760	760	760	760	568	568	568	568
Number of country	95	95	95	95	71	71	71	71
Year FE	YES	YES	YES	YES	YES	YES	YES	YES
AR(2)		-0.449		-0.277		-1.516		-1.468
[p-value]		0.653		0.782		0.129		0.142
Hansen test		84.76		85.33		65.44		63.82
[p-value]		0.144		0.135		0.207		0.249

Note1: *** p<0.01, ** p<0.05, and * p<0.1.

Table 5.2. FE and system GMM results: growth effect of industrial upgrading DCA index

	All countries		Non-developed countries	
	(1)	(2)	(3)	(4)
VARIABLES	FE	Sys. GMM	FE	Sys. GMM
Weighted index				
Log(1+initial DCA index)	0.0207	0.061	0.0232	0.031
- lower(~86) →higher(87~) tech	(0.0500)	(0.047)	(0.0568)	(0.044)
Initial GDP per capita, log	0.762***	0.950***	0.766***	0.978***
	(0.0415)	(0.016)	(0.0485)	(0.019)
log(I/GDP) - log(η+0.05)	0.0957***	0.088***	0.0788***	0.094***
	(0.0226)	(0.023)	(0.0267)	(0.025)
Trade Openness	0.0390***	0.035**	0.0366***	0.015
	(0.0125)	(0.017)	(0.0132)	(0.020)
Observations	760	760	568	568
Number of country	95	95	71	71
Year FE	YES	YES	YES	YES
AR(2)		-0.377		-1.492
[p-value]		0.706		0.136
Hansen test		86.13		63.98
[p-value]		0.200		0.245

Note1: *** p<0.01, ** p<0.05, and * p<0.1.
Note2: Constant term is included in the growth regression but omitted in the report.

Table 5.3 exhibits the cross-sectionally augmented distributed lag (CS-DL) estimation results of regressing per capita GDP on the DCA indices in higher and lower technology with baseline control variables following the Equation (4.4). The CS-DL approach estimates the long-run effects in large dynamic heterogeneous panel data models with cross-sectionally dependent errors (Chudik et al., 2016). The coefficients of the DCA index in higher/lower technology came out insignificant in all model specifications. The results are different from the FE and system GMM estimations which showed that new comparative advantage in lower technology has positive and significant effects on per capita GDP. The results of the system GMM and the CS-DL estimations indicate that new comparative advantage in lower-technological sectors may have positive effects on per capita income in the short run. However, it may be insufficient to achieve sustained, continuous economic growth in the long run. The results are in line with implications from Solow's neoclassical growth model.

Table 5.4 exhibits the CS-DL estimation results of regressing per capita GDP on the industrial upgrading DCA index with baseline control variables. The industrial upgrading DCA index is calculated following the Equation (5.3) with year 1992 chosen as the turning point year from lower to higher technology. To test the robustness of results, the year 1989 is chosen as the additional turning point year. The coefficients of the industrial upgrading DCA index continued to come out positive and significant for non-developed countries sample. The results indicate that for non-developed countries, new comparative advantage associated with industrial upgrading from lower- to higher-technological sectors have positive and significant effects on per capita income in the long run. This finding differs from the system GMM estimation results showing limited evidence to support the growth effects of new comparative advantage with industrial upgrading on per capita income. The results of the system GMM and CS-DL estimations indicate that new comparative advantage associated with industrial upgrading over the course of time may not have a significant impact on per capita income in the short run but have a positive, significant impact on per capita income in the long run.

Table 5.3. CS-DL regression results: growth effect of DCA index in higher/lower technology

Dependent Variable	Per GDP capita, Real in log							
	All countries				Non-developed countries			
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Compared with early1960s								
Log(1+DCA index*)	0.595	0.827			0.102	0.162		
- higher technology	(1.131)	(0.971)			(1.179)	(1.635)		
Log(1+ DCA index*)			0.223	-0.509			0.180	0.228
- lower technology			(0.766)	(0.746)			(0.884)	(0.732)
Control Variables								
log(I/GDP) - log(η+0.05)	0.202***	0.153***	0.182***	0.122***	0.212***	0.120***	0.176***	0.136***
	(0.032)	(0.038)	(0.026)	(0.030)	(0.034)	(0.044)	(0.029)	(0.034)
Trade Openness		0.065*		0.043		0.064		0.010
		(0.037)		(0.039)		(0.047)		(0.036)
Constant	-0.220	0.564	1.564	1.020	0.429	-0.291	0.829	-0.642
	(1.141)	(1.300)	(1.036)	(1.156)	(1.082)	(1.264)	(0.944)	(1.380)
Observations	3,315	3,315	3,315	3,315	2,481	2,481	2,481	2,481
Number of countries	95	95	95	95	71	71	71	71
CD stats	2.420	-0.0319	2.102	0.463	0.176	-0.641	-0.704	0.600
CD stats[p-value]	0.0155	0.975	0.0356	0.643	0.860	0.522	0.482	0.549

Note1: Robust standard errors in parentheses.
Note2: *** p<0.01, ** p<0.05, and * p<0.1.
Note3: DCA index* indicates the past three-year averages of DCA index.

Table 5.4 CS-DL regression results: growth effect of industrial upgrading DCA index

Dependent Variable	Per Capita GDP, real in log			
	All countries		Non-developed countries	
	(1)	(2)	(3)	(4)
Weighted index				
Log(1+ DCA index*)	0.113		1.534*	
- lower(~91) → higher(92~)	(0.617)		(0.797)	
Log(1+ DCA index*)		1.337**		1.401*
- lower (~88) → higher(89~)		(0.641)		(0.849)
log(I/GDP) - log(η+0.05)	0.214***	0.176***	0.113**	0.120***
	(0.034)	(0.035)	(0.049)	(0.032)
Trade Openness	-0.030	0.028	0.117	0.091
	(0.060)	(0.050)	(0.081)	(0.064)
Constant	1.397	-0.466	-0.305	0.534
	(1.990)	(1.050)	(1.090)	(1.058)
Observations	3,315	3,315	2,481	2,481
Number of countries	95	95	71	71
CD stats	0.749	1.784	0.538	-0.636
CD stats[p-value]	0.454	0.0745	0.591	0.525

Note1: Robust standard errors in parentheses.
Note2: *** $p<0.01$, ** $p<0.05$, and * $p<0.1$.
Note3: DCA index* indicates the past three-year averages of DCA index.
Note 4: Similar results are found when the industrial upgrading year is modified from 1988 to 1989.

5.4. Concluding remarks

This chapter measures the changes in the composition of comparative advantage by tracking different technological contents across industries. It then empirically examines the impact of such changes on economic growth. Apart from applying FE and system GMM estimations following the literature on trade and growth, this study additionally applies the CS-DL approach to estimate the long-run effects. Acknowledging the implications from the literature on specialization which emphasizes different growth effects for different compositions of specialization, the weighted DCA index is divided into higher and lower levels of technology classified by technological intensity.

Mixed results are observed which resulted from applying different econometrical methodologies between the fixed-effects, system GMM estimations, and the CS-DL estimations. For a sample of non-developed countries, the FE, system GMM estimation results suggest that new comparative advantage in lower technological sectors has positive effects on growth, but it is statistically insignificant for the effects of technological upgrading in the shift in comparative advantage on growth. On the other hand, the CS-DL estimation results show that new comparative advantage in lower technological sectors has insignificant long-run effects on per capita income. This finding is in line with Solow's neoclassical growth model which implies that dwelling in existing comparative advantage in lower technological sectors results in per capita income stagnation (Redding, 1999; Lin, 2010). Meanwhile, the CS-DL estimation results find positive and significant effects of new comparative advantage with technological enhancement on per capita income in the long run.[8] The findings of the CS-DL approach are in line with the argument of Lin (2010) which states that for non-developed countries, initial comparative advantage in lower technological sectors provides the opportunity to accumulate the resources (e.g., capital and infrastructure) required to search for new comparative advantage with higher technology and productivity which is another important determinant for economic development (Krugman, 1987; Grossman & Helpman, 1991; Redding, 1999; Dosi & Matteo, 2018).

The regression results from FE, system GMM, and CS-DL estimations consistently show that new comparative advantage in higher technological sectors has insignificant effects on per capita income. The findings are contrary to the literature on specialization which argues that the composition of specialization referring to high-income countries has higher growth potential (e.g., Lee, 2010; Hausmann et al., 2007; Hausmann et al., 2013).

[8] The drawbacks of the industrial upgrading DCA index caused by an arbitrary, universal selection of dividing year across countries require caution in interpretation.

Chapter 6. Conclusion

This thesis attempts to measure the DCA and empirically verifies its effects on economic growth in the long run. The literature on DCA and growth which highlights the important role of change in comparative advantage on economic development provides the theoretical framework for the study (Lin, 2010; Saviotti & Pyka, 2011). To empirically investigate the effects of DCA on economic growth, the system generalized methods of moments (GMM) approach and the cross-sectionally augmented distributed lag (CS-DL) approach are used. Notably, the CS-DL approach directly estimates the long-run effects in large dynamic heterogeneous panel model with cross-sectionally dependent errors (Chudik et al., 2016). This empirical work is one of the first, to my knowledge, to apply the CS-DL approach to the literature on trade and growth.

One of the main contributions of the study is the measurement of DCA calculated by the share of new top exports compared with the initial period of top exports. The generation of new top exports captures the emergence of new comparative advantage. Based on traditional trade theories arguing that under an opened economy, countries specialize in and trade products based on their own comparative advantage.

The FE, system GMM, and the CS-DL estimation results consistently confirm that DCA has positive and significant effects on economic growth in the long run. The robustness of the DCA index weighted by top export ratio is observed with additional control variables including the ECI, whereas the ECI loses significance in the CS-DL estimations. The results are in line with those of Saviotti and Pyka (2011) which argue that countries which overcome the increasing barriers to entry and succeed in creating new comparative advantage will achieve economic growth by reallocating underutilized resources to a growing market.

Confirming the significant growth effects of the DCA, the second major contribution of this paper is related to the important feature of the DCA index which represents both aspects of export diversification and specialization for which the emergence of new export specialization leads to export diversification. The index shows that export diversification and specialization are not opposite concepts but are actually related as pointed out by Nomaler and Verspagen (2021). The results of the study imply that change in comparative advantage, which leads to diversification, matters for growth.

Finally, another contribution relies on verifying the effect of the level of technology embedded in the new comparative advantage on growth in the long run. The second part of the thesis distinguishes the composition of new comparative advantage through the lenses of the OECD classification on technological intensity. Empirical literature on specialization finds that specialization pattern with higher productivity or technology, often referring to the specialization patterns of higher-income countries, generates higher growth potential based on higher productivity (e.g., Hausmann et al., 2007; Lee, 2010, Hausmann et al., 2013). By contrast, the CS-DL estimation results, which estimate the long-run effects, find insufficient evidence to support that new comparative advantage in higher technological sectors over the course of time promotes per capita income. The regression results based on a sample of non-developed countries which show the insignificant effects of new comparative advantage in higher technological sectors on long-run growth indicate that targeting industries in higher technology irrespective of the endowments structure is not a viable development strategy. In addition, the insignificant effects of new comparative advantage in lower technological sectors on long-run growth indicate that dwelling in specialization in lower technological sectors without technological enhancement cannot result in economic growth (Solow, 1956; Lin, 2010; Redding, 1999). Instead, the CS-DL estimation results indicate that for non-developed countries, a gradual approach to achieve new comparative advantage in higher technological sectors in the long run can be a viable alternative development strategy.

Meanwhile, several limitations to the proposed DCA index provide reasons to observe caution on the results and suggest future research.

First, the DCA index tracking different levels of technology applies the OECD industrial classification which overlooks the different levels of technologies within products. Existing indices used in the literature on specialization also share the same limitations (e.g. Hausmann et al., 2007;

Lee, 2010; Hausmann et al., 2013; Dosi et al., 2022), thereby suggesting the need for further research on the subject.

Second, to reflect the industrial upgrading of comparative advantage pattern over the course of time, the industrial upgrading DCA index applies a universal and arbitrary selection for the dividing year which does not reflect the heterogeneous country characteristics (e.g., endowments). The drawbacks of the industrial upgrading DCA index address the need for future work to improve the index to reflect the heterogeneous country characteristics when selecting the year for technological upgrading.

Third, while this study applies the CS-DL approach which allows for heterogeneity in coefficient estimates across countries, a considerable amount of heterogeneity across a sample of 95 countries with varying development path may exist which may not be controlled for by the model. Future research on grouping countries which share relatively similar relationship between shift in comparative advantage and growth may lead to a more concrete implication for development policy.

Appendices

Appendix 1. List of countries

Non-Developed Countries (71)			Developed Countries (24)
Angola,	Hungary,	Panama,	Australia,
Albania,	Indonesia,	Peru,	Austria,
Argentina,	India,	Philippines,	Belgium,
Bulgaria,	Iran,	Poland,	Canada,
Bolivia,	Jamaica,	Portugal,	Switzerland
Brazil,	Jordan,	Paraguay,	Germany,
Chile,	Kenya,	Romania,	Denmark,
China,	Cambodia,	Sudan,	Spain,
Cote D'ivoire,	Korea, Rep.,	Senegal,	Finland,
Cameroon,	Laos,	Singapore,	France,
DR Congo	Lebanon,	El Salvador	United Kingdom
Congo	Sri Lanka,	Syria	Hong Kong,
Colombia,	Morocco,	Togo,	Ireland,
Costa Rica,	Madagascar,	Thailand,	Israel,
Dominican Rep.,	Mexico,	Tunisia,	Italy,
Algeria,	Myanmar,	Turkey,	Japan,
Ecuador,	Mozambique,	Taiwan	Kuwait,
Egypt,	Mauritania	Tanzania,	Netherlands,
Ethiopia,	Malaysia,	Uruguay,	Norway,
Ghana,	Nigeria,	Venezuela,	New Zealand,
Guinea,	Nicaragua,	Vietnam,	Saudi Arabia,
Greece,	Oman,	South Africa,	Sweden,
Guatemala,	Pakistan	Zambia,	Trinidad Tobago,
Honduras		Zimbabwe	United States,

Appendix 2. Data and sample definitions

Code	Definition and Construction	Source	Coverage
Real GDP per capita	GDP per capita, PPP (US$ 2011)	PWT 10.0	1972-2010
Initial GDP per cap.	Initial value of per capita GDP in the beginning of each five-year period	PWT 10.0	1972-2010
Investment	Gross capital formation (% of GDP)	PWT 10.0	1972-2010
Population growth	Population growth	PWT 10.0	1972-2010
Dynamic Comparative Advantage index	Log(1+DCA index) CSDL estimation used the past three-year-averages DCA index	Feenstra UN Comtrade	1972-2010
Economic Complexity Index	ECI (in SITC rev.2)	oec.world Downloaded on April. 19 2020	1972-2010
Trade Openness	Trade volume(Export+Import)/GDP	PWT 10.0	1972-2010
Human Capital	Percentage of Secondary Schooling Completed in Pop.	Barro and Lee	1972-2010
Increase in exports	Increase of exports in each period/ GDP Increase of exports from t-1 to t/GDP	Feenstra UN Comtrade PWT 10.0	1972-2010
Increase in primary exports	Increase of primary exports in each period/ GDP Increase of primary exports from t-1 to t/GDP	Feenstra UN Comtrade PWT 10.0	1972-2010
Government consumption	Government consumption divided by GDP	PWT 10.0	1972-2010

Appendix 3. Descriptive Statistics

Five-year averages data

VARIABLES	Mean	Std. dev.	Min	Max
Real GDP/c	15,479	16,058	400	88,999
GCF(% of GDP)	0.220	0.096	0.020	0.835
Population growth	0.018	0.012	-0.043	0.063
Openness(trade % of GDP)	0.478	0.512	0.006	5.388
Initial human capital	31.449	17.552	1.07	81.03
Initial weighted DCA index	0.379	0.274	0.002	1
Initial equally-weighted DCA	0.573	0.180	0.08	1
Initial ECI	0.014	1.026	-2.214	2.612
Government Consumption	0.182	0.089	0.007	0.682
Increase in exports/real GDP	3.507	10.698	-47.306	216.927
Increase in primary exports /real GDP	1.598	9.586	-51.330	202.173

Annual data

VARIABLES	Mean	Std. dev.	Min	Max
Real GDP/c	14,989	15,758	395	130649
GCF(% of GDP)	0.219	0.101	-0.101	0.950
Population growth	0.018	.0126	-0.073	0.071
Openness(trade % of GDP)	0.478	.520	0.001	6.214
Weighted DCA index	0.400	.271	0.002	1
Equally weighted DCA index	0.595	.168	0.12	1
ECI	0.013	1.02	-2.764	2.625
Government Consumption	0.183	.095	0.005	1.792
Increase in exports/real GDP	0.719	5.460	-181.569	122.612
Increase in primary exports /real GDP	0.279	5.065	-168.555	123.351

Appendix 4. OECD Industry classification according to technological intensity

Technology level	Industries
High	Aerospace Computers, office machinery ICT equipments Pharmaceuticals
Medium-high	Scientific instruments Motor vehicles Electrical machinery (excl. ICT equipment) Chemicals (excl. pharmaceuticals) Other transport Non-electrical machinery
Medium-low	Rubber and plastic products Shipbuilding Other manufacturing Non-ferrous metals Non-metallic mineral products Metal products Petroleum refining Ferrous metals
Low	Paper printing Textile and clothing Food, beverages and tobacco Wood and furniture

Source: Hatzichronoglou (1997)

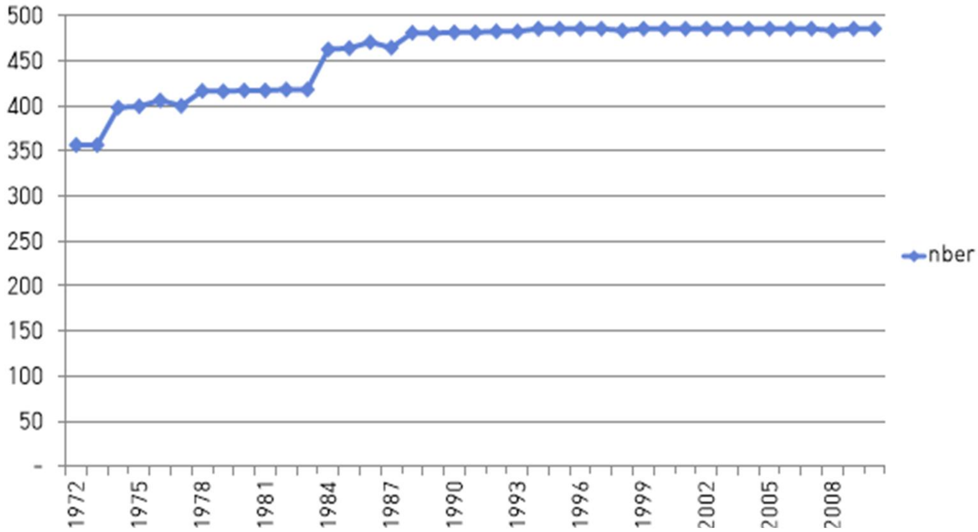
Appendix 5. Robustness test

Appendix 5.1. Modification of DCA index with SITC rev.2 dataset

This section provides further sensitivity tests to check if different computation methods for the DCA index affect the main findings of this research: the importance of dynamic comparative advantage on long-run economic growth. Table 1 and Table 2 show that the modification of the numbers of top exports does not change the main findings for both system GMM and CS-DL estimations. DCA index rev.1 in column (1) and (4) is reflects the changing numbers of world exports. The numbers of world export products started from 357 during the period between 1962 and 1973, the numbers gradually increased from 357 to 486 from year 1974 to 1984 and from 1984 onwards the numbers are fixed to 486, except for year 1998 (See Figure 1). Accordingly, DCA index rev.1 is calculated based on changes in top 18~25 exports: from 1972~73, top 18 exports; from 1974 to 83, top 20 exports; from 1984 to 1987 top 24 exports; and top 25 exports from 1988 onwards. DCA index rev.2 in column (2) and (4) captures change in top 20 exports which account for 4% of the total 486 world exports, instead of top 25 exports which account for 5% of total world exports. The median share of the top 20 export products is 79% for each 95 countries. DCA index rev.3 in column (3) and (6) applies SITC rev.2 3-digits with a total of 236 world export products while the DCA index utilizes SITC rev.2 4-digits with a total of 486 world export products. Accordingly, DCA index rev.3 focuses on the changes in top 12 exports, 5% of the total numbers of world exports.

Table 3 and Table 4 show that modification of comparing year does not affect the main findings. DCA index rev.4 in column (1) and (3) for Table 3 and in column (1) and (2) for Table 4 calculates change in top 25 exports with fixed comparison year of 1965. Accordingly, the time span of the panel dataset is between 1975 and 2010. DCA index rev.5 in column (2) and (4) for Table 3 calculates the change in top 25 exports with fixed comparison year of 1970. However, due to the limited time span of 29 years, CS-DL estimations for DCA index rev.5 were not conducted. Chudik et al. (2016) indicates that the minimum time span required for applying the CS-DL method is over 30 years.

Figure 1. Total numbers of world export products



Source: Feenstra and UN Comtrade

Appendix Table 5.1. Robustness check with system GMM regression: modification of numbers of top exports

	All countries			Non-developed countries		
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
Log(1+DCA1)	0.165***			0.195***		
- Top18~25	(0.042)			(0.042)		
Log(1+DCA2)		0.136***			0.167***	
- Top 20		(0.040)			(0.044)	
Log(1+DCA3)			0.134***			0.141***
- 3-digits			(0.041)			(0.045)
Initial GDP/cap	0.957***	0.958***	0.953***	0.975***	0.992***	0.978***
	(0.012)	(0.013)	(0.012)	(0.018)	(0.022)	(0.019)
log(I/GDP) – log(η+0.05)	0.069***	0.072***	0.078***	0.076***	0.069***	0.082***
	(0.026)	(0.026)	(0.024)	(0.023)	(0.022)	(0.025)
Openness	0.029*	0.030*	0.033**	0.004	-0.003	0.004
	(0.017)	(0.016)	(0.015)	(0.010)	(0.013)	(0.010)
Constant	0.401***	0.394***	0.431***	0.193	0.038	0.178
	(0.104)	(0.105)	(0.100)	(0.135)	(0.187)	(0.145)
Observations	760	760	760	568	497	568
Number of country	95	95	95	71	71	71
Year FE	YES	YES	YES	YES	YES	YES
AR(2)	-0.350	-0.357	-0.417	-1.557	-0.610	-1.587
AR(2) [p-value]	0.726	0.721	0.677	0.120	0.542	0.112
Hansen test	88.83	88.52	86.37	64.52	60.92	65.53
Hansen test [p-value]	0.211	0.217	0.267	0.231	0.271	0.205

Note1: Robust standard errors in parentheses
Note2: *** p<0.01, ** p<0.05, and * p<0.1

Appendix Table 5.2. Robustness check with CS-DL regression: modification of numbers of top exports

	All countries			Non-developed countries		
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
Log(1+DCA1*)	0.510**			0.501**		
- Top18~25	(0.224)			(0.236)		
Log(1+DCA2*)		0.478**			0.451*	
- Top 20		(0.237)			(0.265)	
Log(1+DCA3*)			0.683**			0.442*
- 3-digits			(0.300)			(0.255)
log(I/GDP) –log(η+0.05)	0.181***	0.172***	0.163***	0.193***	0.192***	0.196***
	(0.028)	(0.029)	(0.030)	(0.032)	(0.034)	(0.034)
Constant	0.401***	0.495	0.735	0.193	0.114	0.632
	(0.104)	(1.576)	(1.385)	(0.135)	(1.123)	(1.306)
Observations	3,315	3,315	3,315	2,481	2,481	2,481
Number of country	95	95	95	71	71	71
CD stats	2.375	1.596	4.151	0.662	1.352	2.145
CD [p-value]	0.0176	0.111	0.00	0.508	0.176	0.032

Note1: Robust standard errors in parentheses
Note2: *** p<0.01, ** p<0.05, and * p<0.1
Note3: DCA1*, DCA2* and DCA3* indicate the past three-year averages of DCA index rev1, rev2, and rev3 respectively.

Appendix Table 5.3. Robustness check with system GMM regression: modification of comparison year

	All countries		Non-developed countries	
VARIABLES	(1)	(2)	(3)	(4)
Log(1+DC4)	0.173***		0.129***	
- 1965	(0.040)		(0.038)	
Log(1+DC5)		0.214***		0.270***
- 1970		(0.051)		(0.076)
Initial GDP per capita	0.983***	0.963***	0.992***	0.987***
	(0.011)	(0.011)	(0.022)	(0.015)
log(I/GDP) – log(η+0.05)	0.052**	0.076***	0.069***	0.036*
	(0.022)	(0.019)	(0.022)	(0.020)
Openness	-0.004	0.008	-0.003	-0.007
	(0.017)	(0.018)	(0.013)	(0.021)
Constant	0.118	0.252**	0.038	0.033
	(0.095)	(0.105)	(0.187)	(0.148)
Observations	665	570	497	438
Number of country	95	95	71	73
AR(2)	0.786	0.643	-0.610	-0.830
AR(2) [p-value]	0.432	0.520	0.542	0.406
Hansen test	90.08	86.33	60.92	57.07
Hansen test [p-value]	0.207	0.175	0.271	0.229

Note1:Robust standard errors in parentheses

Note2: *** p<0.01, ** p<0.05, and * p<0.1

Appendix Table 5.4. Robustness check with CS-DL regression: modification of comparison year

	All countries	Non-developed countries
VARIABLES	(1)	(2)
Log(1+DCA4*)	0.801***	0.587*
- 1965	(0.289)	(0.323)
log(I/GDP) –log(η+0.05)	0.188***	0.198***
	(0.031)	(0.033)
Constant	0.374	0.887
	(1.241)	(1.009)
Observations	3,004	2,268
Number of country	94	71
Time Period	1976~2010	1976~2010
CD stats	0.990	-0.0691
CD [p-value]	0.322	0.945

Note1: Robust standard errors in parentheses
Note2: *** p<0.01, ** p<0.05, and * p<0.1
Note3: DCA4* indicates the past three-year averages of DCA index rev.4

Appendix 5.2. Modification of DCA index with HS code dataset

Table 5 presents the estimation results DCA index calculated with HS96, 6-digits. Out of a total of 3,156 world export products, the DCA index_revised5 focused on measuring the changes in top 150 exports, which accounts for 5% of total number of world exports, compared with top 150 exports in year 2000. The sample consists of 65 countries which includes 15 developed countries and 50 non-developed countries with the time period from 2001 to 2019. Developed countries are defined as countries having a per capita GDP exceeding the first quartile of the wealthiest per capita GDP in year 2001 and 2019. Fixed effect estimations are applied using five-year averages panel data. A non-overlapping three five-yearly observations per country is constructed for analysis from 2006~2010, 2011~2015, and 2016~2019. All variables are five-year averages (four-year averages for 2016~2019) including variables of interest: DCA index rev.6 and Economic Complexity Index (ECI).[9] Results are reported in Table 6. In all countries sample, both variables of interest came out positive and statistically significant in the first and second column. However, as shown in column 3, both variables of interest lose significance when both variables are included in the growth equation. In non-developed countries sample, both variables of interest came out positive and significant as presented in the fourth and fifth column. The coefficient of DCA index rev.6 came out positive and significant even when ECI is additionally controlled for, while the ECI loses

[9] The initial DCA index and initial ECI came out insignificant in all models.

significance.

Box 1. Description statistics

VARIABLES	Obs.	Mean	Std. dev.	Min	Max
Real GDP/c	194	27,411	20,237	2,337	96,812
GCF (% of GDP)*	194	0.243	0.066	0.071	0.465
Population growth*	194	0.012	0.010	-0.007	0.070
Openness (trade % of GDP)*	194	0.725	0.671	0.113	4.896
Weighted DCA index*	194	0.212	0.131	0.005	0.830
Initial ECI*	194	0.403	0.935	-2.185	2.205

Appendix Table 5.5. Robustness check with fixed-effects regression results with DCA index calculated with HS6

VARIABLES	All countries			Non-developed countries		
	(1)	(2)	(3)	(4)	(5)	(6)
DCA6*	0.152*		0.115	0.222**		0.181**
	(0.0876)		(0.0890)	(0.0909)		(0.0877)
ECI*		0.0683*	0.0443		0.0901**	0.0544
		(0.0373)	(0.0380)		(0.0423)	(0.0430)
Log(initial per capita GDP)	0.594***	0.587***	0.588***	0.602***	0.600***	0.598***
	(0.0478)	(0.0495)	(0.0481)	(0.0511)	(0.0542)	(0.0518)
Log(I/GDP*) - log(η*+0.05)	0.226***	0.230***	0.226***	0.223***	0.226***	0.221***
	(0.0356)	(0.0342)	(0.0353)	(0.0392)	(0.0373)	(0.0395)
Openness*	0.0333	0.0359	0.0306	0.0461	0.0466	0.0401
	(0.0360)	(0.0367)	(0.0347)	(0.0356)	(0.0351)	(0.0334)
Constant	3.708***	3.775***	3.756***	3.531***	3.581***	3.573***
	(0.437)	(0.453)	(0.441)	(0.452)	(0.480)	(0.461)
Observations	194	194	194	149	149	149
Number of countries	65	65	65	50	50	50
Year FE	YES	YES	YES	YES	YES	YES
Adjusted R-squared	0.851	0.850	0.851	0.871	0.868	0.872

Note1: Robust standard errors in parentheses
Note2: *** p<0.01, ** p<0.05, and * p<0.1
Note3: DCA6*　indicates five-year averages(four-year averages in the last period) of DCA index rev.6
Note4: All variables excluding the log(initial per capita GDP) variable uses five-year averages(four-year averages for the last period).

Appendix 6. Robustness test with DCA index in Chapter 5.

Table 6.1. presents the estimation results using lag DCA index introduced in Chapter 5 which takes into account the heterogenous technological level across products instead of past three-year averages DCA index. Results show that DCA index in higher technology and DCA index in lower technology have insignificant effect on long-run economic growth which is consistent with the main findings of the paper. Meanwhile, the industrial upgrading DCA index loses significance in non-developed countries which indicates weak robustness results concerning industrial upgrading DCA index compared with other DCA indices.

Appendix Table 6.1. Robustness test of CS-DL regression results: applying lag variable

Dependent Variable	per Capita GDP, real in log					
	All countries			Non-developed countries		
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
Weighted index						
Log(1+ lag DCA index)	0.370			1.019		
- higher-technology	(0.527)			(1.121)		
Log(1+ lag DCA index)		-0.107			0.266	
- lower-technology		(0.509)			(0.652)	
Log(1+ lag DCA index)			0.994**			0.910
- lower(~88)→higher(89~) tech.			(0.453)			(0.639)
log(I/GDP) - log(η+0.05)	0.223***	0.177***	0.197***	0.234***	0.197***	0.211***
	(0.030)	(0.027)	(0.033)	(0.034)	(0.031)	(0.031)
Constant	0.100	1.270	0.091	0.609	0.991	0.662
	(1.162)	(0.975)	(1.021)	(1.096)	(0.920)	(1.052)
Observations	3,311	3,311	3,311	2,481	2,481	2,481
Number of countries	95	95	95	71	71	71
CD stats	0.899	4.203	1.452	-1.080	0.621	-0.956
CD stats [p-value]	0.369	2.64e-05	0.147	0.280	0.535	0.339

Note1: Robust standard errors in parentheses

Note2: *** p<0.01, ** p<0.05, and * p<0.1

Appendix 7. Modification of DCA index with dataset

To test the robustness of results, Tables 7.1 to 7.3 show the CS-DL estimation results in Chapter 5 applying different choices of lag length of explanatory variables. The first and fourth column applied the first difference of explanatory variables while the third and sixth column applied first, second and third differences of explanatory variables. The results consistently came out insignificant.

Appendix Table 7.1 Robustness test of CS-DL regression results on DCA index in higher technology: different lag of orders (p_x = 3)

	All countries			Non-developed countries		
lag of orders	*p*=2	*p*=3	*p*=4	*p*=2	*p* =3	*P*= 4
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
Weighted index						
Log(1+ DCA index*)	0.453	0.595	0.624	0.998	0.102	0.323
- higher technology	(0.698)	(1.131)	(1.198)	(1.295)	(1.179)	(1.184)
log(I/GDP) - log(η +0.05)	0.205***	0.202***	0.209***	0.201***	0.212***	0.230***
	(0.027)	(0.032)	(0.037)	(0.029)	(0.034)	(0.037)
Constant	0.120	-0.220	0.445	0.691	0.429	0.963
	(1.100)	(1.141)	(1.247)	(1.039)	(1.082)	(1.199)
Observations	3,317	3,315	3,218	2,482	2,481	2,409
Number of countries	95	95	95	71	71	71
CD stats	1.368	2.420	1.538	-0.320	0.176	1.016
CD stats [p-value]	0.171	0.0155	0.124	0.749	0.860	0.310

Note1: Robust standard errors in parentheses

Note2: *** p<0.01, ** p<0.05, and * p<0.1

Note3: DCA index* indicates the past three-year average of DCA index

Appendix Table 7.2 Robustness test of CS-DL regression results on DCA index in lower technology: different lag of orders (p_x = 3)

	All countries			Non-developed countries		
lag of orders	*p*=2	*p*=3	*p*=4	*p*=2	*p* =3	*P*= 4
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
Weighted index						
Log(1+ DCA index*)	-0.020	0.223	0.180	0.044	0.180	-0.048
- lower technology	(0.561)	(0.766)	(0.773)	(0.654)	(0.884)	(0.864)
log(I/GDP) - log(η+0.05)	0.175***	0.182***	0.188***	0.178***	0.176***	0.205***
	(0.021)	(0.026)	(0.033)	(0.023)	(0.029)	(0.038)
Constant	1.480	1.564	1.837	1.350	0.829	0.962
	(0.933)	(1.036)	(1.121)	(0.838)	(0.944)	(1.066)
Observations	3,317	3,315	3,218	2,482	2,481	2,409
Number of countries	95	95	95	71	71	71
CD stats	2.252	2.102	3.897	-0.192	-0.704	0.373
CD stats [p-value]	0.0243	0.0356	0.00	0.848	0.482	0.709

Note1: Robust standard errors in parentheses

Note2: *** p<0.01, ** p<0.05, and * p<0.1
Note3: DCA index* indicates the past three-year averages of DCA index

Appendix Table 7.3. CS-DL regression results on industrial upgrading DCA index: robustness test with different lag of orders (p_x= 3)

	All countries			Non-developed countries		
lag of orders	*p*=2	*p*=3	*p*=4	*p*=2	*p*=3	*p*=4
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
Weighted index						
Log(1+ DCA index*)	1.141**	1.268*	1.273**	1.110*	1.577*	1.437*
- lower(~88) to higher(89~) technology	(0.577)	(0.685)	(0.648)	(0.671)	(0.898)	(0.852)
log(I/GDP) - log(η+0.05)	0.180***	0.205***	0.245***	0.187***	0.201***	0.237***
	(0.031)	(0.042)	(0.054)	(0.027)	(0.034)	(0.043)
Constant	0.280	0.630	0.338	0.606	0.970	0.853
	(1.114)	(1.086)	(1.160)	(1.099)	(0.993)	(0.999)
Observations	3,317	3,315	3,218	2,482	2,481	2,409
Number of countries	95	95	95	71	71	71
CD stats	0.126	0.665	0.339	-1.571	-1.682	-1.719
CD stats [p-value]	0.900	0.506	0.734	0.116	0.0926	0.0856

Note1: Robust standard errors in parentheses

Note2: *** $p<0.01$, ** $p<0.05$, and * $p<0.1$
Note3: DCA index* indicates the past three-year averages of DCA index

Bibliography

Abdelhadi, S., A. G. Bashayreh, and M. Alomari (2019). The impact of export instability on economic growth: Sample of MENA countries. *International Journal of Economics and Business Research,* 18(4), 429-435.

Aditya, A., and R. Acharyya (2013). Export diversification, composition, and economic growth: Evidence from cross-country analysis. *The Journal of International Trade and Economic Development,* 22(7), 959-992.

Amin, A., and N. Thrift (2000). What kind of economic theory for what kind of economic geography? *Antipode,* 32(1). https://onlinelibrary.wiley.com/doi/pdf/10.1111/1467-8330.00117.

Anderson, T. W., and C. Hsiao (1981). Estimation of dynamic models with error components. *Journal of the American Statistical Association,* 76(375), 598-606.

Ardiansyah, M., A. Djuraidah, I. M. Sumertajaya, A. H. Wigena, and A. Fitrianto (2021). Development of the panel ARDL by adding space-time effect to modeling monthly paddy producter price in Java. *Journal of Physics: Conference Series,* 1863 012053.

Arellano, M., and S. Bond (1991). Some tests of specification for panel data: Monte carlo evidence and an application to employment equations. *Review of Economic Studies,* 58(2), 277-297.

Arellano, M., and O. Bover (1995). Another look at the instrumental-variable estimation of error component models. *Journal of Econometrics,* 68(1), 29-52.

Bahar, D. (2016). Diversification or specialization: What is the path to growth and development? Global Economy and Development at Brookings. Policy Brief. The Brookings Institution.

Balassa, B. (1965). Trade liberalization and revealed comparative advantage. The Manchester School, 33(2), 327-345.

Blundell, R., and S. Bond (1998). Initial conditions and moment restriction in dynamic panel data model. *Journal of Econometrics,* 87, 115-143.

Cadot, O., C. Carrere, and V. Strauss-Kahn (2011). Export diversification: What's behind the hump? *Review of Economics and Statistics,* 93(2): 590-605.

Caselli, F., G. Esquivel, and F. Lefort (1996). Reopening the convergence debate: A new look at cross-country growth empirics. *Journal of Economic Growth,* 1(3): 363-89.

Cavalcanti, T., K. Mohaddes, and M. Raissi (2015). Commodity price volatility and the sources of growth. *Journal of Applied Econometrics*, 30(6), 857-873.

Chudik, A., and M. H. Pesaran (2015). Common correlated effects estimation of heterogeneous dynamic panel data models with weakly exogenous regressors. *Journal of* Econometrics, 188(2), 393-420.

Chudik, A., K. Mohaddes, M. H. Pesaran, and M. Raissi (2016). Long-run effects in large heterogeneous panel data models with cross-sectionally correlated errors. *Essays in Honor of Aman Ullah* (*Advances in Econometrics,* 36), Emerald Group Publishing Limited, Bingley, 85-135.

De Benedictis, L., M. Gallegati, and M. Tamberi (2009). Overall trade specialization and economic development: countries diversify. *Review of World Economics,* 145, 37-55.

Di Salvo, M., and E. Pelkmans-Balaoing (2015). *Non-linearity between export diversification and economic growth*. Working Paper.

Dosi, G. and T. Matteo (2019). *The role of comparative advantage, endowments and technology in structural transformation*. LEM Working Paper Series, No. 2018/33. Scuola Superiore Sant'Anna, Laboratory of Economics and Management (LEM), Pisa.

Dosi, G., F. Riccio, and M. E. Virgillito (2022). Specialize or diversify? And in what? Trade composition, quality of specialization and persistent growth. *Industrial and Corporate Change,* 31(2): 301-337.

Dulauf, S. N. (2009). The rise and fall of cross-country growth regressions. *History of Political Economy*, 41 (Suppl_1), 315-333.

Fidrmuc, J. (2004). Migration and regional adjustment to asymmetric shocks in transition economies. *Journal of Comparative Economics,* 32(2), 230-247.

Fosu, A. (1990). Export composition and the impact of exports on economic growth of developing economies. *Economic Letters,* 34(1), 67-71.

Grossman, G,, and E. Helpman (1991). Trade, knowledge spillovers and growth. *European Economic Review* 35, 517-526.

Hatzichronoglou, T. (1997). *Revision of the high-technology sector and product classification*. OECD Science, Technology and Industry Working Papers, No. 1997/02, OECD Publishing, Paris, https://doi.org/10.1787/134337307632.

Hausmann, R., C. A. Hidalgo, S. Bustos, M. Coscia, A. Simoes, and M. A. Yildirim (2013). *The atlas of economic complexity: Mapping paths to prosperity*. MIT, Harvard University.

Hausmann, R.., J. Hwang, and D. Rodrik (2007). What you export matters. *Journal of Economic Growth*, 1-25.

Hesse, H. (2008). *Export diversification and economic growth.* Commission on Growth and Development Working paper, No. 21, The World Bank, Washington, DC..

Hidalgo, C.A., and R. Hausmann (2009). The building blocks of economic complexity. *Proceedings of the National Academy of Science,* 106(26), 10570-10575.

Hoeffler, A. E. (2002). The augmented Solow model and the African growth debate. *Oxford Bulletin of Economics and Statistics*, 64(2), 135-158.

Im, F. G. and D. Rosenblatt (2013). *Middle-income traps A conceptual and empirical survey*. Policy Research Working Paper No. 6594, World Bank.

Islam, N. (1995). Growth Empirics: A Panel Data Approach. *The Quarterly Journal of Economics*, 110(4), 1127-1170.

Jarreau, J. and S. Poncet (2012). Export sophistication and economic growth: evidence from China. *Journal of Development Economics* 97(2), 281-292.

Krugman, P. (1979). Increasing returns, monopolistic competition and international trade. *Journal of International Economics,* 9, 469-479.

Krugman, P. (1981). Intra-industry specialization and the gains from trade. *Journal of Political Economy,* 89(5), 959-973.

Krugman, P. (1987). The narrow moving band, the Dutch disease, and the competitive consequences of Mrs. Thatcher: Notes on the presence of dynamic scale economies. *Journal of Development Economics,* 27, 41-55.

Laursen, K. (1998). *Revealed comparative advantage and the alternatives as measures of international specialisation*. DRUID Working Papers 98-30, Danish Research Unit for Industrial Dynamics, Copenhagen Business School, Department of Industrial Strategy/Aalborg University, Department of Business Studies.

Lee, J. (2010). Export specialization and economic growth around the world. *Economic Systems.* doi: 10.1016/j.ecosys.2010.11.002.

Lee, K., and B-Y. Kim (2009). Both institutions and policies matter but differently for different income groups of countries: Determinants of long-run economic growth revisited. *World Development,* 37(3), 533-549.

Lee, K., and J. Lee (2020). National innovation systems, economic complexity, and economic growth: country panel analysis using the US patent data. *Journal of Evolutionary Economics,* 30, 897-928.

Lee, J. (2010). Export specialization and economic growth around the world. *Economic Systems*. doi:10.1016/j.ecosys.2010.11.002

Lin, Y. (2010). *New structrual economics: A framework for rethinking development*. Policy Research Working Paper 5197, The World Bank.

Lombardi, M. J., M. Mohanty, and I. Shim (2017). *The real effects of household debt in the short and long run*. BIS Working Papers 607, Bank for International Settlements.

Mankiw, N. G., D. Romer, and D. N. Weil (1992). A contribution to the empirics of economic growth. *The Quarterly Journal of Economics,* 107(2), 407-437.

Nomaler, Ö., and B. Verspagen (2021). 'Patterns of diversification and specialization in international trade,' in Ludovico Alcorta and others (eds), *New perspectives on structural change: causes and consequences of structural change in the global economy* (Oxford, 2021; online edn, Oxford Academic, 22 Apr. 2021), https://doi.org/10.1093/oso/9780198850133.033.0014., 298-316.

Observatory of Economic Complexity (2020). Economic Complexity Index. The Observatory of Economic Complexity

Palmer, J., and I. Richards (1999). Get knetted: network behaviour in the new economy. *Journal of Knowledge Management*, 3(3), 191-202.

Parteka, A. (2010). Employment and export specialisation along the development path: some robust evidence. *Review of World Economics,* 145(4), 615-640.

Pesaran, M. H. (2006). Estimation and inference in large heterogeneous panels with multifactor error structure. *Econometrica,* 74, 967-1012.

Pesaran, M. H. (2015). *Time Series and Panel Data Econometrics.* Oxford Universifity Press

Pesaran, M. H., and R. Smith (1995). Estimating long-run relationships from dynamic heterogeneous panels. *Journal of Econometrics*, 68(1), 79-113.

Plumper, T., and M. Graff (2001). Export specialization and economic growth. *Review of International Political Economy*, 8(4), 661-688.

Redding, S. (1999). Dynamic comparative advantage and the welfare effects of trade. *Oxford Economic Papers*, 15-39.

Redding, S. (2002). Specialization dynamics. *Journal of International Economics*, 299-334.

Rodrik, D., A. Subramanian, and F. Trebbi (2004). Institutions rule: The primacy of institutions over geography and integration in economic development. *Journal of Economic Growth,* 9, 131-165.

Sarin, V., S. Mahapatra, and N. Sood (2020). Export diversification and economic growth: A review and future research agenda. *Journal of Public Affairs*, 22, https://doi.org/10.1002/pa.2524.

Saviotti, P. P., and A. Pyka (2004). Economic development by the creation of new sectors. *Journal of Evolutionary Economics,* 14, 1-35.

Saviotti, P. P., and A. Pyka (2008). Product variety, competition and economic growth. *Journal of Evolutionary Economics,* 18, 323-347.

Saviotti, P. P., and A. Pyka (2011). Generalized barriers to entry and economic development. *Journal of Evolutionary Economics,* 21, 29-52.

Schott, P. K. (2003). One size fits all? Heckscher-Ohlin specialization in global production. *American Economic Review,* 93(3), 686-708.

Solow, R. M. (1956). A contribution to the theory of economic growth. *The Quarterly Journal of Economics,* 70(1), 65-94.

Toya, H. and M. Skidmore (2007). Economic development and the impacts of natural disasters. *Economics Letters,* 94(1), 20-25.

Vollrath, T. L., and D. H. Vo (1988). *Investigating the nature of world agricultural competitiveness.* Technical Bulletin 312299, U.S. Department of Agriculture, Economic Research Service.

국 문 초 록

비교우위의 동태적 변화와 경제성장 간의 관계에 대한 실증분석 연구

본 논문은 경제성장과 동태적 비교우위 변화 간의 관계를 분석하는 데 목적이 있다. 경제성장 전략의 일환으로 수출 다변화와 수출 특화의 경제적 효과에 대한 논의가 지속되는 가운데 본 연구는 장기적인 경제성장을 위한 수출전략을 모색해 보고자 하는 관점에서 출발하였다. 본 연구는 개도국의 성공적인 경제발전 모델로 거론되는 한국과 대만의 변화하는 수출특화 패턴에 주목하였다. 한국과 대만의 수출은 지속적으로 소수의 상위 수출품에 집중되어 있는 한편 상위 수출품이 크게 변화한 특징을 보였다. 또한 변화하는 상위 수출품 구성은 자원 및 노동집약산업 중심에서 자본집약산업 중심으로 산업적 도약을 한 것으로 관측되었다. 한국과 대만의 공통된 수출 특화의 동태적 변화 현상은 비교우위 변화가 경제성장의 주요한 결정요인임을 주장한 이론연구와 맥락을 같이 한다.

동아시아 주요국의 수출패턴과 동태적 비교우위 변화에 대한 이론연구를 기반으로 본 연구는 비교우위의 동태적 변화가 경제성장에 미치는 장기적인 효과를 분석한다. 분석에는 내생성을 통제한 횡단면 동태적 패널분석 방법론인 시스템 GMM 추정과 함께 변수들 간 피드백 관계를 고려함으로써 내생성을 통제하며 설명변수의 장기적 효과를 분석하는 시계열 패널분석 방법론의 하나인 CS-DL (cross-sectionally augmented distributed lag) 추정을

경제성장 모형에 적용하였다.

논문의 핵심기여는 다음과 같다. 첫째, 새로운 상위 수출품 창출로 비교우위 변화를 사후적으로 추정하는 인덱스를 제시하고 비교우위 변화가 장기적인 경제효과가 있음을 실증적으로 보였다. 이러한 분석결과는 경제복잡성지수 (economic complexity index: ECI)를 포함한 추가적인 통제에도 일관되게 나타난 한편, ECI는 CS-DL 모형에서는 통계적 유의성이 없는 것으로 나타났다. 이러한 분석결과는 국가별 특성에 대한 고려 없이 선진국의 특화패턴을 지향하는 것이 비선진국의 장기적인 경제성장을 보장하지 않는다는 함의를 지닌다.

둘째, 비교우위 변화 인덱스를 통해 수출특화와 다변화는 상반된 개념이 아닌 상호 연관된 개념임을 보였다. 이는 일반적으로 새로운 특화 창출이 수출 다변화로 이어진다는 데에 기인한다.

셋째, 비선진국을 대상으로 기술수준별 비교우위 변화의 장기적인 경제효과를 분석한 결과 고기술 기반 비교우위 변화, 저기술 지반 비교우위 변화의 경제적 효과는 각각 유의하지 않은 것으로 나타났다. 이는 고기술 기반 비교우위 변화, 즉 선진국의 특화구조가 경제적 효과가 있음을 보인 선행연구와 대조되는 결과이다.

한편 비선진국을 대상으로 한 CS-DL 분석결과 1992년을 기점으로 기술증진을 동반한 비교우위 변화는 장기적인 경제효과가 있는 것으로 나타났다. 이는 단기적으로 현 시점의 비교우위 구조를 받아들이되 장기적 관점에서 비교우위 산업의 기술적 증진을 도모하는 점진적인 전략이 비선진국에게 유용한 성장전략이 될 수 있음을 시사한다.

주 제 어: 경제성장, 동태적 비교우위 변화, 수출 다변화, 수출 특화, 수출 전략, 동태적 패널 분석, 패널 시계열 분석

학 번: 2015-30062