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KUZNETS BEYOND KUZNETS

Structural Transformation and Income Inequality in the Era of Globalization in Asia

Edited by Saumik Paul

ASIAN DEVELOPMENT BANK INSTITUTE

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Abbreviations

ADF	Augmented Dickey–Fuller
ASEAN	Association of Southeast Asian Nations
CHIP	China Household Income Project
EDE	equally distributed equivalent
FDI	foreign direct investment
GDP	gross domestic product
GE	generalized entropy
GIC	growth incidence curve
GMM	generalized method of moments
GRDE	gross regional domestic expenditure
GRDP	gross regional domestic product
GSO	General Statistics Office
IFLS	Indonesian Family Life Survey
IPP	intertemporal pro-poorness
LIS	Luxembourg Income Study
MLD	mean log deviation
NBS	National Bureau of Statistics
ODA	official development assistance
OECD	Organisation for Economic Co-operation and Development
OLS	ordinary least square
PP	Phillips–Perron
PPP	purchasing power parity
PRC	People's Republic of China
RIF	recentered influence function
SDGs	Sustainable Development Goals
SOE	state-owned enterprise
SSA	sub-Saharan Africa
TFP	total factor productivity
UN	United Nations
UQR	unconditional quantile regression
US	United States
VAR	vector autoregression
VECM	vector error correction model
VHLSS	Viet Nam Household Living Standard Survey
WAEMU	West African Economic and Monetary Union

Preface

"Distinctions must be kept in mind between quantity and quality of growth, between its costs and return, and between the short and the long term. Goals for more growth should specify more growth of what and for what."

– Simon Kuznets, 1962

Inequality persists, and so does a global concern over it. Kuznets's views about the inverted-U relationship between inequality and development and the subsequent transformation process have been under the lens of researchers for a long time. The theory proposed the inverted-U relationship through (i) the declining share of agriculture in total output, and (ii) migration from the low-income agriculture sector to the high-income industry sector (Kuznets 1955). The second-half of the 20th century marked the global slowdown of the pace of industrialization, and services became the primary destination for labor and capital flow. The role of premature deindustrialization cannot be ignored here, with the service economies peaking even before completing the due process of industrialization. This has proven to be tumultuous for the Kuznets theory as it challenged the typical inverted U-shaped path followed by a country as it develops, with globalization and premature industrialization making the turning point for developing countries to arrive sooner compared with developed countries. Alongside, we observed a global decline in the labor income share, exacerbating the distribution of income especially since the turn of the millennium. These observations prompted many researchers to argue for a reversal of the Kuznets curve in many developed countries since the 1970s. The aim of this book is not to question the relevance of the Kuznets inverted-U framework in this day and age. Rather, it looks to explore the definitive nature of the relationship between structural transformation and income distribution. It acknowledges Kuznets's role in providing insights to structural transformation in income distribution even today, but extends it into more complex modeling agreeable to the dynamics of present economics.

The process of structural transformation in Asia, in both scale and speed, has been unprecedented. Over the last 2 decades, immense potential for growth in Asia has been facilitated by a shrinking agriculture sector and structural transformation. However, it remains undecided whether the contribution of structural transformation will stay as one of the crucial factors in determining potential productivity growth. This book brings together novel conceptual frameworks and empirical evidence from country case studies on topics related to structural transformation, globalization, and income distribution. The focus of the book is on the imperative and crucial role of structural transformation in distributional consequences of income. However, with structural transformation turning into a complex mechanism over time, the very mechanisms that link the process of structural transformation and inequality are posited to have outgrown the naïve inverted-U relationship. The empirical studies in this book cover a broad range of Asian countries and suggest some policy frameworks. For regional convergence in labor productivity growth, development of infrastructure remains the key whereas development of better urban management facilities continues to be a crucial policy task for emerging Asia as fast growth of services exacerbates income distribution through the rapid growth of services. At the same time, the heterogeneous role of structural transformation in productivity growth across Asia remains a concern. Likewise, the evidence is mixed on the role of globalization behind industrialization and highlights two potential areas for further research. The specific tasks of import substitution and technological progress in the process of structural transformation and new insights into the growth of domestic demand could provide useful policy frameworks to address the concerns over growing inequality in Asia.

I hope that readers in the policy, development, and teaching communities will find this book insightful. This book reflects the Asian Development Bank Institute's primary involvement in the deeper understanding of the role of structural transformation in income distribution. This book makes a timely entry as the concern for income distribution is once again at the center of economics with the much-celebrated book by Piketty (2014). The Kuznets waves, as proposed by Milanovic (2016), shows considerable merit in explaining changes in inequality for both the pre- and post-industrialization periods. However, in comparison with its predecessors, this book works more closely with the original Kuznetsian framework. I thank Saumik Paul, research fellow at the Asian Development Bank Institute, for putting together this well-timed book. I wish the readers an enriching and pleasant read.

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1

Introduction

Saumik Paul

Almost three quarters of a century ago, Kuznets (1955) predicted an inverted-U relationship between development through changes in the structure of production and inequality. In Kuznets' influential study, the main aspects of structural transformation were (i) the declining share of agriculture in total output, and (ii) migration from the low-income agriculture sector to the high-income industry sector (Kuznets 1955). Over time, the process of structural transformation grew into a multifarious mechanism (see Herrendorf, Rogerson, and Valentinyi [2014] for a comprehensive literature review on this topic). The observed skill-biased technological change (SBTC) increased the demand for skilled labor (Griliches 1969; Acemoglu and Autor 2011) as capital became more complementary to skilled labor. Concurrently, a systematic reallocation of value-added shares toward high-skill-intensive sectors led to the skill-biased structural transformation (Bueara, Kaboski, and Rogerson 2015). The second half of the 20th century also marked the global slowdown of the pace of industrialization, which led many developing countries to experience the process of deindustrialization at a premature stage. Manufacturing typically follows an inverted U-shaped path as a country develops. Rodrik (2016) observed that the turning point for developing countries arrives sooner and at much lower levels of income than what has been the case for developed countries in the previous decades. Simultaneously, services became the primary destination of labor and capital flow.

In today's world where most countries are connected through trade, it is only natural to ask how trade affects the patterns of structural transformation. Several scholars have noted that comparative advantage in agriculture can slow down the process of industrial growth in an open economy (Mokyr 1976; Field 1978; Wright 1979; Krugman 1987). Matsuyama (2009) argued that employment growth in manufacturing depends on a country's relative comparative advantage in manufacturing over its trade partners. On the other hand, Rodrik

(2016) claimed that manufacturing typically follows an inverted U-shaped path as a country develops, and globalization makes the turning point for developing countries arrive sooner compared with developed countries. Alongside, we observed a global decline in labor income share, exacerbating the distribution of income especially since the turn of the millennium (Elsby, Hobijn, and Sahin 2013; Karabarbounis and Neiman 2014). These observations prompted many researchers to argue for a reversal of the Kuznets curve in many developed countries since the 1970s. It has also been argued that inequality dynamics are primarily shaped by other factors, such as government policies and institutional changes (Piketty 2006). The plan of this book is not to wade into the question of whether Kuznets' inverted-U framework can stand the test of time. Instead, it explores more nuanced features of the relationship between structural transformation and income distribution by extending the Kuznetsian framework.

This book aims primarily to bring together novel conceptual frameworks and empirical evidence from country case studies on topics related to structural transformation, globalization, and income distribution. Structural transformation, in a broader sense, entails a change in quantities and/or a change in prices. This process embodies changes in the weights of different parts (could be sectors, geographic regions, etc) of the economy (through output, employment, and other activities). For example, Fields (1979) considered "modern sector enlargement" as a quantity transformation, whereas "modern sector enrichment" and "traditional sector enrichment" reflected price transformations. Throughout this book, we use a somewhat narrower definition of structural transformation. In the development–inequality frameworks studied in the subsequent chapters, structural transformation is modelled as reallocation of labor across sectors (e.g., agriculture to industry). Following the overview (Chapter 2) two theoretical frameworks highlight different mechanisms through which the process of structural transformation affects income inequality. The first framework (Chapter 3) addresses how structural transformation affects income growth at different quantiles of the income distribution, whereas the second framework (Chapter 4) provides a novel decomposition technique to show that σ-convergence in regional productivity growth can be approximated by σ-convergence in sectoral productivity growth and σ-convergence in structural transformation-led productivity growth. The next two theoretical frameworks address the role of international trade behind the structural transformation. Using a three-sector model, including the demand approach and the supply approach to structural transformation in addition to balanced trade, Chapter 5 finds that foreign demand is a crucial element in explaining sectoral employment composition. Our last theoretical model highlights the joint role of technology and factor endowments, the two primary drivers of comparative advantage behind the process of structural transformation.

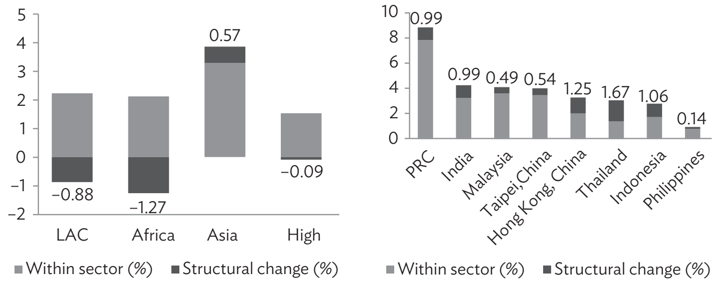
The empirical studies in this book cover a broad selection of Asian countries. Most of the empirical studies are country case studies on the People's Republic of China (PRC), Indonesia, Japan, the Philippines, Singapore, the Republic of Korea, Sri Lanka, and Viet Nam. Only Chapter 7 uses a large sample of 217 economies during the period 1991–2014. The empirical studies presented in Part I and II can be conveniently categorized into three broad areas. The first group of studies examines the effect of trade liberalization on structural transformation and inequality (Chapters 5, 6, 7, and 9). The second group consists of studies that examine the role of structural transformation in regional convergence (Chapters 4 and 11). And the rest of the empirical studies examine the role of different aspects of structural transformation on income inequality. Chapter 8 shows that the growth of services drives urban inequality in the PRC, whereas Chapter 10 finds empirical evidence on the role of the labor movement from agriculture to nonagriculture sectors in growing inequality in Indonesia.

Why Asia?

Over the last 20 years, structural transformation with a shrinking agriculture sector has created enormous potential for growth in Asia (McMillan, Rodrik, and Verduzco-Gallo, 2014). As shown in Figure 1.1, the contribution of structural change to labor productivity has been positive (about 15%) only in Asia. Asia's labor productivity growth in 1990–2005 exceeded that of Africa by 3 percentage points per annum and that of Latin America by 2.5 percentage points per annum. The contribution of structural transformation accounted for almost 61% and 58% of these differences between Asia and Africa, and Asia and Latin America, respectively.

While the process of structural transformation in Asia, both in its scale and speed, has been unprecedented (Aizenman, Lee, and Park 2012), the question is whether the contribution of structural transformation will remain one of the important factors in determining potential productivity growth (McGregor and Verspagen 2016). In developing Asia, the large labor productivity gaps between the traditional sectors (e.g., agriculture) and the modern sectors of the economy can also lead to inefficiencies in the allocation of labor and the growth potential of structural change in developing countries (McMillan, Rodrik, and

Figure 1.1: Decomposition of Labor Productivity Growth into "Within Sector" and "Structural Change"



LAC = Latin American countries, PRC = People's Republic of China, High = high-income countries.
Note: Vertical axis measures growth in labor productivity.
Source: Adapted from McMillan, Rodrik, and Verduzco-Gallo (2014).

Verduzco-Gallo 2014). Inefficiency and the misallocation of labor have direct consequences on the income distribution as the growth effect of structural change varies across countries within Asia, from more than 50% in Viet Nam to about 11% in the PRC.

Chapter Overview

Chapter 2 provides an overview of the country-specific structural transformation since the early 1990s in Thailand; Viet Nam; India; the Republic of Korea; Singapore; the Philippines; Indonesia; and Hong Kong, China. In Chapter 3, we extend the dual-sector model that has long been used to explain the Kuznets curve both in the presence (Robinson 1973) and in the absence (Fields 1979) of within-sector inequality. The chapter considers the disparity in each sector and models the heterogeneity of the structural transformation process (between-sector growth) and within-sector growth across income distribution. The gap between returns to nonagriculture and agriculture sectors and variations in the rate of structural transformation across income quantiles jointly determine the direction of the development–inequality relationship.

Chapter 4, written jointly by Kyoji Fukao and Saumik Paul, aims to show that σ-convergence in regional productivity growth can be decomposed into σ-convergence in sectoral productivity growth and σ-convergence in structural transformation-led productivity growth.

With the help of novel historical data sets at the Japanese prefecture-level from 1874 to 2008, this chapter finds that regional convergence in prewar Japan (1874–1940) was driven primarily by productivity growth in the secondary sector. The rapid productivity convergence within the secondary sector in the prewar era provided an essential base for the large convergence effects of structural transformation in the postwar years through a more significant sectoral productivity gap in the lagging regions compared with the leading regions.

In Chapter 5, Cesar Blanco studies the effect of agricultural trade on structural change. This chapter aims to determine the importance of trade in explaining the structural change pattern of two small open economies: Paraguay and the Republic of Korea. The former experienced rising net agricultural exports, and the latter increasing net manufacturing exports. This chapter uses a three-sector model, including the demand approach and the supply approach to structural change in addition to balanced trade, and finds that foreign demand is a crucial element in explaining employment composition in both economies. Without trade, the model cannot tell why agricultural employment remains large, given data on economic growth and relative prices in Paraguay. Using the model, we simulate a counterfactual scenario. Our results show that even if Paraguay had experienced the same productivity and income growth as the Republic of Korea, the country would still need to employ a large workforce in agriculture to satisfy growing foreign demand.

Chapter 6 evaluates the effect of trade liberalization on sectoral employment and value-added shares in four Asian countries based on synthetic control methodology. It also provides a theoretical framework to evaluate the role of trade liberalization in structural transformation. If productivity growth of a sector is related to its expansion and leads to structural transformation, then in the Ricardian tradition, trade facilitates such process in the presence of productivity differences across industries and countries. Coauthored by Cesar Blanco, Rasyad Parinduri, and Saumik Paul, this chapter provides mixed evidence. Trade liberalization seems to increase employment shares of manufacturing only in the Republic of Korea, but it does not seem to matter in the Philippines. Moreover, trade liberalization is associated with growing value-added shares of manufacturing in Indonesia, Singapore, and the Republic of Korea.

In Chapter 7, Rudra Prosad Roy and Saikat Sinha Roy examine the process of structural change and its relationship with inequality for a sample of advanced and transition economies. The process of transition from low-income developing country to high-income developed country involves structural transformation of the economy in which the distributional structure of the economy also changes. Trade liberalization through the removal of tariff and nontariff barriers gears up the process of structural transformation and at the same time changes the income and wealth distribution of an economy. This study investigates the determinants of income inequality and, specifically, whether structural change has a bearing on inequality. Using data from 217 economies during 1991–2014 and the system-generalized method of moments technique for our dynamic panel data analysis, we found that the process of structural change increases income inequality, while more trade liberalization and foreign direct investment inflow help to reduce the same.

Chapter 8 promotes a joint work by Yuan Zhang and Guanghua Wan. The PRC is thought to be one of the unequal economies in the world, but very few studies ever touched the determinations and the revolution of its urban inequality. This chapter first applies the inequality decomposition method to an urban household sample covering the period 2003–2012 and finds that wage inequality of urban households is dominated by the inequality component within the service industry, and also that its decline after 2008 is attributable mainly to the declining inequality component within the service industry. Second, we provide evidence indicating that the change of employment structure and wage determination in the urban labor market can help reduce wage income inequality in urban PRC. These results can help explain why inequality in urban PRC no longer deteriorates after 2008. Policy implications are also proposed at the end of this chapter.

In Chapter 9, S. P. Jayasooriya discusses the impact of structural adjustment of Sri Lanka's economy on sectoral growth to provide pragmatic evidence for policy reforms. This study advocates policy scenarios, investigating the nexus between agricultural, industrial, and service-related gross domestic product (GDP) in (i) an open economic policy setting, (ii) different government policy regimes, and (iii) major policy eras from 1950 to 2015 in the country. Secondary data from the Central Bank and from Institute of Policy Studies publications were used for the analysis. The time-series econometric approach, a vector autoregression, was used—including causality analysis and co-integration—for estimating a long-term relationship in sectoral growth with policy diversions. The empirical investigations revealed in the Sri Lankan economy the existence of unidirectional causality toward agricultural to industrial GDP and bidirectional causality between agricultural and service GDPs.

In Chapter 10, Teguh Dartanto, Edith Zheng, Wen Yuan, and Yusuf Sofiyandi examine the link between structural transformation and inequality in Indonesia by applying Theil's L decomposition (both static and dynamic) on the national socioeconomic surveys (SUSENAS) of 1996, 2005, and 2014 and panel data analysis of the provincial macroeconomic data set. From the static and dynamic decomposition of Theil's L, this study found that (i) the root of increasing inequality in Indonesia is dominated by the pure inequality effect (unexplained effect); (ii) the population shift from the agriculture sector to either the industry or service sector, from rural to urban, and from informal to formal, is the second contributor to a rise in inequality; (iii) an increase of educational attainment also contributes to growing inequality during the last 2 decades; and (iv) even though the contribution is canceled out, the growing income of those working in the agriculture sector, in the informal sector, those living in rural areas, and those without formal education, has curbed inequality increase.

Finally, Chapter 11 examines whether structural transformation leads to growth and income inequality in Viet Nam. Using three rounds of the Viet Nam Household Living Standards Survey (2002, 2006, and 2010), Vengadeshvaran Sarma and Saumik Paul estimated recentered influence functions to construct a decomposition analysis. The primary results indicate that Viet Nam continues to experience sustained structural transformation and growth, but this growth is heterogeneous across regions. The growth exhibits pro-rich gains, with returns to agriculture and manufacturing increasing only for the top 10th to 20th percentiles. Such growth incidences increase income inequality in Viet Nam; and change in income inequality is heterogeneous across regions. Differences in growth and income inequality are driven by differences in the rate of industrialization across regions and by structural effects such as access to seaports. For more inclusive growth, access to nonfarm activities may need to be provided for households in areas that do not have high levels of structural transformation.

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2

Structural Transformation, Growth, and Inequality in Asia since the 1990s

Saumik Paul

2.1 Introduction

In recent years, there has been renewed interest in finding the real cause of inequality in incomes and wealth (Piketty 2014; Milanovic 2016). At the same time, structural transformation through movement out of agriculture remains commonplace and creates enormous potential for growth, particularly in Asia and Africa (McMillan, Rodrik, and Verduzco-Gallo 2014). This chapter provides a brief overview of the process of structural transformation and its link to growth and inequality in Asia since the 1990s.

Dual economy models, starting from Lewis (1954), characterize the inefficiencies in the allocation of labor and the growth potential of structural change in developing countries. Throughout this book, structural transformation refers to the reallocation of economic activity across the broad sectors of agriculture, manufacturing, and services. It is characterized by a flow of resources—primarily labor—from agriculture to modern economic activities with higher labor productivity such as manufacturing and services. For this reason, structural transformation may result in a rise in productivity and in income (McMillan and Rodrik 2011; Herrendorf, Rogerson, and Valentinyi 2013). Developing countries are defined by large labor productivity gaps between traditional sectors of the economy (e.g., agriculture) and modern sectors of the economy. Productivity gain from structural transformation varies across countries, and the speed of structural transformation is the key factor that explains differences between successful and unsuccessful countries (McMillan and Rodrik 2011; Felipe, Mehta, and Rhee 2015). This could also be partly driven by allocative inefficiencies within sectors, e.g., between formal and informal sectors (World Bank 2013).

One of the underlying forces behind recent structural transformations is globalization, which favors technology transfers and improves production efficiencies. However, globalization does not necessarily produce growth-enhancing structural changes (McMillan and Rodrik 2011). The extent to which structural changes increase economy-wide productivity growth depends on how globalization contributes to the reallocation of workers across sectors. In the case of Asia, these workers ended up in higher-productivity activities, and structural transformation favored growth (World Bank 2013). According to McMillan and Rodrik (2011), three factors determine whether structural change spurs economy-wide productivity growth. First, countries with a large share of natural resources in their exports are less likely to exhibit productivity-enhancing structural change. Although the sectors exploiting natural resources are usually of high productivity, they cannot absorb large segments of the labor force from traditional sectors of the economy. Second, countries with competitive or undervalued currencies, or with effective industrial policy, are likely to experience more growth-enhancing structural transformation—for example, the People's Republic of China (PRC), Republic of Korea, and Taipei,China. Finally, flexible labor markets are associated with more growth-enhancing productivity growth—they ease the flow of labor across sectors and firms. The productivity gap between agricultural and non-agricultural sectors evolves non-monotonically during economic growth, following a U-shape pattern. The ratio of agriculture sector productivity to non-agriculture sector productivity first declines as the structural transformation starts and economic diversification takes place. Then, the move of labor from traditional agriculture to modern economic activities increases, which reduces the productivity gap (McMillan and Rodrik 2011).

2.2 Structural Change in Asia since the 1990s

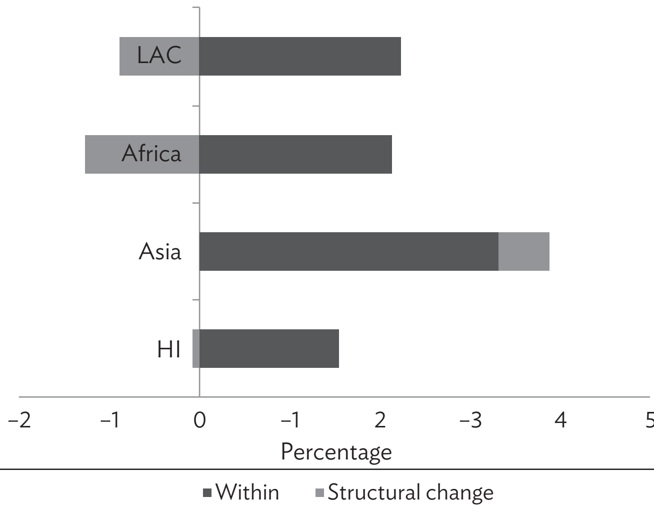
Structural transformation in developing Asia has been unprecedented in its scale and speed (Aizenman, Lee, and Park 2012). Productivity growth within sectors, as contrasted with structural change, is the largest component of productivity growth in Asia. Sen (2016) pointed to two major determinants of structural transformation in Asia: government failures that affect the demand for labor from high-productivity sectors (labor regulation, product market regulation) and the supply of labor from low-productivity sectors (land reforms, migration policy) (World Bank 2013). In addition, he argued that market failures affect both the demand and supply of labor such as coordination problems in investment, credit market imperfections, and failure in human capital formation. As McMillan and Rodrik (2011) showed, roughly 15% of annual productivity growth between 1990 and 2005 is explained by structural changes (labor reallocation across sectors), while 85% is due to the "within" component of increase in productivity within economic sectors. However, the structural effects in economic structure are the most important factor in determining potential productivity growth (Foster–McGregor and Verspagen 2016).

When compared to other regions—Africa and Latin America—the key difference in regional growth comes from diverging patterns of structural changes. Asia's labor productivity growth in 1990–2005 exceeded Africa's by 3 percentage points per year and Latin America's by 2.5 percentage points per year. Of this difference, the structural change term accounted for 1.84 percentage points in Africa (61%) and 1.45 percentage points in Latin America (58%). While Latin America and Africa have done broadly equally well on productivity growth within individual sectors of the economy, their underperformance compared to the Asian success mainly comes from productivity-reducing structural changes (Figure 2.1) (McMillan and Rodrik 2011). Asian countries are those where the magnitude of the structural change is the largest in explaining productivity growth between 1990 and 2005 (McMillan and Rodrik 2011). A notable difference between Latin America/Africa and Asia is that, in the former, many workers have relocated to market services industries (e.g., retail trade and distribution) since the 1990s rather than to manufacturing. Those industries have higher productivity than agriculture, but, compared to manufacturing, lack technological dynamism, i.e., they are not catching up with the world's technological frontier (Timmer, de Vries, and de Vries 2014).

2.2.1 Overview of Structural Transformation at the Country Level

We describe the process of structural transformation in nine major Asian countries. A detailed analysis is provided of Indonesia and the Philippines. But we begin with Thailand, where the contribution of structural change to overall productivity growth was the largest between 1990 and 2005. The employment share of the agriculture sector to the overall economy was reduced by 20 percentage points over the period, and workers moved to relatively higher-productivity sectors such as

Figure 2.1: Decomposition of Productivity Growth by Country Group, 1990–2005



LAC = Latin American Countries, HI = high-income countries.
Source: McMillan and Rodrik (2011).

manufacturing, and wholesale and retail trade (McMillan and Rodrik 2011). On the other hand, Viet Nam experienced a large productivity-enhancing structural change between 1990 and 2008. In the late 1980s, three-quarters of the labor force was employed in agriculture. During 1990–2008, the employment share of agriculture was reduced by 20% as workers moved to sectors with relatively higher productivity such as services, construction, and retail trade where productivity was four times higher than in agriculture. This structural transformation was accompanied by productivity growth within sectors due to two important phenomena: the transition from state-owned firms to private employment and from family farms to formal firms (McCaig and Pavcnik 2013).

India benefitted from growth-enhancing structural change. During 1990–2005, there was a move of workers from the traditional, low-productivity agriculture sector to modern sectors of the economy such as manufacturing and construction, and community, social, personal, and government services (McMillan and Rodrik 2011). This process of structural transformation can be contrasted with other Asian countries.

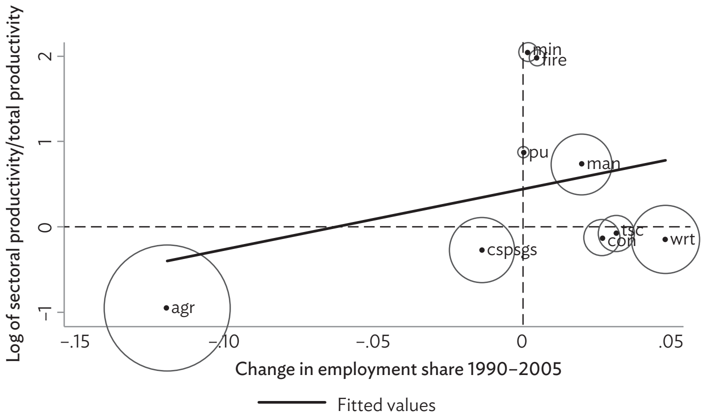
During 1960–2004, the share of employment in agriculture fell by only 10 percentage points (from 71.5% to 61.5%) and the manufacturing sector's share rose by only 2.6 percentage points (Ahsan and Mitra 2013). Restricting the period to 1990–2005, agriculture's share was reduced by less than 4 percentage points, and manufacturing's share increased by about 1 percentage point (McMillan and Rodrik 2013), while, during the same period, both Thailand and Viet Nam reduced the size of their agricultural sector by 20 percentage points. Structural transformation in India relied on information technology and business process outsourcing—sectors with high productivity activities, but that are also highly skill-intensive and could not absorb large segments of the Indian workforce (Ahsan and Mitra 2013).

Turning to Republic of Korea and Singapore, structural change was productivity-reducing between 1990 and 2005, with high productivity sectors shrinking in favor of relatively lower-productivity activities. However, labor productivity of the individual sectors offset the negative contribution of the structural change (McMillan and Rodrik 2011). Hong Kong, China has reached the deindustrialization phase of development. Labor forces moved from manufacturing (a reduction of 20 percentage points of its employment share between 1990 and 2005) to more productive activities in services (wholesale and retail trade, finance, etc.). Prior to that period, Hong Kong, China achieved high levels of industrialization and was able to raise its human capital base significantly, allowing its labor force to move massively to highly productive and skill-intensive activities (McMillan and Rodrik 2011; Rodrik 2013).

2.2.2 Structural Transformation in Indonesia since the 1990s

Using data from Timmer and de Vries (2009), we have computed the correlation between sectoral productivity and change in employment share during 1990–2005 for Indonesia to measure the extent of structural transformation. Indonesia shows a clear pattern of growth-enhancing structural change, with labor productivity increasing economy-wide due to changes in the economic structure (Figure 2.2). The sector with the largest loss in employment is agriculture, which was also the least productive sector in 1990. Agriculture's share of employment was reduced by 12 percentage points between 1990 and 2005. This reduction in agricultural employment benefited relatively higher-productivity sectors such as manufacturing and wholesale and retail trade. While the economy moved towards services, the structural transformation in Indonesia has been less dramatic compared to other fast-growing

Figure 2.2: Structural Transformation in Indonesia, 1990–2005



agr = agriculture; min = mining; man = manufacturing; pu = public utilities; con = construction; wrt = wholesale and retail trade; tsc = transport and communication; firebs = finance, insurance, real estate, and business services; cspsgs = community, social, personal, and government services.

Note: Size of circle represents employment share in 1990.

Sources: Authors' own calculation. Timmer and de Vries (2009).

economies. In particular, Indonesia's structural transformation shows important differences compared to the PRC, India, and the Republic of Korea (World Bank 2014). For example, the relative decline of agriculture (as a share of total production and employment) has been slower in Indonesia than in the PRC, India and the Republic of Korea over the past 3 decades. This could be partly because some branches of agriculture in Indonesia benefited from the commodities boom of the past decade (palm oil, rubber, and to a lesser extent coffee and tea). Consequently, the relative rise in services in Indonesia is also smaller than in the PRC, Republic of Korea, and India, reflecting the fact that lower value-added services increased much more in size than modern services in Indonesia (World Bank 2014).

While manufacturing also declined as a share of gross domestic product (GDP) over the past decade, the availability of a large pool of labor in Java (with a population of 139 million), where most manufacturing firms are located, helped Indonesia avoid an absolute contraction of manufacturing and contracting the so-called Dutch Disease.[1] At the same time, the commodities boom has supported exports

1 Dutch disease refers to an appreciation of real exchange rates due to the discovery of new resources relative to the size of the recipient economy (Corden and Neary, 1982).

toward commodities (65% of total exports in 2012), exposing Indonesia to large terms-of-trade shocks that could rapidly translate into external trade imbalances. Sen (2016) gave other reasons for the limitations of the structural transformation in Indonesia.

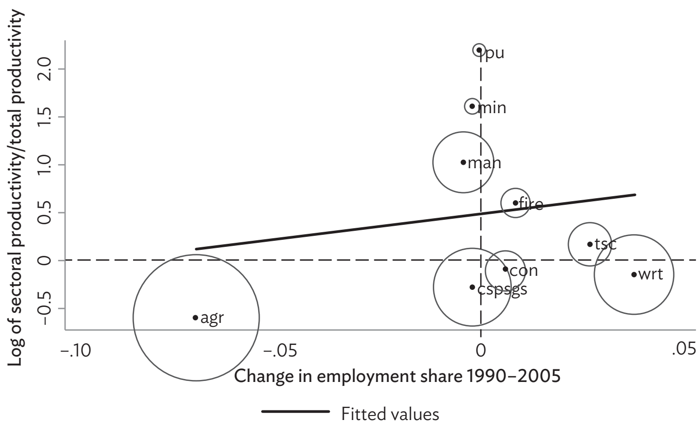
A tightly regulated labor market prevented the flow of labor across sectors. This was due to high rates of redundancy payments (Manning 2014) and an increase of the minimum wage higher than the rate of inflation, which reduced the demand for labor in the formal urban sector (Suryahadi et al. 2003). Land policy in Indonesia is also partly responsible for this, as land acquisition has been a long and complex process causing delays and corruption in, further reducing investment in land and infrastructure projects (Reerink and Bakker 2015). At the same time, market regulation played a crucial role. Indonesia is ranked 109th in the ease of doing business, which is very poor compared with Singapore (1st); Republic of Korea (3rd); and Hong Kong, China (5th), for example. Tight product market regulations are likely to reduce private investment and constrain growth in highly productive sectors (World Bank 2015).

2.2.3 Structural Transformation in the Philippines since the 1990s

Using the same dataset (Timmer and de Vries 2009), we have computed the correlation between sectoral productivity and change in employment share during 1990–2005 for the Philippines to measure the extent of structural transformation (Figure 2.3). Structural change started in the Philippines in the 1990s, but did not fully transform the economy until 2005. While there has been a modest reduction in agriculture's share of employment—7 percentage points compared to more than 20 for Viet Nam or Thailand—the sectors that benefited most from the flow of labor were not the most highly productive sectors. Manufacturing's employment share was slightly shrinking over the period. The flow of workers from agriculture benefitted most the wholesale and retail trade sector, which has a labor productivity below the economy-wide labor productivity.

A number of factors are arguably responsible for this sluggish pace of structural transformation, including a tightly regulated labor market, which reduces the flow of labor across sectors (Sen 2016; Campos and Nugent 2012) and a failed land reform despite several attempts (Hayami, Quisumbing, and Adriano 1990), with most of the land in the country being cropped by landless peasants. This resulted in reducing the productivity in the agriculture sector and preventing the moving of workers to more productive sectors (Sen 2016). In addition, product

Figure 2.3: Structural Transformation in the Philippines, 1990–2005



agr = agriculture; min = mining; man = manufacturing; up = public utilities; con = construction; wrt = wholesale and retail trade; tsc = transport and communication; firebs = finance, insurance, real estate and business services; cspsgs = community, social, personal, and government services.

Note: Size of circle represents employment share in 1990.

Sources: Authors' own calculation. Timmer and de Vries (2009).

market regulation also supposedly played a crucial role. The Philippines is ranked only 103rd in the ease of doing business. Tight product market regulations are likely to reduce private investment and constrain growth in highly productive sectors (World Bank 2015).

2.3 Growth Potential of Structural Transformation in Indonesia and the Philippines

As argued by McMillan, Rodrik, and Verduzco-Gallo (2014), structural transformation may be a less likely scenario for growth in the future for developing countries. First, the success of previous East Asian countries reduces the scope for newcomers. Second, new trade rules limit the scope of industrial policies. Third, financial crisis in developed countries reduces the demand for more manufactured goods. In addition, the manufacturing sectors, where most of the resources from agriculture were reallocated, has become more capital- and skill-intensive. Finally, climate change and greater awareness of the risks related to pollution have raised the costs of industrialization.

Indonesia is one of the 13 economic success stories according to the Commission for Growth and Development (2008). Indonesia is part of the "Growth 13" group of countries defined by high, sustained growth since the postwar period, i.e., it has grown at an average rate of 7% a year or more for 25 years or longer (Commission for Growth and Development 2008). However, recent growth in Indonesia has in large part been supported by employment growth and capital accumulation, with a limited contribution of total factor productivity (TFP). Van der Eng (2008) found that only 33% of growth in 2000–2007 is explained by TFP, and TFP played no role in growth prior to 2000. In contrast, TFP explained more than 50% of growth in the PRC and the Republic of Korea during 2000–2007 (Van der Eng 2008). The economy-wide labor productivity level of Indonesia is also low by regional standards. Average labor productivity in Indonesia is lower than in the PRC, the Philippines, and Thailand and more than five times lower than Malaysia (World Bank 2014). Estimating the wage–employment relationship and the employment–GDP relationship separately for both pre- and post-1997 financial crisis, Chowdhury, Islam, and Tadjoeddin (2009) noted that structural changes in the Indonesian economy have not been conducive to broad-based employment creation and structural changes are more likely to have caused "jobless" growth than the rise in labor costs.

Large productivity gaps across Indonesia's economic sectors are still providing scope for boosting productivity through structural change. Taking advantage of the positive momentum of Indonesia's manufacturing sector and the unfinished structural transformation of the economy will be beneficial for income growth and long-term prosperity. Manufacturing offers greater opportunities for job creation (both quantitatively and qualitatively), facilitates positive structural transformation, exhibits higher labor productivity than other sectors, provides an important conduit for social upgrading, and promotes opportunities to close the gender gap (World Bank 2012; World Bank 2014). Foster–McGregor and Verspagen (2016) found that Indonesia would benefit from labor productivity growth resulting from structural change. Based on their counterfactual analysis, Indonesia would experience labor productivity growth of nearly 2% per year if it were to achieve structural change necessary to reach the middle-income employment structure (Foster–McGregor and Verspagen 2016).

Next, we analyze the growth potentials of structural transformation in the Philippines. Manufacturing is the key sector in the Philippines, as it has a high potential for stimulating production in the rest of the economy. In particular, the scale-intensive and resource-intensive manufacturing industries have the largest impact on the economy (Magtibay–Ramos, Estrada, and Felipe 2011). Unfortunately, the sector's output share has been virtually stagnant for the past several decades. And within manufacturing, the resource-intensive and scale-intensive industries that are most highly linked to the rest of the economy have seen their shares in total GDP decline over time (Magtibay–Ramos, Estrada, and Felipe 2011).

Instead, with the Philippines's failure to industrialize, the largest contribution to overall growth has been from the service sectors, particularly in recent years. This is probably due to the globalization of these activities (Magtibay–Ramos, Estrada, and Felipe 2011). Given its high backward and forward linkages with the rest of the economy, had the manufacturing sector's output share increased, its capacity to stimulate overall economic growth would have been more significant. This implies that with the strong potential of manufacturing to stimulate overall growth, the Philippines cannot afford to leapfrog industrialization and depend (exclusively) on a service-oriented economy (Magtibay–Ramos, Estrada, and Felipe 2011). Foster–McGregor and Verspagen (2016), performing a counterfactual analysis in which the country's employment structure is changed to become equal to one of a reference middle-income country, found that the Philippines would benefit from labor productivity growth from a structural change. Based on their counterfactual analysis, the Philippines would experience a labor productivity growth of nearly 2% per year if it were to achieve structural change necessary to reach the middle-income employment structure (Foster–McGregor and Verspagen 2016).

2.4 Conclusion

The PRC's slowdown in poverty reduction in recent years shows that growth alone is not sufficient to tackle poverty. At least in the short run, there exists a trade-off between efficiency (growth) and equity (redistribution). The growth–inequality relationship is found to be non-linear and negative in post-reform PRC (Wan, Lu, Chen 2006; Wan 2008). We conclude this chapter with some implications of the structural transformation-led growth for inequality in Indonesia and the Philippines.

Economic growth has been effective in reducing poverty in Indonesia. The poverty rate was cut in half from 24% to 12% in 1990–2012, with growth-driven job creation the key driver (World Bank 2014). However, growth in Indonesia has not been inclusive. In 2012, about 65 million people were near the national poverty line and almost 35 million above the national poverty line, making them vulnerable to being driven back into poverty. Moreover, in 2003–2010, real growth of per capita consumption was 1.3% per year for the poorest 40% of households, compared with 3.5% for the next 40%, and 5.9% for the top 20% (World Bank 2014). Poor and vulnerable households benefited the least from income growth between 2003 and 2010. In the same period, the real annual growth of per capita consumption was 1.3% for the poorest 40% of households, compared with 3.5% for the next 40%, and 5.9% for the top 20% (World Bank 2014).

The effect of growth on poverty reduction is sector-specific. The sectors employing the largest number of vulnerable workers (including agriculture, wholesale trade, hotels, and restaurants, among others) have the lowest levels of labor productivity (World Bank 2014). While growth in non-mining sectors significantly reduces poverty and inequality, growth in general and growth in the mining sector has no effect on poverty and inequality (Bhattacharyya and Resosudarmo 2015). Sumarto and Suryahadi (2007) found that agriculture has a significant impact on poverty reduction and Suryahadi, Suryadarma, and Sumarto (2009) found that growth in rural agriculture is the most effective channel for reducing rural poverty. When considering growth acceleration—defined as at least four consecutive years of positive growth in GDP per capita—Bhattacharyya and Resosudarmo (2015) found that growth acceleration in non-mining reduces poverty and inequality whereas growth acceleration in mining increases poverty.

The growth elasticity of poverty reduction in the Philippines is also low by international standards. The estimated growth elasticity of poverty reduction is around 1.6, while the international standard appears to be around 2.5. Therefore, the slow poverty reduction in the Philippines compared to its Asian neighbors can be attributed not only to the relatively slower aggregate income growth, but also to the low responsiveness of poverty reduction to aggregate growth (Balisacan and Fuwa 2004). Relatively high unemployment and the imbalance in productivity have contributed to the disappointing poverty record of the Philippines. After falling between 1991 and 2003, the proportion of people below the poverty line increased consistently between 2006 and 2012 (Yap and Majuca 2013). The number of poor people increased between 2003 and 2009 despite GDP growth rate of nearly 6% between 2004 and 2007. The poverty rate of the Philippines is relatively high compared with its regional neighbors in Asia (Yap and Majuca 2013). Small and medium-sized enterprises account for roughly 99% of Filipino firms. However, those small and medium-sized enterprises account for only 35% of national output—in sharp contrast with Japan and the Republic of Korea, where the same ratio of small and medium-sized enterprises accounts for roughly half of total output. This translates into far fewer high-paying jobs on the local level for Filipino employees and exacerbates the huge income inequality across the country (Yap and Majuca 2013).

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3

Structural Transformation, Growth Incidence, and Inequality: A Framework

Saumik Paul

3.1 Introduction

In 1955, an influential study (Kuznets 1955) predicted an inverted-U relationship between development and inequality through changes in the structure of production. The main aspects of the structural transformation he envisioned were (i) declining share of agriculture in total output, and (ii) migration from the low-income agriculture to the high-income industry sector (Kuznets 1955). Since then a large body of research has tested Kuznets' hypothesis empirically, but a consensus is far less evident.[1] A couple of issues help shed light on this puzzle. First, empirical research on the Kuznets curve has been dominated by cross-country studies, which might allow for factors other than the Kuznets curve to set the development–inequality relationship, while the Kuznets hypothesis was meant primarily for income inequality within a country (Kuznets 1955). Second, as Kanbur (2000) aptly points out, attention has mostly been paid to fit data to the inverted-U relationship. But, application of theoretical models that justify the Kuznets curve's inverted-U shape has been limited.[2]

We begin with a brief review of the literature on theoretical explanations for the existence of the Kuznets curve. The first strand of research relates growth theories to inequality based on imperfections in the capital market (Banerjee and Newman 1991 Aghion and Bolton

1 See Gallup (2012) for a comprehensive summary.

2 Deutsch and Silber (2004) provide an excellent overview of the academic work that has been done on the Kuznets curve.

1992). Another group of studies focus on economic structure and political participation (Alesina and Rodrik 1994; Persson and Tabellini 1994) and how they explain the nexus between growth and inequality over time. And finally, the literature on the dual economy model relates directly to this chapter. Based on these models, the shift of population between sectors (owing to the original work by Kuznets 1955) and intersectoral differences in average income explain the shape of the Kuznets curve (Robinson 1976; Fields 1979; Bourguignon and Morrisson 1990). The dual economy structure has been used to accommodate other explanatory factors such as mineral resources (Bourguignon and Morrisson 1990) and various sources of income (Deutsch and Silber 2004), among others. A relatively less-researched area on this topic is individual migration decisions and their effects on the development–inequality relationship due to population shift. To put it differently, do population movements at different parts of the distribution and at different points in time contribute to the development–inequality relationship? This issue was highlighted by Anand and Kanbur (1993) but has not been followed up since then.

Building on a dual-economy framework, we link structural transformation to income growth across the distribution. As highlighted in the introductory chapter, we model structural transformation as reallocation of labor across sectors (e.g., agriculture to industry). The structural transformation of moving out of agriculture not only has enormous potential for productivity growth (Mcmillan and Rodrik 2014), but also exposes the population to new challenges with varying levels of adjustment capacity (Aizenman, Lee, and Park 2012). Less is known on how structural transformation affects income growth at different quantiles of the income distribution. Bourguignon and Morrisson (1990) show that per capita income differentials between agricultural and nonagricultural households are disparate and constitute a substantial explanatory factor for the total inequality. We specifically examine the heterogeneity in income growth resulting from the structural change across income quantiles and, consequently, its impact on inequality. Repeating this exercise for multiple periods provides a link between inequality and growth through the structural transformation over time. We use this relationship to predict the shape of the Kuznets curve depending on two factors: (i) heterogeneity in the level of structural transformation across the distribution, and (ii) differences in returns to agriculture and nonagriculture sectors. This is not the first study that decomposes total income growth into structural transformation. In an early and influential work on this topic, Fields (1979) decomposed total income growth into the sum of “modern sector enlargement” (more like a quantity transformation), “modern sector enrichment” and "traditional sector enrichment" (both as price transformations) plus an interaction effect. Empirical evidence drawn from the Ivoirian household survey provides support. However, the relative contribution of structural transformation to total changes in inequality compared with other factors is weak, which leads us to conclude the following. First, heterogeneous structural transformation across the distribution opens up various possible relationships between development and inequality other than the inverted "U" relationship, and second, there could be factors other than structural transformation that more closely explain the development–inequality relationship. Together, they help explain why the existing empirical evidence on the Kuznets curve remains inconsistent.

This chapter is organized as follows. Section 3.2 provides a dual economy framework where we derive conditions about the shape of the development–inequality relationship. Section 3.3 is divided into three parts. In the first part, using three rounds of household survey data (1993, 2002, and 2008) from Cote d'Ivoire, we provide summary evidence on structural transformation moving out of agriculture for the period from 1993 to 2008. The second part explains unconditional quantile regression outcomes on the link between structural transformation and inequality across the distribution. And the third part discusses the relative contribution of structural transformation to inequality as demonstrated by generalized Oaxaca-Blinder decomposition outcomes. Section 3.4 concludes.

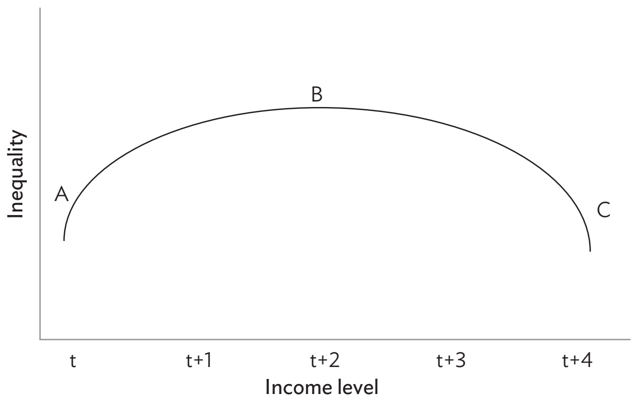
3.2 A Simple Theoretical Framework

3.2.1 Development–Inequality Relationship Using Growth Incidence Curves

Figure 3.1 depicts the development–inequality relationship. Inequality is low at point A, where earnings are predominantly from agriculture. At point B, inequality rises through structural transformation moving out of agriculture and differences in earnings between agriculture and nonagriculture sectors. With further movement out of agriculture, inequality drops at point C when the economy fully transforms into an industrial economy.

Let's consider any two consecutive points in time on the Kuznets curve. We adopt the concept of growth incidence curve (GIC). As defined by Ravallion and Chen (2003), the GIC identifies how the gains from aggregate economic growth are distributed across households

Figure 3.1: The Kuznets Curve



Source: Author.

based on their initial welfare status. More formally, the GIC shows the mean growth rate $g(p)$ in y at each quantile p. In particular, the growth rate of income at the pth quantile from t = 0 to t = 1 can be written as

$$g(p) = \frac{\Delta y(p)}{y_0(p)} = \frac{y_1(p)}{y_0(p)} - 1 \qquad (1)$$

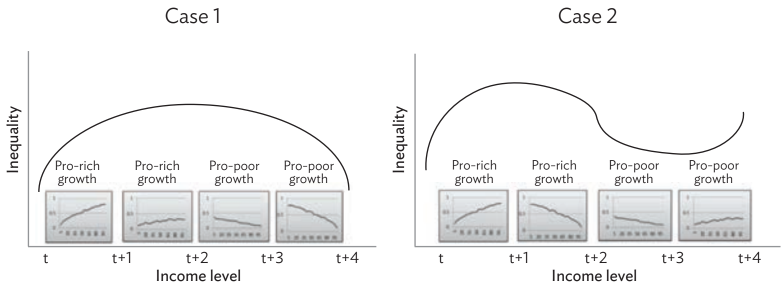
In continuous time, this can simply be written as $g(p) = \frac{dy(p)}{y(p)}$.

Letting p vary within the closed interval [0,1] traces out the growth incidence curve.[3] If the GIC is a decreasing function for all p in its domain of definition, then all inequality measures that respect the Pigou-Dalton principle of transfer will indicate a fall in inequality over time. If instead, the GIC is an increasing function of p, then the same measures will register an increase in inequality (Ravallion and Chen 2003). When inequality does not change, the GIC will show the same growth rate for all p—it satisfies both the first-order and second-order dominance criteria (Son 2004).

Next, we present the development–inequality relationship using the GICs. In Figure 3.2, we consider two cases. Case 1 shows the inverted

3 Alternatively, we have $g(p) = dln(y)$ where $\int_0^y f(v)dv$, and f(·) is the density function characterizing the distribution of the standard living indicator.

Figure 3.2: The Development–Inequality Relationship Using Growth Incidence Curves



GIC = growth incidence curve.

Note: GICs are shown in the boxes below the Kuznets curve.

Source: Author.

"U" Kuznets curve, where the rising part of the curve is associated with pro-rich growth spells represented by the GICs as an increasing function for all p. After period t + 2, a fall in inequality is associated with pro-poor growth spells, and the GIC becomes a decreasing function for all p. Thus, with continuing structural transformation through movement out of agriculture, the pro-rich growth spells are followed by the pro-poor growth spells.

However, structural transformation exposes the population to new challenges with varying levels of adjustment capacity (Aizenman, Lee, and Park 2012). As a result, we may expect a different order of growth spells, as shown in Case 2, in which pro-rich and pro-poor growth spells appear alternately, starting with a pro-rich growth spell between t and t + 1. Other hypothetical cases may have different orderings of growth spells. The primary purpose of this expositional exercise is to understand that heterogeneity in growth incidence across the distribution may not necessarily produce an inverted U-shaped relationship between development and inequality. As a next step, we derive conditions under which the Kuznets curve may deviate from its predicted inverted U shape.

3.2.2 Model Assumptions

We consider a simple theoretical framework with the following assumptions:

- The growth in income and total employment is positive (following Kuznets 1955).
- The economy is divided into agriculture (A), and nonagriculture (N), with different income distributions and within-sector inequality (Robinson 1973).
- Total income in the economy is Y distributed across two income quantiles, h-quantile and l-quantile; and, mean income in h-quantile ($\overline{Y}_H$) > mean income in l-quantile ($\overline{Y}_L$). The mean income in quantile p is $\overline{Y}_p = S_p^A \overline{Y}^A + S_p^N \overline{Y}_p^N$ where quantile is denoted by p (= L, H), $\overline{Y}_p^k$ denotes mean income of sector k (= A or N) in quantile p, and the population share in non-agri (agriculture) sector in l-quantile and h-quantile are denoted as $S_L^N (S_L^A)$ and $S_H^N (S_H^A)$, respectively.
- The population growth in both sectors is constant.
- Define structural change from agriculture to the nonagriculture sector in the p^{th} quantile as an increase in the ratio between population shares, $\frac{S_p^N}{S_p^A}$.
- Define earnings ratio in the i^{th} quantile as the proportion of average returns to the nonagriculture sector to the average returns to the agriculture sector, $\frac{\overline{R}_l^N}{\overline{R}_l^A}$.
- Considering any two consecutive points in time on the Kuznets curve, the GIC indicates a fall in inequality over time if $g\left[\overline{Y}_H\right] < g\left[\overline{Y}_L\right]$ satisfying the Pigou-Dalton principle of transfer. Similarly, the GIC indicates a rise in inequality over time if $g\left[\overline{Y}_H\right] > g\left[\overline{Y}_L\right]$ satisfies the Pigou-Dalton principle of transfer.
- Last but not the least, growth is affected only by structural transformation. We relax this assumption later.

3.2.3 Inequality and Structural Change

Considering any two consecutive points in time on the Kuznets curve, we write the development–inequality relationship from period t to $t + 1$ below:

Inequality rises with structural transformation

$$g\left[\overline{Y}_H\right] > g\left[\overline{Y}_L\right] \text{ if } \Delta\left[\frac{S_L^N}{S_L^A}\right] < \Delta\left[\frac{S_H^N}{S_H^A}\right] \text{ and } \Delta\left[\frac{\overline{R}_L^N}{\overline{R}_L^A}\right] < \Delta\left[\frac{\overline{R}_H^N}{\overline{R}_H^A}\right] \quad [1]$$

If the growth in earnings ratio over time is higher in the h-quantile compared with the l-quantile, then a faster rate of structural transformation in the h-quantile increases inequality by expanding the rich–poor gap. In other words, if gainers from structural transformation appear at a large number from the h-quantile, then following the Pigou-Dalton principle of transfer, resources move from the poor to the rich and increase the level of inequality.

Inequality falls with structural transformation

$$g\left[\overline{Y}_H\right] < g\left[\overline{Y}_L\right] \text{ if } \Delta\left[\frac{S_L^N}{S_L^A}\right] > \Delta\left[\frac{S_H^N}{S_H^A}\right] \text{ and } \Delta\left[\frac{\overline{R}_L^N}{\overline{R}_L^A}\right] > \Delta\left[\frac{\overline{R}_H^N}{\overline{R}_H^A}\right] \qquad [2]$$

Similarly, if the growth in earnings ratio over time is lower in the h-quantile compared with the l-quantile, then a faster rate of structural transformation in the l-quantile is associated with a drop in inequality by contracting the rich–poor gap. In this case, the gainers from structural transformation predominantly come from the l-quantile and, following the Pigou-Dalton principle of transfer, resources move from the rich to the poor and decrease the level of inequality.

Borderline cases

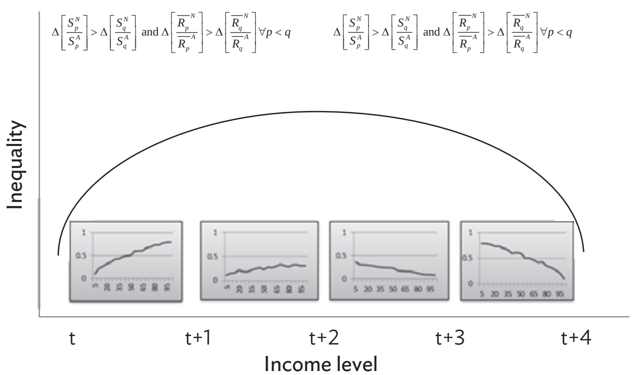
We show two other examples where the net effect of development on inequality depends on the relative strength of the rate of transformation from agriculture to nonagriculture and the growth of the earnings ratio. These cases may arise, in particular, when structural transformation and increasing returns to the nonagriculture sector are observed in different quantiles. For example, a faster rate of structural transformation in the l-quantile can be associated with a slower movement in the earnings ratio (Case 3). The net effect on inequality, in this case, depends on the relative strength of these two factors. If the impact of structural transformation outweighs the growth effect of the earnings ratio, then there will be a drop in inequality with resources moving from the rich to the poor. In the opposite case, there will be a rise in inequality. Case 4 can be explained similarly.

$$g\left[\overline{Y}_H\right] < g\left[\overline{Y}_L\right] \text{ if } \Delta\left[\frac{S_L^N}{S_L^A}\right] > \Delta\left[\frac{S_H^N}{S_H^A}\right] \text{ and } \Delta\left[\frac{\overline{R}_L^N}{\overline{R}_L^A}\right] < \Delta\left[\frac{\overline{R}_H^N}{\overline{R}_H^A}\right] \qquad [3]$$

$$g\left[\overline{Y_H}\right] > g\left[\overline{Y}_L\right] \text{ if } \Delta\left[\frac{S_L^N}{S_L^A}\right] < \Delta\left[\frac{S_H^N}{S_H^A}\right] \text{ and } \Delta\left[\frac{\overline{R_L}^N}{\overline{R_L}^A}\right] > \Delta\left[\frac{\overline{R_H}^N}{\overline{R_H}^A}\right] \quad [4]$$

We generalize these rules for any number of quantiles (more than two). In this case, the GIC indicates a fall in inequality over time if $g^p > g^q \ \forall \ p < q$ satisfying the Pigou-Dalton principle of transfer, where g^p and g^q represent income growth at the p^{th} and the q^{th} quantile, respectively.[4] The rules, (1) and (2), now become more binding as we extend the model from two to multiple-income quantiles. Figure 3.3 provides a graphic illustration of the generalized rules.

Figure 3.3: Structural Transformation and the Development–Inequality Relationship



Source: Author.

Inequality rises with structural transformation

$$g\left[\overline{Y_q}\right] > g\left[\overline{Y}_p\right] \text{ if } \Delta\left[\frac{S_p^N}{S_p^A}\right] < \Delta\left[\frac{S_q^N}{S_q^A}\right] \text{ and } \Delta\left[\frac{\overline{R_p}^N}{\overline{R_p}^A}\right] < \Delta\left[\frac{\overline{R_q}^N}{\overline{R_q}^A}\right] \forall\, p < q \quad [1]$$

[4] GICs ignore the issue of re-ranking individuals through income mobility over time. As a result, the dominance criteria remain ambiguous across different growth trajectories (Bourguignon 2011). However, this issue is not central to this chapter.

Inequality falls with structural transformation

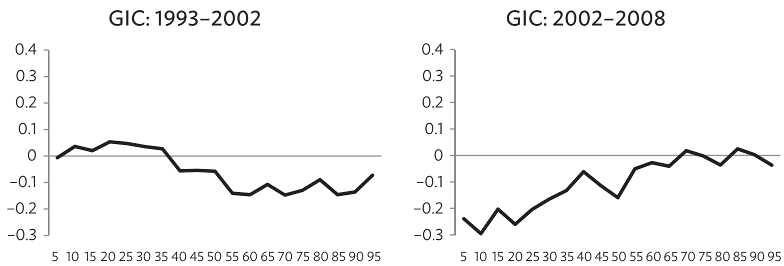
$$g\left[\overline{Y_q}\right] < g\left[\overline{Y}_p\right] \text{ if } \Delta\left[\frac{S_p^N}{S_p^A}\right] > \Delta\left[\frac{S_q^N}{S_q^A}\right] \text{ and } \Delta\left[\frac{\overline{R_p}^N}{\overline{R_p}^A}\right] > \Delta\left[\frac{\overline{R_q}^N}{\overline{R_q}^A}\right] \forall\, p < q \qquad [2]$$

3.3 The Ivoirian Case

3.3.1 Trends in Inequality: 1993–2008

Figure 3.4 presents the growth incidence curves for Cote d'Ivoire for two periods: 1993–2002 and 2002–2008.[5] The GICs in both periods reveal some heterogeneity in the impact of growth on the living standards. During 1993–2002, the bottom half of the distribution shows a higher level of income growth. People located between the 5th and the 35th percentiles experienced a positive income growth. Overall, the shape of the GIC in 1993–2002 suggests a drop in inequality as households experienced more income gain in the bottom half than in the top half of the distribution. In 2002–2008, an opposite trend exists. The average growth in income at each quantile up to the 65th percentile remains negative and depicts an overall positively sloped GIC, suggesting a rise in inequality from 2002 to 2008.

Figure 3.4: Growth Incidence Curves in Cote d'Ivoire, 1993–2002 and 2002–2008



GIC = growth incidence curve.

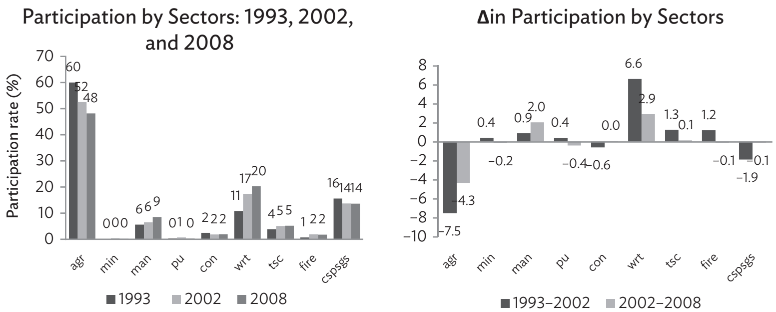
Source: Author.

[5] We use three rounds (1993, 2002, and 2008) of nationally representative household survey (Enquête Niveau de Vie des Ménages [ENV]) data collected by the National Institute of Statistics in Cote d'Ivoire.

3.3.2 Structural Transformation, 1993–2008

Figure 3.5 presents a snapshot of the changing structure of the Ivoirian economy from 1993 to 2008. The share of participation in the agriculture sector dropped by almost 8 percentage points from 60% between 1993 and 2002, and continued to drop by another 4 percentage points between 2002 and 2008. Among nonagriculture sectors, participation only in manufacturing; wholesale and retail trade; and transport, storage, and communications increased from 1993 to 2008. Notably, in the transport, storage, and communications sector, the number of employees almost doubled during this period.

Figure 3.5: Changing Structure of the Ivoirian Economy from 1993 to 2008

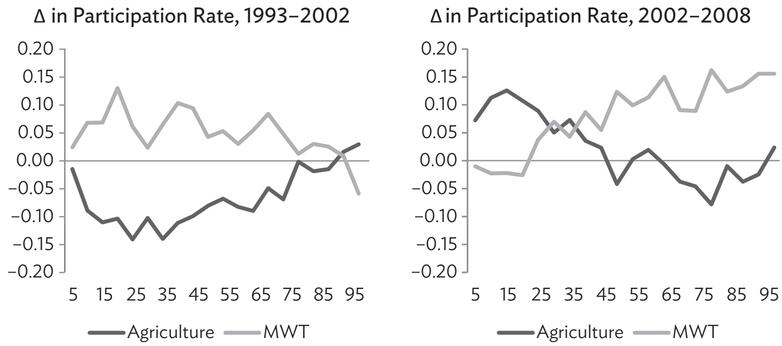


Note: Industry classifications as follows: agr = agriculture, hunting, forestry and fishing; con = construction; cspsgs = community, social, personal, and government services; fire = finance, insurance, real estate, and business services; man = manufacturing; min = mining and quarrying; pu = public utilities; tsc = transport, storage, and communications; wrt = wholesale and retail trade, hotels, and restaurants (based on McMillan and Rodrik 2014).

Source: Author.

Figure 3.6 shows changes in participation rates in agriculture across the distribution. During 1993–2002, structural transformation was prominent in the bottom 70 percentile, in which participation in agriculture dropped, on average, by 5 to 10 percentage points. However, from 2002 to 2008, we see a reverse trend. Participation in agriculture increased in the bottom half of the distribution, whereas structural transformation is evident mostly in the 50th percentile and above. We created a combined sector, MWT, consisting of three industrial categories where participation rate improved from 1993 to 2008:

Figure 3.6: Change in Participation Rate in Agriculture across Income Quantiles



MWT = Manufacturing, Wholesale Retail Trade, and Transport.
Source: Author.

manufacturing; wholesale and retail trade, hotels and restaurants (wrt); and transport, storage, and communications (tsc). In both periods, MWT shows an exactly opposite trend of participation. In the absence of panel data it is difficult to argue that migration from agriculture to MWT is the main channel of structural transformation. However, Figure 3.7 strongly suggests the existence of such possibilities.

3.3.3 Returns to Structural Transformation across Quantiles

To find the returns to structural transformation across the distribution, we needed a way to link unconditional (marginal) quantiles to observables including household characteristics. Recentered influence function (RIF) regression offers a simple way of establishing this link and performing both aggregate and detailed decompositions for any statistic for which one can compute an influence function (Firpo, Fortin, and Lemieux 2009). For a distributional statistic, θ (F) (where F is the underlying distribution function of the random variable y), we denote the corresponding influence function as IF(y; θ, F). The influence function of the pth quantile of the distribution of y is given by the following expression

$$IF(y;q_p) = \frac{\left[p - I(y \le q_p)\right]}{f_y(q_p)}$$

where the distribution function is kept implicit, I(·) is an indicator function for whether the outcome variable is less than or equal to the pth quantile, and $f_y(q_p)$ is the density function of y evaluated at the pth quantile. Firpo, Fortin, and Lemieux (2009) define the recentered or rescaled influence function (RIF) as the leading terms of a von Mises (1947) linear approximation of the associated functional. It is equal to the functional plus the corresponding influence function. Given that the expected value of the influence function is equal to zero, the expected value of the RIF is equal to the corresponding distributional statistic. The rescaled influence function of the pth quantile of the distribution of y is

$$RIF(y;q_p) = q_p + IF(y;q_p) = q_p + \frac{\left[p - I(y \le q_p)\right]}{f_y(q_p)}$$

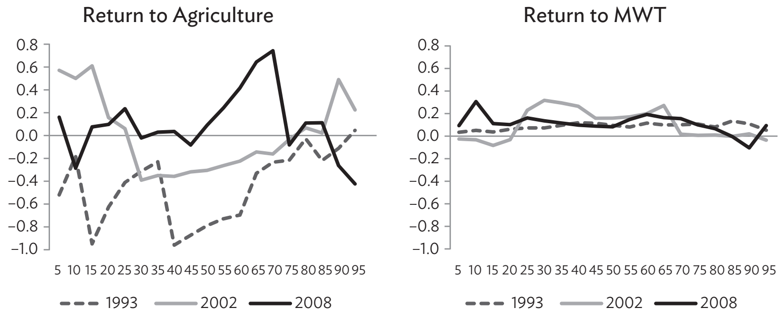
By the law of iterated expectation, the distributional statistic of interest can be written as the conditional expectation of the rescaled influence function (given the observable covariates). This conditional expectation is known as a RIF regression. We express the RIF regression for the pth quantile of the distribution of y, as $E[RIF(y;q_p)|X]$ so that the unconditional or marginal quantile is equal to $q_p = \int E[RIF(y;q_p F_y)|X]\, dF(X)$. Thus, the RIF regression for the pth quantile of the distribution of income (y) is

$$RIF(y;q_p) = \beta_0 + \beta_1 Agri + \beta_2 MWT + X'\gamma + \varepsilon$$

where the unconditional or marginal quantile $q_p = \int E[RIF(y;q_p, F_y)|X]\, dF(X)$. Agri refers to participation in the agriculture sector and MWT refers to participation in the manufacturing, wholesale and retail trade and transport sector. Choice of the base group influences the decomposition outcomes (Oaxaca and Ranson 1999). The goal is to emphasize the change in participation in agriculture; we consider the rest of the sectors as the base group to minimize the role of the unobserved component. The omitted group is composed of participation in other industry categories. X refers to other predictors including demographic and household characteristics and ε stands for the error term. We use five broad groups of covariates: household characteristics (household head's gender, education, marital status, household size, number of children in different age groups, land holding size); geography (urban, regions); occupation categories; and agriculture (participation dummy).

Figure 3.7 depicts returns (estimated RIF coefficients) to agriculture and MWT for 1993, 2002, and 2008. In 1993, return to agriculture

Figure 3.7: Unconditional Quantile Regression Coefficients



MWT = Manufacturing, Wholesale Retail Trade, and Transport.
Source: Author.

remained negative across the distribution. In 2002, it improved significantly in the bottom 25 percentiles and the top 20 percentiles. In 2008, the estimated coefficients showed a somewhat opposite trend. Returns to agriculture improved mainly for the people between the 25th and the 75th percentiles. Turning to MWT, returns across the distribution were less volatile in general. In 1993, returns to MWT were positive across the distribution. Returns to MWT dropped in the bottom 20th percentile and the top 30 percentiles in 2002. But in 2008, it improved especially for the people in the bottom 20th percentile.

A fall in inequality during 1993–2002 can be attributed to structural transformation mainly in the bottom half of the distribution coupled with a steady increase in returns to MWT for people above the 20th percentile. In other words, the pro-poor growth could be driven partly by more people moving out of agriculture with prospects of better earnings in the nonagriculture sectors, particularly in MWT. This closely resembles Case 2 as described in the previous section. Similarly, a rise in inequality is associated with structural transformation in the top half of the distribution. The returns to MWT remained steady across the distribution, but returns to agriculture dropped especially in the top 30th percentile of the distribution. Case 1 firmly explains this rise in inequality during the period 2002–2008. Overall, the empirical evidence in Cote d’Ivoire is in line with the theoretical predictions, with minor exceptions.

3.3.4 Relative Contribution of Structural Change to Inequality

Until this point, the nature of the discussion has mostly been bivariate, considering structural transformation and inequality through the GICs. Even if we find reliable statistical evidence on the correlation between structural transformation–led growth and inequality, other potential factors could be contributing to this nexus between development and inequality. Conceivably, the presence of such factors weakens the predictive power of the theoretical model. Next, as a robustness check, we consider a generalized Oaxaca-Blinder decomposition analysis (Firpo, Fortin, and Lemieux 2009) to estimate the relative contribution of structural change to inequality.

Let $y_{0|t=1}$, and $y_{1|t=0}$ represent counterfactual outcomes for period 1 and period 0, respectively, and $F_{y_0|t=1}$ be the distribution of the (potential) outcome y_0 for individuals in period 1. If $\theta(F_{y_0|t=1})$ expresses any distributional statistic associated with this distribution, then the standard decomposition between the periods 0 and 1 can be written as

$$\Delta^{\theta}_{Overall} = \left[\theta\left(F_{y_1|t=1}\right) - \theta\left(F_{y_0|t=1}\right)\right] + \left[\theta\left(F_{y_0|t=1}\right) - \theta\left(F_{y_0|t=0}\right)\right]$$

where we use the counterfactual for period 1 to obtain the aggregate decomposition. We continue to work with a linear approximation of the RIF regression of the pth quantile, which makes the extension of the standard Oaxaca-Blinder decomposition to RIF regressions both simple and meaningful. Let γ^{qp} be the estimated coefficients from a regression of RIF(y;qp) on X. Based on Firpo, Fortin, and Lemieux (2009) the generalized version of the Oaxaca-Blinder decomposition technique can be written as

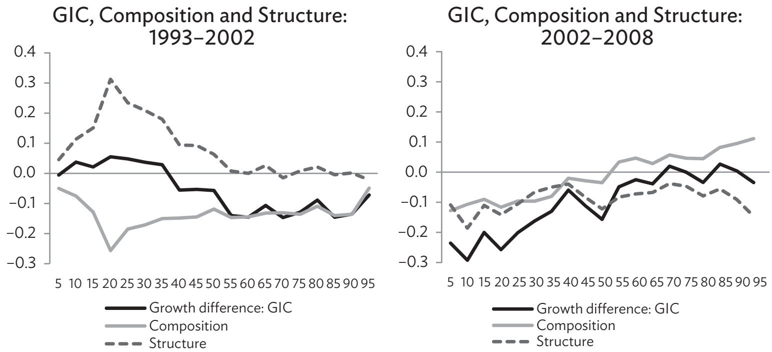
$$\begin{aligned}\Delta^{\theta}_{Overall} &= E\left(X\,|\,t=1\right)(\beta^{\theta}_{1} - \beta^{\theta}_{C}) + E\left(X\,|\,t=1\right)\beta^{\theta}_{C} \\ &-E\left(X\,|\,t=0\right)\beta^{\theta}_{0}\end{aligned}$$

This is a linear approximation of the true conditional expectation with the expected approximation error being zero. The linear RIF regressions of the pth quantile of the distribution of y is estimated by replacing y with the estimated value of $\widehat{RIF}(y; q^p)$. This decomposition may involve a bias since the linear specification is only a local approximation that may not hold in the case of large changes in covariates. The solution to this problem is to combine reweighing with the RIF regression and compute the structural effect as follows: $E(X\,|\,t=1)^T.(\hat{\gamma}^{qp}_{1} - \hat{\gamma}^{qp}_{C})$. Similarly, the composition effect is $E(X\,|\,t=1)^T.\hat{\gamma}^{qp}_{C} - E(X\,|\,t=0)^T.\hat{\gamma}^{qp}_{0}$. $\hat{\gamma}^{qp}_{C}$ is the vector of coefficients from the RIF regression at t = 0 sample reweighted to have the same distribution of covariates as in t = 1. Reweighing ensures that $(\gamma_1^{q_p} - \gamma_c^{q_\tau})$ reflects a true change in the outcome structure.

The use of a linear approximation of the RIF regression also allows to separate out the contribution of different subsets of covariates to the structure effect and the composition effect as parts of the aggregate decomposition similar to the Oaxaca-Blinder decomposition.[6] The differences in participation rates between 1993 and 2002 (and consequently between 2002 and 2008) in agriculture identify structural transformation.[7]

Figure 3.8 shows the total change in growth incidence decomposed into the structure and the composition effect. Overall, the pro-poor growth in 1993–2002 is mainly driven by the structure effect whereas the composition effect solely explains the changes in the top half. In other words, changes in the returns to observable factors including structural change among others, determine the shape of the GIC. In the next period, the composition effect plays the critical role. The pro-rich growth between 2002 and 2008 is explained mostly by a positively

Figure 3.8: Total Decomposition of Growth Incidence into Composition and Structure Effect



GIC = growth incidence curve.

Source: Author.

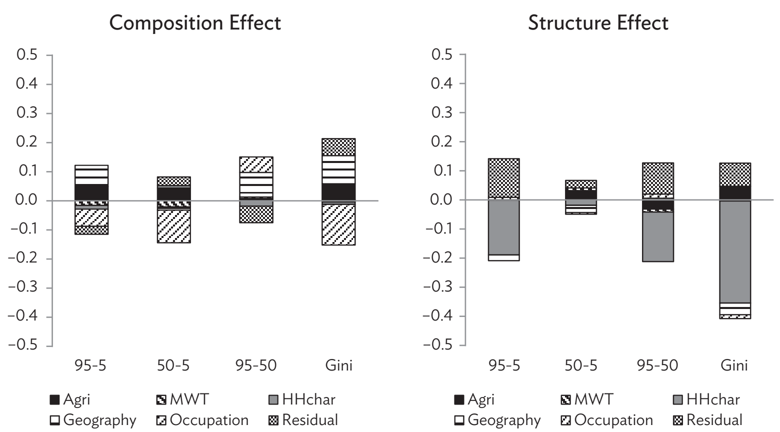
6 Essama-Nssah, Paul, and Bassol´e (2013) used this tool to decompose growth incidence in Cameroon.

7 A richer specification including interaction terms between occupations and sectors of work is used for better estimates of the reweighting factor (Firpo, Fortin, and Lemieux 2009).

sloped composition effect, which indicates that during this period, changes in the level of observable factors explain the growth incidence.

Next, we elaborate on the decomposition outcomes. Figure 3.9 summarizes decomposition outcomes between 1993 and 2002 for three standard measures of inequality: income ratios for quantiles 95 to 50, 50 to 1, and the Gini coefficient. We consider six broad categories of explanatory factors. Agri and MWT refer to participation in agriculture and MWT, respectively. HHchar represents household characteristics; Geography accounts for rural, urban, and district fixed effects; Occupation category represents all occupational groups; and finally Residual measures the unexplained part. In the period 1993–2002, household characteristics remain as the primary driving factor behind a fall in inequality through the structure effect. Structural transformation, in fact, is associated with a rise in inequality, except for the 95–50 income ratio.

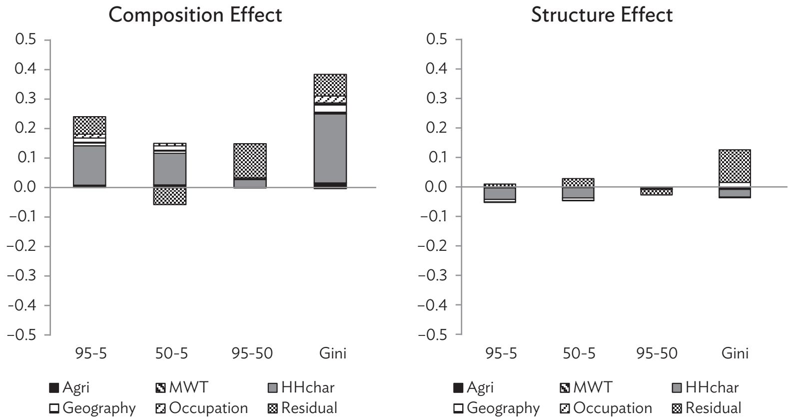
Figure 3.9: Detailed Composition and Structure Effects, 1993–2002



HH = household, MWT = Manufacturing, Wholesale Retail Trade, and Transport.
Source: Author.

Figure 3.10 shows the detailed decomposition outcomes for the period between 2002 and 2008. In this period also, changes in the levels of household characteristics contribute significantly to a rise in inequality but through the composition effect. The contribution of structural transformation to the level of inequality is positive, evident

Figure 3.10: Detailed Composition and Structure Effects, 2002–2008



HH = household, MWT = Manufacturing, Wholesale Retail Trade, and Transport.

Source: Author.

mainly in the composition effect. Among other factors, unexplained variation also contributed to a rise in inequality through the composition effect.

Overall, as evident from Figures 3.9 and 3.10, the relative contribution of structural transformation to inequality is weak. The primary drivers of change in inequality from 1993 to 2008 were household characteristics, geography, occupational categories, and unexplained parts both in the composition and the structure effects.

3.4 Concluding Remarks

Dual-sector models have long been used to explain the development–inequality relationship both in the presence (Robinson 1973) and in the absence (Fields 1979) of within-sector inequality. This chapter extends the literature by considering disparity within each sector. We model heterogeneity of structural transformation and within-sector inequality across the distribution. We argue that the gap between returns to nonagriculture and agriculture sectors and the variation in the rate of structural transformation change across income quantiles jointly determines the direction of the development–inequality relationship. Also, the relationship between structural transformation and inequality depends in no small extent on the earnings ratio and how it varies across income quantiles, which is in line with the findings of Bourguignon and Morrisson (1990).

Empirical evidence based on Ivoirian household survey data for three periods—1993, 2002, and 2008—supports the theoretical model prediction. However, the relative contribution of structural transformation to total changes in inequality is weak, which could be linked to the following factors. First, the identification of structural transformation is based merely on the difference in the percentage of households that consider agriculture as the primary source of livelihood. Second, in the case of Cote d'Ivoire, the overall growth in income has been slow especially in the period from 2002 to 2008, which is evident from the shape of the GIC. Slow growth may provide weak links between structural transformation and growth in the first place, which in turn makes the prediction on the Kuznets motion based on structural transformation insignificant. Another caveat is that the GIC is based on an anonymity principle, and as a result, ignores the issue of re-ranking of individuals through income mobility over time. Although this issue is not central to our main argument, the theoretical framework developed in this chapter is incapable of linking individual mobility features to the Kuznets curve.

Nonetheless, the different process of structural transformation across the distribution provides a novel way to explain the development–inequality relationship; and it also paves the way for more theoretically satisfying models to come. Furthermore, empirical evidence from a broad and diverse range of countries may provide more robust support to the contribution of structural transformation to the development–inequality relationship.

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4

A Framework to Study the Role of Structural Transformation in Productivity Growth and Regional Convergence

Kyoji Fukao and Saumik Paul

4.1 Introduction

Structural transformation has been regarded as a key mechanism for aggregate labor productivity growth[1] and convergence in regional labor productivity (Caselli and Coleman 2001; Duarte and Restuccia 2010; Hnatkovska and Lahiri 2012). In a multisector growth framework, a standard shift-share analysis decomposes aggregate labor productivity growth into the contribution of structural transformation (between-sector effect) and the contribution of sectoral productivity (within-sector effect). Even if structural transformation makes a positive contribution to aggregate labor productivity growth, it could also lead to regional divergence in labor productivity if the degree and contribution of structural transformation to economic growth vary across regions (McMillan, Rodrik, and Verduzco-Gallo 2014). In this chapter, we offer a new decomposition framework to examine the role of structural transformation in regional convergence by addressing these concerns.

We study productivity convergence using the notion of σ-convergence and measure σ-convergence regarding changes in the Gini coefficient for aggregate productivity (the sum of sectoral productivity and structural transformation) over time (O'Neill and Van Kerm 2008).

[1] Structural transformation through resource allocation can have a significant impact on growth and convergence as labor, and other resources move from less productive to more productive sectors (Kuznets 1955).

As Yitzhaki (2003) points out, it is difficult to decompose the Gini index of the sum of two random variables unless certain assumptions are met. We derive the conditions under which σ-convergence (changes in the Gini coefficient) in aggregate productivity is closely approximated by a summation of changes in the Gini coefficient for productivity growth through sectoral productivity and changes in the Gini coefficient for productivity growth through structural transformation. We apply this framework to a novel historical data set on sectoral productivity and employment shares (across three sectors primary, secondary, and tertiary) over 9 benchmarks years (1874–2008)[2] and across 47 Japanese prefectures. The empirical findings provide evidence that convergence in regional productivity is closely approximated by the sum of σ-convergence through sectoral productivity growth and σ-convergence through the growth led by structural transformation.

The rest of the chapter is organized as follows. In section 4.2, we describe the methodological framework. Section 4.3 provides the main findings on the relationship between structural transformation and regional convergence. Section 4.4 concludes.

4.2 Methodological Framework

Consider a framework with three production sectors—primary (*P*), secondary (*S*), and tertiary (*T*)—as well as two regions, H (high productivity) and *L* (low productivity).[3] In the context of Japan, *H* can be thought of as Tokyo, while *L* represents the other prefectures. Production in *P, S*, and *T* takes place in both regions. Labor is reallocated across sectors within each of the regions between two points in time, t and $t+1$, and θ_{ki}^{t} denotes the sectoral labor share of sector i in region k and period t. Following a variant of the canonical shift-share decomposition methodology (see Fabricant [1942] for the original decomposition, and de Vries, Timmer, and de Vries [2013] and Foster-McGregor and Verspagen [2016] for the variant), we write changes in aggregate labor productivity between t and $t+1$ as follows:

$$\text{(1)} \qquad \begin{aligned} \Delta V_k = {} & \textstyle\sum_{i=P,\,S,\,T}(\theta_{ki}^{t})(\Delta V_{ki}) + \sum_{i=P,S,T}(\theta_{ki})(\Delta V_{ki}^{t}) \\ & + \textstyle\sum_{i=P,S,T}(\Delta\theta_{ki})(\Delta V_{ki}) \end{aligned}$$

2 1874, 1890, 1909, 1925, 1935, 1940, 1955, 1970, 1990, and 2008 (Fukao et al. 2015).

3 To convey the main idea, we simplify the framework by considering only two regions. In our empirical analysis, we considered 47 regions (prefectures).

where V_{ki} is the log of labor productivity in sector i (primary, secondary, or tertiary) and region k, and θ_{ki} denotes the labor share in sector i in region k. On the right-hand side of equation (1), we have three terms. The first term shows the contribution of own-sector productivity growth due to capital accumulation, technological progress, or a reduction in the misallocation of resources among firms within a sector. The second term represents the static effect of the reallocation of labor through differences in sectoral productivity at the beginning of each period. Finally, the third term measures the covariance effect between the reallocation of labor across sectors and changes in sectoral productivity. The last two terms together measure the contribution of structural transformation to changes in aggregate labor productivity. Thus, productivity growth in region k (as well as aggregate productivity growth) can be decomposed as follows:

$$(2) \qquad V_k^{t+1} - V_k^{t} = \Phi\,(WS)_k + \Phi\,(ST)_k$$

where $\Phi(WS)_k$ and $\Phi(ST)_k$ represent labor productivity growth in region k due to within-sector productivity growth and due to structural transformation, respectively.

Next, to examine the mechanism through which structural transformation is linked with productivity growth, we consider the term $\Phi(ST)_k$ from equation (1). By adding a time suffix to $V(x)_k$, and after some simple algebraic manipulations, the structural transformation effect is transformed into the sum of two factors:

$$(3) \qquad \Phi\,(ST)_k = \left(\theta_{kT}^{t+1} - \theta_{kT}^{t}\right)\left(V_{kT}^{t+1} - V_{kP}^{t+1}\right) + \left(\theta_{kS}^{t+1} - \theta_{kS}^{t}\right)\left(V_{kS}^{t+1} - V_{kP}^{t+1}\right).$$

The first term on the right-hand side of equation (3) shows the change in the share of tertiary sector employment multiplied by the productivity gap between the tertiary and the primary sector in region k. Meanwhile, the second term shows the same relationship between the secondary and the primary sector in region k. Using vector notation, the equation can be rewritten as $\boldsymbol{V_k}^{ST} = [\boldsymbol{\Delta\theta}_k] \times [\boldsymbol{PG_k}]$, where $\boldsymbol{\Delta\theta}_k$ and $\boldsymbol{PG_k}$ represent the change in the share of non-primary sector labor and the productivity gap between the non-primary and the primary sector in region k. If both of these vectors are either positive or negative, the contribution of structural transformation to productivity growth is positive.[4] However, reallocation of labor from

[4] McMillan, Rodrik, and Verduzco-Gallo (2014) distinguish between growth-enhancing structural transformation (mostly in Asia) and growth-reducing structural transformation (as seen in many countries in Africa and Latin America).

the primary sector may lower the level of aggregate labor productivity if labor productivity in the primary sector is higher than in the other two sectors. Moreover, if the levels of sectoral productivity are equal, then labor reallocation does not lead to any change in aggregate productivity. The poor region (k') catches up with the rich region through structural transformation (k) if $[\Delta\theta_{k'}] \times [PG_{k'}] > [\Delta\theta_{k}] \times [PG_{k}]$, which shows regional convergence.

As suggested by equation (2), in the context of a multisector model for each region or for the whole economy, structural transformation makes a partial contribution to aggregate productivity growth. The contribution of the within-sector effect to aggregate productivity growth is typically larger than that of the between-sector effect (Kaldor 1961; Syrquin 1988; Roncolato and Kucera 2014; Timmer and de Vries 2009).[5] Moreover, structural transformation may not lead to convergence if the degree and contribution of structural transformation to economic growth vary across regions (McMillan, Rodrik, and Verduzco-Gallo 2014). This implies that even if sectoral productivity growth and structural transformation both make a positive contribution to productivity growth, they could work in opposite directions in terms of regional convergence or divergence and hence (partially) offset each other.

Table 4.1 compares the link between productivity growth and regional convergence in a one-sector and a multisector model. The left-hand panel shows regional convergence in a one-sector model, while the right-hand panel shows the same in a multisector model (with two sources of productivity growth). The shaded cells show that the net

Table 4.1: Productivity Growth and Regional Convergence in a One-sector and a Multi-sector Model

<table>
<tr><th colspan="2">One-sector model</th><th colspan="5">Multi-sector model</th></tr>
<tr><td colspan="2">σ-conv</td><td colspan="3" rowspan="3"></td><td colspan="2">Sectoral productivity growth (within-sector)</td></tr>
<tr><td rowspan="2">Yes</td><td rowspan="2">No</td><td colspan="2">σ-conv</td></tr>
<tr><td>Yes</td><td>No</td></tr>
<tr><td colspan="2" rowspan="2"></td><td rowspan="2">Structural transformation (between-sector)</td><td rowspan="2">σ-conv</td><td>Yes</td><td>Yes</td><td>?</td></tr>
<tr><td>No</td><td>?</td><td>No</td></tr>
</table>

Source: Authors.

[5] These studies show that 75%–79% of aggregate labor productivity growth is explained by the within-sector effect.

impact on σ-convergence is jointly determined by σ-convergence in sectoral productivity growth and growth from structural transformation when the σ-convergence based on these two factors has the opposite sign.

Next, let us construct a framework to decompose convergence in regional aggregate productivity into (1) the contribution of convergence in sectoral productivity growth, and (2) the contribution of convergence in the growth effect of the reallocation of labor across sectors (structural transformation). To do so, we define $V_{WS}^{t+1} = V^t + \Phi(WS)$, where V^t represents productivity in period t; $\Phi(WS)$ represents the change in productivity due to the within-sector effect; and V_{WS}^{t+1} represents the hypothetical productivity level in period $t + 1$ if productivity growth is driven only by the within-sector effect. To simplify our notation, we omit suffix k when this does not result in confusion. In a similar manner, we define $V_{ST}^{t+1} = V^t + \Phi(ST)$ when productivity growth is driven only by the between-sector effect (structural transformation). Using the definitions of V_{WS}^{t+1} and V_{ST}^{t+1} and equation (2), we can write

$$(4) \qquad V^{t+1} - V^t = V_{WS}^{t+1} - V^t + V_{ST}^{t+1} - V^t$$

We use the Gini coefficient of regional labor productivity to measure regional disparities in labor productivity. In many studies, measures of income inequality are the coefficient of a variation of gross domestic product (GDP) (Friedman 1992) or the standard deviation of log GDP (e.g., Sala-i-Martin 1996). The Gini coefficient is most similar to the variance and shares many properties with it (Yitzhaki 2003). In addition, as Yitzhaki (2003) shows, the Gini mean difference[6] can be more informative about the properties of distributions that are nearly normal, such as stochastic dominance between two distributions and stratification (when the overall distribution is decomposed into subpopulations). The Gini coefficient of regional labor productivity is written as

$$(5) \qquad G(V) = 1 - 2\int_{\alpha}^{\beta}[1 - F(V)]\tfrac{V}{\mu} f(V)$$

where μ is the mean value of labor productivity (V), α and β are the lower and upper bounds of V, F is the cumulative distribution of V, and f is the density function of V. The Gini coefficient represents the

[6] The Gini mean difference and the Gini coefficient are defined as $G_{MD} = 4Cov(x, F(x)$ and $G(x) = \frac{Cov(x, F(x))}{E(x)}$, respectively (where x is a random variable and F is the cumulative distribution of x). Thus, the relationship between these two terms becomes $G_{MD} = 4G(x)E(x)$.

weighted average of mean-normalized productivity $\left(\frac{V}{\mu}\right)$, where the weights, $1 - F(V)$, are determined by the relative rank of each region's labor productivity. By adding a time suffix to $G(V)$, changes in inequality between t and $t + 1$ can be written as.

$$(6) \qquad \Delta G(V) = G^{t+1} (V^{t+1}) - G^{t} (V^{t}).$$

From equation (4), we can write $V^{t+1} = V_{WS}^{t+1} + V_{ST}^{t+1} - V^{t}$. Based on the properties of the Gini coefficient of the sum of two or more random variables (Yitzhaki 2003), $\Delta G(V) = G^{t+1} (V^{t+1})$ can be approximated as

$$(7) \qquad G^{t+1}(V^{t+1}) = G^{t+1}V_{WS}^{t+1} + G^{t+1} V_{ST}^{t+1} - G^{t}(V^{t}) + \varphi^{t},$$

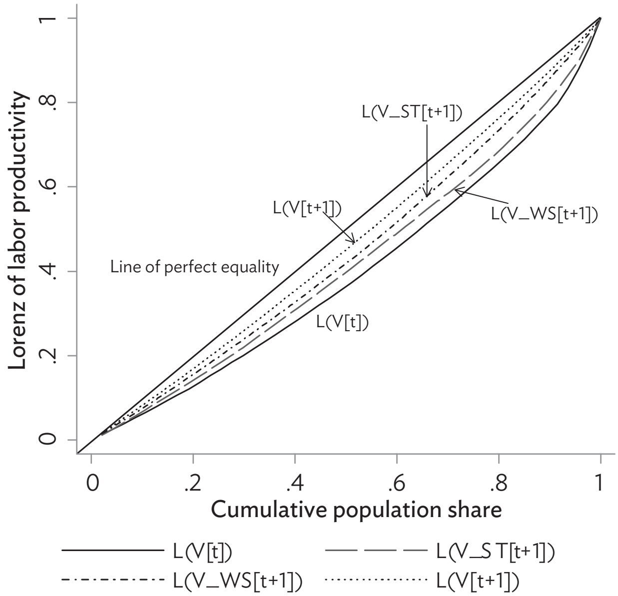
where φ^{t} denotes the adjustment term of this approximation. The detailed derivation of equation (7) is provided in Appendix 1. If we subtract $G^{t}(V^{t})$ from both sides of equation (7), we obtain

$$(7') \qquad G^{t+1}(V^{t+1}) - G^{t}(V^{t}) = \{G^{t+1}V_{WS}^{t+1} - G^{t}(V^{t})\} + \{(G^{t+1} V_{ST}^{t+1} - G^{t}(V^{t})\} + \varphi^{t}.$$

Equation (7') implies that given a smaller value of (φ^{t}, σ-convergence in labor productivity (a drop in the left-hand side of equation ([7']) can be approximated by the net sum of σ-convergence due to the within-sector effect (a drop in the difference in the first two terms on the right-hand side of equation ([7']) and σ-convergence due to structural transformation (a drop in the difference in the last two terms on the right-hand side of equation ([7']). Figure 4.1 provides a graphic representation of this argument using some hypothetical Lorenz curves and assuming that the value of φ^{t} is equal to zero. Using the Lorenz curves of labor productivity, σ-convergence in labor productivity is represented by the area between L(V[t + 1]) and L(V[t]). σ-convergence due to the within-sector effect is represented by the area between L(V_WS[t + 1]) and L(V[t]), and σ-convergence due to structural transformation is represented by the area between L(V_ST[t + 1]) and L(V[t]).

We next provide a theoretical explanation of the size of the approximation error, φ. In Appendix 1, we show that the magnitude of the approximation error φ becomes large if the Gini correlation coefficients are far from 1. In addition, the size of φ becomes small if the expected values of the four key variables, $E(V^{t+1})$, $E(V_{WS}^{t+1})$, $\mathrm{E}(V_{ST}^{t+1})$, and $E(V^{t})$, are similar in magnitude. If these terms differ greatly, then the magnitude of φ becomes large. To check how the stochastic dynamic process of these factors affects the distribution of φ across different periods, we perform a t-test of the null hypothesis that $\varphi = 0$. Empirically, the value of φ for

Figure 4.1: Lorenz Curves Illustrating the Decomposition of Labor Productivity Growth



L(V) = Lorenz Curve of Labor Productivity, L(V_ST) = Lorenz Curve of Labor Productivity driven by Structural Transformation, L(V_WS) = Lorenz Curve of Labor Productivity driven by Within Sector Growth.

Source: Authors.

each period can be calculated for any time period as long as $G^{t+1}(V^{t+1}) - G^{t}(V^{t})$, $[G^{t+1}V_{WS}^{t+1} - G^{t}(V^{t})]$, and $[(G^{t+1}V_{ST}^{t+1} - G^{t}(V^{t})]$ are measured separately. We use these values to test the above hypothesis about φ using the benchmark years from 1874 to 1955 and then annual figures for the rest of the period from 1955 to 2008.

Until this point, we have mainly focused on σ-convergence. However, as many studies on convergence have shown (e.g., Barro and Sala-i-Martin 1992), analysis based on β-convergence is also useful and provides important insights on the dynamic process of convergence. As a next step, we incorporate the mechanism of β-convergence into our decomposition framework of structural transformation and productivity convergence. Following the lead of Jenkins and Van Kerm (2006) and O'Neill and Van Kerm (2008), we extend the relationship between

σ-convergence and β-convergence in the context of a multisector model. We rewrite equation (6) as

$$(8) \qquad G^{t+1}(V^{t+1}) - G^t(V^t) = [G^{t+1}(V^{t+1}) - C_t^{t+1}(V^{t+1},V^t)] \\ - G^t(V) - C_t^{t+1}(V^{t+1},V^t)],$$

where $C_t^{t+1}(V^{t+1},V^t) = 1 - 2\int_\alpha^\beta \int_\alpha^\beta [1 - F^t(V^t)] \frac{V^{t+1}}{\mu^{t+1}} h(V^{t+1},V^t) dV^{t+1} dV^t$ is the concentration index (Schechtman and Yitzhaki 2003; Lambert 2001) indicating the distribution of regional productivity levels in period $t + 1$, with the regions being arranged according to the productivity ranking in period t, and where h is the bivariate density function of productivity in periods t and $t + 1$. In general, the concentration index reveals the relationship between two random variables. Unlike the Gini coefficient, which measures the cumulative shares of a variable plotted against the cumulative frequencies of that variable, the concentration coefficient shows the degree of association between two variables, and its value lies in the range [–1, 1]. Equation (8) shows that changes in the Gini index between two periods can be decomposed into two factors. The last two terms on the right-hand side of equation (8) show the change in the Gini index caused by productivity catch-up between t and $t + 1$ keeping the ranking of the regions as in period t. We express this part by $Progress(V^{t+1}, V^t)$. If productivity growth of a poorer region is higher than that of a richer region, then the value of $Progress(V^{t+1}, V^t)$ becomes negative. The first two terms show the change in the Gini index caused by the re-ranking of regions by aggregate productivity level. We express this part by $Rank(V^{t+1}, V^t)$. If there is no change in the ranking of regions between t and t+1, then the value of $Rank(V^{t+1}, V^t)$ becomes zero. If there is a change in the ranking, then it has a positive value. Therefore, $Rank(V^{t+1}, V^t) \geq 0$, implying that the re-ranking of regions dampens the pace of σ-convergence.

Thus, a change in the inequality of labor productivity (σ-convergence) between two points in time can be decomposed into the effect of productivity catch-up (β-convergence) and the effect of re-ranking:

$$(8') \qquad G^{t+1}(V^{t+1}) - G^t(V^t) = Rank(V^{t+1}, V^t) - Progress(V^{t+1}, V^t).$$

O'Neill and Van Kerm (2008) have shown that $[G^{t+1}(V^{t+1}) - G^t(V^t)]$ can be interpreted as an indicator of the magnitude of σ-convergence, and the term $Progress(V^{t+1}, V^t)$ can be interpreted as an indicator of the magnitude of β-convergence.[7] Using this decomposition framework, we can find the contribution of β-convergence to σ-convergence net of the re-ranking of regions.

In a similar manner, we define the concentration index for V_{WS}^{t+1} as

$$(9) \qquad C_t^{t+1}(V_{WS}^{t+1}, V^{t+1}) = 1 - 2\int_\alpha^\beta \int_\alpha^\beta [1 - F^t(V^t)] \frac{V_{WS}^{t+1}}{\mu_{WS}^{t+1}} h(V_{WS}^{t+1}, V^t) dV_{WS}^{t+1} dV^t$$

where μ_{WS}^{t+1} is the mean of labor productivity ($V_{\downarrow}WS^{\uparrow}(t+1)$), α and β are the lower and upper bounds of V_{WS}^{t+1} and V^t, F is the cumulative distribution of V, and f is the density function of V. The concentration index is a weighted average of mean-normalized productivity $\left(\frac{V_{WS}^{t+1}}{\mu_{WS}^{t+1}}\right)$, where the weights, $1 - F^t(V^t)$, are determined by the relative rank of each region's labor productivity in period t. Moreover, h is the bivariate density function of productivity in periods t and $t + 1$. We use $C_t^{t+1}(V_{WS}^{t+1}, V^t)$ to replicate the decomposition shown in equation (8) for $G^{t+1}(V_{WS}^{t+1}) - G^t(V^t)$:

$$(10) \qquad G^{t+1}(V_{WS}^{t+1}) - G^t(V^t) = Rank(V_{WS}^{t+1}, V^t) - Progress(V_{WS}^{t+1}, V^t).$$

Intuitively, equation (10) shows the relationship between σ-convergence and β-convergence when $\Phi(ST) = 0$. In a similar manner, when $\Phi(WS) = 0$, the relationship between β-convergence and σ-convergence can be written as

$$(11) \qquad G^{t+1}(V_{WS}^{t+1}) - G^t(V^t) = Rank(V_{ST}^{t+1}, V^t) - Progress(V_{ST}^{t+1}, V^t).$$

With the help of equations (10) and (11), we can separately analyze the contribution of sectoral productivity growth and structural transformation to β-convergence and σ-convergence.

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[7] In the growth literature, β-convergence represents the catching-up by poorer regions and σ-convergence shows changes in the dispersion of income across regions. Thus, β-convergence is a necessary but not a sufficient condition for σ-convergence to occur. Using our framework, this can be shown as follows:

- No β-convergence & no σ-convergence $\begin{cases} if \ \ \Delta G(x) = 0 \ \& \ Progress\ (x) = 0 \\ if \ \ \Delta G(x) > 0 \ \& \ Progress\ (x) < 0 \end{cases}$
- β-convergence but no σ-convergence $if \ \ \Delta G(x) < 0 \ \& \ Progress\ (x) > 0 \ \& \ Rank\ (x)|$ $> 0 \ \& \ Rank\ (x)| > |Progress\ (x)|$
- β-convergence & σ-convergence $\begin{cases} if \ \ \Delta G(x) < 0 \ \& \ Progress\ (x) = 0 \\ if \ \ \Delta G(x) < 0 \ \& \ Progress\ (x) > 0 \ \& \ |Rank\ (x)| < |Progress\ (x)| \end{cases}$

4.3 Data and Empirical Evidence

4.3.1 Data

The data set on sectoral productivity and employment shares comprise 9 benchmark years (1874, 1890, 1909, 1925, 1940, 1955, 1970, 1990, and 2008) spanning almost 135 years. To cover the whole economy, we use three broad sectors of production: primary, secondary, and tertiary. The primary sector consists of agriculture, forestry, and fishery, while the secondary sector consists of mining, manufacturing, and construction. The tertiary sector covers all other sectors. The data on real aggregate labor productivity (calculated as the gross prefectural domestic product over the number of workers) for the period 1874–1940 (in yen) are measured in 1934–1936 prices and for the period 1955–2008 (in ¥1,000) are measured in 2000 prices. For this reason, we do not compare the figures on productivity between 1940 and 1955. By-employment is considered while calculating sectoral employment shares in the post-war period.[8]

4.3.2 Some Stylized Facts: Structural Transformation, 1874–2008

The process of structural transformation in Japan started during the Meiji era (1868–1912). Some early initiatives helped reallocate labor across sectors: (i) the abolition of barrier stations and the caste system (in which society was divided into four classes—samurai, farmers, merchants, and craftsmen) in 1868; and (ii) the granting to farmers official permission in 1872 to engage in commercial activities. Restrictions on the selection of occupation and residence from the Tokugawa period were also removed. From 1874 to 1890, the share of manufacturing activities increased substantially in all prefectures. As we will show later, national average labor productivity in the secondary sector remained at almost the same level as that in the primary sector. Therefore, it seems that the expansion of the manufacturing sector during this period was driven mainly by the expansion of traditional manufacturing activities such as food processing, wood products, labor-intensive textile production, etc. An important exception was Osaka, where capital-intensive industries such as the heavy chemical industry and the machinery industry started. During the Edo period, Osaka had been the hub of nationwide wholesale

8 Detailed descriptions of the data and estimation techniques are available in Fukao et al. (2015). Note that data for Okinawa from 1955 to 1970 are not available.

and banking networks. In addition, Osaka borders on Kyoto and Hyogo. Kyoto had been Japan's capital until the Meiji Restoration and the center of traditional manufacturing activities. Kobe, Japan's most important seaport for imports, is in Hyogo, and import substitution activities developed around this area. In the case of East Japan, manufacturing activities expanded particularly in the silk-reeling prefectures of Gunma, Nagano, and Yamanashi.[9] Around this time, new industrialized areas specializing in heavy industry, machinery, and shipbuilding also emerged in Fukuoka, Nagasaki, and Akita, which had international seaports (Fukao et al. 2015).

In addition, with the abolition of protectionist measures introduced by feudal clans during the Edo period, the expansion of nationwide trade activities, and international trade without tariff autonomy, traditional manufacturing activities expanded throughout Japan. For example, traditional production of candle, paper, and salt in Yamaguchi, which was governed by an influential feudal clan during the Edo period, declined substantially as a result of domestic and international competition (Nishikawa 1985). At the turn of the 20th century, high-productivity manufacturing sectors multiplied, mostly in the urbanized areas (Tanimoto 1998; Nakabayashi 2003; Nakamura 2010). Heavy manufacturing-based industrialization evolved with the extensive use of electricity, chemicals, metals, and machinery (Fukao et al. 2015). The labor force in the primary sector declined from 15.4 million in 1874 to 13.1 million in 1909. At the same time, the dependency ratio (the ratio of nonworking to working people) rose from 60% in 1874 to 92% in 1909 as a result of significant population growth from 40 million in 1874 to 49 million in 1909.

As depicted in Figure 4.2(a), employment shares in Japan based on labor input data show a steady fall for the primary sector, a steady increase for the tertiary sector, and a hump shape for the secondary sector. Over 135 years from 1874, the employment share of the primary sector fell from 72% to 5%, whereas that of the tertiary sector rose from 16% to 69%. During the same period, the secondary sector's employment share grew from 14%, peaked at 34% in the 1970s, and then eventually dropped to 26% in 2008. The value-added trends in sectoral shares in GDP (Figure 4.2[b]) are consistent with the literature on growth and structural transformation in early industrialized countries.[10]

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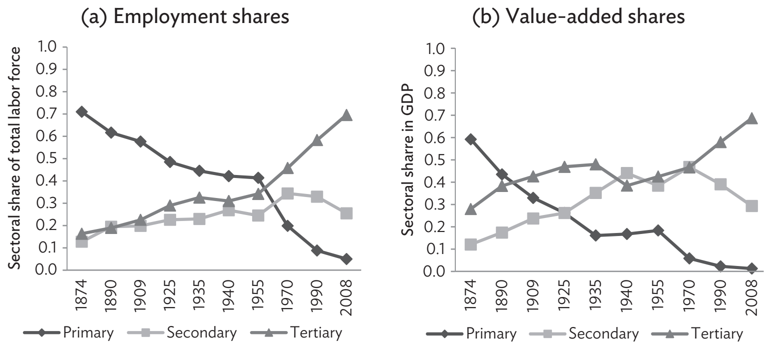
9 After the abolition of strict regulations on international trade in 1954, Japan enjoyed comparative advantage in silk products and suffered from a disadvantage in cotton products. Consequently, prefectures that specialized in cotton products—such as Aichi and Osaka—suffered.

10 See the recent survey by Herrendorf, Rogerson, and Valentinyi (2014).

Figure 4.2: Structural Transformation in Japan



GDP = gross domestic product.

Note: By-employment is considered while calculating man-hour input shares. See Fukao et al. (2015) for a detailed discussion on the data estimation methodology. Sectoral shares in GDP are calculated using real GDP in constant 1934–1936 prices for 1874–1940 and constant 2000 prices for 1955–2008.

Source: Authors.

A few factors have slowed down the labor reallocation process in Japan. One of them, according to Nakamura (1983), is the opening of new foreign markets for Japanese silk and tea. Saito (1998) showed that the level of income across peasant households wielded a decisive influence on migration as peasants were able to earn from both agriculture and cottage industries that had sprung up in the course of proto-industrialization [11] during the Tokugawa period, which provided less incentive for agricultural workers to reallocate to nonagricultural activities. Other factors that perhaps may have also contributed to the slow process of structural transformation include institutional barriers related to agriculture (Hayashi and Prescott 2008), the reallocation of capital to war industries and labor to the munitions industry (Okazaki 2016), and cost linkages between inputs and suppliers of inputs between prefectures (Davis and Weinstein 2002).

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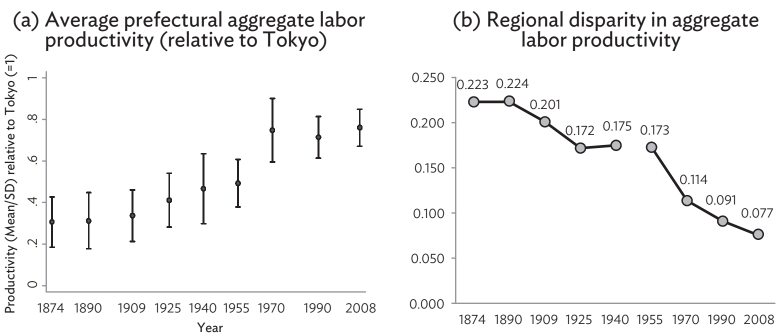
[11] Proto-industrialization refers to pre-modern industrialization without energy and capital-intensive modern factories. See Saito (1983) and Smith (1988) for details on proto-industrialization in Japan.

4.3.3 Convergence of Labor Productivity, 1874–2008

Both regional convergence in productivity and the decline in the employment share in agriculture in Japan[12] started in the late 19th century (Fukao et al. 2015) when the process of industrialization gained momentum (see Figure 4.3[a]). The average labor productivity (over 46 prefectures) benchmarked to the level of Tokyo increased from 32% in 1874 to almost 77% in 1970. During the period of the post-war growth miracle from 1955 to 1970, Japan's aggregate productivity rose remarkably, but the regional disparity in productivity also narrowed to an unprecedented level in this phase. Since the 1970s, the average prefectural labor productivity level (excluding Tokyo) remained in the vicinity of 75% of that of Tokyo. The Gini coefficient for labor productivity also continued to drop in the second half of the 20th century, and did so at a faster rate than in the pre-World War II period (Figure 4.3[b]).

Figure 4.3: Convergence of Aggregate Labor Productivity, 1874–2008



Notes: In both figures, real GDP figures are in constant 1934–1936 prices for 1874–1940 and constant 2000 prices for 1955–2008. In panel (a), the points indicate the average and the vertical range represents the spread (2 standard deviations) around the mean.

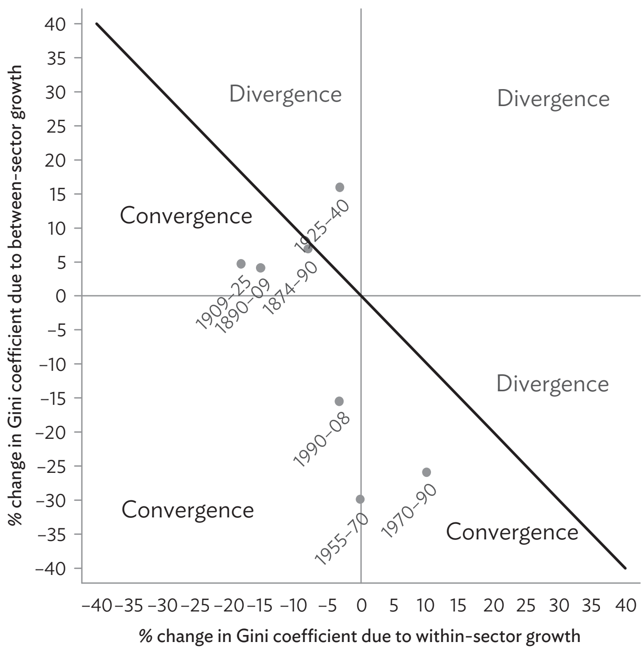
Source: Authors.

12 For developments in the United States, see Easterlin (1960), Barro and Sala-i-Martin (1992), Kim (1998), and Mitchener and McLean (1999).

4.3.4 Productivity Catch-Up and Convergence through Structural Transformation

In this section, we examine the role of structural transformation in productivity convergence. Figure 4.4 provides a graphic summary of the main results and indicates two distinct patterns of regional convergence. Specifically, during the pre-war period, the within-sector effect primarily led to regional convergence, while during the post-war

Figure 4.4: Contribution of Structural Transformation and the Within-Sector Effect to Regional Convergence (σ) in Labor Productivity



Note: This figure only shows the sign of the σ-convergence of aggregate productivity (resulting from the magnitudes and signs of σ-convergence of the within-sector and the between-sector effects). It does not show the actual measure of σ-convergence of aggregate productivity. The vertical and horizontal axes represent the percentage change in the Gini coefficient (of the initial year of each period) in regional labor productivity due to the between-sector and within-sector effects, respectively.

Source: Authors.

period, the between-sector effect (i.e., structural transformation) did. In other words, convergence was the result of two countervailing forces: within-sector productivity growth and productivity growth driven by structural transformation. Appendix Figure A4.1 shows that except in a few periods the distribution of the adjustment term is close to zero. We conduct a t-test which accepts the null hypothesis that φ=0 at the 10% significance level.

Table 4.2 reports the detailed empirical results of the decomposition of the change in the Gini coefficient. The top panel shows the results

Table 4.2: Evidence on Productivity Catch-up and Convergence

	Change in Gini index	Rank	(−) Progress	β-convergence	σ-convergence
A. Decomposition results for σ-convergence in labor productivity					
1874–1890	0.5	9.3	−8.8	Yes	No
1890–1909	−11.6	3.7	−15.4	Yes	Yes
1909–1925	−14.4	3.2	−17.6	Yes	Yes
1925–1940	1.3	5.4	−4.1	Yes	No
1955–1970	−36.8	11.6	−48.4	Yes	Yes
1970–1990	−19.5	12.5	−32.0	Yes	Yes
1990–2008	−14.1	19.0	−33.2	Yes	Yes
B. Decomposition results for σ-convergence in the structural transformation effect					
1874–1890	6.9	1.2	5.7	No	No
1890–1909	4.1	0.5	3.6	No	No
1909–1925	4.7	0.3	4.4	No	No
1925–1940	16.0	3.5	12.6	No	No
1955–1970	−29.9	8.3	−38.2	Yes	Yes
1970–1990	−25.9	2.9	−28.7	Yes	Yes
1990–2008	−15.5	0.6	−16.0	Yes	Yes
C. Decomposition results for σ-convergence in the within-sector effect					
1874–1890	−8.0	9.2	−17.2	Yes	Yes
1890–1909	−15.2	3.6	−18.8	Yes	Yes
1909–1925	−18.1	3.8	−21.9	Yes	Yes
1925–1940	−3.2	15.3	−18.5	Yes	Yes
1955–1970	−0.1	8.0	−8.1	Yes	Yes
1970–1990	10.0	11.8	−1.9	Yes	No
1990–2008	−3.3	13.8	−17.2	Yes	Yes

Note: All figures are given as a percentage of the Gini index in the initial year of each period.

Source: Authors.

for the decomposition for σ-convergence in labor productivity, while the second and third panels show the results for the decomposition of σ-convergence in the between-sector and within-sector effects. Labor productivity converged across regions in all periods except in 1874–1890[13] and in 1925–1940. The second column in each of the panels shows the change in productivity in terms of the percentage change in the Gini coefficient from the starting year of each period to the end year. Panel A suggests that β-convergence in the post-war era was much larger than in the pre-war era. Our estimates show that the Gini coefficient, on average, dropped by almost 35% in the post-war period compared with only 10% in the pre-war period. The highest rate of productivity catch-up was observed in the high-speed growth era from 1955 to 1970. The estimates for Rank (the re-ranking of prefectures) were also higher for the post-war era, but the difference is less pronounced than in the case of β-convergence.

Next, panel B shows the decomposition results for the structural transformation effect. Here, let us focus on the column labeled "(–) Progress," which represents productivity catch-up or β-convergence. The figures indicate that while there was β-divergence (positive figures) in the pre-war period, the post-war period is characterized by β-convergence (negative figures). The estimates for Rank (the re-ranking of prefectures) show slightly higher values in the post-war period than in the pre-war period. The results on regional convergence (σ-convergence) closely follow the productivity catch-up trend (β-convergence). Between 1955 and 1970, structural transformation–led growth alone contributed almost 30% to the drop in the Gini coefficient for aggregate productivity.

Finally, panel C presents the decomposition results for the within-sector effect. The figures indicate that Japan experienced a productivity catch-up of lagging regions through within-sector productivity growth in all periods. However, the pattern is the opposite of that observed for the between-sector effect: the high rate of productivity catch-up was observed only in the post-war period. The within-sector effect made a particularly prominent contribution to regional convergence (σ-convergence) during the pre-war era, which was driven by many factors, including the introduction of motors at small factories in rural Japan (Minami 1976) as well as the transfer of management skills through mergers and acquisitions (Braguinsky et al. 2015). Overall,

13 This is the only period for which the change in the Gini index and the sum total of the decomposed factors have the opposite sign. This is because the magnitude of the approximation error was relatively large. However, the magnitude of convergence in labor productivity was negligible (only 0.5% of the Gini coefficient of labor productivity in 1874).

the sum total of σ-convergence in the within-sector effect (sectoral productivity growth) and σ-convergence in the reallocation effect (structural transformation-led productivity growth) provides a good approximation of the regional convergence in labor productivity.

Our results suggest that the contribution of structural transformation to regional convergence varies over time, as already highlighted by McMillan, Rodrik, and Verduzco-Gallo (2014). In addition, depending on the period, the contributions of the between-sector effect on growth and within-sector growth to regional convergence potentially offset each other.

4.4 Conclusion

The primary purpose of this study was to estimate the potential role played by the process of structural transformation in regional productivity convergence in Japan. Using a novel data set for 47 Japanese prefectures spanning a period of nearly 135 years (from 1874 to 2008), and based on a simple theoretical framework, we find that the process of structural transformation played a crucial role in aggregate productivity growth, productivity catch-up, and regional convergence, especially in the second half of the 20th century. However, since the early 1970s, the pace of convergence slowed down as convergence in the growth effect of structural transformation was frequently offset by the divergence effect of within-sector productivity growth.

Appendix

Appendix A4.1

Following Yitzhaki (2003), we define two additional terms: the Gini mean difference, $G_{MD} = 4Cov(x, F(x))$, where x is a random variable that represents labor productivity (x), and F is the cumulative distribution of x, and the Gini correlation coefficient between two random variables, $\Upsilon_{xy} = , \dfrac{Cov(x, F(y))}{Cov(y, F(y))}$ where x and y are two random variables.

Lemma 1.
A necessary and sufficient condition for two Gini correlation coefficients to be equal, i.e., $\Upsilon_{xy}=\Upsilon_{yx}$, is $C_x^y = C_y^x$, where C_x^y represents the area

enclosed by the concentration curve of x with respect to y, and similarly C_y^x represents the area enclosed by the concentration curve of y with respect to x (Yitzhaki 2003).

Since by construction $V^{t+1} = V^t + \Phi(WS) + \Phi(ST)$, using the definitions of V_{WS}^{t+1} and V_{ST}^{t+1}, we can write the linear relationship $V^{t+1} = V_{WS}^{t+1} + V_{ST}^{t+1} - V^t$.

Assuming that Lemma 1 holds, we can express the Gini mean difference of V^{t+1} in the following manner:

$$(1) \qquad [G_{MD}(V^{t+1})]^2 = [G_{MD}(V_{WS}^{t+1})]^2 = [G_{MD}(V^t)]^2 + 2G_{MD}(V_{WS}^{t+1})G_{MD}V_{ST}^{t+1}$$
$$\Upsilon_{V_{WS}^{t+1}V_{ST}^{t+1}} - 2G_{MD}(V_{WS}^{t+1})G_{MD}(V^t) - \Upsilon_{V_{WS}^{t+1}V^t} - 2G_{MD}V_{ST}^{t+1}G_{MD}(V^t)\Upsilon_{V_{ST}^{t+1}V^t}.$$

Equation (1) closely resembles the variation decomposition expression for the sum of three random variables. Using the covariance definition (Lerman and Yitzhaki 1984), we can write the Gini coefficient of V^t as $G^tV^{t+1} = , \dfrac{Cov\ (V^t,\ F(V^t))}{E(V^t)}$, where V^t is labor productivity in period t, F is the cumulative distribution of V^t, and $E(V^t)$ is the expectation of V^t. This yields the following relationship between G_{MD} and $G^t(V^t)$: $G_{MD} = 4E(V^t)$ G^tV^t. Plugging this back into equation (1), we obtain an expression for equation (1) in terms of the Gini indexes:

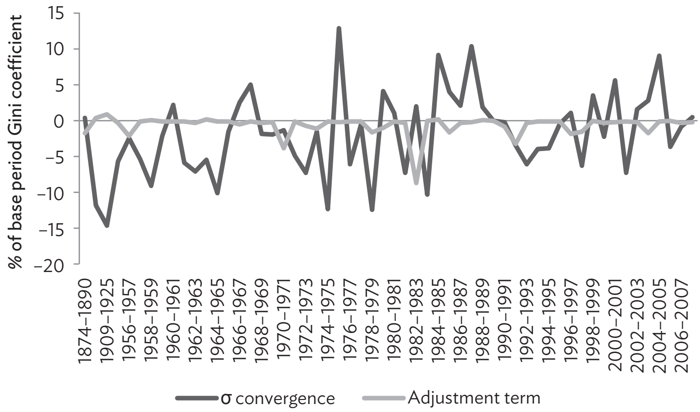
$$(2) \qquad \begin{aligned} &[E](V^{t+1})\ G^{t+1}(V^{t+1})]^2 = \\ &[E(V_{WS}^{t+1})G^{t+1}(V_{WS}^{t+1})]^2 + [E(V_{ST}^{t+1})G^{t+1}(V_{ST}^{t+1})]^2 + [E(V^t)G^t(V^t)]^2 \\ &\quad + 2E(V_{WS}^{t+1})G^{t+1}\left(V_{WS}^{t+1}\right)E(V_{ST}^{t+1})G^{t+1}\left(V_{ST}^{t+1}\right)\Upsilon_{V_{WS}^{t+1}V_{ST}^{t+1}} \\ &\quad - 2E(V_{WS}^{t+1})G^{t+1}\left(V_{WS}^{t+1}\right)E(V^t)G^t\left(V^t\right)\Upsilon_{V_{WS}^{t+1}V^t} \\ &\quad - 2E(V_{ST}^{t+1})G^{t+1}\left(V_{ST}^{t+1}\right)E(V^t)G^t\left(V^t\right)\Upsilon_{V_{ST}^{t+1}V^t} \end{aligned}$$

If we assume that the ϒs are equal to 1, then equation (2) can be transformed into

$$(3) \qquad [E](V^{t+1})\ G^{t+1}(V^{t+1})]^2 =$$
$$[E](V_{WS}^{t+1})\ G^{t+1}(V_{WS}^{t+1})] + E(V_{ST}^{t+1})\ G^{t+1}(V_{ST}^{t+1}) - E(V^t)\ G^t(V^t)],^2$$

where the right-hand side becomes a squared term of a linear relationship with three variables. Depending on whether the square-root term is positive or negative, we get two expressions for equation $G^{t+1}(V^{t+1})$. Since the value of the Gini coefficient lies between 0 and 1 and it can be plausibly assumed that $|G^{t+1}(V_{WS}^{t+1}) + G^{t+1}(V_{ST}^{t+1})|>|G^t(V^t) + \varphi,$

Figure A4.1: Distribution of the Adjustment Term



Note: The figure shows that the distribution of the adjustment term is close to zero except in a few periods. A t-test accepts the null hypothesis that $\varphi = 0$ at the 10% significance level. Empirically, the value of φ for each period can be calculated for any period as long as $G^{t+1}(V^{t+1}) - G^t(V^t)$, $[G^{t+1}(V^{t+1}_{WS}) - G^t(V^t)]$ and $[G^{t+1}(V^{t+1}_{ST}) - G^t(V^t)]$ are measured separately. We use these values to test the above hypothesis about φ using the benchmark years from 1874 to 1955 and then annual figures for the rest of the period from 1955 to 2008.

Source: Authors.

we consider only the positive root and express equation (3) with an approximation error term (φ), written in implicit form as

$$(4) \qquad G^{t+1}(V^{t+1}) = G^{t+1}(V^{t+1}_{WS}) + G^{t+1}(V^{t+1}_{ST}) - G^t(V^t) + \varphi.$$

Subtracting $G^t(V^t)$ from both sides, we get

$$(5) \qquad \varphi = [G^{t+1}(V^{t+1}) - G^t(V^t)] - [G^{t+1}(V^{t+1}_{WS}) - G^t(V^t)] + [G^{t+1}(V^{t+1}_{ST}) - G^t(V^t)]$$

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5

Accounting for Structural Change Patterns in Small Open Economies: A Comparison of Paraguay and the Republic of Korea

Cesar Blanco

5.1 Introduction

The reallocation of employment from agriculture to manufacturing and later to services was described by Kuznets (1973) as one of the main features of modern economic growth. This process is known in the economic growth literature as structural change. The movement of employment out of agriculture in currently developed countries was documented by Gollin, Parente, and Rogerson (2004) and Herrendorf, Rogerson, and Valentinyi (2014), among others.

To explain the process of structural change in the United States, Kongsamut, Rebelo, and Xie (2001) proposed non-unitary income elasticity across sectors. Alternatively, Ngai and Pissarides (2007) argued in favor of biased technical change in the presence of complementarity of goods and services in preferences. According to Dennis and Iscan (2009), both of these mechanisms account for most of the secular reallocation of employment in the United States. Moreover, Alvarez–Cuadrado and Poschke (2011) found that the same mechanisms account for much the patterns of structural change in 12 industrialized countries.

The views outlined by Kongsamut, Rebelo, and Xie (2001) and Ngai and Pissarides (2007) are referred to in the literature as the demand approach and the supply approach to structural change. They imply that as an economy develops, employment shifts away from sectors with low income-elasticity and growing relative productivity. However, as argued by Matsuyama (2009), this is contrary to the evidence observed in East Asian countries, where manufacturing productivity and employment in this sector experienced a simultaneous increase. This author argues that an open economy framework is necessary to explain the positive link between productivity growth and employment in manufacturing.

In a recent study, Uy, Yi, and Zhang (2013) found that a combination of non-homothetic preferences and international trade explain most of the structural change patterns observed in the Republic of Korea during 1971 to 2005. Without trade the model considered by the authors is unable to account for observable changes in employment shares in this country. Therefore, they found evidence that international trade is a crucial element for the rapid reallocation of employment in a small open economy with comparative advantage in manufacturing. Betts, Giri, and Verma (2013), Sposi (2015), and Teignier (2017) obtained similar results. These authors studied the case of the Republic of Korea and concluded that international trade is important to explain structural change patterns observed in this country.

The focus of much of the literature on structural change in small open economies is on countries with comparative advantage in manufacturing, such as the Republic of Korea. A notable exception is that of Matsuyama (1992), who argued, using a theoretical model, that trade liberalization could prevent industrialization in a country with initial comparative advantage in agriculture.

In Blanco (2017), the focus is on a small open economy with large net agricultural exports, a proxy for comparative advantage in this sector. The conclusion of this study is that rising net agricultural exports led to high agricultural employment in Paraguay. In addition, it led to a movement of employment from agriculture into services, bypassing manufacturing. In this chapter, we expand the analysis in Blanco (2017) and contrast the case of Paraguay, a net exporter of agricultural products, with that of the Republic of Korea, a net exporter of manufactures. For this purpose, we consider a three-sector structural change model including non-homothetic preferences, biased technical change, and international trade. Using data on income, relative prices, and international trade we quantify the contribution of trade in explaining structural change out of agriculture in Paraguay. Similarly, we quantify the contribution of trade in explaining the rise in manufacturing employment in the Republic of Korea.

Results show that the role of trade is crucial to account for employment patterns in both countries. The demand and supply mechanisms of structural change alone cannot explain observed data on employment shares in these economies. In addition, we consider a counterfactual scenario where Paraguay is subject to the rise in income, productivity, and net manufacturing exports observed in the Republic of Korea, and ask what employment in agriculture would be under these circumstances. We find that income and productivity play a relevant role in explaining the evolution of employment shares. However, results indicate that trade still accounts for a large fraction of employment reallocation.

The rest of this chapter is organized as follows. Section 5.2 describes the data for Paraguay and the Republic of Korea. Sector 5.3 introduces the structural change model. Section 5.4 simulates the model and provides the results. Finally, Section 5.5 concludes.

5.2 Data

The data for Paraguay is obtained from Blanco (2017). The data for the Republic of Korea on employment shares and relative prices is obtained from the Groningen Growth and Development Center (GGDC) 10-Sector database, on gross domestic product (GDP) per capita from the World Development Indicators database and trade data from the United Nations (UN) Comtrade database.

Panel (a) of Figure 5.1, shows the observed pattern of structural change in Paraguay during the period 1963–2010. Employment in agriculture declined from 54.8% in 1963 to 27.3% in 2010, while employment in services rose from 26.4% in 1963 to 56.1% in 2010. Manufacturing employment remained at around 20% during the entire period. In Panel (b) we observe an annual increase of income of 1.8%.

We compute relative prices of agriculture and of services in units of manufacturing goods in Panel (c). This panel indicates a decline of prices in both sectors. The decline is faster in agriculture. Panel (d) reports observed net agricultural exports as a percentage of GDP and the trend component.[1] As the figure indicates, net agricultural exports accounted for 8.7% of GDP in 1963 and 16.1% at 2010, indicating a near twofold increase.[2]

Figure 5.2 shows the data for the Republic of Korea. Panel (a) reports employment shares for the period 1963–2013. The Republic of Korea experienced rapid structural change out of agriculture, from 61%

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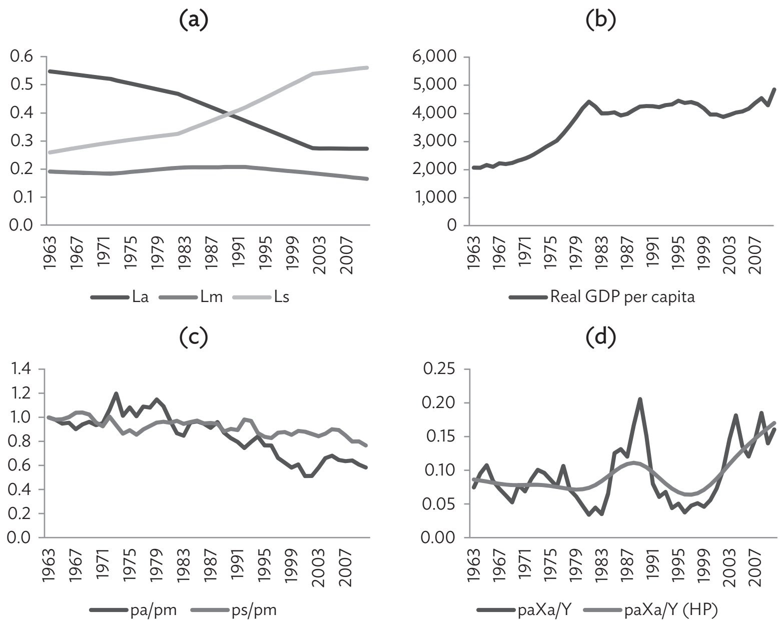
1 We use the Hodrick–Prescott filter to obtain the trend component.

2 Net agricultural exports include exports minus imports of products in Standard International Trade Classification (SITC) Rev 1, sections 0, 1, 2, 4 minus divisions 27 and 28 from the UN Comtrade Database.

Figure 5.1: Data for Paraguay



(a) La, Lm, and Ls indicate employment in agriculture, manufacturing, and services, respectively, as % of total employment. (b) GDP per capita measured at constant 2005 National Prices (in 2005 US dollars). (c) pa/pm and ps/pm indicate relative prices of agriculture and of services in units of manufacturing goods. Sectoral prices computed as value added in current prices divided by value added in constant prices. (d) paXa/Y indicates net agricultural exports as % of GDP. HP denotes trend component obtained from using the Hodrick–Prescott filter.

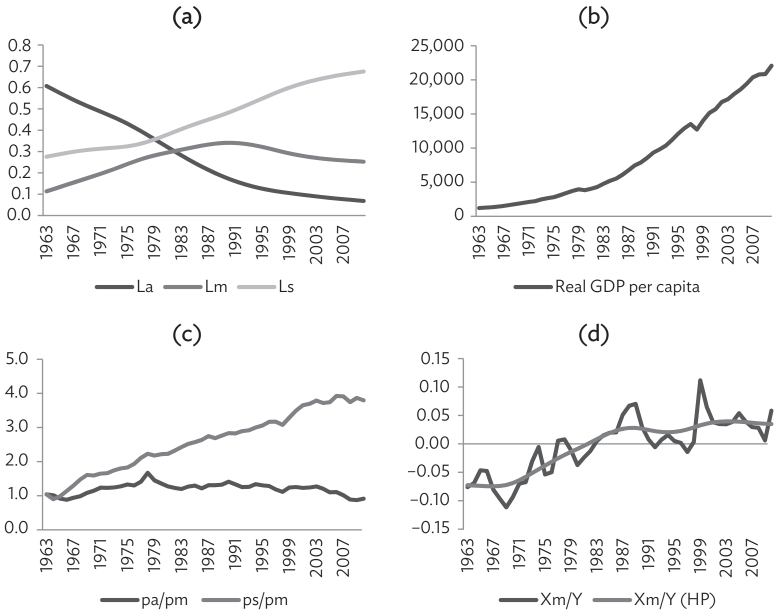
Source: GGDC 10-Sector database, World Development Indicators, UN Comtrade, and Central Bank of Paraguay.

of employment in 1963 to 6.7% in 2010. Manufacturing employment initially increased from 12.3% in 1963 to 34.2% in 1990, and later declined to 25.3% in 2010. Employment in services increased steadily from 27.6% to 68%.

This process of rapid structural change was fueled by a rise in income (Panel b), productivity growth reflected in relative prices (Panel c) and increasing net manufacturing exports (Panel d)[3].

[3] Net manufacturing exports includes exports minus imports of products in Standard International Trade Classification (SITC) Rev 1, sections 3, 5, 6, 7, 8, and divisions 27 and 28 from UN Comtrade Database.

Figure 5.2: Data for the Republic of Korea



(a) La, Lm, and Ls indicate employment in agriculture, manufacturing and services, respectively, as % of total employment. (b) GDP per capita measured at constant 2005 National Prices (in 2005 US dollars). (c) pa/pm and ps/pm indicate relative prices of agriculture and of services in units of manufacturing goods. Sectoral prices computed as value added in current prices divided by value added in constant prices. (d) Xm/Y indicates net manufacturing exports as % of GDP. HP denotes trend component obtained from using the Hodrick–Prescott filter.

Source: GGDC 10-Sector database, World Development Indicators, and UN Comtrade.

In the next section, we introduce a structural change model to explain the evolution of agricultural employment in Paraguay and manufacturing employment in the Republic of Korea. The aim is to determine the contribution of international trade in the reallocation of employment in both countries.

5.3 The Model

The model considered includes non-homothetic preferences over agriculture, manufacturing, and services, denoted by $i = \{a, m, s\}$, and sector specific exogenous productivity growth. A complete derivation of this model, including capital accumulation and different capital intensities across sectors, is available in Blanco (2017).

The representative household maximizes utility given by[4]

$$U = ln\left[(C_a - \tilde{C}_a)^{\theta_a} C_m{}^{\theta_m} (C_s + \tilde{C}_s)^{\theta_s}\right],$$

subject to the following budget constraint

$$p_a C_a + C_m + p_s C_s = E. \qquad (1)$$

where C_a, C_m, C_s indicate consumption of agriculture, manufacturing, and services, respectively. The variables p_a and p_s denote relative prices of agriculture and of services in units of manufacturing goods. Total expenditure is reported as E, while θ_a, θ_m, and θ_s are the weights in utility and satisfy $\theta_a + \theta_m + \theta_s = 1$. Finally, when $C_a \neq 0$ or $C_s \neq 0$, preferences are non-homothetic.

Utility maximization implies the following equations that determine sectoral consumption allocation

$$\frac{\theta_a}{\theta_m} \frac{C_m}{C_a - \tilde{C}_a} = p_a \qquad (2)$$

and

$$\frac{\theta_a}{\theta_m} \frac{C_m}{C_s - \tilde{C}_s} = p_s. \qquad (3)$$

Firms use capital and labor as inputs and production technologies are given by

$$Y_i = K_i^{\alpha} (A_i L_i)^{1-\alpha}, \qquad (4)$$

where Y_i, K_i, A_i, L_i, and α denote output, capital, labor productivity, labor, and capital intensity, respectively, in sector $i = \{a, m, s\}$. Profit maximization and equal factor prices across sectors imply

$$\frac{K_a}{L_a} = \frac{K_m}{L_m} = \frac{K_s}{L_s}, \qquad (5)$$

$$p_a = \left(\frac{A_m}{A_a}\right)^{1-\alpha}, \qquad (6)$$

[4] We remove the time sub-index to simplify notation.

and

$$p_s = \left(\frac{A_m}{A_s}\right)^{1-\alpha}, \qquad (7)$$

that is, capital per worker is equalized across sectors and relative prices are determined by sectoral labor productivity. Hence, the relative price of a sector falls (rises) when labor productivity in this sector is growing faster (slower).

Goods market clearing and balanced trade imply the following conditions

$$Y_a = C_a + X_a, \qquad (8)$$

$$Y_m = C_m + X_m, \qquad (9)$$

$$Y_s = Y_s, \qquad (10)$$

and

$$P_a X_a + X_m = 0, \qquad (11)$$

where X_a denotes net agricultural exports and X_m net manufacturing imports. As equations (8)– (11) suggest, the value of net agricultural exports (imports) is equal to the value of net manufacturing imports (exports) in every period. In addition, services are non-tradable. In turn, inputs markets clearing conditions imply

$$L_a + L_m + L_s = 1, \qquad (12)$$

and

$$K_a + K_m + K_s = K, \qquad (13)$$

where total employment is normalized to 1 and aggregate capital K is constant.

Using equations (1)–(13), we can determine employment shares as

$$L_a = \theta_a + (1-\theta_a)\frac{p_a\tilde{C}_a}{Y} + \theta_a \frac{p_s\tilde{C}_s}{Y} + \frac{p_a X_a}{Y}, \qquad (14)$$

$$L_m = \theta_m - \theta_m \frac{p_a\tilde{C}_a}{Y} + \theta_m \frac{p_s\tilde{C}_s}{Y} + \frac{X_m}{Y}, \qquad (15)$$

$$L_s = \theta_s - \theta_s \frac{p_a \tilde{C}_a}{Y} - (1-\theta_s)\frac{p_s \tilde{C}_s}{Y}, \qquad (16)$$

where $Y = A_m^{1-\alpha} K^{\alpha}$ is total output.

According to equations (14)–(16), if $C_a \neq 0$ and $C_s \neq 0$, structural change is driven by income growth (Y) and changes in relative prices (P_a, P_s), as argued in Kongsamut, Rebelo, and Xie (2001) and Ngai and Pissarides (2007). Structural change out of agriculture takes place as income expands and the relative price of agriculture declines due to increasing relative productivity in this sector. However, as long as net agricultural exports $P_a X_a / Y$ rises, agricultural employment could remain large. Assuming balanced trade, an increase in net agricultural exports implies increasing net manufacturing imports, which in turn involves declining employment share in this sector. These equations allow us to determine how international trade affects the evolution of employment shares.

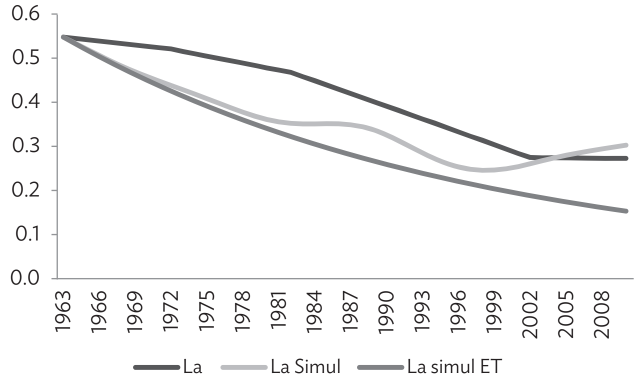
5.4 Results

We set $\theta_a = 0.02$, $\theta_m = 0.13$, and $\theta_s = 0.85$ as in Blanco (2017). In addition, C_a and C_s are set to match initial values of employment shares in both countries. We use data available on relative prices, income per capita, net agricultural exports, and net manufacturing exports to simulate the path of employment shares in Paraguay and the Republic Korea. Results are summarized in figures 5.3 and 5.4.

Figure 5.3 reports observed employment share in agriculture (La), the result of the benchmark model simulation including trade (La Simul), and the result of the simulation of the model excluding trade (La Simul ET). As we can observe in the figure, the model including trade offers a better account of agricultural employment in Paraguay. Without trade, the model predicts a much larger decline in agricultural employment. Given data on net agricultural exports for Paraguay, the benchmark model predicts an employment share of 30.3% in the sector in 2010, above the 27.3% observed in the data. Based on relative prices and income data alone, the model excluding trade predicts an employment share in agriculture of 15.3%, a value far below observed data.

In Figure 5.4, we can observe the case of the Republic of Korea. As before, the figure shows observed data (Lm), the result of the simulation of the benchmark model including trade (Lm Simul), and the result of the simulation of the model excluding trade (Lm Simul ET). As the figure indicates, net manufacturing imports explain part of the increase in employment in this sector, from 11.3% in 1963 to 18.7% in 2010, a value

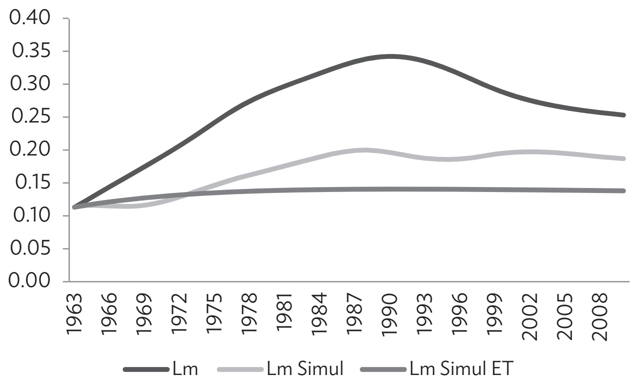
Figure 5.3: Employment in Agriculture in Paraguay



La = employment in agriculture, Simul = simulation including trade, Simul ET = simulation excluding trade.

Source: Author.

Figure 5.4: Employment in Manufacturing in the Republic of Korea



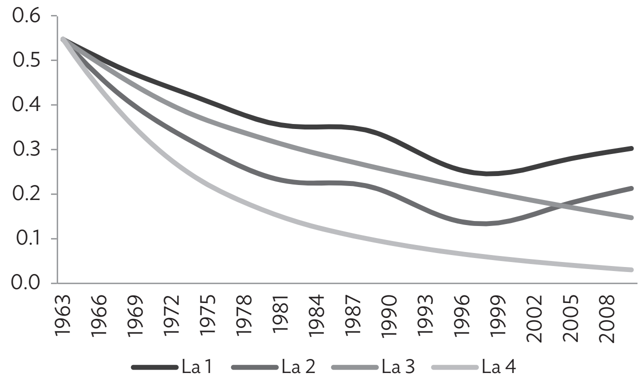
Lm = employment in manufacturing, Simul = simulation including trade, Simul ET = simulation excluding trade.

Source: Author.

below the 25.3% observed in the data. However, the model without trade predicts a much smaller increase, from 11.3% to 13.8%.

As Figures 5.3 and 5.4 show, international trade is a crucial element in explaining employment shares in both Paraguay and the Republic of

Figure 5.5: Counterfactual Simulations



La = employment in agriculture.

Source: Author.

Korea. In a different exercise, we ask the following question: what would agricultural employment in Paraguay be if the country had experienced the productivity gains and trade patterns of the Republic of Korea? This counterfactual exercise is summarized in Figure 5.5, where La 1 results from the simulation of the benchmark model including trade. La 2 is the simulation of the model using data on relative prices and income from the Republic of Korea and trade data from Paraguay. La 3 shows the simulation of the model using income and relative price data from Paraguay and trade data from the Republic of Korea. Finally, La 4 shows the simulated series using income, relative price, and trade data from the Republic of Korea.

As we can observe, even with the income and productivity growth of the Republic of Korea, Paraguay would have had a large share of employment in agriculture by 2010. This is, in part, due to the rise of net agricultural exports depicted in Panel (d) of Figure 5.1. Therefore, sufficiently large net agricultural exports can attenuate the effect of other structural change mechanisms that push agricultural employment downwards. In fact, the figure shows that given income, productivity, and trade patterns of the Republic of Korea, Paraguay would have experienced a decline of agricultural employment to 3% of total employment by 2010. Of course, we assume that the level of income and productivity achieved by the Republic of Korea can be attained while sustaining large net agricultural export flows.

5.5 Conclusion

The purpose of this chapter is to determine the importance of trade in explaining the structural change pattern of two small open economies: Paraguay and the Republic of Korea. The former experienced rising net agricultural exports, the later rising net manufacturing exports. Using a three-sector model including the demand approach and the supply-approach to structural change in addition to balanced trade, we find that foreign demand is a key element in explaining employment composition in both economies. Without trade, the model cannot explain why agricultural employment remains large given data on economic growth and relative prices. Likewise, the model cannot account for the rise of manufacturing employment in the Republic of Korea without considering trade.

Using the model, we simulate a counterfactual scenario and check what agricultural employment in Paraguay would look like, given the income and productivity patterns of the Republic of Korea. Our results show that even if Paraguay had experienced the productivity and income growth of the Republic of Korea, the country would still need to employ a large workforce in agriculture to satisfy a growing foreign demand.

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6

Trade Liberalization, Productivity Growth, and Structural Transformation: A Synthetic Control Approach

Cesar Blanco, Rasyad Parinduri, and Saumik Paul

6.1 Introduction

As countries develop, they tend to diversify away from agriculture and enjoy higher productivity growth in manufacturing and services. At more advanced stages of development, services become the dominant sector of economic activity. Such phenomena of structural transformation have long been considered as one of the crucial tenets of economic development.[1] Differences in sectoral productivity growth rates drive structural change, and in the Ricardian tradition, trade facilitates such process in the presence of productivity differences across industries and countries. In today's world where most of the countries are connected through trade, it is only natural to ask how trade affects such patterns of structural transformation.

There is extensive literature on the role of international trade in explaining productivity differences across countries. The static gains from trade have been analyzed as countries' access to foreign inputs raises domestic productivity level (Grossman and Helpman 1991; Rivera-Batiz and Romer 1991). On the other hand, the dynamic gains from trade emerge as new foreign inputs lower the cost of innovation and facilitate creation of new varieties (Feenstra 1994; Broda and Weinstein 2006; Goldberg et al. 2008). Export opportunities and competition enable countries to have aggregate productivity gain as resources allocate from

1 See Herrendorf, Rogerson, and Valentinyi (2013) for a recent review on this topic.

less to more productive firms (Melitz 2003; Melitz and Ottaviano 2008). At the same time, improvement in firm productivity through reallocation of resources across products within firms (Bernard, Redding, and Schott 2006) and use of imported inputs (Amiti and Konings 2007) have also been highlighted as trade provides domestic firms with cheaper inputs.

Surprisingly, very little empirical work has been done on the effect of trade on sectoral reallocation of resources. While productivity differences across countries are frequently modeled in trade literature,[2] structural differences across countries in most of the cases are considered exogenous. Notable exceptions are the works of Matsuyama (1992, 2009). He developed theoretical models to show that faster productivity gains in manufacturing does not necessarily imply faster decline in manufacturing employment in open economies.[3] Thus, employment growth in manufacturing in a country depends on its relative comparative advantage in manufacturing over its trading partners. On the other hand, several scholars have noted that comparative advantage in agriculture can slow down the process of industrial growth in an open economy (Mokyr 1976; Field 1978; Wright 1979; Krugman 1987). Using a standard one-factor model, Matsuyama (1992) argued that only supply channels are operative in a small open economy that faces a perfectly elastic demand for both agricultural and manufacturing goods at the world market. Extending Matsuyama's argument, Bustos, Caprettini, and Ponticelli (2016) show that the effect of agricultural productivity on structural transformation in open economies depends on the factor bias of technical change.

In this chapter, using the Groningen Growth and Development Center (GGDC) 10-sector database (Timmer, de Vries, and de Vries 2015) and the Penn World Table (version 9.0) we empirically test the effect of trade openness on the pattern of structural transformation. We use trade liberalization as a natural experiment and evaluate its effect on agriculture and manufacturing employment share over time using synthetic control methodology. Data constraints on sectoral employment shares enable us to examine trade liberalization episodes for only four Asian countries[4] during the period from 1960 to 2010. We use a binary indicator of trade openness, used in a recent paper by Billmeier and

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2 Empirical evidence on technological difference has largely been in the context of one sector model (Hall and Jones 1999); a notable exception is a recent study by Levchenko and Zhang (2016), where they provide empirical evidence on cross-country technological differences on 19 manufacturing sectors.

3 Baumol's cost-disease argument suggests the faster decline in employment share in sectors that experience increasing productivity gains.

4 The countries in our sample are Indonesia, Singapore, the Republic of Korea, and the Philippines.

Nannicini (2013)—initially derived by Sachs and Warner (1995) and modified by Wacziarg and Welch (2008). We discuss the strengths of the synthetic control method (Abadie and Gardeazabal 2003) especially for addressing endogeneity concerns in section 6.3.

To guide the empirical study, we integrate the main theoretical drivers of structural change into a unified framework. The objective is to gain insights on the role of trade in structural transformation in the presence of relative comparative advantages in agriculture or manufacturing. The theoretical literature suggests that comparative advantage depends on several factors: Hicks-neutral technical change versus factor-augmenting technological change, the nature of factor-bias in technical change, and the degree of complementarity between labor and other factors of production. In this case, we are interested in the effect of differences in the margin of comparative advantages across sectors.

We calculate employment and valued-added shares of manufacturing and agriculture from the GGDC 10-sector database and the country characteristics, i.e., human capital, capital stock, gross domestic product (GDP) per capita, and population, from the Penn World Table. Among the countries in the GGDC database that liberalized their trade in the late 1960s, 1970s, or 1980s are four Asian countries: Singapore, the Republic of Korea, Indonesia, and the Philippines. We consider one of the treated countries at a time, and we form a pool of donors that includes countries that had not liberalized their trade when the treated country did. Trade liberalization seems to increase employment shares of manufacturing in the Republic of Korea, but does not seem to matter in the Philippines. Moreover, trade liberalization is positively correlated with an increase in value-added shares of manufacturing in Indonesia, Singapore, and the Republic of Korea. The magnitude of the effects after liberalization is significant. In the Republic of Korea, for example, employment shares of manufacturing are, respectively, 3.2 and 11.2 percentage points higher 5 and 10 years after the Republic of Korea liberalized its trade—in 10 years, employment shares of manufacturing double.

Our study contributes to the empirical analysis of the relationship between trade and structural transformation. Despite the abundant theoretical literature, the empirical evidence on the role of trade in structural transformation is limited. Uy, Yi, and Zhang (2013) study the role of international trade in the process of structural transformation in the Republic of Korea. They conclude that globalization played a prominent role in the Republic of Korea's structural change. However, Swiecki (2016) in a later study using a unified model to compare different forces behind structural transformation shows that sector-based productivity growth and non-homothetic preferences are quantitatively more important than trade as drivers of structural change for a panel of countries. Sposi (2015) extends this methodology to study transmission of sectoral productivity shocks to the composition of sectoral value added in a multi-country setting. Other quantitative studies of structural transformation in an open economy context include Betts et al. (2015) and Teignier (2014). Both papers examine how trade affected structural change in individual countries.

Our study is also related to the literature on the causes and consequences of "premature deindustrialization" advocated by Rodrik (2016) and others (McMillan and Rodrik 2011). Manufacturing typically follows an inverted U-shaped path as countries develop; however, as Rodrik (2016) observes, the turning point for developing countries arrives sooner and at much lower levels of income than what has been the case for developed countries in the previous decades. He further argues that globalization and labor-saving technological progress in manufacturing play crucial roles in such process of industrialization to deindustrialization along the paths of development.

The rest of the chapter is organized as follows. In section 6.2, we reconcile the existing theories on trade, productivity, and structural transformation. Section 6.3 explains the data and data sources and also describes the methodological framework. Section 6.4 provides the main findings on the relationship between trade and structural transformation. Finally, section 6.5 concludes.

6.2 Trade, Productivity, and Structural Transformation: Theory

This section brings together the existing theoretical arguments on the role of trade in structural transformation. The primary goal of this exercise is to spell out different effects of trade on structural transformation when the gains from comparative advantage are realized at the sectoral level, particularly in agriculture and manufacturing. Consider a small open economy with three sectors: agriculture and manufacturing as traded and services as the nontraded sector. For the empirical purpose, it is sufficient to show the effects of trade on employment shares only in agriculture and manufacturing, as services will have the residual effect. For example, if employment shares drop in both agriculture and manufacturing, there will be an unambiguously positive effect on the employment share of services. However, for the analytical purpose, we need to have a third sector that contains such outcomes.

We assume that manufacturing goods are produced using labor (L_m) and sector-specific labor productivity (A_m), then $Q_m = A_m L_m$ denotes the production of the manufacturing goods. The output of services (Q_s) follows a similar production function, $Q_s = A_s L_s$, where A_s and L_s denote the labor productivity in services and labor allocated to this sector. For agriculture, we consider a one-factor production technology, as opposed to Bustos, Caprettini, and Ponticelli (2016) who consider a two-factor production technology. Therefore, output in agriculture (Q_a) is obtained using labor (L_a) and labor productivity in agriculture (A_a).

Using a standard two-sector and one-factor model, Matsuyama (1992) showed that comparative advantage is the main driver of structural change in an open economy. In this case, there is a positive link between the productivity and employment shares in the same sector. However, productivity and employment growth show a negative relationship in a closed economy environment. Moreover, several scholars have noted that comparative advantage in agriculture can slow down industrial growth in an open economy (Mokyr 1976; Field 1978; Wright 1979; Krugman 1987). Foster and Rosenzweig (2004, 2008) show empirical evidence from India that villages with the larger improvement in crop yields had lower manufacturing growth.

We can summarize the effect of technological change in a closed economy as follows:[5]

(1) Employment in agriculture: $$\frac{\partial L_a}{\partial A_a} < 0$$

(2) Employment in manufacturing: $$\frac{\partial L_m}{\partial A_m} < 0$$

We now turn to the case of an open economy. Matsuyama (2009) argues that higher productivity gains in manufacturing in a country imply a decline of employment in manufacturing somewhere in the world, but not necessarily in same country that enjoys the productivity gain. In an open economy, employment in manufacturing expands if it enjoys comparative advantage and productivity gains in manufacturing. We call this the integration effect. However, Matsuyama (2009) argues that this not always the case; in fact, it is ambiguous. Trade and comparative advantage in manufacturing allow employment in this sector to rise only when productivity in manufacturing is increasing much faster in a country than in its trading partners.

5 For this result to hold we require non-homothetic preferences. In particular, agricultural and manufacturing goods should have lower income elasticity than services. Alternatively, there should be complementarity in preferences among goods and lower productivity growth in services.

Following the same logic for the agricultural sector, we can summarize the effect of productivity growth in an open economy as follows:

$$(3) \qquad \text{Employment in agriculture:} \quad \frac{\partial L_a}{\partial A_a} \gtreqless 0$$

$$(4) \qquad \text{Employment in manufacturing:} \quad \frac{\partial L_m}{\partial A_m} \gtreqless 0$$

Thus, in autarky, productivity growth leads to a drop in employment in both agriculture and manufacturing, which leads to a further concentration of economic activity in services—a phenomenon known as the Baumol "cost disease" effect. With trade, the effect of productivity growth is ambiguous—and depends on comparative advantage and on how fast productivity is growing with respect to the trading partners. In an open economy, the employment share could grow in either agriculture or manufacturing due to the integration effect.

In Table 6.1, we summarize the effect on employment of productivity growth in different sectors. The direction of changes in employment in services is predominantly positive. For this reason, in the empirical section, we primarily examine the employment trends in agriculture and manufacturing.

Using the results summarized in Table 6.1, we predict two broad trends or typologies of structural transformation resulting from trade-induced sectoral productivity growth:

- Typology A: An increase in employment in agriculture and a decline in manufacturing, compared with autarky.
- Typology B: An increase in employment in manufacturing and a decline in agriculture, compared with autarky.

Notice that it is not possible to observe a simultaneous rise in employment in both agriculture and manufacturing.

6.3 Empirical Strategy

We use the synthetic control method of Abadie and Gardeazabal (2003) to examine the effect of trade liberalization on some measures of structural transformation, i.e., sectoral employment shares or value-added shares of manufacturing or agriculture.[6] We want to compare each country that liberalized its trade in the late 1960s, 1970s, or 1980s

6 See also Abadie, Diamond, and Hainmueller (2010). Recent papers that use this approach include Billmeier and Nannicini (2013) and Cavallo et al. (2013).

Table 6.1: Technical Change and Employment Growth across Sectors

Sector	Autarky/Trade	Employment Share
Agriculture	Closed Economy	$\frac{\partial L_a}{\partial A_a} < 0$
	Open Economy	$\frac{\partial L_a}{\partial A_a} \gtreqless 0$
Manufacturing	Closed Economy	$\frac{\partial L_m}{\partial A_m} < 0$
	Open Economy	$\frac{\partial L_m}{\partial A_m} \gtreqless 0$

Source: Authors.

(a treated unit) and another country (untreated unit) whose employment shares of manufacturing before trade liberalization resemble that of the treated unit, but such an untreated unit usually does not exist. The solution offered by Abadie and Gardeazabal (2003) is (i) to find a synthetic unit, a combination or weighted average of all untreated units, such that the trend of the manufacturing employment share and the characteristics of this synthetic unit before liberalization resemble that of the treated unit; and (ii) to consider the trend of the manufacturing employment share in the synthetic unit after liberalization as the counterfactual to estimate the effects of trade liberalization.

6.3.1 The Model

Suppose the sample has J + 1 countries—the first is a country that liberalized its trade in the late 1960s, 1970s, or 1980s, and the remaining J are countries that did not. The first country is, therefore, a treated unit, while the others form a donor pool from which we create a synthetic control unit.

Let Y_{it}^1 and Y_{it}^0 be the employment share of manufacturing in country i at time t for country i = 1,…, J, and time periods t = 1,… T if the country did and did not, respectively, liberalize its trade. Let T_0 be the number of periods before trade liberalization, where $1 \leq T_0 \leq$ T, so that the first country had liberalized trade from period T_0 + 1 to T. Assume that the trade liberalization did not affect structural transformation in those countries before $T_0 + 1$ (a plausible assumption because trade liberalization mattered only after T_0), so that $Y_{it}^1 = Y_{it}^0$ for $i = 1, \ldots, J$, and time periods $t = 1, \ldots T_0$. Assume also that the trade liberalization did not affect any country in the donor pool.[7]

Define $\alpha_{it} = Y_{it}^1 - Y_{it}^0$ as the effect of trade liberalization in country i at time t; the lead-specific causal effect of the liberalization is

$$(9) \qquad \alpha_{1t} = Y_{1t}^1 - Y_{1t}^0 = Y_{1t} - Y_{1t}^0$$

for $t = T_0 + 1, \ldots T$. We observe Y_{1t} but not Y_{1t}^0. Therefore, to obtain α_{1t}, we need to estimate Y_{1t}^0 using a weighted average of countries in the donor pool.

Consider a $(J \times 1)$ vector of weights $W = (w_2, \ldots, w_{J+1})'$, such that $w_J \geq 0$ for $j = 2, \ldots, J+1$ and $w_2 + w_3 + \ldots + w_{J+1} w_{J+1} = 1$, with each element the weight of a country in the donor pool. Let also Z_i be an $(r \times 1)$ vector of the observed predictors of labor shares of manufacturing.

Abadie, Diamond, and Hainmueller (2010) suggest that, if $W^* = (w_2^*, \ldots, w_{j+1}^*)$ exists such that

$$(10) \qquad \sum_{j=2}^{J+1} w_j^* Y_{jt} = Y_{1t}$$

$$(11) \qquad \sum_{j=2}^{J+1} w_j^* Z_j = Z_1$$

for $t = 1, \ldots, T_0$, then we can use

$$(12) \qquad \widehat{\alpha_{1t}} = Y_{1t} - \sum_{j=2}^{J+1} w_j^* Y_{jt}$$

as an estimator of α_{1t}.

6.3.2 Implementation

Let $X_1 = \left(Z_1^{'}; \overline{Y}_1^{K_1}, \ldots, \overline{Y}_1^{K_M}\right)'$ be the vector pre-liberalization characteristics and linear combinations of employment shares of manufacturing of a treated country and $X_0 = \left(Z_j^{'}; \overline{Y}_j^{K_1}, \ldots, \overline{Y}_j^{K_M}\right)'$ be a matrix of the same variables for countries in the donor pool. We want to minimize the distance between X1 and a weighted average of X_0, $\| X_1 - X_0 W \|$. In particular, we minimize.

---

7 This assumption of no interference between countries is analogous to the stable unit-treatment value assumption (Rosenbaum 2007).

$$(13) \qquad \| X_1 - X_0 W \| V = \sqrt{(X_1 - X_0 W)' V (X_1 - X_0 W)}$$

where V is a diagonal matrix whose elements reflect the importance of the predictors of employment shares of manufacturing.

First, we estimate W and V using observations before trade liberalization. Then, we extrapolate this model to the post-liberalization period and to obtain estimates of Y_{1t}^{0}. The difference between the employment shares of manufacturing in the treated country and its synthetic unit for each of the years in the post-liberalization period is $\widehat{\alpha_{1t}}$, the effect of trade liberalization.

6.3.3 Data

We follow Billmeier and Nannicini (2013), who use the definitions of Wacziarg and Welch (2003), to identify economic liberalizations. A country is a closed economy if it satisfies one of the following: (1) average tariffs exceed 40%, (2) nontariff barriers cover more than 40% of its imports, (3) a socialist economy, (4) black market premiums of the exchange rates exceed 20%, and (5) state monopolies control much of its exports. A country is open if it has none of the above.

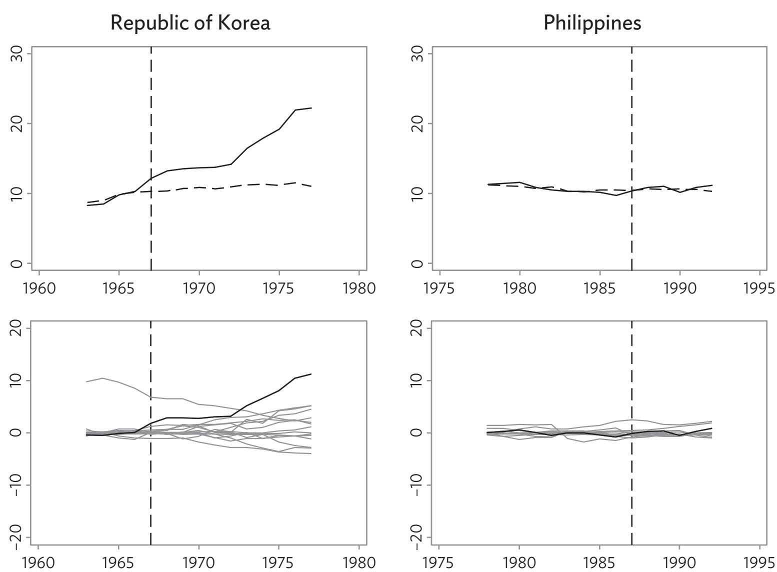
For the measures of structural transformation and country characteristics, we use the GGDC 10-sector database and the Penn World Table version 9.0. We calculate employment and value-added shares of manufacturing and agriculture from the GGDC database. We get the country characteristics, i.e., human capital, capital stock, GDP per capita, and population, from the Penn World Table.

There are 25 countries whose measures of structural transformation and country characteristics are available 5 to 10 years before trade liberalization and 5 to 10 years after the period of analysis. Among the countries in the GGDC database, four Asian countries (Singapore, the Republic of Korea, Indonesia, and the Philippines) liberalized their trade in the late 1960s, 1970s, or 1980s. We consider one of the treated countries at a time, and we form a pool of donors that includes countries that had not liberalized their trade when the treated country did. In addition to some of the above countries, other countries that potentially form the pool of donors are South Africa, Peru, Argentina, Brazil, Zimbabwe, Kenya, Tanzania, Egypt, Ethiopia, Nigeria, India, the People's Republic of China, Malawi, and Senegal. We have 10 to 14 countries in the pool of donors, which depends on whether a country liberalized its trade earlier or later, and whether the GGDC database have the characteristics of the countries before the treated country liberalized its trade.

6.4 Results

Figure 6.1 shows that liberalization affects countries' employment shares of manufacturing differently. The top graph in each panel shows the trend of employment shares in manufacturing in the treated (the solid line) and synthetic (dash) units; the bottom graph shows the effect of liberalization in the treated country (the solid line) and the placebo effect in each of the countries in the pool of donors. Liberalization seems to increase employment shares of manufacturing in the Republic of Korea, but does not seem to matter in the Philippines. The magnitude of the effects, when liberalization matters, is large. In the Republic of Korea, for example, employment shares of manufacturing are, respectively, 3.2 and 11.2 percentage points higher 5 and 10 years after the Republic of Korea liberalized its trade—in 10 years, employment shares of manufacturing double.

Figure 6.1: Employment Shares of Manufacturing



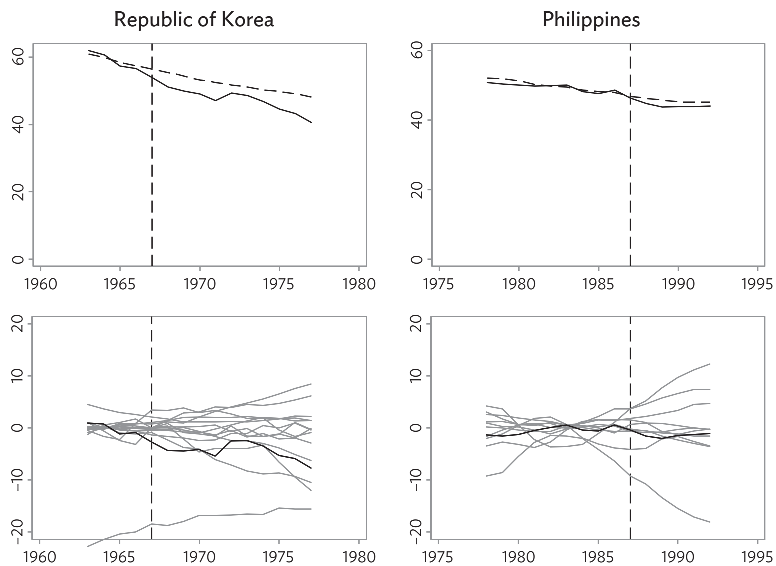
Source: Authors.

We need to make the statistical inferences cautiously, however, because we do not have many countries in the pool of donors. Even if one or two countries have placebo effects that resemble the effects of liberalization in a treated country, the p-values of the estimates may be higher than 5%, which makes them statistically insignificant at the conventional level.

Figure 6.2, which presents the picture of possible effects of liberalization on employment shares in agriculture, shows that liberalization seems to matter only in the Republic of Korea (though, again, they may be statistically significant for the Republic of Korea only). In 10 years since liberalization, employment shares of manufacturing fall by 7.7 percentage points in the Republic of Korea.

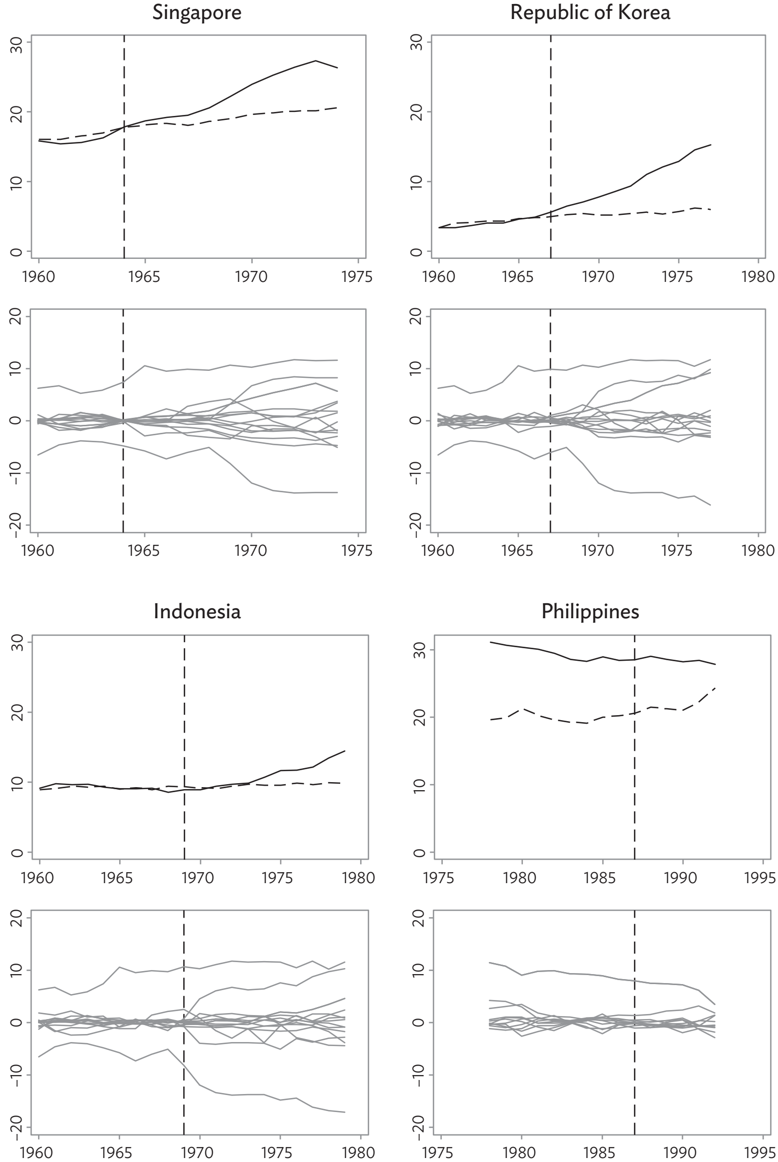
Figure 6.3, which presents the value-added shares of manufacturing, shows a similar picture: Liberalization seems to increase value-added share of manufacturing in the Republic of Korea. We also find that liberalization increases value-added shares of manufacturing

Figure 6.2: Employment Shares of Agriculture



Source: Authors.

Figure 6.3: Value-added Shares of Manufacturing



Source: Authors.

in Singapore and Indonesia. (We do not observe employment shares in these two countries before liberalization.) The magnitude of the estimates in these Asian countries is large: In 10 years, value-added shares of manufacturing in the Republic of Korea, Singapore, and Indonesia increase by 9.2, 5.7, and 4.6 percentage points, respectively. We do not find a good synthetic unit for the Philippines.

Figure 6.4, which presents the value-added shares of agriculture, shows that liberalization decreases the value-added shares of agriculture in the Republic of Korea and Indonesia. In other countries, liberalization does not seem to matter, and we do not find suitable synthetic units for Singapore.

6.5 Conclusions

In today's world where most of the countries are connected through trade, it is only natural to ask how trade affects the patterns of structural transformation through productivity growth. In this chapter, we use trade liberalization as a natural experiment and evaluate its effect on agriculture and manufacturing employment share in four Asian economies using synthetic control methodology. We find mixed evidence. Trade liberalization seems to increase employment shares of manufacturing in the Republic of Korea but does not seem to matter in the Philippines. On the other hand, trade liberalization is positively correlated with an increase in value-added shares of manufacturing in Indonesia, Singapore, and the Republic of Korea. This is consistent with evidence provided in Levchenko and Zhang (2016), where they report that the Republic of Korea, Indonesia, and Singapore enjoyed a relative comparative advantage in manufacturing which resulted in the expansion of the manufacturing sector.

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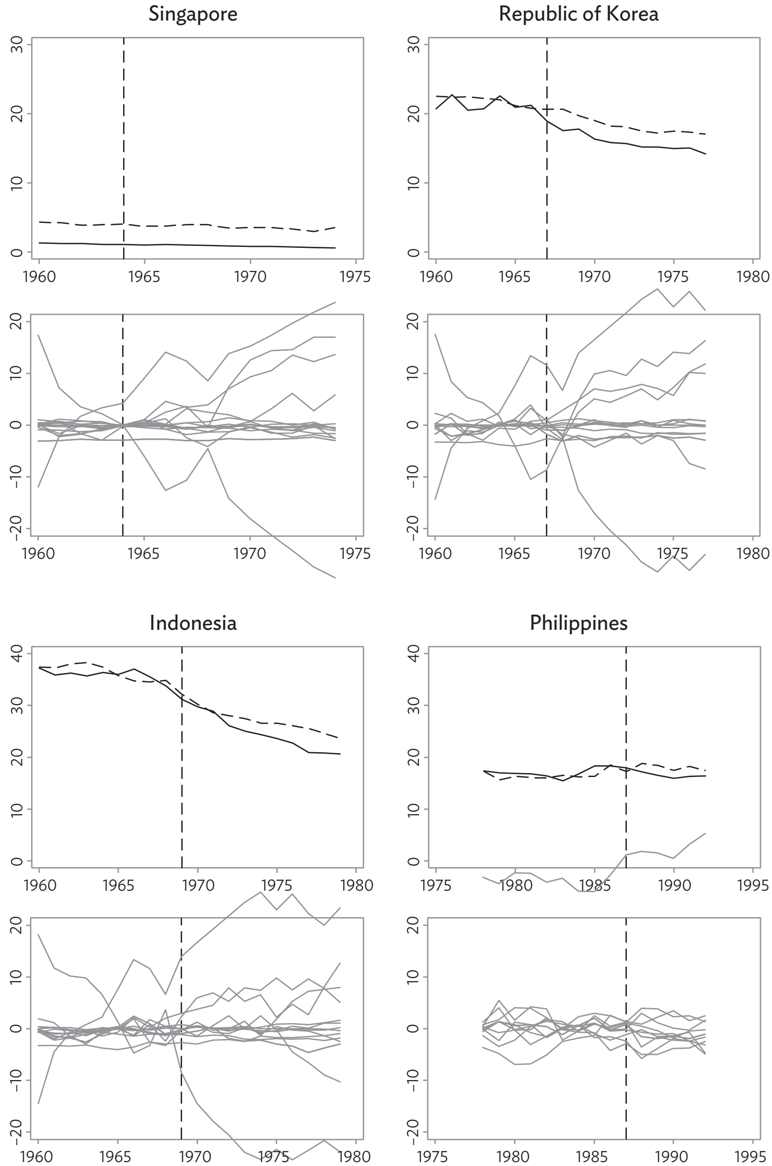
Figure 6.4: Value-added Shares of Agriculture



Source: Authors.

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7

Structural Change, Trade, and Inequality: Cross-country Evidence

Rudra Prosad Roy and Saikat Sinha Roy

7.1 Introduction

Reduction in inequality within and across countries is one of the main targets of the recent Sustainable Development Goals (SDGs). Even though global inequality is found to have remained stable or, at best, declined,[1] there has been a rising incidence of income inequality in many countries since the 1980s. There is great heterogeneity in within-country inequality across countries and regions (Klasen et al. 2016). Inequality is seen to increase in developing countries, transition economies, and emerging market economies; these are the economies that have undergone structural transformation in the recent past. Within-country inequality is associated with drivers, which vary across countries. Structural change is one such driver. This study aims to examine the causal relationship between income inequality and structural transformation, while considering the role of international trade and foreign direct investment (FDI), as it is widely believed that globalization is one of the key drivers of increasing inequality both in advanced and developing countries.

Structural change at a narrow level refers to changes in the structure of the economy, while at a broader level, it refers to social, political, cultural, societal, and other changes (Aizenman, Lee, and Park 2012).

1 Nino–Zarazua, Roope, and Tarp (2016) showed that while relative global inequality declined substantially during the period 1975–2010, global inequality measured using "absolute" and "centrist" measures registered a pronounced increase during this period of time.

Although there are many definitions of structural change, the most common meaning refers to long-term and continual shifts in the sectoral composition of economic systems (Chenery, Robinson, and Syrquin 1986; Syrquin 2007; UNIDO 2009). According to Machlup (1991: 76), structural change is "the different arrangements of productive activity in the economy and different distributions of productive factors among various sectors of the economy, various occupations, geographic regions, types of product, etc…" Thus, in the process of structural change, a gradual shift of resources is observed from traditional to more-advanced sectors. A rise in the relative share of the manufacturing sector is seen to occur, followed by a rise in the relative share of the services sector.[2]

There is a large body of literature discussing the relationship between structural change and income inequality. One strand of these studies discusses the macroeconomic impact of inequality, while the other school of thought relates inequality to structural transformation and growth in the economy. While discussing the former, inequality of outcomes (as measured by income, wealth, or expenditure) and inequality of opportunities need to be distinguished. To understand the nature and extent of inequality, it is important to consider the distribution of opportunities and of outcomes (Rawls 1971). Some economists believe that a certain degree of inequality is good as it provides incentives for individuals to excel and compete. Lazear and Rosen (1981) argued that by providing incentives for innovation and entrepreneurship, inequality can influence growth positively. Inequality to a tolerable extent is necessary, especially in developing countries, as it allows at least a few individuals to accumulate startup capital (Barro 2000). However, inequality of outcomes does not generate the "right" incentives if it relies on rents (Stiglitz 2012). In that case, it results in resource misallocation, corruption, nepotism, and hence adverse social and economic consequences as individuals have an incentive to divert their efforts toward securing favored treatment and protection.

Several empirical studies have found that inequality negatively affects economic growth and its sustainability (see Berg and Ostry 2011; Ostry, Berg, and Tsangarides 2014; Roy and Sinha Roy 2017). Economic inequality may weaken the progress of health and education, lead to political and economic instability, and hence reduce investment, undermine the social consensus required to adjust in the face of major shocks, and thus reduce the pace and durability of economic growth (Persson and Tabellini 1994; Easterly 2007; Berg, Ostry, and Zettelmeyer 2012). A more equitable distribution of income encourages investment

2 See Johnston (1970) for some other definitions of structural change.

in human capital and thus induces economic growth (Berg and Ostry 2011; Wilkinson and Pickett 2009); and inequality deprives the poor of the ability to stay healthy and accumulate human capital (Perotti 1996; Galor and Moav 2004; Aghion, Caroli, and Garcia–Penalosa 1999). In the presence of economic inequality, if political power is found to be distributed in a more egalitarian manner, any effort to redistribute income or wealth may lead to lower economic growth by creating disincentives for investment (Rodrik 1999). On the other hand, if economic elites try to resist this process of redistribution, it may hamper economic growth (Barro 2000). Investment incentive also dwindles if uncertainty and risk increase due to income inequality (Alesina and Perotti 1996). Inequality and political instability may hamper the effectiveness of economies in responding to external shocks (Rodrik 1999).

The idea behind the nexus between structural change and inequality follows from the seminal papers by Kuznets (1955, 1963). With globalization, structural change across developed and developing economies, along with rising productivity and growth, has increased the wage gap between skilled and unskilled labor (ILO 2014). More precisely, structural change in developing economies has increased productivity and helped them to catch up with developed economies. This process of reducing the productivity gap has created a huge demand for skilled labor and thus results in higher inequality by intensifying the wage gap with unskilled labor (Zhu and Trefler 2005). Although in the long term structural change is expected to create job opportunities and as a result increase the income level of the population and lead to a more equal society, in the medium and short term it causes an increase in wage inequality and therefore income inequality, by increasing the demand for skilled workers in the expanding high-productivity sector (ECLAC 2012). With the contraction of traditional sectors such as agriculture and mining, and the expansion of modern sectors such as manufacturing and services with more sophisticated skill- and technology-intensive activities, a shift in labor demand is also observed. With the expansion of the skill- and technology-intensive sectors, the relative demand for high-skilled labor increases and, at the same time, low-skilled workers are seen to be replaced more and more by “automatization” (Henze 2014). During this transition, the wage gap is seen to increase between high-skilled and low-skilled workers (see Blum 2008; OECD 2008; OECD 2011, among others) and this wage gap is the key link between structural heterogeneity and income inequality (ECLAC 2012). Some recent studies have considered the relationship between structural change and wage inequality. Aizenman, Lee, and Park (2012) show that although structural change has widened the wage gap and hence increased the level of inequality, it has helped to reduce the level of poverty, especially in developing Asia. In relation to German microdata, Henze (2014) studies the causal relationship between wage premium and structural change.

In the literature, studies examining the nexus between the wage gap and structural change can be found. However, there are hardly any studies examining the impact of structural change on income inequality as a whole. On the other hand, studies examining the relationship between wage inequality and structural change focus on countries of one particular region or any specific income group (see Ghosh Dastidar 2004, 2012, for example). The study by Ghosh Dastidar (2004) focuses on the Asian and Latin American developing countries and found a weak relationship between structural change and income inequality. On the other hand, data show that there is an important difference in the pattern of structural transformation between developed and developing countries. While in developed countries service orientation is seen to follow the industrialization, the pattern is the opposite in developing countries (Ghosh Dastidar 2012). Under these circumstances, it is important to understand the consequences of structural change and more precisely the service orientation for income inequality. This empirical study on the one hand considers a large group of countries from all geographical regions and income groups, and on the other hand seeks to examine the relationship between structural change and overall income inequality.

The chapter thus investigates whether structural change determines inequality in countries across regions during globalization. The rest of the chapter is structured as follows. This short introduction is followed by stylized facts on inequality and structural change in Section 7.2. In Section 7.3, data, the empirical model, and empirical methodological issues are discussed. Empirical results are discussed in Section 7.4, and Section 7.5 presents a summary of the findings.

7.2 Stylized Facts on Structural Change and Income Inequality

Heterogeneity in income inequality, measured in terms of the Gini coefficient, can be found across countries in different geographical regions. Cross-country comparison of inequality is difficult on account of the lack of coverage and inconsistent data and methodology. In this exercise, the World Bank database on inequality is used for purposes of comparison. Three indicators are considered—the difference between income shares of the top 20% and bottom 20% of the population, the difference between income shares of the top 10% and bottom 10% of the population, and the Gini index; these indicators can, however, be used interchangeably. From the yearly data on different indicators of inequality, the average indicators are calculated for the periods 1991–2000 and 2001–2010, as given in Table A7.2. The highest level of inequality is found in African countries, followed by South American and North American countries. Inequality is the lowest in European countries.

In Africa, very high inequality is seen in countries like Botswana, the Central African Republic, Namibia, and South Africa. In Botswana, Kenya, Ethiopia, Nigeria, and Cameroon, all three indicators show a downward trend from the 1990s to the 2000s, whereas in countries like Egypt, Morocco, and South Africa they show an upsurge. As an emerging market economy, South Africa showed high economic growth in the 2000s, and also experienced an increase in inequality, as the Gini coefficient was found to increase from 57.96 to 63.33.

Inequality in Asia Pacific countries is not as severe as in African countries. From the 1990s to the 2000s, when the People's Republic of China (PRC) economy showed a huge increase in inequality, the Indian and Indonesian economies experienced a moderate increase. Small countries like Jordan, Kazakhstan, Malaysia, Pakistan, and the Philippines, and large countries like the Russian Federation and Thailand, showed a decline in inequality, whereas Bangladesh and Sri Lanka experienced an increase in inequality. The inequality measured in terms of the Gini coefficient for Bangladesh increased from 30.5 to 32.9. The PRC economy showed an almost 15% increase in inequality in the last 2 decades. In the case of India, the Gini coefficient increased from 30.8 to 33.6. Among Association of Southeast Asian Nations (ASEAN) countries, in Indonesia, Lao People's Democratic Republic, and Viet Nam, the Gini coefficient increased from 29.37 to 34.3, from 32.7 to 34.7, and from 35.6 to 36.8, respectively. Some other ASEAN countries like the Philippines and Thailand showed a downward trend in inequality. In Australia, inequality increased slightly.[3] In the 1990s, the average inequality measured in terms of the Gini coefficient was 33.7, and, in the 2000s, it increased to 34.1.

In general, inequalities across countries in Europe are lower than those among Asian and African countries. In the 21st century, European countries show a mixed trend with regards to inequality. Inequality has declined in countries such as Austria, France, Greece, Ireland, Moldova, the Netherlands, Spain, and Ukraine and increased in all other countries. At the same time, Switzerland has successfully reduced its

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3 Data for New Zealand are not available.

level of inequality from 37.10 to 32.70 (in terms of the Gini coefficient) between 1990s and 2000s; and in countries like Belgium it has gone up from a level of 26.75 to 33.14 (in terms of the Gini coefficient).

Inequality in North American countries is higher than that in Asian and European countries but lower than in African countries. Inequality has increased in the 21st century in almost all major countries in this continent, though the magnitude varies across countries. In the United States, inequality measured in terms of all three indicators has increased marginally. Some countries, such as Guatemala, Mexico, Nicaragua, and Panama, however, have shown a marginal decline in inequality. In all South American countries, inequality is very severe. A high level of income and consumption inequality persists in countries like Bolivia, Brazil, Chile, Colombia, and Paraguay. From the last decade of the 20th century to the beginning of the 21st century, inequality increased in all countries except Brazil, Chile, and Ecuador. In Paraguay and Peru, it increased marginally.

Within-country inequality is thus found to be highest in the Latin American countries followed by the Caribbean and sub-Saharan African countries, while it is the lowest in countries in Europe, and Central and South Asia (Table 7.1). On the other hand, inequality across countries in Europe and North America is lower than that in East Asian and the Pacific and African countries. Inequality in all countries across regions is seen to have increased in 2000 and to have decreased thereafter, with high inequality persisting in some African countries. Since 2000, the largest decline in the level of inequality can be seen among countries

Table 7.1: Trend in Income Inequality across Regions

	Time Period				
Region	1990	1995	2000	2005	2010
East Asia and Pacific	35.63	38.48	50.06	40.86	37.29
Europe and Central Asia	NA	33.19	33.34	32.15	31.25
Latin America and Caribbean	49.20	51.38	53.42	51.61	48.82
Middle East and North Africa	41.01	38.50	40.73	37.71	37.42
North America	NA	NA	37.06	NA	37.07
Sub-Saharan Africa	NA	46.46	45.69	44.26	45.32
South Asia	32.85	34.52	33.06	32.71	31.44
World	42.67	43.25	43.57	38.40	36.41

NA = not available.

Source: Authors' own calculation on the basis of data obtained from the World Bank's World Development Indicators.

in East Asia and the Pacific (25.51%) followed by countries in Latin America and the Caribbean (8.61%), and the Middle East and North Africa (8.12%).

Although structural change can only be observed over the long term, countries across geographical regions are found to have undergone structural transformation over a period of 25 years (1990–2014). By the early 1990s, most countries had started moving away from the agricultural sector towards the manufacturing and services sectors. Table 7.2 provides a snapshot of structural change across regions. Across

Table 7.2: Sectoral Shares of GDP across Regions

	Sector								
	Agriculture	Manufacturing	Services	Agriculture	Manufacturing	Services	Agriculture	Manufacturing	Services
	Time Period								
Region	**1990**			**1995**			**2000**		
East Asia and Pacific	13.69	27.36	47.90	10.46	26.33	51.00	8.05	25.52	54.82
Europe and Central Asia	NA	NA	NA	4.12	19.79	65.32	3.28	18.74	67.38
Latin America and Caribbean	8.77	NA	53.66	6.76	18.53	62.04	5.60	17.54	62.62
Middle East and North Africa	NA	NA	NA	NA	NA	NA	8.62	12.75	45.06
North America	NA	NA	NA	NA	NA	NA	1.19	15.51	75.66
South Asia	29.08	15.91	44.99	26.28	16.93	46.90	23.39	15.15	51.03
Sub-Saharan Africa	23.62	13.62	41.78	22.91	12.12	43.54	19.86	11.40	44.18
World	NA	NA	NA	8.12	21.39	58.30	5.23	19.20	64.27
Region	**2005**			**2010**			**2014**		
East Asia and Pacific	6.37	25.16	56.91	5.59	24.40	58.27	5.34	NA	60.04
Europe and Central Asia	2.55	17.03	69.50	2.21	15.76	71.49	2.20	14.79	72.31
Latin America and Caribbean	5.67	17.61	60.23	5.35	15.85	61.36	5.50	13.69	65.53
Middle East and North Africa	6.69	NA	41.45	5.75	NA	45.42	6.09	NA	46.45
North America	1.18	13.33	76.89	1.20	12.32	77.68	1.33	12.33	77.98
South Asia	19.16	15.74	53.06	18.73	14.86	54.86	17.97	15.92	53.18
Sub-Saharan Africa	20.93	11.19	47.61	18.21	10.36	54.77	17.09	10.61	56.48
World	4.37	17.98	65.67	3.88	16.81	67.52	3.88	14.71	68.47

GDP = gross domestic product, NA = not available.

Source: Authors' own calculation on the basis of data obtained from the World Bank's World Development Indicators.

geographical regions, the shares of the agriculture and manufacturing sectors are found to have decreased over time and that of services has increased. For Latin American and Caribbean countries, where inequality is the greatest, the share of the agricultural sector fell from 8.77% to 5.50% and that of the services sector increased from 53.66% to 65.53% between 1990 and 2014. In sub-Saharan Africa, where inequality is also very high, the share of the agricultural sector decreased from 23.62% to 17.09%, and that of the manufacturing sector decreased from 13.62% to 10.61%. Interestingly, in South Asian countries the share of the manufacturing sector remained more or less unchanged over the period. A shift is found to occur from agriculture to the services sector. Another interesting fact that can be observed is that the share of agriculture in North American countries is increasing marginally along with a shift from manufacturing to the services sector. On the whole, it can be seen that structural change is widespread in regions where inequality is high. Thus, a relationship between the two is expected to exist.

7.3 Data, Empirical Model, and Estimation Method

Despite common perceptions, casual observation does not suggest an obvious association between changes in inequality and structural change. For a more profound understanding of the relationship between structural change and income inequality, an empirical analysis has been carried out with a panel of 217 countries. All data used in this analysis are collected from the database of World Development Indicators.[4] A panel[5] of all developing, emerging, and developed countries for the period 1991–2014 has been considered. The selection of the time period is very important here. Since the early 1990s, the developing countries have become more integrated with the world economy. On the other hand, the growth of countries in Asia, Latin America, and sub-Saharan Africa since the 1990s and especially after the 2000s can be explained by the variation in the contribution of structural change to labor productivity (McMillan and Rodrik 2011). At the same time, inequality has increased in most of the developed countries and has remained stable in emerging market economies (Dabla–Norris et al. 2015).

Apart from structural change, the estimated panel data model incorporates some other explanatory variables that directly or indirectly determine a country's level of income inequality. The inclusion of past

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4 A detailed discussion of data sources is presented in Table A7.1 in the Appendix.

5 Panels are unbalanced as the data are driven largely by the availability of information on the inequality variable.

levels of inequality or initial levels of inequality helps us to understand the nature of path dependence. To control for a country's economic size or level of development, per capita real income is also incorporated. Further, the problem of endogeneity between structural change and inequality can exist.

The relationship between trade liberalization or globalization and inequality is expected to operate through multiple channels. On the one hand, trade openness and the quantity and quality of infrastructure have been used as indicators of trade liberalization; on the other hand, FDI has been employed as an indicator of financial globalization or financial openness. Some studies have considered the relationship between wage inequality and international trade (see, for example, Aizenman, Lee, and Park 2012; Henze 2014), and some other studies have considered the international trade to be a major determining factor for both growth and inequality (Attanasio, Goldberg, and Pavcnik 2004; Wood 1997). Some studies have found that trade ends up resulting in an increase in the wage gap and thus inequality (Cornia 2005; Zhu and Trefler 2005; Avalos and Savvides 2006; Chari, Henry and Sasson 2012). This relationship is not unique in the sense that some other studies show that trade openness significantly reduces income inequality (White and Anderson 2001; Dollar and Kraay 2002; Edwards 1997; Higgins and Williamson 1999). Some studies have considered the relationship between FDI and inequality. However, in the existing literature, the relationship between the two is far from conclusive. A few studies have found that FDI may increase inequality in host countries by benefiting high-skilled workers more than low-skilled workers (see Aitken, Harrison and Lipsey 1996; Freenstra and Hansen 1997; Lipsey and Sjöholm 2004; Mah 2002; Hansen 2003). On the other hand, inward FDI is found to worsen income distribution by raising wages in the corresponding sectors in comparison with traditional sectors (Girling 1973; Rubinson 1976; Bornschier and Chase–Dunn 1985; Tsai 1995; Sylwester 2005; Choi 2006; Raychaudhuri and De 2016). However, some other studies show the inequality-dampening role of FDI (see Markusen and Venables 1997; Blonigen and Slaughter 2001; Aghion and Howitt 1998; among others). A number of studies find that improvement in income distribution is possible with the development of infrastructure (World Bank 1994; Schady and Paxson 2000; Chong and Calderon 2000; 2001; Sinha Roy, and Roy 2016). Some other studies show that some specific categories of public spending, such as public investments in infrastructure, health and education, and social insurance provision, may be pro-growth and pro-equality (Benabou 2000, 2002; Bleaney, Gennell, and Kneller 2001). Some other empirical studies have checked the effect of infrastructure development on overall inequality by regressing the Gini coefficient on different indicators of infrastructure (López 2003; Calderon and Chong 2004).

The estimated empirical model is as follows:

$$(\ln INQ)_{it} = \beta_0 + \beta_1(\ln INQ)_{it-j} + \beta_2(\ln PCGDP)_{it} + \beta_3(\ln TO)_{it} + \beta_4(\ln FDI)_{it} + \beta_5(\ln Infra)_{it} + \beta_6(\ln Manu\_Share)_{it} + \beta_7(\ln Serv\_Share)_{it} + \beta_8(\ln Infra\_Q)_{it} + \beta_9(Urban)_{it} + \varepsilon_{it} \quad (1)$$

where

lnINQ = log of inequalitymeasure;
lnPCGDP = log of per capita GDP;
lnTO = log of trade openness;
lnFDI = log of FDI;
lnInfra = log of infrastructure stock index;
lnManu_share = log of GDP share of manufacturing sector;
lnServ_share = log of GDP share of service sector;
lnInfra_Q = log of infrastructure quality;
lnurban = log of urbanization.

In this empirical analysis, the selection of the dependent variable follows Deininger and Squire (1996) and Calderon and Chong (2004). As a measure of inequality, the Gini index has been used for the analysis following several other former studies (López 2003; Calderon and Chong 2004, among others). The Gini index is considered to be the best known and most commonly used measure of inequality (Klasen et al. 2016). The index has many advantages over other measures of inequality.[6] The Gini index and some other indices such as the Theil Index and the Atkinson Index all give information about the overall income distribution of the population. However, to check the robustness of results, three other models have been estimated considering three different measures of inequality. The income share of the top 20% of the population, the income share of the bottom 20% of the population, and the ratio of the two quintiles have been used as three indicators of income inequality. Some other studies have also used the income share of the top 20% of the population and the income share of the bottom 20% of the population as measures of inequality (see Calderon and Chong 2004).

While estimating equation (1), the possibility of endogeneity cannot be ruled out. The bidirectional relationship between growth and inequality is well documented in the literature. On the other hand, trade

6 For a comparative analysis on different measures of inequality, see Klasen et al. (2016).

openness, FDI, and infrastructure are determinants of both inequality and per capita GDP. Structural change also depends upon factors like trade openness, infrastructure, and FDI. Thus, the empirical model described above cannot be interpreted as causal until the possibility of endogeneity has been ruled out. To address this problem, a dynamic generalized method of moments (GMM) estimator (System GMM)—also known as Arellano–Bover/Blundell–Bond linear dynamic panel-data estimation—was used to analyze changes across countries and over time.[7] One of the main advantages of the System GMM estimator is that it does not require any external instruments other than the variables already included in the dataset. It uses lagged levels and differences between two periods as instruments for current values of the endogenous variable, together with external instruments. More importantly, the estimator does not use lagged levels or differences by themselves for the estimation, but instead employs them as instruments to explain variations in infrastructure development. This approach ensures that all information will be used efficiently, and that focus is placed on the impact of regressors (such as trade openness) on inequality, and not vice versa.

Dynamic relationships among economic variables are identified by the presence of a lagged dependent variable among regressors. In a panel data setup, this can be discerned by the presence of autocorrelation and other individual effects account for heterogeneity among individuals:

$$y_{it} = \delta y_{i,t-1} + x_{it}^{'}\beta + u_{it} \quad i = 1, 2, \ldots\ldots, \quad N; t = 1, 2, \ldots\ldots, T \qquad (2)$$

where δ is a scalar, $x_{it}^{'}$ is a $1 \times K$ vector of strictly exogenous regressors, and β is a $K \times 1$ vector of coefficients. The u_{it} is assumed to follow a one-way error component model

$$u_{it} = \mu_i + v_{it} \qquad (3)$$

where u_{it} and v_{it} are independent of each other and independent, identically distributed (IID) with a mean of 0 and variance of σ_μ^2 and σ_v^2 respectively. The ineluctable correlation between $y_{i,t-j}$, i.e., the lagged dependent variables, and u_i, i.e., the unobserved panel-level effects, makes the ordinary least squares (OLS) estimator biased and inconsistent even though v_{it} is not serially correlated. Anderson and Hsiao (1981) showed that first differencing of the model gives a consistent estimator. But this does not necessarily produce an efficient estimator. A GMM procedure suggested by Arellano and Bond (1991) gives us a consistent

[7] First introduced by Arellano and Bond (1991).

estimator that is certainly more efficient than Anderson and Hsiao's 1981 estimator. Before using GMM, the Arellano–Bond (1991) technique transforms all regressors by taking the first difference, and hence the technique is popularly known as the "difference GMM" technique (Hansen 1982). However, in the presence of autoregressive parameters that are too large, or if the ratio of the panel-level effect to the variance of idiosyncratic error is too large, this estimator can perform poorly.

Based on the study of Arellano and Bover (1995), Blundell and Bond (1998) developed an estimator assuming the absence of autocorrelation in the idiosyncratic errors and no correlation between panel-level effects and the first difference of the dependent variable. The first difference GMM model is found to have very poor finite sample properties in terms of biasness and precision, especially when the series is persistent as the instruments are then weak predictors of endogenous changes. As a remedy, the level restrictions and the use of extra moment conditions that depend on certain stationarity conditions of the initial observation suggested by Arellano and Bover (1995) are factual and also augmented by Blundell and Bond (1998) by making an additional assumption of no correlation between the first difference of instrument variables and fixed effects. In doing so, one can increase efficiency by introducing more instruments. This method is called "System GMM" as it deals with a system of two equations—the original equation and the transformed equation. This System GMM estimator not only improvises precision, but also reduces finite sample bias even when covariates are weakly exogenous. With a large sample of individuals or cross section of units observed for a small number of time periods, difference GMM estimators have been found to produce unsatisfactory results (Mairesse and Hall 1996). However, with large T, a first difference GMM estimator performs relatively well. Blundell and Bond (1998) suggested use of extra moment conditions with small T. In this study, since we have considered many panels with few time periods, we consider a system estimator as suggested by Blundell and Bond (1998).

7.4 Empirical Results and Discussions

Table 7.3 shows summary statistics of the Gini index and some other important determinants of income inequality. It can be seen that the average level of inequality is highest in South American countries. Among African countries, the average level of income, (measured by average per capita GDP) is the lowest and at the same time the average inequality is very high. Interestingly, among North American countries, both the average inequality and average income are very high in contrast

Table 7.3: Summary Statistics

		Variable						
Continent	Statistics	Gini	PCGDP	TO	FDI	Infrastructure	Manu	Serv
Africa	Mean	44.89	3,545.89	0.76	704,000,000	43,323.08	11.01	48.06
	SD	8.46	10,936.72	0.46	2,010,000,000	108,750.90	7.09	13.43
	Min	29.81	115.44	0.05	100	1,682.33	0.24	12.87
	Max	65.76	94,903.20	3.38	23,700,000,000	591,906.50	45.67	93.22
Asia	Mean	36.50	10,422.48	0.88	5,880,000,000	89,230.85	15.55	51.64
	SD	6.38	14,744.27	0.60	225,00,000,000	175,048.70	7.56	13.56
	Min	19.49	314.88	0.09	10	1,682.33	0.86	16.56
	Max	69.47	74,632.24	4.00	291,000,000,000	1525,740.00	40.45	83.70
Europe	Mean	31.65	26,171.71	0.94	13,400,000,000	49,724.03	16.95	62.82
	SD	4.27	22,939.06	0.48	41,600,000,000	78,080.52	7.95	15.08
	Min	16.23	690.92	0.17	1,000	1,925.26	0.69	2.43
	Max	44.42	145,221.20	3.61	734,000,000,000	591,906.50	47.34	93.76
North America	Mean	49.23	10,982.34	0.95	13,400,000,000	34,612.17	12.52	65.57
	SD	6.61	12,630.64	0.74	46,100,000,000	40,693.69	6.91	11.00
	Min	31.15	662.28	0.16	300,000	1,682.33	1.28	33.40
	Max	60.91	50,662.41	4.48	350,000,000,000	220,406.50	29.01	92.98
Oceania	Mean	41.13	8,596.69	0.58	2,200,000,000	33,510.30	7.29	63.56
	SD	8.05	13,273.78	0.28	88,000,000,00	38,402.92	5.19	12.44
	Min	33.72	1,047.45	0.24	10	1,682.33	0.38	22.81
	Max	61.18	54,232.66	1.32	65,600,000,000	200,919.90	19.93	88.02
South America	Mean	51.54	6,624.60	0.53	7,490,000,000	104,135.30	15.84	55.13
	SD	5.03	3,728.78	0.26	16,600,000,000	171,701.40	4.11	8.69
	Min	40.20	1,397.18	0.10	7,300,000	1,925.26	3.68	26.12
	Max	63.00	14,687.98	1.31	112,000,000,000	591,906.50	28.31	72.85

PCGDP = per capita, TO = trade openness, FDI = foreign direct investment, Manu = manufacturing, Serv = services, SD = standard deviation, Min = minimum, Max = maximum.

Source: Authors' own calculation on the basis of data obtained from the World Bank's World Development Indicators.

to European countries, where the average income is very high and average inequality is the lowest. Across countries, variation in inequality can also be understood from the standard deviation of the Gini index. The highest variability is observed among African countries and the least variability is found to exist among European countries. On the other hand, the size of the manufacturing sector and service sector (measured in terms of average GDP share of manufacturing and service sectors, respectively) is largest in European countries and smallest in African countries. Before the empirical estimation, it is important to check the possibility of the presence of multicollinearity. Table A7.3 presents the correlation matrix of the explanatory variables. It can be seen that the GDP share of the service sector, FDI, and the quality of the infrastructure have high correlations with per capita GDP. Thus, while estimating the empirical model, per capita GDP has been considered an endogenous variable. Low correlation among any other pairs of explanatory variables provides evidence in favor of absence of multicollinearity.

Table 7.4 presents the results of the first set of estimations. In each model, the Sargan test (Sargan 1958) has been carried out to check the validity of the overidentifying restriction. The Sargan test accepts the null hypothesis of valid overidentifying restrictions. Instrumental variables must be uncorrelated with the structural error term and correlated with the endogenous regressors. Here all models are overidentified or the number of additional instruments used in each model exceeds the number of endogenous regressors, and instruments are uncorrelated with the error term. In Table 7.4, four different specifications of equation (1), with changes only in the measure of inequality, have been shown. Regression equations using four different dependent variables—the Gini index, income share of the top quintile, income share of the bottom quintile, and the ratio of the two quintiles, and controlling for a group of basic variables (per capita GDP, TO, FDI, quantity and quality of infrastructure, urbanization), as well as the two variables of interest, share of manufacturing sector, and share of service sector—are estimated.

In the first model, log of Gini index has been used as the dependent variable. Clear evidence of path dependence can be seen from the result as the lagged dependent variable is found to be positive and significant. So it is likely that if inequality exists in the present period, it will prevail in the future period as well, if not controlled. Per capita GDP is found to be negative and significant, and thus there is evidence of a trickledown effect. Trade openness—as measured by the ratio of exports and imports to GDP—tends to make income distribution more equal. This clearly confirms the findings of White and Anderson (2001), Dollar and Kraay (2002), Edwards (1997), and Higgins and Williamson (1999); however, it contradicts the findings of Barro (2000), Calderon and Serven (2004, 2008), and Wan, Lu, and Chen (2006a). The coefficient of FDI is significant and negative, suggesting that FDI reduces income inequality. This is consistent with Markusen and Venables (1997), Blonigen and Slaughter (2001), and Aghion and Howitt (1998); however, it contradicts the findings of Wan, Lu, and Chen (2006b). A negative and significant

Table 7.4: Estimation Result (Overall)

	Model 1		Model 2	
	Dependent Variable			
	lnGini		ln Q1	
	Coef.	SE	Coef.	SE
lnInequality$_{t-1}$	0.7663	(0.0321)***	0.8328	(0.0367)***
lnInequality$_{t-2}$	0.1795	(0.0326)***	0.0981	(0.0355)***
lnPCGDP$_t$	−0.0267	(0.0107)**	−0.0185	(0.0086)**
lnManufacturing_Share$_t$	0.0366	(0.0156)**	0.0228	(0.0127)*
lnServices_Share$_t$	0.1031	(0.0296)***	0.0540	(0.0214)**
lnTO$_t$	−0.0227	(0.0122)*	−0.0236	(0.0101)**
lnFDI$_t$	−0.0047	(0.0027)*	−0.0038	(0.0021)*
lnInfrastructure_Quantity$_t$	−0.0135	(0.0053)**	−0.0013	(0.0037)
lnInfrastructure_Quality$_t$	−0.0222	(0.0116)*	−0.0057	(0.0090)
lnUrbanization$_t$	0.0185	(0.0108)*	0.0008	(0.0080)
Constant	0.1785	(0.1757)	0.2367	(0.1475)
Sargan test p value	0.5654		0.9719	
	Model 3		Model 4	
	Dependent Variable			
	ln Q5		ln (Q1/Q5)	
	Coef.	SE	Coef.	SE
lnInequality$_{t-1}$	0.7029	(0.0361)***	0.7408	(0.0358)***
lnInequality$_{t-2}$	0.1837	(0.0338)***	0.1629	(0.0338)***
lnPCGDP$_t$	0.0179	(0.0265)	−0.0406	(0.0332)
lnManufacturing_Share$_t$	−0.0667	(0.0388)*	0.0942	(0.0486)*
lnServices_Share$_t$	−0.1192	(0.0682)*	0.1716	(0.0843)**
lnTO$_t$	0.0527	(0.0300)*	−0.0735	(0.0378)*
lnFDI$_t$	0.0100	(0.0068)	−0.0125	(0.0084)
lnInfrastructure_Quantity$_t$	0.0083	(0.0117)	−0.0100	(0.0145)
lnInfrastructure_Quality$_t$	−0.0250	(0.0270)	0.0142	(0.0341)
lnUrbanization$_t$	−0.0053	(0.0247)	0.0079	(0.0310)
Constant	0.5139	(0.3526)	−0.1259	(0.4522)
Sargan test p value	0.2332		0.4514	

ln = logarithm, Coef. = coefficient, SE = standard error, PCGDP = per capita gross domestic product, TO = trade openness, FDI = foreign direct investment.

Notes:
(a) Standard errors are given in parentheses.
(b) *, **, and *** imply significance respectively at the 10%, 5%, and 1% levels.
(c) PCGDP, Manufacturing Share, and Services Share are considered to be endogenous.

Source: Authors' own calculation on the basis of data obtained from the World Bank's World Development Indicators.

relationship between infrastructure stock and income inequality is found. That is, the larger stock of infrastructure, the more equal the distribution of income. This result is consistent with the findings of Calderon and Chong (2004) and Seneviratne and Sun (2013). Similarly, there is a negative and significant relationship between the quality of infrastructure and income inequality. In short, the better the quality of infrastructure, the more equal the distribution of income. This confirms the findings of Seneviratne and Sun (2013); however, it contradicts the findings of Calderon and Chong (2004). Urbanization is found to have a positive significant relationship with income inequality. This is consistent with the finding of Wan, Lu, and Chen (2006b) but at the same time contradicts the result of Wan, Lu, and Chen (2006a).

The two variables of interest—the share of the manufacturing sector and that of the service sector—are found to be positive and significant. This implies that the process of structural transformation results in a more unequal distribution of income. A 1% increase in the share of the manufacturing sector in GDP results in a 3% increase in income inequality. On the other hand, a 1% increase in the GDP share of the service sector increases income inequality by 0.10%. To confirm this, three models have been estimated considering three other dependent variables. In the second model, where the income share of the top 20% of the population has been used as the dependent variable, GDP shares of the manufacturing and service sectors are found to be positive and significant. A 1% increase in the GDP share of the manufacturing and service sectors increases the income share of the top 20% of the population by 0.02% and 0.05%, respectively, and thus increases income inequality. On the other hand, when the income share of the bottom 20% of the population has been considered as the dependent variable, the two coefficients have been found to be negative and significant. It can be seen that a 1% increase in the GDP share of the manufacturing and service sectors decreases the income share of the bottom 20% of the population by 0.06% and 0.11%, respectively, and thus makes the income distribution more unequal. The result is the same even when the ratio of the income shares of the two groups or the difference between the income groups has been considered as the dependent variable. The gap in the income shares between the two income groups increases by 0.09% and 0.17% when the share of the manufacturing sector and that of the service sector, respectively, increase by 1%. This clearly proves the robustness of the results.

To check the heterogeneity across regions, instead of GDP shares of the manufacturing and service sector as a whole, the interaction of sectoral shares with region dummies has been considered. For each region, a high correlation has been found between the share of the manufacturing sector and that of the service sector (Table A7.4). Models 5–8 presented in Table 7.5 thus consider interaction dummies only with the manufacturing share, and Models 9–12 in Table 7.6 consider interaction dummies only with the service share. Due to insufficient data on inequality measures, estimation for two regions—Africa and Oceania—has not been done. It can be seen that the expansion of the manufacturing sector is significantly increasing inequality in two regions—North America and South America (see Model 5 in Table 7.5). On the other hand, in all four regions, income distribution is found to become more unequal due to the expansion of the service sector (see Model 9 in Table 7.6).

Furthermore, these interactive dummies are found to have a positive and statistically significant association with respect to the top 20% income share (see Model 6 in Table 7.5 and Model 10 in Table 7.6), and a negative and statistically significant relation with respect to the bottom 20% share of income (see Model 7 in Table 7.5 and Model 11 in Table 7.6). A positive relationship is found even when the ratio of the two income groups or the gap between the two income groups has been considered (see Model 8 in Table 7.5 and Model 12 in Table 7.6). All these econometric results with variants of income inequality measure are therefore found to be robust, and thus structural change is found to increase income inequality.

7.5 Conclusions

In the literature on economic development, one of the earliest and most central themes is structural change. The countries that developed in the last few centuries are those that are able to diversify away from the production and consumption of traditional goods to modern sectors. Since the early 1990s, the developing countries have experienced rapid structural change and, at the same time, have become more integrated with the world economy. The reduction of import tariffs and nontariff barriers (through infrastructure development), FDI flows, and thus globalization facilitated technology transfers to these countries. This reduction in trade barriers, FDI flows, and technology transfers not only promotes growth, but also leads to structural change. In the process, the demand for skilled labor increases, leading to a wage gap, and thus inequality increases.

This study empirically shows the positive impact of structural change on income inequality, that is, how structural change results in

Table 7.5: Region-specific Estimation Result (Manufacturing)

	Model 5		Model 6	
	Dependent Variable			
	lnGini		ln Q1	
	Coef.	SE	Coef.	SE
lnInequality$_{t-1}$	0.7432	(0.0327)***	0.7915	(0.0393)***
lnInequality$_{t-2}$	0.0984	(0.0354)***	0.0439	(0.0369)
lnPCGDP$_t$	0.0120	(0.0106)	0.0019	(0.0082)
D_EuropexlnManufacturing_Share$_t$	0.0207	(0.0138)	0.0135	(0.0114)
D_NorthAmericaxlnManufacturing_Share$_t$	0.0483	(0.0146)***	0.0305	(0.0117)***
D_SouthAmericaxlnManufacturing_Share$_t$	0.0473	(0.0170)***	0.0319	(0.0131)**
D_AsiaxlnManufacturing_Share$_t$	0.0226	(0.0147)	0.0136	(0.0118)
lnTO$_t$	−0.0270	(0.0143)*	−0.0199	(0.0106)*
lnFDI$_t$	−0.0050	(0.0028)*	−0.0026	(0.0021)
lnInfrastructure_Quantity$_t$	−0.0065	(0.0049)	−0.0016	(0.0034)
lnInfrastructure_Quality$_t$	0.0077	(0.0121)	0.0096	(0.0091)
lnUrbanization$_t$	−0.0138	(0.0122)	−0.0156	(0.0092)*
Constant	0.5356	(0.1659)***	0.6018	(0.1604)***
Sargan test p value	0.8600		0.9198	
	Model 7		Model 8	
	Dependent Variable			
	ln Q5		ln (Q1/Q5)	
	Coef.	SE	Coef.	SE
lnInequality$_{t-1}$	0.6028	(0.0373)***	0.6498	(0.0375)***
lnInequality$_{t-2}$	0.1064	(0.0343)***	0.0883	(0.0345)**
lnPCGDP$_t$	−0.0419	(0.0243)*	0.0450	(0.0305)
D_EuropexlnManufacturing_Share$_t$	−0.0460	(0.0341)	0.0642	(0.0432)
D_NorthAmericaxlnManufacturing_Share$_t$	−0.1267	(0.0344)***	0.1658	(0.0438)***
D_SouthAmericaxlnManufacturing_Share$_t$	−0.1525	(0.0402)***	0.1911	(0.0509)***
D_AsiaxlnManufacturing_Share$_t$	−0.0444	(0.0363)	0.0685	(0.0457)
lnTO$_t$	0.0269	(0.0322)	−0.0475	(0.0406)
lnFDI$_t$	0.0017	(0.0063)	−0.0042	(0.0081)
lnInfrastructure_Quantity$_t$	0.0143	(0.0106)	−0.0153	(0.0131)
lnInfrastructure_Quality$_t$	−0.0653	(0.0252)***	0.0752	(0.0323)**
lnUrbanization$_t$	0.0783	(0.0292)***	−0.0921	(0.0367)**
Constant	1.0554	(0.2976)***	−0.0714	(0.3711)
Sargan test p value	0.2989		0.5016	

ln = logarithm, Coef. = coefficient, SE = standard error, PCGDP = per capita gross domestic product, TO = trade openness, FDI = foreign direct investment.

Notes:
(a) Standard errors are given in parentheses.
(b) *, **, and *** imply significance respectively at the 10%, 5%, and 1% levels.
(c) PCGDP, Manufacturing Share, and Services Share are considered to be endogenous.

Source: Authors' own calculation on the basis of data obtained from the World Bank's World Development Indicators.

Table 7.6: Region-specific Estimation Result (Service)

	Model 9		Model 10	
	Dependent Variable			
	lnGini		ln Q1	
	Coef.	SE	Coef.	SE
$lnInequality_{t-1}$	0.6909	(0.0327)***	0.7524	(0.0404)***
$lnInequality_{t-2}$	0.0801	(0.0332)**	0.0211	(0.0367)
$lnPCGDP_t$	−0.0111	(0.0100)	−0.0038	(0.0080)
$D\_Europe x lnServices\_Share_t$	0.0813	(0.0288)***	0.0398	(0.0210)*
$D\_NorthAmerica x lnServices\_Share_t$	0.1066	(0.0293)***	0.0567	(0.0212)***
$D\_SouthAmerica x lnServices\_Share_t$	0.1087	(0.0300)***	0.0573	(0.0217)***
$D\_Asia x lnServices\_Share_t$	0.0853	(0.0296)***	0.0438	(0.0216)**
$lnTO_t$	−0.0024	(0.0115)	−0.0165	(0.0099)*
$lnFDI_t$	−0.0042	(0.0027)	−0.0016	(0.0021)
$lnInfrastructure\_Quantity_t$	−0.0022	(0.0045)	0.0004	(0.0032)
$lnInfrastructure\_Quality_t$	0.0046	(0.0105)	0.0127	(0.0078)
$lnUrbanization_t$	−0.0006	(0.0120)	−0.0132	(0.0088)
Constant	0.6529	(0.1609)***	0.7033	(0.1611)***
Sargan test p value	0.4712		0.8877	
	Model 11		Model 12	
	Dependent Variable			
	ln Q5		ln (Q1/Q5)	
	Coef.	SE	Coef.	SE
$lnInequality_{t-1}$	0.6146	(0.0377)***	0.6501	(0.0382)***
$lnInequality_{t-2}$	0.1012	(0.0343)***	0.0810	(0.0345)**
$lnPCGDP_t$	−0.0048	(0.0238)	−0.0019	(0.0299)
$D\_Europe x lnServices\_Share_t$	−0.0831	(0.0630)	0.1328	(0.0791)*
$D\_NorthAmerica x lnServices\_Share_t$	−0.1419	(0.0629)**	0.2090	(0.0793)***
$D\_SouthAmerica x lnServices\_Share_t$	−0.1438	(0.0645)**	0.2109	(0.0813)**
$D\_Asia x lnServices\_Share_t$	−0.0924	(0.0645)	0.1473	(0.0810)*
$lnTO_t$	0.0233	(0.0293)	−0.0367	(0.0370)
$lnFDI_t$	0.0019	(0.0065)	−0.0035	(0.0082)
$lnInfrastructure\_Quantity_t$	0.0094	(0.0101)	−0.0110	(0.0126)
$lnInfrastructure\_Quality_t$	−0.0592	(0.0227)***	0.0694	(0.0287)**
$lnUrbanization_t$	0.0390	(0.0270)	−0.0470	(0.0338)
Constant	0.9834	(0.2882)***	−0.0818	(0.3489)
Sargan test p value	0.2217		0.3912	

ln = logarithm, Coef. = coefficient, SE = standard error, PCGDP = per capita gross domestic product, TO = trade openness, FDI = foreign direct investment.

Notes:
(a) Standard errors are given in parentheses.
(b) *, **, and *** imply significance respectively at the 10%, 5%, and 1% levels.
(c) PCGDP, Manufacturing Share, and Services Share are considered to be endogenous.

Source: Authors' own calculation on the basis of data obtained from the World Bank's World Development Indicators.

a more unequal distribution of income. While all previous studies have shown impacts of structural change on wage inequality, this study is the first to show the impact of structural transformation on overall income inequality. The data include a panel of a large number of countries from all income groups and all regions. To check the robustness of the results, different indicators of inequality have been considered. Analysis considering regional interactive dummies shows that among North and South American countries, both expansion of manufacturing and expansion of services are found to increase income inequality. On the other hand, in Asia and Europe the problem of inequality has worsened with expansion of the service sector only. The study also shows the strong negative impact of trade liberalization on income inequality and weak negative impact of FDI inflow on the same in the long run. The study thus contributes to the literature by raising many important dimensions for policy analysis. The results are of particular importance with regard to Sustainable Development Goal 10 on Reduced Inequalities within and between countries. The widening disparity requires the adoption of sound policies to empower the bottom deciles of income earners through structural transformation, infrastructure development, and focusing on those groups of people where it is most required. Trade liberalization and FDI can be chosen as policy instruments to reduce inequality. This study, however, does not take into account the role of migration and development assistance in bridging the inequalities.

Appendix

Table A7.1: Description and Sources of Data

Label	Content	Sources
Inequality (INQ)	Gini coefficient	World Development Indicators
Top Quintile (Q1)	Income Share of top or richest 20% of population	World Development Indicators
Bottom Quintile (Q5)	Income Share of bottom or poorest 20% of population	World Development Indicators
Quintile ratio (Q)	Ratio of Income Share of top or richest 20% of population and Income Share of bottom or poorest 20% of population	World Development Indicators

continued on next page

Table A7.1 *continued*

Label	Content	Sources
Per capita income (PCGDP)	GDP per capita (constant 2005 $)	World Development Indicators
Share of Manufacturing Sector (Manu)	Value added of the manufacturing sector as a percentage of GDP	World Development Indicators
Share of Service Sector (Serv)	Value added of the service sector as a percentage of GDP	World Development Indicators
Trade openness (TO)	Trade (export and import) as percentage of GDP (%)	World Development Indicators
Foreign Direct Investment (FDI)	Foreign direct investment inflows (current $)	UNCTAD
Infrastructure Stock Index (Infra)	Infrastructure quantity, which is estimated using the method of principal component analysis (PCA) on normalized indicators such as (a) total road network (km); (b) air transport, passengers carried (per 1,000 population); (c) per capita energy consumption; (d) Internet users (per 1,000 population); (e) fixed telephone subscribers (per 1,000 population); (f) domestic credit provided by the public sector	World Development Indicators
Infrastructure Quality (Infra_Q)	Electric power transmission and distribution losses (percentage of output)	World Development Indicators
Urbanization (Urban)	Ratio of urban and rural population	World Development Indicators

GDP = gross domestic product, US = United States, UNCTAD = United Nations Conference on Trade and Development.

Source: Authors.

Table A7.2: Average Inequality across Countries in 1990s and 2000s

		1990s						
		Income Share			Income Share			
Continent	Country	Highest 20%	Lowest 20%	Difference between Quintiles	Highest 10%	Lowest 10%	Difference between Deciles	Gini
Africa	Botswana	65.0	3.13	61.87	51.2	1.3	49.91	61.0
Africa	Burkina Faso	55.1	5.51	49.62	41.0	2.3	38.64	48.8
Africa	Burundi	44.8	6.54	38.27	29.7	2.6	27.11	37.9
Africa	Cameroon	51.6	6.20	45.36	36.5	2.8	33.78	44.6
Africa	Central African Republic	65.0	1.99	62.99	47.7	0.7	47.04	61.3
Africa	Central African Republic	65.0	1.99	62.99	47.7	0.7	47.04	61.3
Africa	Egypt, Arab Rep.	40.5	9.11	31.39	26.4	4.0	22.37	31.1
Africa	Ethiopia	43.6	8.17	35.4	29.6	3.4	26.22	35.0
Africa	Gambia, The	55.3	4.02	51.23	38.2	1.6	36.56	50.2
Africa	Ghana	46.0	6.13	39.90	30.0	2.5	27.52	39.4
Africa	Guinea	50.5	4.15	46.33	33.3	1.6	31.68	45.9
Africa	Guinea–Bissau	53.5	5.15	48.35	39.2	2.1	37.13	47.8
Africa	Kenya	54.1	4.80	49.33	39.4	1.9	37.48	48.6
Africa	Lesotho	64.4	2.05	62.34	46.2	0.7	45.51	60.6
Africa	Madagascar	48.6	5.69	42.92	33.1	2.3	30.81	42.4
Africa	Malawi	56.0	4.84	51.12	42.0	1.9	40.08	50.3
Africa	Mali	56.1	4.64	51.46	40.6	2.0	38.58	50.5
Africa	Mauritania	50.1	5.78	44.29	35.4	2.3	33.15	43.7
Africa	Morocco	46.4	6.55	39.87	30.8	2.8	27.99	39.3
Africa	Mozambique	50.7	5.63	45.06	35.9	2.2	33.73	44.5
Africa	Namibia	78.3	1.48	76.77	65.0	0.6	64.39	74.3
Africa	Niger	46.0	6.74	39.28	31.1	2.8	28.34	38.8
Africa	Nigeria	50.7	4.50	46.24	34.3	1.7	32.66	45.7
Africa	Senegal	53.5	4.98	48.55	38.4	2.0	36.37	47.8
Africa	Seychelles	48.9	5.68	43.23	34.0	2.1	31.86	42.7
Africa	South Africa	63.1	3.26	59.82	45.9	1.4	44.49	58.0

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Table A7.2 *continued*

		1990s						
		Income Share			Income Share			
Continent	Country	Highest 20%	Lowest 20%	Difference between Quintiles	Highest 10%	Lowest 10%	Difference between Deciles	Gini
Africa	Swaziland	64.3	2.74	61.59	49.9	1.0	48.81	60.7
Africa	Tanzania	41.6	7.43	34.18	26.6	3.0	23.57	33.8
Africa	Tunisia	47.1	5.76	41.34	31.2	2.3	28.93	41.0
Africa	Uganda	47.9	6.43	41.42	33.1	2.7	30.46	40.9
Africa	Zambia	56.3	3.54	52.77	40.2	1.3	38.88	52.0
Asia	Bangladesh	39.9	9.14	30.8	25.7	4.0	21.64	30.5
Asia	Cambodia	46.8	8.04	38.79	33.0	3.7	29.32	38.3
Asia	PRC	43.4	7.26	36.09	27.5	3.1	24.37	35.7
Asia	India	40.1	9.09	31.05	26.0	4.0	22.03	30.8
Asia	Indonesia	39.4	9.36	30.04	25.3	4.2	21.18	29.7
Asia	Iran, Islamic Rep.	49.5	5.29	44.18	33.5	2.1	31.41	43.6
Asia	Israel	43.4	6.53	36.86	27.6	2.6	24.95	36.8
Asia	Jordan	47.2	6.78	40.42	32.4	2.9	29.51	39.9
Asia	Kazakhstan	41.4	7.17	34.24	25.7	2.9	22.73	34.0
Asia	Kyrgyz Republic	50.3	4.84	45.45	34.1	1.9	32.2	44.8
Asia	Lao PDR	41.7	8.65	33.03	27.4	3.8	23.61	32.7
Asia	Malaysia	53.8	4.51	49.25	37.8	1.8	35.96	48.4
Asia	Maldives	65.7	1.41	64.33	48.1	0.4	47.75	62.7
Asia	Mongolia	39.5	7.55	31.91	23.9	3.1	20.89	31.7
Asia	Nepal	43.5	7.87	35.65	29.1	3.4	25.69	35.2
Asia	Pakistan	40.9	8.93	31.99	26.9	3.9	22.95	31.6
Asia	Philippines	50.8	5.73	45.05	35.0	2.5	32.5	44.3
Asia	Russian Federation	49.4	5.01	44.39	33.8	1.8	32.0	44
Asia	Slovak Republic	33.1	10.3	22.81	19.5	4.1	15.41	22.7
Asia	Sri Lanka	42.7	8.37	34.34	28.3	3.7	24.62	34.0

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Table A7.2 *continued*

		1990s						
		Income Share			Income Share			
Continent	Country	Highest 20%	Lowest 20%	Difference between Quintiles	Highest 10%	Lowest 10%	Difference between Deciles	Gini
Asia	Tajikistan	38.1	8.34	29.77	23.3	3.3	20.05	29.5
Asia	Thailand	50.9	6.01	44.91	35.1	2.5	32.59	44.0
Asia	Turkey	47.7	5.80	41.88	32.3	2.3	29.99	41.5
Asia	Uzbekistan	49.6	3.91	45.65	33.4	1.1	32.27	45.3
Asia	Viet Nam	44.0	7.92	36.08	29.2	3.5	25.64	35.6
Asia	Yemen, Rep.	41.2	7.41	33.75	25.9	3.0	22.88	33.4
Europe	Armenia	47.3	6.57	40.73	32.4	2.7	29.69	40.2
Europe	Austria	38.6	7.64	31.00	23.5	2.8	20.76	31.0
Europe	Azerbaijan	42.3	6.94	35.31	27.0	2.8	24.29	35.0
Europe	Belarus	36.0	9.40	26.62	21.7	3.9	17.79	26.5
Europe	Belgium	36.0	9.03	26.92	21.5	3.5	18.04	26.8
Europe	Bulgaria	37.9	9.09	28.81	23.6	3.8	19.85	28.5
Europe	Croatia	37.1	9.00	28.13	22.5	3.7	18.87	28.1
Europe	Czech Republic	36.7	10.3	26.41	23.2	4.5	18.68	26.2
Europe	Denmark	34.2	9.93	24.29	20.2	3.8	16.42	24.3
Europe	Estonia	43.2	7.16	36.05	27.9	3.0	24.99	35.7
Europe	Finland	34.1	10.7	23.32	20.1	4.6	15.54	23.2
Europe	France	40.5	7.92	32.62	25.7	3.2	22.47	32.4
Europe	Georgia	45.8	5.44	40.4	30.1	1.9	28.14	40.1
Europe	Germany	38.4	8.31	30.13	23.7	3.3	20.37	30.0
Europe	Greece	43.3	5.78	37.50	27.4	1.9	25.49	37.2
Europe	Hungary	37.1	9.58	27.55	23.2	4.0	19.13	27.4
Europe	Ireland	44.1	6.96	37.09	28.4	2.8	25.62	36.5
Europe	Italy	41.6	6.36	35.23	26.3	2.2	24.18	35.1
Europe	Latvia	39.2	8.04	31.2	24.7	3.0	21.68	31.0
Europe	Lithuania	40.8	7.87	32.94	26.2	3.1	23.05	32.7
Europe	Macedonia, FYR	36.7	8.48	28.20	22.1	3.3	18.88	28.1

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Table A7.2 *continued*

Continent	Country	1990s Income Share Highest 20%	Income Share Lowest 20%	Difference between Quintiles	Income Share Highest 10%	Income Share Lowest 10%	Difference between Deciles	Gini
Europe	Moldova	45.0	6.38	38.61	29.4	2.5	26.93	38.1
Europe	Netherlands	38.8	7.80	30.96	23.2	2.5	20.68	30.7
Europe	Norway	35.8	9.44	26.32	21.4	3.8	17.63	26.4
Europe	Poland	39.6	8.40	31.22	24.8	3.5	21.26	31.1
Europe	Romania	37.1	8.82	28.24	22.5	3.6	18.86	28.1
Europe	Slovenia	38.2	9.19	28.99	23.8	4.0	19.81	28.8
Europe	Spain	41.8	6.78	35.05	26.4	2.4	24.02	34.7
Europe	Sweden	34.6	9.23	25.36	20.1	3.4	16.72	25.5
Europe	Switzerland	42.5	5.32	37.2	27.2	0.8	26.4	37.1
Europe	Ukraine	40.4	7.91	32.46	25.5	3.3	22.27	32.3
Europe	United Kingdom	43.5	6.32	37.17	27.9	2.2	25.66	36.9
North America	Canada	39.5	7.32	32.21	24.2	2.7	21.5	32.0
North America	Costa Rica	50.9	3.94	46.91	34.2	1.1	33.07	46.2
North America	Ivory Coast	45.3	6.51	38.81	29.6	2.7	26.92	38.4
North America	Dominican Republic	54.3	4.19	50.10	38.8	1.5	37.31	49.2
North America	El Salvador	56.2	2.84	53.39	39.8	0.7	39.11	52.4
North America	Guatemala	59.7	3.14	56.53	44.8	1.0	43.81	55.8
North America	Honduras	58.9	3.09	55.77	42.9	1.0	41.93	54.6
North America	Jamaica	47.3	6.16	41.14	32.0	2.5	29.48	40.6
North America	Mexico	55.1	4.19	50.93	39.4	1.7	37.72	50.1
North America	Nicaragua	55.9	3.74	52.12	40.1	1.3	38.81	51.3

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Table A7.2 *continued*

Continent	Country	1990s Income Share Highest 20%	Lowest 20%	Difference between Quintiles	Income Share Highest 10%	Lowest 10%	Difference between Deciles	Gini
North America	Panama	60.5	1.55	58.99	43.1	0.2	42.94	57.6
North America	United States	44.6	5.28	39.28	28.3	1.8	26.52	39.1
Oceania	Australia	40.8	6.80	33.98	24.9	2.1	22.78	33.7
South America	Argentina	52.8	4.00	48.76	36.0	1.3	34.68	47.9
South America	Bolivia	57.2	3.15	54.06	40.7	1.1	39.64	53.0
South America	Brazil	63.1	2.42	60.65	46.6	0.7	45.9	59.0
South America	Chile	61.0	3.56	57.40	45.5	1.3	44.2	55.8
South America	Colombia	58.9	2.94	55.97	43.1	0.8	42.32	54.6
South America	Ecuador	58.0	3.27	54.69	42.2	0.9	41.25	53.4
South America	Paraguay	56.5	3.38	53.09	40.1	1.1	38.98	52.1
South America	Peru	53.6	4.49	49.08	37.8	1.7	36.1	48.1
South America	Uruguay	47.9	5.10	42.84	31.6	1.8	29.75	42.3
South America	Venezuela, RB	51.1	4.14	47.00	34.7	1.3	33.48	46.3
Africa	Botswana	67.3	2.56	64.70	51.4	0.9	50.41	62.6
Africa	Burkina Faso	48.4	6.27	42.10	33.1	2.7	30.40	41.5
Africa	Burundi	42.8	8.96	33.79	28.0	4.1	23.90	33.3
Africa	Cameroon	48.3	6.26	42.04	32.8	2.7	30.09	41.4
Africa	Central African Republic	55.0	4.29	50.71	39.6	1.7	37.92	49.9
Africa	Egypt, Arab Rep.	41.3	9.05	32.24	27.5	3.9	23.61	31.9

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Table A7.2 *continued*

Continent	Country	1990s						
		Income Share			Income Share			
		Highest 20%	Lowest 20%	Difference between Quintiles	Highest 10%	Lowest 10%	Difference between Deciles	Gini
Africa	Ethiopia	40.6	8.61	32.02	26.6	3.6	22.95	31.7
Africa	Gambia, The	52.8	4.79	48.05	36.9	2.0	34.99	47.3
Africa	Ghana	48.6	5.24	43.31	32.8	2.0	30.72	42.8
Africa	Guinea	45.0	6.77	38.2	29.7	2.8	26.91	37.8
Africa	Guinea–Bissau	43.2	7.28	35.93	28.1	3.1	25.08	35.5
Africa	Kenya	53.2	4.84	48.36	38.0	2.0	36.03	47.7
Africa	Lesotho	56.7	2.94	53.78	39.7	1.0	38.66	52.9
Africa	Madagascar	49.3	6.14	43.18	33.9	2.5	31.45	42.3
Africa	Malawi	49.8	6.16	43.60	35.1	2.5	32.57	43.1
Africa	Mali	44.7	6.87	37.78	28.9	2.9	26.00	37.3
Africa	Mauritania	46.9	6.17	40.72	31.5	2.5	28.95	40.3
Africa	Morocco	47.8	6.5	41.30	32.8	2.7	30.04	40.8
Africa	Mozambique	52.4	5.33	47.05	38.0	2.0	35.94	46.4
Africa	Namibia	67.4	3.26	64.13	53.3	1.4	51.83	62.6
Africa	Niger	45.2	7.38	37.77	30.6	3.1	27.47	37.3
Africa	Nigeria	47.5	5.51	41.99	31.4	2.2	29.2	41.5
Africa	Senegal	47.1	6.28	40.77	31.6	2.6	28.97	40.3
Africa	Seychelles	69.6	3.71	65.92	60.2	1.6	58.52	65.8
Africa	South Africa	68.3	2.67	65.58	52.0	1.1	50.84	63.3
Africa	Swaziland	57.9	4.35	53.54	42.2	1.9	40.37	52.4
Africa	Tanzania	44.3	7.17	37.11	29.2	3.0	26.2	36.7
Africa	Tunisia	44.9	6.39	38.54	29.3	2.6	26.7	38.1
Africa	Uganda	50.8	5.85	44.96	35.9	2.4	33.44	44.3
Africa	Zambia	56.4	4.24	52.15	40.8	1.7	39.11	51.2
Asia	Bangladesh	42.2	8.78	33.37	27.8	4.0	23.79	32.9
Asia	Cambodia	43.9	8.05	35.81	29.1	3.6	25.54	35.3
Asia	PRC	47.9	4.98	42.91	31.2	1.9	29.29	41.4

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Table A7.2 *continued*

		1990s						
		Income Share			Income Share			
Continent	Country	Highest 20%	Lowest 20%	Difference between Quintiles	Highest 10%	Lowest 10%	Difference between Deciles	Gini
Asia	India	42.6	8.59	34.00	28.5	3.7	24.81	33.6
Asia	Indonesia	42.2	8.40	33.77	27.5	3.7	23.81	34.3
Asia	Iran, Islamic Rep.	45.2	6.43	38.73	29.6	2.6	27.01	38.3
Asia	Israel	46.3	4.99	41.29	29.9	1.8	28.09	41.3
Asia	Jordan	43.1	7.87	35.20	28.2	3.4	24.79	34.8
Asia	Kazakhstan	39.1	8.65	30.41	24.2	3.6	20.54	30.3
Asia	Kyrgyz Republic	41.9	7.75	34.14	26.4	3.2	23.22	33.8
Asia	Lao PDR	43.2	8.06	35.15	28.7	3.5	25.16	34.7
Asia	Malaysia	49.2	5.23	43.98	32.7	2.1	30.62	43.4
Asia	Maldives	44.2	6.51	37.73	28.0	2.7	25.32	37.4
Asia	Mongolia	42.3	7.28	34.99	26.6	3.1	23.53	34.7
Asia	Nepal	46.2	7.40	38.82	31.6	3.3	28.34	38.3
Asia	Pakistan	40.5	9.35	31.12	26.6	4.2	22.42	30.8
Asia	Philippines	50.6	5.66	44.89	34.3	2.4	31.91	44.1
Asia	Russian Federation	45.5	6.51	38.97	29.5	2.6	26.93	38.4
Asia	Slovak Republic	37.1	9.25	27.84	23.0	3.8	19.24	27.6
Asia	Sri Lanka	46.9	7.14	39.8	32.2	3.1	29.07	39.2
Asia	Tajikistan	40.4	7.87	32.57	25.4	3.1	22.25	32.3
Asia	Thailand	48.5	6.40	42.08	32.7	2.7	29.99	41.4
Asia	Turkey	46.3	5.66	40.59	30.2	2.1	28.09	40.1
Asia	Uzbekistan	42.7	7.79	34.86	27.8	3.1	24.74	34.2
Asia	Viet Nam	44.3	7.13	37.21	29.0	3.0	25.98	36.8
Asia	Yemen, Rep.	44.2	7.84	36.31	29.9	3.3	26.61	35.9
Europe	Armenia	41.6	8.49	33.07	27.3	3.6	23.69	32.7
Europe	Austria	38.1	8.51	29.61	23.4	3.3	20.03	29.5
Europe	Azerbaijan	34.5	11.20	23.29	21.1	5.0	16.08	23.1
Europe	Belarus	36.9	8.94	27.99	22.3	3.7	18.66	27.9

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Table A7.2 *continued*

		1990s						
		Income Share			Income Share			
Continent	Country	Highest 20%	Lowest 20%	Difference between Quintiles	Highest 10%	Lowest 10%	Difference between Deciles	Gini
Europe	Belgium	41.7	8.35	33.34	28.3	3.3	25.03	33.1
Europe	Bulgaria	40.0	7.23	32.74	25.0	2.6	22.36	32.4
Europe	Croatia	39.9	8.36	31.54	25.1	3.5	21.59	31.2
Europe	Czech Republic	36.4	9.45	26.99	22.6	3.8	18.81	26.5
Europe	Denmark	35.1	9.68	25.45	21.0	3.7	17.3	25.4
Europe	Estonia	41.3	7.27	34.01	25.9	2.7	23.26	33.6
Europe	Finland	37.3	9.32	27.99	23.0	3.8	19.18	27.9
Europe	France	39.6	7.94	31.69	24.6	3.2	21.4	31.5
Europe	Georgia	46.5	5.46	41.02	30.5	1.9	28.51	40.6
Europe	Germany	39.4	8.38	31.05	24.7	3.4	21.34	30.9
Europe	Greece	41.1	6.70	34.38	25.8	2.3	23.51	34.2
Europe	Hungary	37.4	8.78	28.66	23.0	3.6	19.4	28.5
Europe	Ireland	40.7	7.76	32.93	25.7	3.1	22.65	32.7
Europe	Italy	42.4	6.20	36.2	27.2	2.1	25.03	36.1
Europe	Latvia	42.5	6.66	35.85	27.0	2.4	24.61	35.5
Europe	Lithuania	41.5	7.14	34.32	26.2	2.7	23.5	34.0
Europe	Macedonia, FYR	45.9	5.88	40.00	30.0	2.3	27.7	39.6
Europe	Moldova	42.2	7.43	34.78	27.0	3.0	23.97	34.5
Europe	Netherlands	38.5	8.20	30.30	23.9	3.0	20.91	30.1
Europe	Norway	37.1	9.2v	27.87	23.1	3.5	19.58	27.8
Europe	Poland	41.6	7.70	33.89	26.4	3.2	23.27	33.7
Europe	Romania	37.9	8.48	29.37	23.0	3.5	19.56	29.3
Europe	Slovenia	36.1	9.30	26.82	21.8	3.8	17.97	26.7
Europe	Spain	40.8	6.48	34.29	25.2	2.1	23.08	34.1
Europe	Sweden	36.2	9.32	26.84	21.8	3.7	18.07	26.8
Europe	Switzerland	40.3	7.67	32.65	24.8	2.9	21.89	32.7
Europe	Ukraine	37.4	9.16	28.27	22.8	3.9	18.97	28.1

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Table A7.2 *continued*

		1990s						
		Income Share			Income Share			
Continent	Country	Highest 20%	Lowest 20%	Difference between Quintiles	Highest 10%	Lowest 10%	Difference between Deciles	Gini
Europe	United Kingdom	44.2	5.98	38.17	28.7	2.0	26.7	37.9
North America	Canada	41.0	7.02	33.99	25.8	2.6	23.17	33.8
North America	Costa Rica	54.3	3.92	50.35	37.7	1.3	36.44	49.3
North America	Ivory Coast	48.6	5.69	42.89	33	2.3	30.73	42.3
North America	Dominican Republic	54.9	4.24	50.68	39.1	1.6	37.54	49.6
North America	El Salvador	52.4	4.11	48.32	36.1	1.4	34.73	47.5
North America	Guatemala	58.3	3.13	55.17	42.3	1.0	41.25	54.0
North America	Honduras	60.1	2.52	57.61	43.7	0.8	42.94	56.5
North America	Jamaica	58.5	3.39	55.12	41.9	1.4	40.43	54.3
North America	Mexico	54.1	4.49	49.58	38.8	1.7	37.03	48.8
North America	Nicaragua	49.2	5.50	43.69	33.5	2.2	31.35	43.1
North America	Panama	58.0	2.83	55.22	41.3	0.9	40.44	54.0
North America	United States	46.2	4.95	41.20	30.0	1.5	28.53	40.9
Oceania	Australia	41.1	6.99	34.15	25.2	2.4	22.89	34.1
South America	Argentina	53.1	3.51	49.57	35.9	1.1	34.85	48.9
South America	Bolivia	58.3	2.41	55.87	41.9	0.6	41.29	54.7
South America	Brazil	60.3	2.93	57.32	44.3	0.9	43.4	55.9

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Table A7.2 *continued*

Continent	Country	1990s						
		Income Share			Income Share			
		Highest 20%	Lowest 20%	Difference between Quintiles	Highest 10%	Lowest 10%	Difference between Deciles	Gini
South America	Chile	58.6	4.12	54.44	43.4	1.5	41.86	52.9
South America	Colombia	60.7	2.93	57.74	45.1	0.9	44.26	56.3
South America	Ecuador	56.4	3.61	52.83	40.6	1.1	39.49	51.7
South America	Paraguay	57.0	3.53	53.47	41.6	1.2	40.37	52.6
South America	Peru	53.6	3.93	49.68	37.5	1.4	36.12	49.0
South America	Uruguay	51.0	4.68	46.34	34.4	1.8	32.61	45.7
South America	Venezuela, RB	51.9	3.48	48.4	35.2	0.9	34.29	47.7

PRC = People's Republic of China, Lao PDR = Lao People's Democratic Republic, Macedonia FYR = Macedonia Former Yugoslav Republic, Venezuela RB = Venezuela Bolivarian Republic.

Source: Authors' own calculation on the basis of data obtained from the World Bank's World Development Indicators.

Table A7.3: Correlation Coefficients among Explanatory Variables

	ln PCGDP	lnManufacturing_Share	lnServices_Share	ln TO	ln FDI	lnInfrastructure_Quantity	lnInfrastructure_Quality	ln Urbanization
ln PCGDP	1.00							
lnManufacturing_Share	0.11	1.00						
lnServices_Share	0.52	0.27	1.00					
ln TO	0.19	0.01	0.06	1.00				
ln FDI	0.62	0.10	0.40	0.00	1.00			
lnInfrastructure_Quantity	−0.01	0.03	−0.06	−0.19	0.18	1.00		
lnInfrastructure_Quality	−0.55	−0.24	−0.35	−0.06	−0.36	0.06	1.00	
ln Urbanization	0.74	0.14	0.35	0.12	0.47	0.06	−0.32	1.00

PCGDP = per capita gross domestic product, TO = trade openness, FDI = foreign direct investment.

Source: Authors' own calculation on the basis of data obtained from the World Bank's World Development Indicators.

Table A7.4: Correlation Coefficients among Interaction Dummies

	D_AfricaXlnManufacturing_Share	D_AsiaXlnManufacturing_Share	D_EuropeXlnManufacturing_Share	D_NorthAmericaXlnManufacturing _Share	D_SouthAmericaXlnManufacturing _Share	D_PacificXlnManufacturing _Share
D_AfricaXlnManufacturing_Share						
D_AsiaXlnManufacturing_Share						
D_EuropeXlnManufacturing_Share						
D_NorthAmericaXlnManufacturing_Share						
D_SouthAmericaXlnManufacturing_Share						

continued on next page

Table A7.4 *continued*

	D_AfricaXInManufacturing_Share	D_AsiaXInManufacturing_Share	D_EuropeXInManufacturing_Share	D_NorthAmericaXInManufacturing_Share	D_SouthAmericaXInManufacturing_Share	D_PacificXInManufacturing_Share
D_PacificXInManufacturing_Share						
D_AfricaXInServices_Share	1.00					
D_AsiaXInServices_Share	−0.34	1.00				
D_EuropeXInServices_Share	−0.35	−0.32	1.00			
D_NorthAmericaXInServices_Share	−0.22	−0.20	−0.20	1.00		
D_SouthAmericaXInServices_Share	−0.17	−0.15	−0.16	−0.10	1.00	
D_PacificXInServices_Share	−0.16	−0.14	−0.14	−0.09	−0.07	1.00

Source: Authors' own calculation on the basis of data obtained from the World Bank's World Development Indicators.

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8

Structure Change and Urban Inequality in the People's Republic of China*

Yuan Zhang and Guanghua Wan

8.1 Introduction

Much of the world is watching the People's Republic of China (PRC) with concern. Not only has it created fast economic growth, but it is also thought of as an economy with surprisingly high inequality. During the economic transition over the past 4 decades, inequality in the PRC kept a very clear increasing trend and the World Bank (2007) warned that high inequality could push it into the middle-income trap.

The worsening income inequality in the PRC during its economic transition has attracted worldwide attention, resulting in a sizable literature. There is a rich literature that focuses on determinants of rural–urban gaps, and inequality in the rural sector (Adelman and Sunding 1987; Griffin and Saith 1982; Knight and Song 1993; Knight and Song 1999; Khan et al. 1992; Wan 2004, 2007; Kanbur and Zhang 2004; Bhalla, Yao, and Zhang 2003; Yang 1999; Tian 2001; Zhu 1991; Zhao 1999; Lu 2002; Zhang and Zou 2012; Sicular 2013; Ito 2008). Also, there there have been very good literature reviews on inequality in the PRC (Wan and Zhou 2005; Chen, Lu, and Wan 2010; Gustafsson, Li, and Sicular 2010; Wang, Wan, and Yang 2014). Unfortunately, the National Bureau of Statistics (NBS) of the PRC has only recently started to report time series measuring inequality in urban PRC, although they had reported a

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national level Gini Index and one for rural areas. Very few studies focus on the determinants and evolution of inequality in urban PRC. Based on China Household Income Project (CHIP) survey data, Khan et al. (1992) decomposed the urban Gini index by income sources, and found that the two most important contributors are wages (34%) and housing subsidies (24%). Employing the same data, Meng (2004) found that during the marketization of urban sectors, unemployment and under-employment led to a fall in urban workers' incomes, and reduced inequality in the urban labor market. Li, Xing, and Wu (2016) investigated the evolution of urban inequality from the angle of wage structure between 1995 and 2013, and found that regional gap and inequality of human capital are major contributors to overall wage inequality in urban PRC. Ma and Li (2016) evaluated the effect of minimum wage on urban inequality from 1993 to 2013 and found that the increase of minimum wages had a positive effect on the wage levels of the low-wage group only from 2007–2013; there was no such effect from 1993–1995 and from 1998–2002.

In the PRC, inequality in the urban sector has been low relative to its rural counterpart (Wang, Wan, and Yang 2014). But this cannot be an excuse for economists and policy makers to ignore it. We believe that the determination and evolution of inequality in urban PRC, especially the structural change in the urban labor market, deserves intensive study for the following reasons.

First, employment in the urban sector increased sharply from 23.69% in 1978 to 50.88% in 2014 (NBS 2015), and this urbanization process is likely to continue for a long time into the future. So, the urban sector will play an increasingly important role in the evolution of urban and overall inequality in the PRC.

Second, for most urban households in the PRC, wages are the most important income source. For example, the share of wage income in total income decreased slightly from 71.16% in 2000 to 64.30% in 2012 (NBS 2015). That is to say, wage income still dominates total income of urban households. So, the changes in employment structure and wage determination should have an important effect on inequality within the urban sector and even on overall inequality. There have been some studies on the PRC's structural change, e.g., Fan, Zhang, and Robinson (2003). But there have been few if any attempts to bring structure change and the evolution of inequality together. Dollar (2007) provided a detailed discussion of government policy and social disparities in the PRC, and predicted that the policy shift toward encouraging migration, funding education, and improving the health of people in poor areas and of poor households, and rebalancing the economy away from investment and exports toward domestic consumption and public services, will help reduce social disparities. However, he did not provide any evidence.

Third, most existing studies focus on explaining the driving forces behind increasing urban inequality during the economic transition, but no attention has been paid to new trends of urban inequality in recent years. For example, employing CHIP data, Table 8.1 presents the inequality measures of wage income for both residents with urban household registration identity (thereafter urban locals) and rural migrants, showing that they peaked in 2007 and subsequently decreased.

Using Urban Household Survey samples collected by NBS of the PRC, we measure the Gini Index and Theil Index of wage incomes for urban locals, and present them in Table 8.2. It shows that after 2008 the increase in inequality of wage income for urban locals slowed, which is a positive development for the PRC. Although it is difficult to know whether this is a long-term or a short-term trend, it is an important development that deserves analysis and has important implications. Yet, there have not been any studies so far to explain this new trend. Using a rich data set covering a long time period, this chapter attempts to fill the gap and contribute to the inequality literature.

Finally, compared with the existing literature, which has very limited data resources, we have very good urban household data from the NBS of the PRC, which makes both the inequality decomposition and regressions possible. This chapter is one of the first trying to explain the effect of employment structure change on inequality in urban PRC.

Table 8.1: Inequality of Wage Income in Urban PRC (Urban Locals + Migrants)

	2002	2007	2008	2013
Gini Index	0.4169	0.4293	0.4063	0.3609
Theil Index	0.3094	0.3636	0.2856	0.2386

PRC = People's Republic of China.

Data source: Author's computation based on CHIP survey data.

Table 8.2: Inequality of Wage Income in Urban PRC (Urban Locals)

	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012
Gini Index	0.3726	0.3778	0.3836	0.3807	0.3802	**0.3922**	0.3721	0.3984	0.4016	0.3914
Theil Index	0.2412	0.2512	0.2562	0.2519	0.2486	**0.2653**	0.2364	0.2772	0.2849	0.2722

PRC = People's Republic of China.

Note: Those observations having no information on wages are dropped when measuring inequality.

Data source: Urban Samples from NBS of the PRC.

The inequality decomposition and empirical evidence provided in this chapter can help understand the determinants of inequality in the PRC.

The rest of this chapter is structured as follows. Section 8.2 provides an introduction of the data source. Section 8.3 firstly introduces our inequality decomposition method, and then applies it to the data source from the PRC, which reveals the main driving force behind overall inequality in urban PRC. Section 8.4 links the development of the service industry with the evolution of urban inequality, predicting that the growth of the low-skilled service sector and changes in wage determination in the urban labor market play a positive role in reducing inequality in urban PRC. The last section concludes the chapter and provides some policy implications.

8.2 Data Source

The data source used in this chapter is the Urban Household Survey (UHS) data collected by NBS of the PRC. It includes a large number of urban household samples in 2003–2012. The sampling framework of the NBS of the PRC and the journal of household activities ensure that the quality of this data is among the best collected in the PRC. Table 8.3 presents the number of provinces and individuals covered in the household data set employed in this chapter.

8.3 Inequality Decomposition

8.3.1 Decomposition Method of Inequality Index

To gauge the determinants of inequality in urban PRC, we follow Shorrocks (1980, 1984), and decompose the inequality index as shown below:

The generalized entropy (GE) class of inequality measures can be expressed as follows:

Table 8.3: Sample Size of Survey Data Used in This Study

	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012
Province	16	16	16	16	18	18	18	4	4	4
Individual	90,861	95,326	99,093	98,249	142,778	161,109	151,706	37,414	33,243	32,800

Data source: NBS. Urban Household Survey.

$$GE(y)=\begin{cases}\sum_{i=1}^{n} f(y_i)\left\{\left(\frac{y_i}{\mu}\right)^{C}-1\right\} & \text{for} \quad c\neq 0,1,\\ \sum_{i=1}^{n} f(y_i)\left(\frac{y_i}{\mu}\right) log - \left(\frac{y_i}{\mu}\right) & \text{for} \quad c=1,\\ \sum_{i=1}^{n} f(y_i) log\left(\frac{y_i}{\mu}\right) & \text{for} \quad c=0.\end{cases} \qquad (1)$$

where y_i is the ith income, μ represents the total sample mean, $f(y_i)$ is the population share of y_i in the total population, and n denotes the total population. When c is less than 2, the measure is transfer-sensitive, that is to say, the bottom income group is more sensitive to transfers than the upper income group. $GE(1)$ and $GE(0)$ represent the Theil index and Mean Log Deviation, respectively. GE can be further decomposed by income groups:

$$GE(y)=\sum_{g}^{K} w_g I_g + I\left(\mu_1 e_1,\dots,\mu_k e_k\right), \qquad (2)$$

where

$$w_g=\begin{cases} f_g\left(\frac{\mu_g}{\mu}\right)^{C} & \text{for } c\neq 0,1,\\ f_g\left(\frac{\mu_g}{\mu}\right) & \text{for } c=1,\\ f_g & \text{for } c=0.\end{cases}$$

In Equation (2), I_g denotes inequality within the gth group, μ_g is the mean of the gth group, e_g is a vector of 1s of length n_g, and n_g is the gth group's population. f_g denotes the population share of the gth group in the total population. $\sum_{g}^{K} w_g I_g$ represents the within-group inequality, while $I(\mu_1 e_1, \dots, \mu_k e_k)$ is the between-group inequality. For simplicity, our paper uses $GE(0)$, the Mean Log Deviation.

Applying this decomposition method to the survey data gives us stylized facts about the determinants and evolution of inequality in urban PRC.

8.3.2 Inequality Decomposition: Components of Wage Inequality within Urban Locals

Employing the samples of urban locals from NBS of the PRC, Table 8.4 presents the Gini Index of all urban locals in three industries.[1] It is revealed that, firstly, the Gini Index in the primary industry is always much lower than that in other industries, suggesting that it contributes very little to overall inequality in urban PRC; secondly, the Gini Index in the third industry is always higher than that in the second industry.

Because most agricultural production is concentrated in rural areas, the share of the primary industry workers in urban PRC is very low, and their contribution to overall inequality in the urban labor market can be ignored.[2] So, we drop those samples from the primary industry to simplify the decomposition and analysis. Table 8.5 presents the Theil Mean Log Deviations of wage incomes for urban locals in the second and the third industry, and it can be seen that they have similar patterns as in Table 8.4.

The results of applying the decomposition method to the sample of urban locals in the second and third industries are presented in Figure 8.1.

It can be seen that the inequality component in the service industry is much higher than any other components. And also, it has a pattern very similar to that of the total inequality index. This suggests that the increase and decrease of overall inequality in the second and third

Table 8.4: Gini Index of Wage Income for Urban Locals

	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012
Total	0.3726	0.3778	0.3836	0.3807	0.3802	0.3922	0.3721	0.3984	0.4016	0.3914
Primary Industry	0.3106	0.3242	0.3268	0.3069	0.2947	0.3546	0.3309	0.3204	0.3675	0.3252
Second Industry	0.3636	0.3685	0.3741	0.3710	0.3646	0.3734	0.3539	0.3706	0.3770	0.3750
Third Industry	0.3758	0.3808	0.3872	0.3851	0.3871	0.3994	0.3790	0.4083	0.4097	0.3968

Data source: Computed from the samples from NBS of the PRC.

[1] In this chapter, we do not distinguish between the term third industry and the term service industry.

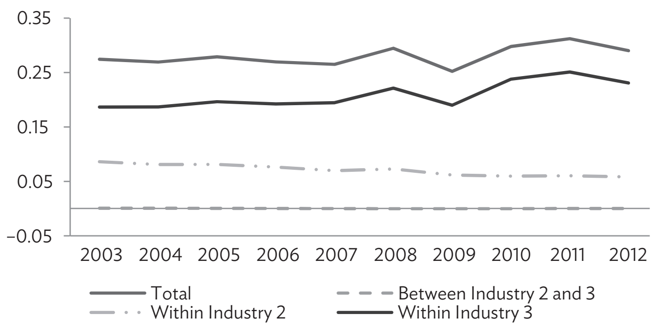
[2] For example, according to NBS of the PRC, its share was basically less than 1% in recent decades, and the share of primary industry workers in the urban samples used in this study is also lower than 1%.

Table 8.5: Theil Mean Log Deviation of Wage Incomes for Urban Locals

	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012
Second and third Industry	0.2745	0.2693	0.2789	0.2696	0.2650	0.2946	0.2522	0.2980	0.3122	0.2901
Second Industry	0.2487	0.2444	0.2518	0.2435	0.2326	0.2561	0.2198	0.2390	0.2479	0.2453
Third Industry	0.2865	0.2800	0.2906	0.2809	0.2785	0.3097	0.2646	0.3177	0.3324	0.3033

Source: Computed from the samples from NBS of the PRC.

Figure 8.1: Inequality Decomposition of the Second and Services Industry



Source: Computed from the urban household samples from NBS of the PRC.

industries in urban PRC was dominated by the inequality component within services.

The decomposition result is actually not surprising because of two facts: first, in urban PRC, a larger share of labor is employed in the service industry from the 1990s;[3] second, the service industry includes a very wide array of jobs from modern services like insurance and banking, and traditional services like lodging and catering. The former generally

[3] According to the NBS of the PRC, before 1995, the employment share of the service industry in total employment was lower than that of the second industry. This situation began to change in 1995, in which year the former was 24.8%, while the latter was 23%. After 1995, the former was always higher than the latter.

needs high levels of human capital or skills and pays very high wages, while the latter does not need much knowledge or high skills and pays low wages. It can be assumed then that the change in inequality inside the service industry may be related to the change in the employment structure and the change in the wage structure.

8.4 Explanation and Evidence: Structure Change and Decreasing Inequality

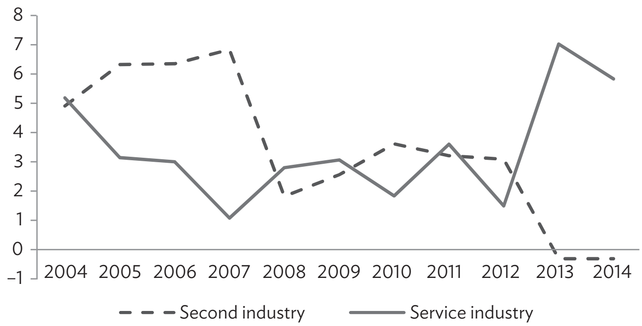
Given the potential relationship between inequality and economic growth (Lewis 1955; Kuznets 1955) and the intrinsic link between economic growth and structural change, we propose the following theoretical hypothesis to explain the new trend of urban inequality in the PRC after 2008: the development of the service industry and the structural transformation of the PRC economy changed the employment structure and wages of low-skilled workers in the service industry, and consequently reduced inequality in the service industries, and subsequently inequality in urban PRC. Next, we provide some evidence to explain this mechanism.

Theoretically speaking, urbanization, agglomeration of economic activities, and international trade are all important drivers of economic structure transformation, but in this paper, we believe that the development of the service industry played an important role in the evolution of urban inequality in the PRC after 2008. For example, Figure 8.2 presents the growth rate of employment in the second industry and the service industry in the PRC from 2004 to 2014. We see that, before 2008, employment in the second industry had a higher growth rate than that of the service industry. But the situation began to change in 2008, and, after 2012, employment in the service industry grew at a much higher rate than in the second industry. These changes suggest that the development of the service industries meant more and more workers were absorbed by the urban labor market.

Then how about the employment structure in the service industry? Based on the fact that certain services do not require a high level of human capital or skills, whereas others do, we can crudely classify the service industry into low-end and high-end services[4] and then investigate their respective employment and wage structures. In the existing literature,

[4] We do not adopt the classification of consumer services vs. producer services for that; some industries provide services for both consumers and producers, such as transportation and information transmission.

Figure 8.2: Growth Rate of Employment in the Second and Services Industry (%)



Source: Computed from statistics on the website of NBS of the PRC, www.stats.gov.cn.

there is no generally accepted definition or classification of low-end and high-end services. In this chapter, we use the average wage levels of two-digit code services and the characteristics of different services to define high-end services, as shown in Table 8.6. Other services not listed in Table 8.6 are classified as low-end services. In fact, after computing the average wage levels of these high-end services, we find that the high-end services presented in Table 8.9 are always in the top-10 of having the highest wages from 2003 to 2012.

After defining low-end and high-end services, we can explore the employment structure inside services. Figure 8.3 reports the employment share of low-end services in the service industry. It shows that the share of employment in low-end services kept a very clear U-shape trend, decreasing until 2009–2010 when it started to increase. This U-shape suggests that, after 2008, the service industries absorbed more and more low-end workers rather than high-end workers in urban PRC.

Actually, not only did the employment structure change after 2008, but wage determination inside the service industry also saw a dramatic change. For example, Figure 8.4 presents the mean wage gap between low-end services and high-end services in recent years. It can be seen that the wage gap kept a clear U-shape with a turning point in 2009. This indicates that mean wage in low-end services kept a slower growth rate than that in high-end services before 2009, but this trend was completely reversed after 2009.

Summing up, from 2008, the employment structure in the urban labor market saw a dramatic change. Given that the decline in overall

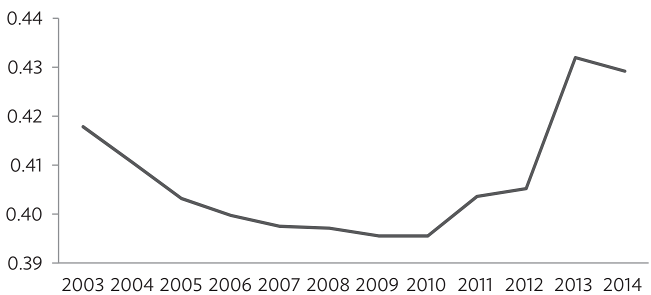
Table 8.6: Definition of High-end Services

Two-digit Code	Industry
07	Information Transmission, Computer Services and Software
10	Banking
11	Real Estate
13	Scientific Research, Technical Services, Geological prospecting
16	Education
19	Public Management and Social Organization
20	International Organization

Note: two-digit codes of industries come from the NBS of the PRC.

Source: Website of the NBS of PRC, http://www.stats.gov.cn/tjsj/tjbz/hyflbz/201710/t20171012_1541679.html

Figure 8.3: Employment Share of Low-end Services in the Services Industry



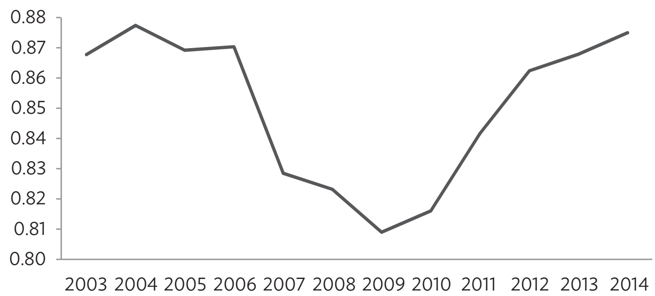
Source: Computed from statistics on the website of NBS of the PRC, www.stats.gov.cn.

inequality is mainly driven by the decline in inequality within services, these changes can help reduce overall inequality in the service industry and subsequently reduce inequality in urban PRC.

Employing individual data, we next provide empirical evidence showing there were also changes to the wage determination in low-end service industries. To test whether wage determinations also changed after 2008, we run the Mincer wage equation in the low-end service industry. Dependent and independent variables are defined in Table 8.7.

In the Mincer wage equation, we add a dummy variable "lowskill" measuring whether labor is low-skilled. From the regression results in

Figure 8.4: Mean Wage Gap between Low-end and High-end Services



Source: Computed from statistics on the website of NBS of the PRC, www.stats.gov.cn.

Table 8.7: Variable Definition of Regression Models

Variable	Variable Definition
Mwage	Monthly wage of workers (in log)
Lowskill	Workers with less than 10 years of schooling
Age	Age of workers
Age_sq	Squared age of workers
Female	Dummy variable for female workers (female=1)
Married	Dummy variable for married workers (married=1)
Education	Schooling years of workers
Experience	Years of working experience of workers

Source: Urban household samples from NBS of the PRC.

Table 8.8, we conclude that, after controlling for individual characteristics that determine a worker's productivity, the dummy variable "lowskill" turned from negative (even significant in the first 2 years) to positive after 2007, and even significantly positive in 2008 and 2009. This suggests that the determinations of low-skilled urban locals' wages in low-end services also dramatically changed after 2007/08. These results provide further evidence that the development of service industries during structural transformation in urban PRC fundamentally changed the wage determination in the urban labor market, which can help reduce inequality in urban PRC.

Table 8.8: Wage Equation for Urban Locals (2003–2012)

	2003	2004	2005	2006	2007
Lowskill	−0.8080***	−0.2540***	−0.0222	−0.0645	0.0365
	(0.0779)	(0.0813)	(0.0822)	(0.0826)	(0.0674)
Age	−0.1270***	−0.1390***	−0.1760***	−0.2260***	−0.1840***
	(0.0223)	(0.0251)	(0.0247)	(0.0252)	(0.0201)
Age_sq	0.0008***	0.0012***	0.0016***	0.0022***	0.0017***
	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0005)
Female	0.0069	−0.2130***	−0.2620***	−0.2770***	−0.2160***
	(0.0405)	(0.0448)	(0.0455)	(0.0455)	(0.0372)
Married	−0.3530***	−0.7030***	−0.6650***	−0.4870***	−0.5640***
	(0.0945)	(0.1050)	(0.1040)	(0.1060)	(0.0864)
Education	0.3230***	0.3260***	0.3610***	0.3490***	0.3220***
	(0.0119)	(0.0145)	(0.0143)	(0.0143)	(0.0116)
Experience	0.112***	0.0946***	0.0933***	0.0899***	0.0838***
	(0.0046)	(0.0043)	(0.0044)	(0.0044)	(0.0039)
Constant	6.3750***	6.6790***	6.8900***	8.0170***	7.8830***
	(0.4280)	(0.4900)	(0.4870)	(0.5020)	(0.4040)
Observation	16,317	18,895	20,047	20,545	30,600
R^2	0.213	0.127	0.2514	0.111	0.087
	2008	**2009**	**2010**	**2011**	**2012**
Lowskill	0.2340***	0.2690***	0.1150	0.0184	0.0340
	(0.0647)	(0.0695)	(0.1370)	(0.1450)	(0.1530)
Age	−0.1480***	−0.1610***	−0.1710***	−0.1340***	−0.1220***
	(0.0180)	(0.0198)	(0.0388)	(0.0396)	(0.0419)
Age_sq	0.0014***	0.0015***	0.0017***	0.0012***	0.0012**
	(0.0002)	(0.0002)	(0.0005)	(0.0005)	(0.0005)
Female	−0.3160***	−0.3890***	−0.2970***	−0.3790***	−0.4410***
	(0.0360)	(0.0386)	(0.0756)	(0.0803)	(0.0856)
Married	−0.6080***	−0.4770***	−0.6500***	−0.9090***	−0.9860***
	(0.0787)	(0.0871)	(0.1680)	(0.1690)	(0.1760)
Education	0.3320***	0.3580***	0.2980***	0.2650***	0.2840***
	(0.0111)	(0.0120)	(0.0236)	(0.0250)	(0.0257)
Experience	0.0675***	0.0654***	0.0414***	0.0481***	0.0456***
	(0.0035)	(0.0037)	(0.0077)	(0.0083)	(0.0089)
Constant	7.2140***	7.2420***	8.7210***	8.7240***	8.1440***
	(0.3600)	(0.3990)	(0.8050)	(0.8220)	(0.8700)
Observation	35,889	33,799	9,012	8,120	7,786
R^2	0.076	0.077	0.060	0.056	0.056

Note: The numbers in brackets are standard errors; *, **, ***, respectively, indicate significant level at 10%, 5%, and 1%.

Source: Urban household samples from NBS of the PRC.

So, this section provides statistical and empirical evidence indicating that, since 2008, there have been significant changes to the employment structure and wage determination in urban PRC and in the low-service industry. These changes helped to reduce inequality in urban PRC after 2008.

8.5 Conclusion and Policy Implications

Even though income inequality in the PRC widened quickly during the economic transition in what was already considered to be one of the most unequal economies in the world, its urban inequality surprisingly declined from 2008. The existing literature fails to note and explain this important issue. Employing a large urban household sample from NBS of the PRC, this chapter fills this gap. Firstly, inequality decomposition suggests that, decreasing wage inequality in urban PRC is mainly attributable to the decrease of inequality components within the service industry, whereas inequality components within the second industry and that between the second and service industry only have a minor effect. Secondly, we explain that the structure change in urban PRC plays an important role in this process. We show that during the structure transformation, development of the service industry in urban PRC was faster than development of the second industry after 2008, and inside the service industry more workers are employed in low-end services than in high-end services. Also, wage determinations in low-end services changed after 2007/08, i.e., gaps between low-skilled workers and skilled labor decreased. All of these changes definitely can help reduce inequality in urban PRC.

The policy implications of this chapter are straightforward. Since the PRC started its economic reform and open-door policies, structural transformation has developed quickly in the urban sector. After 2008, the structural transformation changed the employment structure and wage determination in the urban labor market, which played an active role in reducing wage income inequality. So, one important way to reduce inequality in developing economies is to create more job opportunities for low-skilled or unskilled workers, or to encourage the development of labor-intensive industries. This can provide more opportunities for the majority of those in the urban labor market.

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9

Growth Empirics: Structural Transformation and Sectoral Interdependencies of Sri Lanka

S. P. Jayasooriya

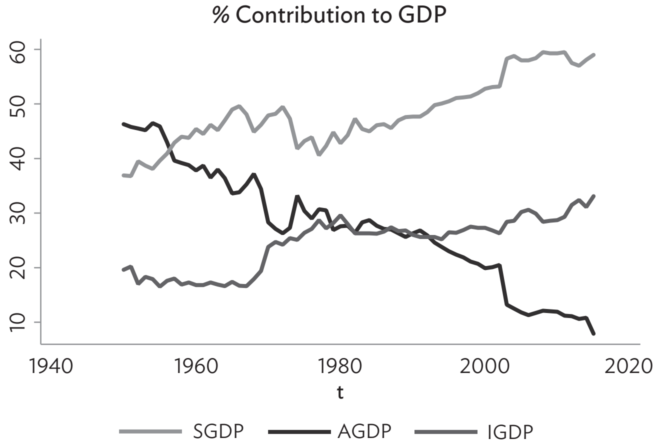
9.1 Introduction

Globalization has brought ample opportunities and benefits to the world in terms of technological advancement and liberalization of trade and capital markets, but many developing countries lag in integrating with the world economy. While economic growth has made drastic strides spurred on by globalization over the last few decades, many developing economies are still advancing at the lower rate of agricultural growth. This also applies to Sri Lanka. Even though the agriculture sector has expanded, its contribution to gross domestic product (GDP) has declined significantly (Figures 9.1 and 9.2). Though it is considered to be the growth engine of Sri Lanka's economy, agricultural growth has fallen to less than 10% of national GDP.

Based on the adoption to the policies, structural change of the economy is unavoidable. Accordingly, the productivity of the sectoral growth change affects total economic growth and sectoral growth independently. The growth empirics phenomenon allows investigating the structural change of Sri Lanka using empirical methods to understand the long-run nexus of sectoral growth and their interdependencies within the economy.

Though substantial research has been conducted to examine the problem of agricultural growth stagnation using numerous approaches, only limited evidence is available to explore structural changes to an economy with the policy changes of Sri Lanka. This chapter contributes to the literature by bridging the knowledge gap and providing a recently developed econometric application of Gregory–Hansen (GH)

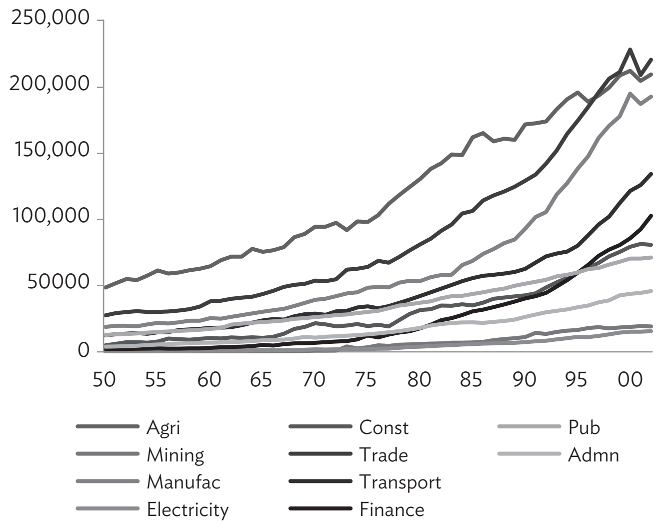
Figure 9.1: Sectoral Growth from 1950–2015



AGDP = agricultural gross domestic product, IGDP = industrial gross domestic product, SGDP = service gross domestic product.

Source: Central Bank of Sri Lanka.

Figure 9.2: Sub-sectoral Growth from 1950–2002



Agri = agriculture, Manufac = manufacturing, Const = construction, Pub = Public Finance, Admn = Public Administration.

Source: Central Bank of Sri Lanka.

cointegration and the Vector Error Correction Models (VECM) for sectoral growth. We advocate open economic policies and a historical review of reforms to agricultural policies in Sri Lanka. Limited economic evidence is supported to understand the policy adjustment process in Sri Lanka, although numerous discussions and forums have been conducted through political approaches, especially focusing on agricultural growth. This chapter attempted to serve the purpose through agricultural development policies on sectoral growth and development policy diversions.

This chapter is organized as follows. Section 9.2 presents a study context of the historical review of policy regimes, which is followed by growth empirics and empirical method. The next section presents the estimates of results. The results and discussion section presents analytical results and policy determinations. Section 9.6 includes conclusion and policy implications.

9.2 Historical Review of Policy Regimes

Sri Lanka's policy changes as a result of the impacts of globalization have had numerous influences on agricultural growth. The historical time frame of policy regimes can be divided into three basic periods: the food self-sufficiency era (1948–1977), open economic policy era I (1977–1994), and open economic policy era II (1994–present). During these periods, various policies were implemented in economic, agricultural and rural development in development administration, which include the land, water, credit, trade, marketing, food, and other sectors. These are the most important sectors as they are at the nexus of agricultural changes and the economic development of the country.

The Government of Sri Lanka has focused on rebuilding and encouraging economic growth through policy administration. In the food self-sufficiency era (1948–1977), land policies were imposed to achieve food self-sufficiency, which included the Paddy Lands Act (1958) and the Land Reform Law (1972), which was extended to cover public land in 1976, the Agricultural Productivity Law (1972), and the Agrarian Service Act (1979). Other than land laws, policies related to water included the Mahaweli Development Board Act, which was initiated as part of the Mahaweli development project in 1970. Moreover, with credit as a facilitating factor, the government established the Peoples' Bank (1963), a new agriculture credit scheme (1967), and a comprehensive rural credit scheme (1973). It also imposed trade restrictions on the import of high-value crops (chilies, potatoes, onions) (1960s) and completely banned import of a range of consumer goods (1970). And it implemented marketing policies, such as a guaranteed price scheme for paddy (1948), establishment of a Paddy Marketing Board (PMB) in 1972, and an increase in guaranteed prices for farmers by 40%. Finally, food policies were most vital policy recommendations in the era with following changes:

- food subsidy scheme through a rice rationing in 1948;
- the basic rice ration was reduced by half a pound per household in 1952;
- phasing out of the subsidy scheme resulting in 300% price increase rice ration in 1953;
- consumer-oriented food policy: reduction of rice and sugar prices, basic ration cut by one half, and issued free of charge in 1966;
- the rice ration was restored to four pounds in 1970; and
- the basic ration was reduced by 50% due to a world food shortage and the high cost of imports, which led to intensified efforts to increase domestic production in 1973.

In open economic policy era I (1977–1994) and open economic policy era II (1994–2007), land policies were imposed, for instance: lands grants; the leasing out of some 24,000 acres of land in the Mahaweli area to a foreign company for oil palm cultivation, and 8,000 acres for sugar production (1980); and implementation of the Land Development (Amendment) Act (1981). Water policies implemented by the government included creation of the Mahaweli Authority of Sri Lanka, established by Act of Parliament (1979) with a privatized supply of irrigation water (1980); cabinet approval for a nationwide water charge program (1983), which amended the agrarian service act so that farmers' organizations collect irrigation service fees; and setting up of a participatory irrigation management system (1980), a capital-intensive Mahaweli river development project (1988), and rice-based irrigation, land development, and settlement programs (Central Bank of Sri Lanka 1990). Further, credit facilities applied as policy concerns included:

- thrift and credit co-operative societies (SANASA Movement, 1978);
- a new comprehensive rural credit scheme (1986);
- a perennial crop development project (1988);
- introduction of *'Praja Naya Niyamaka'* (1988); and
- establishment of a national development bank.

In addition, trade policies were prioritized in the open economy under the globalization:

- many of the government controls were abandoned (1977);

- public sector import monopolies except for some commodities (e.g., rice) were eliminated (1977);
- import tariffs were reduced, the use of import licensing and quotas was almost completely abandoned (1977);
- the financial sector was liberalized (1977);
- foreign export controls were dismantled (1977);
- new export processing zones or free trade zones were established (1977);
- tariff commission was established and export duties were phased out completely (1985);
- rice import by the private sector was authorized—a yearly quota for rice and a government license for imports were introduced (1988);
- duty on rice imports were imposed (1988); and
- public sector import monopolies for sugar and milk powder were eliminated (1988).

Finally, product marketing also supported trade policies such as:

- elimination and reduction of price controls on a few selected commodities (1977);
- a guaranteed price scheme for PMB-paddy and 14 subsidiary food crops to stabilize product prices under the department of marketing;
- purchase of agricultural produce from farmers by sugar corporations (1988); and
- a security price scheme to stabilize prices of minor export crops (1992–1993) (Central Bank of Sri Lanka 1994).

9.3 Growth Empirics Literature

Economic growth theory has been renewed, incorporating new dimensions of empirical methods. The main emphasis in the literature has been on identifying the determinants of economic growth, but only limited efforts have been made to investigate sectoral growth and interdependencies in an individual economy. The study of growth empirics through sectoral growth evolved from the dual economic model (Lewis 1954; Fei and Ranis, 1964). The seminal studies of Lewis (1954) and Fei and Ranis (1964) improved the growth literature to model the development process considering structural transformation. The dual economy model predicts the agriculture sector as the basis of an evolving economy, which is an engine of the capital needed for the second stage of economic development through industrialization. The evidence taken from growth empirics in African countries suggests a long-run nexus and short-run causality among the industry, agriculture, and service sectors using neoclassical growth theories (Blunch and Vemer 1999). The empirical evidences of the interdependencies among the agriculture, industry, and service sectors are contemplated in this study, as agriculture is allocated a lower interdependence (Chenery and Watanabe 1958; Hirschman 1959). Therefore, agriculture is viewed as providing both a demand and supply-side interrelationship with industry and services. Hwa (1989) hypothesized that, all other factors being constant, faster agricultural GDP growth causes earlier growth in the industry sector. Gemmell (1982), Bhagwati (1984), and Dowrick (1990) modeled the changes of service activities of the economic growth and its relationship to the industry sector. However, some empirical studies have identified that interrelationships in service sector activities are vital for economic growth (Fuchs 1968; Blades, Johnson, and Marczewski 1974; Gemmell 1982; Bhagwati 1984).

This chapter focuses on providing pragmatic evidence to quantify these inter-sector dynamics since the development underlines an excessive degree of interdependence between agriculture and industry in Sri Lanka's economy (Figure 9.1). This chapter identifies inter-sector dependencies with empirical evidence on agricultural growth to facilitate economic development policies.

Structural Transformation and Agricultural Growth

Structural transformation is defined as the reallocation of economic activity across three broad sectors (agriculture, manufacturing, and services) that accompany the process of modern economic growth. Agricultural transformation in Sri Lanka will likely take place in line with past trends, though the pace and direction of change will depend on emerging challenges and opportunities related to environmental stress, market instability, future technological breakthroughs, and the rise of global value chains. Over the next 2 decades, many countries of developing Asia will move on to the next phase of agricultural development (Briones and Felipe 2013). However, the reduction in agriculture's employment share will continue to lag the decline in its output share. The comparison of the South Asian countries in terms of changes in employment and sectoral shares is shown in Tables 9.1 and 9.2, respectively.

Comparative Analysis of Changes in Employment Share and Output Share

Table 9.1: Changes in Employment Share and Output Share

Country	Period Covered (OS – Longest Available)	OS Start; End (%)	Speed of Reduction OS (% per annum)	Period Covered (Same for OS and ES)
Bangladesh	1980–2010	31.6; 18.6	1.70	1984–2005
India	1960–2010	42.8; 19	1.58	1994–2010
Nepal	1965–2010	65.5; 36.1	1.29	1991–2001
Pakistan	1960–2010	46.2; 21.2	1.52	1980–2008
Sri Lanka	1960–2010	31.7; 12.8	1.76	1981–2009
Country	**Period Covered (OS – Longest Available)**	**OS Start; End (%)**	**Speed of Reduction OS (% per annum)**	**Period Covered (Same for OS and ES)**
Bangladesh	32.3; 20.1	2.13	58.8; 48.1	0.91
India	28.5; 19	2.36	61.9; 51.1	1.12
Nepal	47.2; 37.6	2.05	81.2; 65.7	1.91
Pakistan	29.5; 20.3	1.28	52.7; 44.7	0.57
Sri Lanka	27.7; 12.7	2.65	45.9; 32.6	1.17

ES = agriculture's employment share, OS = agriculture's output share.
Source: Briones and Felipe (2013).

Table 9.2: Changes in Sectoral Share in South Asian Countries

	Agriculture (% of GDP)			Industry (% of GDP)			Services (% of GDP)		
Country/Year	2000	2010	2013	2000	2010	2013	2000	2010	2013
Bangladesh	25.5	17.8	16.3	25.3	26.1	27.6	49.2	56.0	56.1
Bhutan	27.4	17.5	NA	36.0	44.6	NA	36.6	37.9	NA
India	23.4	18.2	18.4	26.2	27.2	24.7	50.5	54.6	57.0
Maldives	NA	4.1	3.9	NA	14.9	14.5	NA	81.0	81.6
Nepal	37.8	35.4	33.9	17.3	15.1	15.2	44.9	49.5	51.0
Pakistan	25.9	24.3	25.1	23.3	20.6	21.1	50.7	55.1	53.8
Sri Lanka	17.6	12.8	10.8	29.9	29.4	32.5	52.5	57.8	56.8
Afghanistan	38.0	28.8	25.0	24.0	21.3	22.0	38.0	49.8	54.0

GDP = gross domestic product, NA = not available.
Source: ADB (2014).

9.4 Data

A. Unit Root Test without Structural Break

The unit root test explores the stationarity of the time series data. The Augmented Dickey–Fuller (ADF) and Phillips–Perron (PP) tests were applied to probe the stationary behavior of the time series data (Dickey and Fuller 1979, Phillips and Perron 1988). The ADF test can be estimated as;

$$\Delta y_t = \delta_0 + \delta_1 y_{t-1} + \delta_2 t + \sum_{i=1}^{n} \varphi_i \Delta y_{t-1} + \varepsilon_t \qquad (4)$$

where *D* is the difference operator, *y* is the logarithm of the series, *t* is a trend, *δ* and *φ* are the parameters to be estimated, and *ε* is the error term.

B. Unit Root Testing with Trend Break Hypothesis

Perron's 1989 analysis of unit roots in series with trend break is based on the null hypothesis that it has a unit root with possibly nonzero drift against the alternative that the process is trend stationary. He found that the estimation of Equation (9) would have low power in rejecting the null of unit root, even if they are estimated for samples split based on an exogenous change in slope or intercept. For this purpose, he has clearly explained the models under the null and alternative hypotheses as follows:

Null Hypotheses:

Model A: $y_t = \alpha_1 + \delta y_{t-1} + \beta D(TB)_t + \varepsilon_t \qquad (5)$

Model B: $y_t = \alpha_1 + \delta y_{t-1} + (\alpha_2 - \alpha_1)DU_t + \varepsilon_t \qquad (6)$

Model C: $y_t = \alpha_1 + \delta y_{t-1} + \beta D(TB)_t + (\alpha_2 - \alpha_1)DU_t + \varepsilon_t \qquad (7)$

Alternative Hypotheses:

Model D: $y_t = \alpha_1 + \beta_1 t + (\alpha_2 - \alpha_1)DU_t + \varepsilon_t \qquad (8)$

Model E: $y_t = \alpha_1 + \beta_1 t + (\beta_2 - \beta_1)DT_t + \varepsilon_t \qquad (9)$

Model F: $y_t = \alpha_1 + \beta_1 t + (\beta_2 - \beta_1)DT_t + (\alpha_2 - \alpha_1)DU_t + \varepsilon_t \qquad (10)$

where $DT_t{*} = t - TB$ and $DT_t = t$ if $t > TB$ and 0 otherwise.

$DU_t = 1$ if $t > TB$, 0 otherwise.

$D(TB)_t = 1$ if $t = TB + 1$, 0 otherwise.

$A(L)_{\varepsilon t} = B(L)_{vt}$

Subscript 1 on the coefficients denotes those of pre-trend break (TB) and subscript 2 denotes those of post-trend break (TB). By definition, the coefficient on DUt captures the change in intercept, that on DT_{t*} captures the change in trend alone, and that on DT_t captures the change in trend, when change in intercept also co-occurs. Significance of any of these would mean that there has been a change of the corresponding kind after the hypothesized trend break.

Vector Autoregression Specification

A Vector Autoregression (VAR) is a model in which K variables are specified as linear functions of p of their own lags, p lags of the other $K - 1$ variables, and, possibly, additional exogenous variables. A p-order vector autoregressive model, composed VAR (p), with exogenous variables x_t is derived as

$$x_t = \Pi_1 x_{t-1} + \mu + \varepsilon_t \qquad (1)$$

A VAR framework is appealing because it permits the data to determine the robust model specification and considers variables as endogenous. Thus, a general polynomial distributed lag framework or VAR (k) model can be defined as

$$x_t = \Pi_1 x_{t-1} + \Pi_2 x_{t-2} + \ldots \, \Pi_k x_{t-k} + \mu + \varepsilon_t \qquad (2)$$

with an equilibrium-correcting form such that,

$$\Delta x_t = \Gamma_1 \Delta x_{t-1} + \ldots\ldots\ldots\ldots \, \Gamma_{k-1} \Delta x_{t-k} + \Pi x_{t-k} \mu + \varepsilon_t \qquad (3)$$

where $t = 1, \ldots, T$; vector of independent variables that are linear functions of past values of and is an (nx1) vector of constants such that ε_t, an ($n\,'1$) vector of independently distributed disturbances of zero mean and diagonal variance–covariance matrix Ω, i.e. ε_t ~ n.i.d. $(0, \Omega)$.

Vector Autoregression Diagnostics and Inference

Because fitting a VAR of the correct order is vital, *Order Selection Criteria* offer several methods for choosing the lag order *p* of the VAR to fit. After fitting a VAR, and before proceeding with inference, interpretation, or forecasting, checking that the VAR fits the data is important. The *Lagrange Multiplier Test* can be used to check for autocorrelation in the disturbances. *VAR Wald tests* help to determine whether certain lags can be excluded. *Normality* tests the null hypothesis that the disturbances are normally distributed. *Stability* checks the eigenvalue condition for stability, which is needed to interpret the impulse–response functions and forecast-error variance decompositions. The *Unit Root Test* can be used to identify the stationary nature of a series. Gujarati (1999) showed that regression models involving time series data sometimes give results that are spurious, or of dubious value, in the sense that superficially the results look good, but on further investigation they look suspect. This implies that the series might be non-stationary or contain unit root, a highly persistent time series process where the current value equals last period's value, plus a weakly dependent disturbance (Wooldridge 2002). Following Greene (2003), the ADF test is employed to test for unit root.

Granger Causality

Provided that the agricultural, industrial, and service-related GDPs are cointegrated, there is causality between the variables in at least one direction (Granger 1988). Furthermore, Engel and Granger (1987) proposed that the Granger causality for at least one direction could be tested as an error correction model. The model specification can be presented as

$$\Delta y_{1t} = \delta_{1t} + \sum_{i=1}^{k} \alpha_{1i} \Delta y_{lt-1} + \sum_{i=1}^{k} \beta_{1i} \Delta y_{2t-i} + \delta_1 z_{t-1} \varepsilon_{1t} \tag{11}$$

$$\Delta y_{2t} = \delta_{2t} + \sum_{i=1}^{k} \alpha_{2i} \Delta y_{2t-i} + \sum_{i=1}^{k} \beta_{2i} \Delta y_{1t-i} + \delta_2 z_{t-1} \varepsilon_{2t} \tag{12}$$

where y_1 is the logarithm of agricultural GDP (*LAGDP*), y_2 is logarithm of industrial GDP (*LIGDP*), and *z* contains the cointegrating terms implied by the long-run nexus between *AGDP* and *IAGDP*. All coefficients in the first differenced VAR terms can be tested for short-run causality. Finally, the dynamic behavior was estimated by the error correction model and the long-run equilibrium was estimated. The same procedure was adopted with the agricultural GDP and service GDP to find the causation between the two sectors.

Cointegration with Structural Break and Vector Error Correction

The Gregory and Hansen (1996) residual-based test is employed for cointegration to test for structural break in the cointegrating relationship among the included variables. This approach is superior to the Engle and Granger (1987) approach to testing for cointegration, which tends to under-reject the null hypothesis of no cointegration if there is a relationship that has changed at some (unknown) time during the sample period. The Gregory and Hansen test is an extension of the Engle and Granger approach and it involves analysis of the null hypothesis of no cointegration against a complementarity hypothesis of cointegration with a single regime shift at an unknown date based on extensions of the traditional ADF, Za, and Zt test types.

The standard approach for cointegration (Engle and Granger 1987) has no structural change and has four independent variables and is based on the model given as

$$y_t = \mu + \alpha_1 x_t + \alpha_2 z_t + \alpha_3 e_{tt} + \alpha_4 s_t + \varepsilon_t \qquad (13)$$

where x_t, z_t, e_t, s_t, and the dependent variable y_t are I(1), the error term ε_t is I(0), and the μ, α_1, α_2, α_3, α_4 parameters are time invariant. However, it may be desirable to think of cointegration as holding over a fairly long period of time, and then shifting to a new long-run relationship. Thus, the timing of the shift is unknown, but can be determined endogenously. The structural change will be reflected in changes in the intercept and/or changes in slopes. To model the structural change, Gregory and Hansen (1996) defined the indicator variable as follows:

$$\varphi_t = \begin{cases} o, if\ t \le [n\tau] \\ 1, if\ t > [n\tau] \end{cases}$$

where the unknown parameter $\tau \in (0,1)$ denotes the relative timing of the change point and $[n\tau]$ denotes the integer part. To test for cointegration with structural breaks, they proposed some models, among which are level shift, level shift with trend, and intercept with slope shifts.

A. Level Shift (C) Model

$$y_t = \mu_1 + \mu_2 \varphi_t + \alpha_1 x_t + \alpha_2 z_t + \alpha_2 e_{tt} + \alpha_4 s_t + \varepsilon_t \qquad (14)$$

This is a simple case in which there is a level shift in the cointegrating relationship, modeled as a change in the intercept μ, where the slope coefficients are held constant. This implies that the cointegration relationship has shifted in a parallel fashion. In this parameterization, μ1 represents the intercept before the shift and μ2 represents the intercept after the shift.

B. Level Shift with Trend (C/T) Model

$$y_t = \mu_1 + \mu_2\varphi_t + \beta t + \alpha_1 x_t + \alpha_2 z_t + \alpha_3 e_{tt} + \alpha_4 s_t + \varepsilon_t \qquad (15)$$

where β is the coefficient of the trend term, t.

C. Intercept and Slope Shifts (C/S) Model

$$y_t = \mu_1 + \mu_2\varphi_t + \beta t + \alpha_1 x_t + \alpha_{11}\varphi_t x_t + \alpha_2 z_t + \alpha_{22}\varphi_t z_t + \alpha_3 e_{tt} + \alpha_{33}\varphi_t e_{tt} + \alpha_4 s_t + \alpha_{44}\varphi_t s_t + \varepsilon_t \qquad (16)$$

$\alpha_1, \alpha_2, \alpha_3, \alpha_4$ denote the cointegrating slope coefficients before the regime shift and $\alpha_{11}, \alpha_{22}, \alpha_{33}, \alpha_{44}$ denote the change in the slope coefficients.

In principle, the same approach used in Equation (4) could be used for testing models (6) to (8) if the timing of the regime shift were known a priori. However, such breakpoints are unlikely to be known in practice without some appeal to the data. Within this framework, Gregory and Hansen (1996) proposed the test for cointegration with an unknown break date, which involves computing the usual statistics (ADF and PP test statistics) for all possible break points and then selecting the smallest values, since this will potentially present greater evidence against the null hypothesis of no cointegration. In this regard, the relevant statistics are the ADF (τ), $Z_a(\tau)$ and $Z_t(\tau)$.

A need for testing the long-term relationship is established in the model given the short-run disturbances. For this purpose, a dynamic error correction model, which can be used to forecast the short-run behavior of agricultural GDP growth, is estimated based on the cointegration relationship. Given that the lagged residual error derived from the cointegrating vector is incorporated into a highly general error correction model, this leads to the specification of a general error correction model:

$$\Delta x_t = \pi_0 + \pi x_{t-1} + \pi_1 \Delta x_{t-1} + \pi_2 \Delta x_{t-2} + \ldots + \pi_p \Delta x_{t-p} + \varepsilon_t \qquad (17)$$

After a cointegration test is established, a Vector Error Correction Model (VECM) can be estimated subsequently to determine the short-run dynamic behavior of agricultural, industrial, and service growth. The general-to-specific modeling approach was followed, first including two lags of the explanatory variable and of the error correction term, and then gradually eliminates the insignificant variables in the approach (Banerjee et al. 1996).

9.6 Empirical Results

This chapter examines a long-term nexus among the agriculture, industry, and service sectors in Sri Lanka from 1950 to 2015. The empirical model specification follows a unit root analysis, Granger causality test, G–H cointegration, and VECM. The results of the model were investigated through the following analysis. The unit root analysis predicts the $I(1)$ for all the variables, indicating that these variables can be cointegrated (Table 9.3).

The presence of structural breaks in a time series leads the results of a unit root rest to be invalid. It also rejects the null hypothesis even when the series are nonstationary. Therefore, the results of unit root analysis presented above need to be tested by a third method—Zivot and Andrews test (Zandrews test)—which tests for unit root while considering the possibility of structural breaks. A single structural break for each of the series is identified from the results of the Zandrews test. Referring to Table 9.4, for the natural logarithm of AGDP, the break is in 2003 and the t-statistic of –7.679 is less than the critical value at the 1% level reading to the acceptance of the null hypothesis of nonstationarity; hence, the variable is nonstationary. For the natural log of IGDP, the break is in 1978 and the t-statistic of –5.950 is less than the critical value

Table 9.3: Unit Root Test Results

	Augmented Dickey–Fuller		Phillips–Perron	
	Levels	First diff.	Levels	First diff.
LAGDP	–4.56**	–3.18***	–3.53	–5.32***
LIGDP	–4.24	–2.74**	–5.61**	–7.94**
LSGDP	–3.50	–8.73**	–2.74	–6.38***

Diff. = difference, L = logarithm, AGDP = agricultural gross domestic product, IGDP = industrial gross domestic product, SGDP = service gross domestic product.

Source: Author's calculations.

Table 9.4: Zivot and Andrews Unit Root Test

Variable (log)	Break	t-Statistic	Break Year	Critical Values 1%***	Critical Values 5%**
lnAGDP	Intercept	−7.713(1)***	1973	−5.43	−4.80
	Trend	−7.432(0)***	1985	−4.93	−4.42
	Both	−7.679(1)***	2003	−5.57	−5.08
lnIGDP	Intercept	−4.198(0)**	1981	−5.43	−4.80
	Trend	−4.981(1)***	1979	−4.93	−4.42
	Both	−5.950 (1)***	1978	−5.57	−5.08
lnSGDP	Intercept	−4.849(2)**	1967	−5.43	−4.80
	Trend	−4.921(1)**	1983	−4.93	−4.42
	Both	−5.802(1)***	1978	−5.57	−5.08

Diff. = difference, log/L = logarithm, AGDP = agricultural gross domestic product, IGDP = industrial gross domestic product, SGDP = service gross domestic product.

Notes: Number of lags in parenthesis is chosen as the highest significant lag out of a maximum of four lags. * denotes statistical significance at the 10% level, ** denotes statistical significance at the 5% level, and *** denotes statistical significance at the 1% level.

Source: Author's calculations.

at the 1% level reading for the acceptance of the null hypothesis of nonstationarity. For the natural log of IGDP, the break is in 1978 and the t-statistic of –5.802 that is less than the critical value at the 1% level leads to the acceptance of the null hypothesis. Hence, even when structural break is considered, all the three variables are nonstationary.

Vector Autoregression Estimations

VAR has been specified to identify the relationship between the sectoral GDPs and their lags. However, VAR is not stable in predicting the relationship of the sectoral interrelationships as the diagnostic and inference tests revealed. The suspicion is that there can be nonstationary series of GDPs, which affect the prediction. This leads to test for unit roots and adoption of a cointegration analysis.

$$\underset{}{AGDP_t} = \underset{(617.48)}{481.97} + \underset{(0.139)^*}{0.752AGDP_{t-1}} + \underset{(0.154)}{0.011AGDP_{t-2}} + \underset{(0.745)^*}{0.171IGDP} + \underset{(0.867)^*}{0.301IGDP_{t-1}}$$
$$+ \underset{(0.656)^*}{0.215SGDP} - \underset{(0.724)^*}{0.411SGDP_{t-1}}$$

The results of the above model depicted the estimates of the VAR approach under the unstable condition. The post estimations of the VAR model were not stable in forecasting the relationship among the sectoral GDPs. Therefore, the series were tested against the stationary nature using ADF and PP tests of unit roots (Tables 9.3 and 9.4).

Sectoral Interdependencies

Unit root test based on ADF test confirms that the GDP series of the agriculture, industry, and service sectors are difference-stationary $I(1)$ and integrated of order one. Structural change of the series of AGDP, IGDP, and SGDP shows the changes in different time periods from 1950 to 2015. At the outset, causality is checked between agricultural and industrial, and agricultural and service-related GDPs with $I(1)$ of the natural logarithms of each GDP series.

Subsequently, the causality between the sectors is estimated from 1950 to 2015. As depicted in Table 9.6, one-way causality between AGDP and IGDP implies that AGDP in Sri Lanka causes the industrial growth. The pair-wise Granger causality test shows that there is only one-way causality from AGDP to IGDP, but not from IGDP to AGDP. However, the open economic scenario has been addressed with a dummy variable that is used for pre-open and post-open economic scenarios. The selection of the latter period is dictated by the fact that partial economic reforms in the service sector were started in the early 1980s and speeded up during the 1990s. The results obtained from the estimation of equations indicate varying lag lengths in each case. As explained above, optimal lag lengths that minimize the Akaike's Final Prediction Error for testing equation are used for the analysis. The direction of causality is explained along with the F-statistics and their significance at the 5% level in Table 9.5. Our results show that, in a bivariate pair-wise comparison, causality between agricultural growth and service growth is independent from 1950 to 2015, indicating a strong inter-linkage between the sectors in the growth process. Also, when the agriculture sector is linked with both industry and service, results display a statistically significant unidirectional linkage from agricultural to industry at lag 6.

This may be explained by a strong dominance of agriculture during the early years of development. Yet the industrial–manufacturing sector, through increased demand for agricultural inputs such as seeds, fertilizers, machines, and pesticides produced in the manufacturing sector, props up agricultural growth during the early stages of development.

Table 9.5: Granger Causality Results

Regression Analysis	F-value
Δln(*AGDP*) *on* Δln(*SGDP*)	6.1296 (0.0123)***
[Null Hypothesis: AGDP does not Granger Cause SGDP]	
Δln(*SGDP*) *on* Δln(*AGDP*)	5.1867 (0.0030)***
[Null Hypothesis: SGDP does not Granger Cause AGDP]	
Δln(*AGDP*) *on* Δln(*IGDP*)	4.6967 (0.0452)***
[Null Hypothesis: AGDP does not Granger Cause IGDP]	
Δln(*IGDP*) *on* Δln(*AGDP*)	0.4678 (0.0549)
[Null Hypothesis: IGDP does not Granger Cause AGDP]	
Δln(*SGDP*) *on* Δln(*AGDP*)	1.7851 (0.0154)
[Null Hypothesis: SGDP does not Granger Cause IGDP]	
Δln(*IGDP*) *on* Δln(*AGDP*)	18.8534 (0.0865)**
[Null Hypothesis: IGDP does not Granger Cause SGDP]	

log/L = logarithm, AGDP = agricultural gross domestic product, IGDP = industrial gross domestic product, SGDP = service gross domestic product.

* denotes statistical significance at the 10% level, ** denotes statistical significance at the 5% level, and *** denotes statistical significance at the 1% level.

Source: Author's calculations.

Table 9.6: Interdependencies of the Sectoral Gross Domestic Product

Nexus between Inter-sector			Causality
AGDP	→	IGDP	Yes
AGDP	→	SGDP	Yes
IGDP	→	SGDP	Yes
IGDP	→	AGDP	No
SGDP	→	AGDP	Yes
SGDP	→	IGDP	No

AGDP = agricultural gross domestic product, IGDP = industrial gross domestic product, SGDP = service gross domestic product.

Source: Author's calculations.

Long-run Equilibrium

The long-run relationship of the agriculture sector and the other sectors in Sri Lanka has been evaluated using cointegration analysis.

As depicted in Table 9.7, the rate of growth of the sectors is represented in the following specification:

$$\Delta AGDP_t = -0.33 + 1.34\Delta IGDP_t^{***} + 5.80\Delta SGDP_t^{***}$$

The cointegration analysis reveals that a 1% increase in the rate of growth in the service sector results in an increase of 5.80% in the agricultural growth rate. The results can be linked with the existing service sector growth in agricultural trade liberalization provide access to the international market for agricultural goods and facilitating the business environment through credit and service-related economic activities. This implies that the increase in service-related agricultural systems could prop up the agricultural growth in the economy. However, in line with the above results, a 1% increase in industrial growth also increases agricultural growth by 1.34% in Sri Lanka. The basic reason for the agriculture sector's decline is the labor movement from agriculture to the industry and service sectors. In 1963, 52.6% of the labor force worked in the agriculture sector, 9.1% in the industry sector, and 32%

Table 9.7: Gregory–Hansen Test for Cointegration with Regime Shifts

Type	Test Statistics	Date	Asymptotic Critical Values		
			1%	5%	10%
Level					
ADF	−8.22***	2000	−5.44	−4.92	−4.69
Zt	−8.29***	2000	−5.44	−4.92	−4.69
Za	−65.13***	2000	−57.01	−46.98	−42.49
Regime					
ADF	−4.77	1996	−5.97	−5.5	−5.23
Zt	−10.11***	1991	−5.97	−5.5	−5.23
Za	−77.79***	1991	−68.21	−58.33	−52.85
Regime and Trend					
ADF	−11.18***	1991	−6.45	−5.96	−5.72
Zt	−11.28***	1991	−6.45	−5.96	−5.72
Za	−82.88***	1991	−79.65	−68.43	−63.10

* denotes statistical significance at the 10% level, ** denotes statistical significance at the 5% level, and *** denotes statistical significance at the 1% level.

Source: Author's calculations.

in the service sector. In 2000, the agricultural labor force had declined to 34%, while the industrial labor force had increased to 17%, and the service sector labor force had increased to 41%. However, bidirectional causality and a positive relationship between agricultural and service growth imply that service growth is favorable for agricultural growth, which has mutual causality and interdependency in the economy.

Short-term Dynamics

The dynamic nature of sectoral growth can be captured by the error correction model. Given the prediction of VECM, the following specification can be derived from Table 9.8.

$$\Delta AGDP_t = -0.001 + 0.515 AGDP_{t-1}^{***} - 0.882 \Delta AGDP_t^{***} \\ -0.464 \Delta IGDP_t - 2.107 \Delta SGDP_{t-1}^{***}$$

$$\Delta IGDP_t = -0.003 - 0.073 \Delta IGDP_{t-1} + 0.162 \Delta AGDP_t \\ - 0.307 \Delta IGDP_t + 0.673 \Delta SGDP_t$$

$$\Delta SGDP_t = -0.002 + 0.073 SGDP_{t-1}^{***} + 0.179 \Delta AGDP_t^{***} \\ -0.203 \Delta IGDP_t^{***} + 0.573 \Delta SGDP_t^{***}$$

The results show that the underlying rate of growth of agriculture is estimated at 1.6% per year. This implies that the present rate of change in agricultural growth in Sri Lanka is very slow. Cointegration predicts the long-run behavior of sectoral growth: the short-run semi-elasticities are –0.26 and +0.42, implying that a 1% increase in the industrial growth rate retards agricultural growth by 0.26%, while a 1% increase in service growth increases agricultural growth by 0.42%.

Table 9.8: Vector Error Correction Results

		Coefficients	SE	P>|z|
AGDP				
	Ce_I L1	0.515***	0.110	0.000
	AGDP LD2	−0.882***	0.241	0.000
	IGDP LD2	−0.464	0.225	0.069
	SGDP LD2	−2.107***	0.552	0.000
	Cons	0.001	0.011	0.967
IGDP				
	Ce_I L1	−0.073	0.075	0.334
	AGDP LD2	0.162	0.165	0.329
	IGDP LD2	−0.307	0.175	0.080
	SGDP LD2	0.673	0.379	0.067
	Cons	0.003	0.007	0.687
SGDP				
	Ce_I L1	−0.319***	0.047	0.000
	AGDP LD2	0.179**	0.103	0.046
	IGDP LD2	0.203	0.109	0.085
	SGDP LD2	0.573**	0.237	0.016
	Cons	−0.002	0.004	0.763
Adjusted R^2			0.43	
Log Likelihood			313.737	
Akaike Information Criteria (AIC)			–10.059	
HQIC			−9.825	
Schwarz Criteria (SBIC)			−9.460	
Sample (adjusted):			1953–2011	
Included Observations:			59	

SE = Standard Error.

Source: Author's calculations.

9.7 Conclusions and Policy Implications

The growth empirics provide the evidences for policy implications through the quantitative approach of sectoral interdependencies for the revitalization of the sectoral growth. Agriculture sector growth in Sri Lanka is highly dependent on service sector growth, but not on industry sector growth. Both the industry and service sectors are interdependent of agriculture sector growth, which is a driving force behind the country's economics growth. Thus, the policy implementation for an increase in agricultural growth is minimal in Sri Lanka, even after open economics scenario, or at different policy adjustments. Our analysis provides pragmatic evidence of a need to promote service sector-related agricultural systems under the existing production capacity to promote agriculture sector involvement and thereby growth. However, the liberalization of the agricultural market promoting exports and facilitating agricultural services enhances Sri Lanka's economic growth.

It appears from our analysis that Sri Lanka's economy has undergone a structural shift, particularly from the early 1980s when Sri Lanka embarked on a structural adjustment program. A higher rate of growth is observed in the service and industry sectors compared with that in the agriculture sector. Inter-sectoral relationships investigated using the Granger causality test from 1950 to 2007 verify the theoretically recognized causal relationship between agriculture and industry as unidirectional and that between agriculture and services as bidirectional interdependencies. Empirical results, further, support that the two-way linkage between the agriculture and service sectors provides evidence of the need for economic reforms in reviving agriculture–service relationships. Nonetheless, strong evidence of a long-run positive relationship between agricultural growth and service growth suggests that policy reforms related to promotion of the agricultural service sector are beneficial for agricultural growth in the country.

The study points to the benefits of numerous policy actions, such as constructing a national agricultural policy framework; promoting service sector-related agricultural production systems; investing in public agricultural research; agricultural extension services, modernizing technology policies; stabilizing tariff policies; policy reforms in land administration, water, labor, and the commodity market; promoting the commercial private sector; and export market facilitation.

Appendix

Vector Autoregression Post-Estimation Tests

Table A9.1: Eigenvalue Stability Condition

Eigenvalue	Modulus
0.4964 + 0.8792i	1.0097
0.4964 – 0.8792i	1.0097
0.9508	0.9508
0.8087 – 0.1689i	0.8262
0.8895	0.8262
−0.2048	0.2048
0.0481	0.0481

Note: At least one eigenvalue is at least 1.0.
VAR does not Satisfy Stability Condition.
Source: Author's calculations.

Table A9.2: Selection Order Criteria

Lag	LL	LR	P	AIC	HQIC	SBIC
0	−2,012.60			72.0213	72.0774	72.1659
1	−1,667.76	689.68	0.00	60.2770	60.5574	61.0003
2	−1,624.49	86.534*	0.00	59.3032*	59.8080*	60.6052*

Source: Author's calculations.

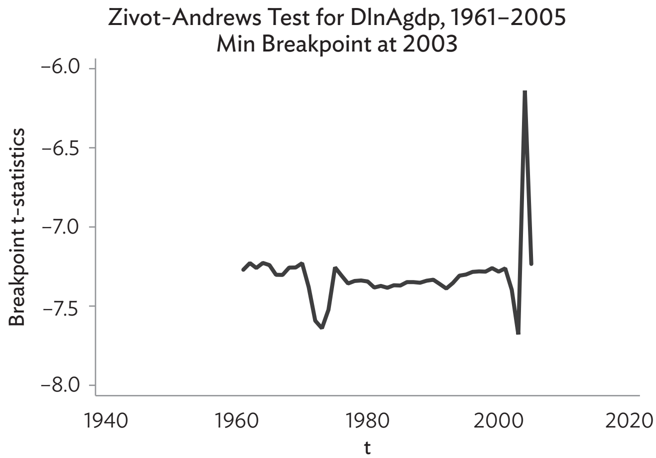
Table A9.3: Normality—Jarque-Bera Test, Skewness Test, Kurtosis Test

Equ	Jarque-Bera Chi^2	p Value	Skewness	P Value	Kurtosis	P Value
0	−2,012.60			72.0213	72.0774	72.1659
1	−1,667.76	689.68	0.00	60.2770	60.5574	61.0003
2	−1,624.49	86.534*	0.00	59.3032*	59.8080*	60.6052*

Source: Author's calculations.

Structural Break of the Series with Zivot–Andrews Test

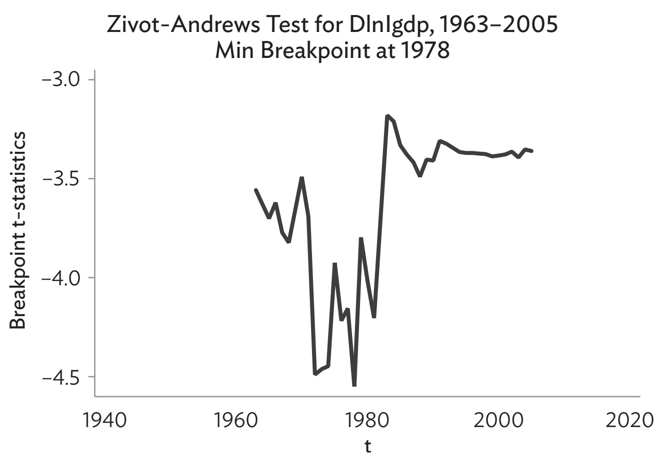
Figure A9.1: Structural Break of Agricultural GDP



GDP = gross domestic product, min = minimum.

Source: Author's calculations.

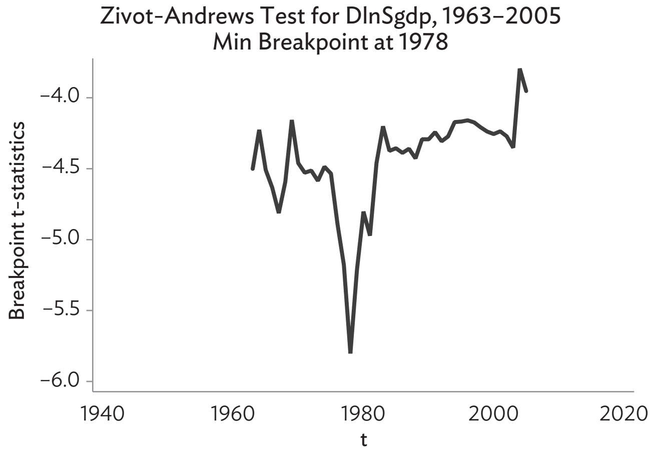
Figure A9.2: Structural Break of Industrial GDP



GDP = gross domestic product, min = minimum.

Source: Author's calculations.

Figure A9.3: Structural Break of Service GDP



GDP = gross domestic product, min = minimum.

Source: Author's calculations.

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10

Structural Transformation and the Dynamics of Income Equality in Indonesia: 1996–2014

Teguh Dartanto, Edith Zheng Wen Yuan, and Yusuf Sofiyandi

10.1 Introduction

Since the 1980s, notwithstanding some setbacks such as the Asian financial crisis of 1997–1998, Indonesia has been remarkably successful at tackling poverty. From 1980 to 2015, socioeconomic conditions in Indonesia improved rapidly. The World Bank reported that Indonesia's per capita gross domestic product (GDP) (in constant 2010 US dollars) jumped from $1,095 (1980) to $3,834 (2015). From 1980 to 2015, a major transformation of the Indonesian economy occurred in terms of the three sectors' relative shares of GDP. The share of agriculture output in GDP declined continuously from 1980, while the share of the industry sector and the service sector increased significantly. This substantial increase in income and the transformation of the Indonesian economy have been accompanied by improvements in social indicators such as a massive decrease in the absolute poverty incidence from 28.60% in 1980 to 11.13% in 2015 in headcount ratios (measured by the national poverty line).

Despite the impressive progress in reducing extreme poverty, growth in Indonesia has not always been inclusive. The rate of poverty reduction has started to slow down with inequality continuing to rise significantly. The Gini coefficient measured by expenditure (consumption) also increased, from roughly 0.33 in 1996 to 0.41 in 2015. Rising inequality can be a catalyst for collective action such as the recent rise in social protests in Indonesia, and thus it may slow down economic growth. Even if social protests or social tensions do not lead to social conflict, rising inequality can increase resistance to a government's economic policy reform and undermine a government's ability to introduce very important reforms needed for economic growth (Coudouel, Dani, and Paternostro 2006).

The structural transformation of the economy affected economic growth and changed employment patterns. Extensive structural change is both a cause and consequence of the exceptionally rapid economic growth that has enabled the region to raise living standards and reduce poverty at historically unprecedented rates (Aizenman, Lee, and Park 2012). However, as the Kuznets hypothesis suggests, the structural transformation to a more market-oriented economy would lead to income inequality. Dastidar (2012) found that in developing countries that undergo structural alteration from the agriculture to service sector, inequality is likely to rise in the process. In the case of Indonesia, De Silva and Sumarto (2013) confirmed that changes in the sectoral composition of growth away from agriculture and toward industry and services, driven in part by increased global integration and rural–urban migration, are thought to be the root causes of rising inequality.

However, looking at the economic transition in the last 2 decades (1996–2015), Indonesia experienced a unique economic transition from agriculture to services, even before the industry sector matured. The share of agriculture output in GDP and employment decreased significantly, while the opposite occurred in the service sector. Surprisingly, the industry sector remained ambiguous as the share of industry sector to GDP fell, from 43.5% in 1996 to 40.0% in 2015, while its employment share increased from 17.35% in 1996 to 20.69% in 2015. This indicates that the industry sector experienced a decline in productivity per worker, as a decrease in its share of GDP was not followed by a decrease in its share of employment.[1] Therefore, this chapter addresses the dynamics of income inequality with respect to structural transformation in Indonesia during 1996–2014.

Using two different approaches—Theil's decomposition approach to observe the static and dynamic changes of inequality, and the econometrics approach—this chapter explores the link between structural transformation and inequality in Indonesia. Inequality decomposition means exploring the structure of inequality, i.e., the disaggregation of total inequality in relevant factors such as rural–urban and sectoral occupation. Theil's T decomposition measures inequality

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1 Due to the limited access of Susenas 2015, this chapter used Susenas 2014. It would be consistent with other macroeconomic data had this chapter used Susenas 2015. But when we wrote this article, the accessible Susenas was 2014.

into "within" and "between" components. Average income may vary from sector to sector that implies "between group" inequality. For policy purposes, decomposition is useful to be able to search the sources of inequality: if most inequality is due to disparities across region (rural and urban), then the policy for tackling inequality should focus on regional economic development, with special attention to helping the poorer regions. Moreover, incomes vary within each sector, adding a "within group" component to total inequality. Moreover, the dynamic decomposition allows us to observe a change in inequality over time that could be separated into four components: pure inequality effect, "within" group allocation effect, "between" group allocation effect and income effect. On the other hand, econometric estimation using provincial data tests statistically whether the relation between structural transformation and growing inequality exists.

The structure of the chapter is as follows. Section 10.2 reviews previous literature that has focused on structural transformation and inequality. Section 10.3 gives a brief overview of the inequality trends and structural changes in Indonesia. Section 10.4 provides details of the method used in this chapter. Section 10.5 scrutinizes the decomposition of inequality within and across sectors as well as estimating econometrically the impact of structural changes on income inequality in Indonesia. Section 10.6 concludes with the important findings.

10.2. Literature Review

Kuznets did one of the earliest pieces of research in economic development, which examined structural transformation and inequality. He argued that as an economy transforms to a more advanced type of economy, market forces first lead to an increase then a decrease in overall economic inequality of a particular society, which is illustrated by the inverted U-shape of the Kuznets curve (Kuznets 1955). Structural change refers to shifts in the relative importance of sectors of the economy on its way to development, including changes in the location of economic activities (urbanization) and other resulting aspects of industrialization (Ibrahim and Ali 2013).

Since his work, research on economic development and its impact on income distribution has been abundant. Some studies demonstrate, even with empirical evidence, the existence of a Kuznets curve in certain countries, whereas some do not. Anand and Kanbur (1993), Deininger and Squire (1998), and Frazer (2006) found no empirical evidence of a Kuznets curve using pooled data from a variety of countries. Specifically, Oyvat (2016) argued that, in Turkey the Kuznetsian argument could be false, as the assumptions made regarding the Kuznets curve do not hold in the Turkish case.

Other researchers suggest the opposite. In Nigeria, Ibrahim and Ali (2013) found that there was a relationship between inequality, poverty, and structural transformation. However, the relationship between inequality and the sluggish structural transformation that occurred in Nigeria as a result of the "Dutch disease" is not significant. Empirical evidence on the effect of structural transformation on inequality was also found for Ivory Coast (Paul 2016). The research found that structural transformation caused changes in the earning ratios between sectors, which, in turn, altered the inequality across sectors. The decomposition of the Gini coefficient showed that inequality within non-agriculture sectors is higher than in agriculture sectors in Ivory Coast.

Ahluwalia (1976), Dastidar (2012), and Cheong and Wu (2014) stressed the significant role of structural changes in driving inequality. Ahluwalia used cross-country data from 60 countries, including 40 developing countries, 14 developed countries, and six socialist countries. The U-shaped relationship is better explained by per capita gross national product than by structural shift variables. But, the results show that the share of agriculture in GDP and the share of the urban population in the total population are both significantly related to the pattern of income inequality, and increasing urbanization may raise the income shares of the lowest income groups.

Dastidar (2012), in his detailed research on different patterns of structural change in developing and developed countries, used panel data from 78 countries over the period from 1980 to 2005. The classic pattern of structural transformation that developed countries experience started from the agriculture sector, moved to the industry sector, and eventually to the service sector. But the experience of developing countries differs in that the service orientation preceded industrialization, whereas in developed nations it followed it. A fixed-panel data regression was used and shows that when the economy moves directly from agriculture to the industry sector, in both developed and developing countries, inequality decreases. However, a high level of initial inequality might prevent the lower middle-income class from reaping the benefits of intersectoral shifts of the economy (e.g., a fall in the share of the agriculture sector and a corresponding rise in the industry sector), and, thus again, it would increase inequality. This is mostly the case for developing countries, i.e., the People's Republic of China (Cheong and Wu 2014). Industrialization in the People's Republic of China has been empirically proven to cause inequality.

The effect of the agriculture–service transition on inequality is different for developing and developed countries. In developing countries, a falling share of agriculture with a corresponding rise in the share of services would raise overall inequality, whereas for developed countries this structural change does not have a significant impact on inequality. While we found differences in the effect of structural transformation on inequality, Aizenmann, Lee, and Park (2012) concluded that each country faces different structural changes and the relative importance of a given structural change differs across countries. They even observed the structural changes in a broader perspective, looking not only at the relative importance of the economy, but also at the non-economic political, social, and cultural spheres. Even structural changes in terms of technological advancement can have different effects on equality, depending on the nature of the technology involved.

10.3. Stylized Facts: Inequality and Structural Changes in Indonesia

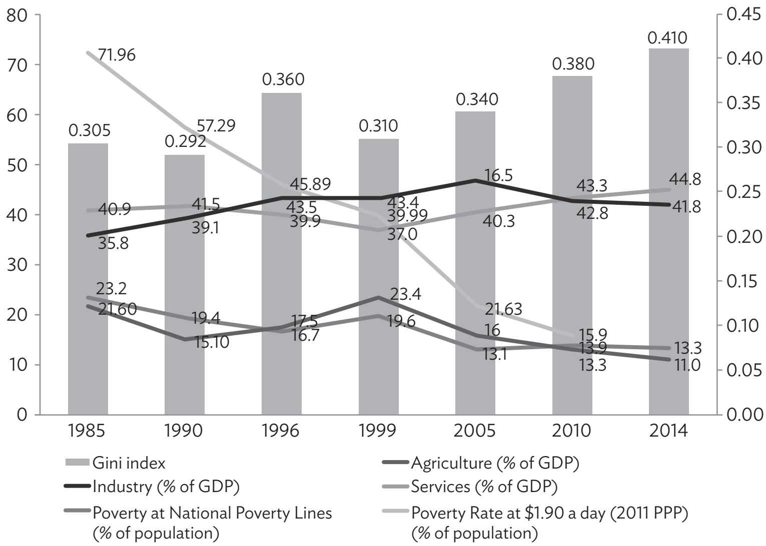
10.3.1 Trends of Poverty, Inequality, and Economic Transformation

Indonesia has been remarkably successful at tackling poverty over the last 30 years, notwithstanding some setbacks, such as the Asian financial crisis of 1997–1998. Improvements in democracy, rapid political and institutional reforms, a combination of proper economic policy packages, and the creation of fair economic institutions have generated substantial and sustained growth and the transformation of the Indonesian economy. These have contributed to large improvements in social welfare, as well as a massive decrease in the incidence of poverty.

The headcount index, measured at the national poverty line, declined from 21.6% in 1985 to 11.13% in 2015, while the headcount ratio of $1.90 per day (purchasing power parity) decreased from 71.96% in 1984 to 15.90% in 2010 (Figure 10.1).[2] Poverty figures, however, fluctuated over

[2] The poverty line in Indonesia is measured by a "basic need" approach (expenditure) rather than an "income" approach. The poverty line consists of a food and non-food poverty line. The food poverty line is calculated based on the minimum nutritional requirement of 2,100 calories/capita/day (National Congress of Nutritionists, 1978) taken from 52 commodities. The non-food poverty line is calculated based on the consumption of essential non-food items, including 51 commodities in the urban area

Figure 10.1: Structural Transformation, Poverty, and Inequality Trends, 1985–2014



GDP = gross domestic product, PPP = purchasing power parity.

Notes: The Gini Index in 1985 is the 1984 figure. Data on the Gini Index from 1996–2014 and the GDP Share of 2010 and 2014 refers to the BPS's publication.

The World Development Indicators category "Industry" includes mining and quarrying, manufacturing, utilities (electricity, gas, and water), and construction.

Source: World Development Indicators and Badan Pusat Statistik (BPS).

time and increased sharply from 17.47% in 1996 to 23.43% in 1999 when the economic crisis hit. Dartanto and Otsubo (2016) observed that the Asian financial crisis in 1997–1998 caused almost 18.5% of non-poor households to fall into poverty. The economic crisis, followed by a massive contraction in both the industry sector and the service sector, hit urban households. The poverty rate in urban areas, where most activities are located, jumped significantly, by around 4.5% compared to the pre-crisis level.

The incidence of poverty in Indonesia appears to have declined significantly, although the rate of the reduction has begun to slow recently. Indonesia follows the same pattern as that of other countries in

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and 47 commodities in the rural area. In 2012, the average monthly money metric of the national poverty line was Rp240,441 ($21) in rural areas and Rp277,382 ($24) in urban areas.

Southeast Asia—a substantial decrease in poverty has been accompanied by increases in the Gini index, particularly during 1996–2014. Similar to poverty figures, income inequality has fluctuated over time. From 1996–1999, inequality dropped slightly from 0.36 to 0.31 due to the Asian financial crisis that hit high-income households and reduced the income gap (Dartanto and Otsubo 2016). Economic recovery after the crisis initiated a growing inequality in Indonesia as the welfare of the rich grows faster than that of the poor. From 2005 to 2014, inequality increased sharply from 0.36 to 0.41 (Figure 10.1).

An increase in inequality is probably a consequence of structural transformation in the Indonesian economy. The economy has moved to more service-oriented sectors before the manufacturing and industry sectors (manufacturing plus mining, utilities, and construction) have matured. Figure 10.1 shows that the trend of the Gini coefficient and the share of the agriculture sector to GDP are moving in opposite directions, while the Gini coefficient and the share of the service sector in GDP are moving in a similar direction. Capital-intensive and skill-intensive sectors such as finance and telecommunications employ fewer people and thus deprive the poor and unskilled labor force of the benefits that result from a rising economy. De Silva and Sumarto (2013) confirmed that the root causes of rising inequality are rural–urban migration, together with changes in the sectoral composition of growth away from agriculture and toward industry and services.

Another measure of inequality (adjusted Palma Ratio) is the ratio of the income share of the lowest 10% and the income share held by the highest 10%.[3] Table 10.1 shows that the income ratio of the highest 10% and the lowest 10% increased continuously from 1985 to 2014, which means a wider income gap between the richest and the poorest. In 1996, the richest had six times more income than the poorest, while in 2014 the richest had 10 times more income than the poorest. The richest 10% of Indonesians accounted for 32.4% and the richest 20% for 47.8% of income in 2014. The wider income gap can lead to social tensions or protests, possibly resulting in social conflict. These numbers indicate a huge concentration of wealth with a small elite.

This income distribution gap is estimated to widen in the foreseeable future. Even when social protests or social tensions do not lead to social conflict, rising inequality can increase resistance to government economic policy reforms and undermine a government's ability to introduce important reforms needed for economic growth (Coudouel, Dani, and Paternostro 2006).

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3 This is an adjusted Palma Ratio. Palma Ratio is the richest 10% of the population's share of gross national income (GNI) divided by the poorest 40%'s share.

Table 10.1: Inequality Trends in Indonesia

Description	Unit	1984	1990	1996	1999	2005	2010	2014
Gini index		0.305	0.2920	0.3130	0.290	0.3400	0.380	0.410
Income share held by lowest 10%	%	3.740	4.170	4.000	4.250	3.670	3.360	3.040
Income share held by lowest 20%	%	8.680	9.390	9.010	9.580	8.340	7.630	7.040
Income share held by highest 20%	%	39.460	38.900	40.710	38.880	42.760	43.650	47.760
Income share held by highest 10%	%	24.910	24.680	26.570	25.080	28.510	28.180	32.410
Ratio of the highest 10% and the lowest 10%		6.660	5.920	6.640	5.900	7.770	8.390	10.670
Ratio of the highest 20% and the lowest 20%		4.550	4.140	4.520	5.130	5.720	6.320	6.780

Source: World Development Indicators and Badan Pusat Statistik (BPS).

10.3.2 Structural Transformation: Sector of Occupation, Employment Status, and Urban–Rural Population

Many countries, including Indonesia, have witnessed tremendous economic growth accompanied by structural transformation. The most visible pattern of structural transformation is the changing trends of sectoral GDP. As we see in Table 10.2, there is undoubtedly structural change in Indonesia, with a growing service sector and a shrinking agriculture sector.

Indonesia saw robust economic growth from 1996 to 2015, with an almost two-fold GDP per capita increase, even though the GDP growth rate slowed moderately from 7.6% in 1996 to 4.8% in 2015. While the industry sector expanded very strongly from 1985 to 2005, with its share of GDP growing from 35.85% to 46.54%, in the latter part of this period its contribution to the economy fell as its growth continued to drop and its share decreased from 2005 to 2015. Its share of employment increased moderately, however, from 17.35% in 1996 to 20.69% in 2015.

The agriculture sector showed decreasing trends, both in its share of GDP and its share of employment, from 23.21% of GDP (1985) to 13.52% (2015), and from 54.36% of employment (1985) to 34.03% (2015). The service industry, on the other hand, shows an increasing trend, reflecting its growing importance in the economy. It was only 29.73%

Table 10.2: Sectoral Gross Domestic Product and Employment

Indicators	Unit	1985	1996	2005	2015
GDP (constant 2010)	$ billion	212.5	471.4	571.2	942.3
GDP per capita (constant 2010)	$	1,288	2,358	2,525	3,703
Sectoral composition of GDP					
Agriculture, value added	% of GDP	23.21	16.7	13.13	13.52
Industry, value added	% of GDP	35.85	43.5	46.54	39.92
Service etc., value added	% of GDP	40.94	39.9	40.33	46.56
GDP growth rate	%	3.48	7.6	5.69	4.8
Per capita GDP growth rate	%	1.38	6	4.19	3.5
Sectoral growth of GDP					
Agriculture, yearly growth	%	4.25	3.1	2.72	4
Industry, yearly growth	%	11.19	10.7	4.60	2.7
Service etc., yearly growth	%	4.45	NA	7.87	NA
Sectoral composition of employment					
Agriculture	% of employment	54.36	44.27	44.93	34.03
Industry	% of employment	8.24	17.35	17.79	20.69
Service, etc.	% of employment	29.73	38.37	37.28	45.29

GDP = gross domestic product, NA = not available.

Source: World Development Indicators and Badan Pusat Statistik (BPS).

of the labor force in the service sector in 1985, and it swelled to 45.29% in 2015.

Aizenmann, Lee, and Park (2012) argued that there is considerable interaction between different kinds of structural changes, which makes it unproductive to think of each structural change in isolation. Economic sectoral transformation inevitably affects employment, hence the evidence of rural–urban migration and the increasing importance of the formal, rather than the informal, sector.

In line with the structural transformation, which reduced the importance of the agriculture sector, Table 10.3 shows that the rural population decreased significantly, from 74% in 1985 to 46% in 2014. From a poverty perspective, poverty in rural areas is significantly higher (3%) than in urban centers. Fortunately, rural poverty decreased in the last decade from 16.0% in 2005 to 11.3% in 2014. And, as more of the labor force leaves agriculture and moves to the industry and service sectors,

Table 10.3: Rural Development and the Informal Sector

Description	Unit	1985	1996	2005	2014
Urban–rural development					
Rural population	% of population	74	63.0	54.0	47.0
Rural poverty: headcount ratio at national poverty lines	% of rural population	NA	23.4*	16.0	11.3
Urban poverty: headcount ratio at national poverty lines	% of urban population	NA	19.4*	11.7	8.3
Informal sector					
Informal employment	million workers	NA	NA	65.69	69.37
Informal employment	% of employment	NA	NA	69.54	59.6

NA = not available.

Note: *1999 figures.

Informal employment is estimated by referring to the procedures of the Badan Pusat Statistik (BPS), the Central Statistical Agency, on informality proxy, which count the following employment statuses: the self-employed, the self-employed assisted by family or temporary workers, agriculture freelance workers, non-agriculture freelance workers, and unpaid workers.

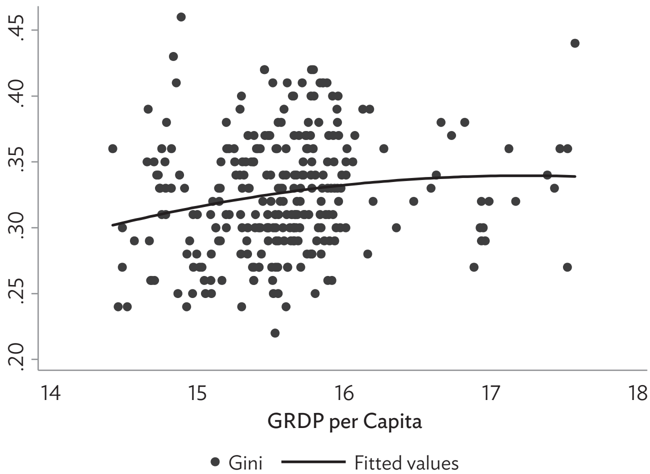
Source: World Development Indicators and Badan Pusat Statistik (BPS), and some figures are the authors' estimation.

more labor moves into formal employment. The informal sector's share in employment fell from 69.54% in 2005 to 59.6% in 2014.

The structural changes in Indonesia, that resulted in the shift away from agriculture and services, as well as the manufacturing sector becoming the main sector of the economy, are undoubtedly associated with the changes in rural–urban population migration and informal–formal labor migration. As the economy moves away from the agriculture sector, the labor force is leaving the informal sector and migrating to urban areas, entering the industry and service sectors of the economy. This shift has been taking place in Indonesia over the past 2 decades. However, despite the growing economy and the structural transformation that accompanies it, Indonesia has also experienced growing inequality (Figure 10.1).

Figure 10.2 shows the well-known "Kuznets curve," which illustrates how inequality increases in the early stages of development (as measured in per capita income) until it reaches an income level beyond which the inequality starts to decline. Figure 10.2 confirms this conjecture (as depicted by the inverted U-curve), albeit not very strongly. Some provinces that have passed the maximum threshold may accelerate economic growth without increasing income inequality. A

Figure 10.2: The Relationship between Income per Capita (Gross Regional Domestic Product) and the Gini Index



GRDP = gross regional domestic product.

Source: Authors' estimation.

possible explanation for the inverted U-curve is that some provinces are moving into more service-oriented economies and capital-intensive sectors—such as mining, financial, and telecommunications—that create fewer job opportunities, particularly for unskilled labor. This deprives the poor of benefiting from a rising economy. However, a substantial increase in income will encourage a significant increase in educational attainments and human capital. These enable more people to benefit and actively participate in the development process that will lead to a reduction in inequality.

10.4. Research Methodology

This chapter uses two approaches—a non-parametric (decomposition) approach and a parametric (panel of data analysis) approach to assess the relationship between structural transformation and the growing inequality in Indonesia. Decomposition, both static and dynamic, aims to see whether changes in inequality can be explained by changes in the composition of the subgroups, while econometric analysis at the provincial level intends to confirm statistically whether the change of economic structure is closely related to the increases in inequality in Indonesia.

10.4.1 Gini Coefficient

The most frequently used income-distribution measurement is the Gini coefficient, or Gini index. The Gini coefficient is derived from the Lorenz curve, which sorts the population from the poorest to the richest, and shows the cumulative proportion of the population on the horizontal axis *x* and the cumulative proportion of income on the vertical axis *y*. A perfect 45-degree diagonal line is drawn above the Lorenz curve, representing perfect equality. The Gini coefficient is defined as the ratio of the area below the diagonal line and above the Lorenz curve to the formed triangle area on the right side of the Lorenz curve.

Let x_i be a point on the x-axis and y_i a point on the y-axis. Then,

$$Gini = 1 - \sum_{i=1}^{N} (x_i - x_{i-1})(y_i + y_{i-1}) \qquad (1)$$

As the Lorenz curve approaches the diagonal line (which represents perfect equality) the numerator area becomes smaller, thus decreasing the Gini coefficient. Conversely, when the Lorenz curve moves away from the diagonal line, the Gini coefficient increases. A high Gini coefficient thus implies deep inequality, and a low Gini coefficient implies a more equal society. Equation 1 also implies that the Gini ratio ranges from 0 to 1, with 0 being perfect equality. The main drawback of the Gini coefficient is that it is not easily decomposable or additive across groups. That is, the sum of the Gini coefficient of its subgroup, is not equal to the total Gini of society.

10.4.2 Static and Dynamic Decomposition of Theil's Index

The most commonly used decomposable of inequality measurements are Theil indexes and the Mean Log Deviation (MLD) (Haughton and Khandker 2009). Both belong to the family of generalized entropy (GE) inequality measures. Equation 2 gives the general formula:

$$GE(\alpha) = \frac{1}{\alpha(\alpha - 1)} \left[\frac{1}{n} \sum_{i=1}^{N} \left(\frac{y_i}{\bar{y}} \right)^{\alpha} - 1 \right] \qquad (2)$$

where $\bar{y}$ is the mean income per person (or expenditure per capita); n is the population number; and α in the GE class represents the weight given to distances between incomes at different parts of the income distribution and can take any real value number. Setting $\alpha = 0$ we can have GE(0), which is also known as Theil's L or MLD.

MLD or Theil's L is often used to decompose the inequality within or between groups. In addition to common decomposition of static inequality, which is decomposing the inequality index at one period (static), MLD also allows us to decompose the change of inequality index for different periods (dynamic). The MLD index of the population is measured using Equation 3 where n is the aggregate of individuals or households and μ is the average of individual income. We denote y_i as the income of the ith individual or household.

$$I_0 = \frac{1}{n}\sum_{i=1}^{n}\log\left(\frac{\mu}{y_i}\right) \qquad (3)$$

Decomposition of inequality breaks down the inequality measure into two components: the unexplained component or "within group" inequality, and the explained component or "between group" inequality. A moderately simple mathematical derivation is used to derive Equation 3 to decompose the inequality index. A population with m subgroups, with each subgroup containing k number of individuals with an average income of μ_k within the subgroups, will have a I_0 value of:

$$I_0 = \sum_{k=1}^{m}\frac{n_k}{n}I_0^k + \sum_{k=1}^{m}\frac{\mathrm{n_k}}{n}\log\frac{\mu}{\mu_k} \qquad (4)$$

with y_{kj} as income of j^{th} individual in k^{th} subgroup.

The first component, $\sum_{k=1}^{m}\frac{n_k}{n}I_0^k$, measures the "within subgroups" inequality, which is the weighted average of inequality in each subgroup, with the population proportion of the subgroup as the weight. A subgroup with a high inequality level will contribute more to population inequality. The second component, $\sum_{k=1}^{m}\frac{n_k}{n}\log\frac{\mu}{\mu_k}$, measures the income inequality in the "between subgroups," which is the weighted average of the subgroup's average income deviation from the population income average. Subgroups with higher inequality than the average will positively affect the inequality index (increasing the total inequality), while large population subgroups with lower inequality will negatively affect the index.

Equation 4, the static decomposition, decomposes the inequality index of a population at one period, within and between the subgroups. A dynamic analysis, however, requires observing the decomposition of the income distribution changes. Starting from the basic alteration of Equation 4 to a dynamic equation, which can be rewritten as:

$$\Delta I_0 = \Delta I_w + \Delta I_B = \Delta\left(\sum_{k=1}^{m} v_k I_0^k\right) - \Delta\left(\sum_{k=1}^{m} v_k \log \lambda_k\right) \qquad (5)$$

with $v_k = \frac{n_k}{n}$ being the subgroup k's population proportion to the total population, and $\lambda_k = \frac{\mu_k}{\mu}$, being the ratio between the average income of subgroup k to the average income of the total population. Furthermore, by using Equation 5, we can derive a new equation:[4]

$$\Delta I_0 \cong \sum_{k=1}^{m} \overline{v_k} \Delta I_0^k + \sum_{k=1}^{m} \overline{I_0^k} \Delta v_k + \sum_{k=1}^{m} (\overline{\lambda_k} - \overline{\log \lambda_k}) \Delta v_k$$
$$+ \sum_{k=1}^{m} (\overline{\theta_k} - \overline{v_k}) \Delta \log \mu_k \qquad (6)$$

Macro variables such as $\overline{v_k}$, $\overline{I_0^k}$, $\overline{\lambda_k}$ and $\overline{\theta_k}$ use the average value of the initial and final period of each variable, with $\theta_k = v_k \lambda_k$. A positive value of a component increases the divergence of income, while a negative value reduces the divergences of income.

The first component in Equation 6, $\sum_{k=1}^{m} \overline{v_k} \Delta I_0^k$, shows the pure inequality or unexplained effect. The second component, $\sum_{k=1}^{m} \overline{I_0^k} \Delta v_k$, is the allocation effect on the "within" group, while the third component, $\sum_{k=1}^{m} (\overline{\lambda_k} - \overline{\log \lambda_k}) \Delta v_k$, is the allocation effect on the "between" group, which can be either positive or negative, depending solely on Δv_k, since the values of $\overline{I_0^k}$ and $(\overline{\lambda_k} - \overline{\log \lambda_k})$ are always positive. Lastly, the fourth component is the income effect, which measures the effect of changes in average income across the group. The value of the coefficient, $\overline{\theta_k} - \overline{v_k}$, depends on whether there are individuals in the subgroup who have incomes that are higher than average. If the rich group raises its average income, the inequality will increase. On the other hand, if the income average of the poor group increases, the inequality will decrease.

10.4.3 Econometrics Model

In estimating the empirical relation between income inequality and structural change, we combined and modified the models of Dastidar (2012), and Dartanto and Patunru (2016). Dastidar sought to capture

[4] For a detailed derivation, see Mockherjee and Shorrocks (1982).

the impact on inequality of the agriculture–industry transition and the agriculture–service transition, while Dartanto and Patunru built econometric models to capture the relationships reflected in the Poverty–Growth–Inequality Triangle. To capture structural transformation, our proposed model includes the sectoral output share variables to capture the effect of alternate patterns of structural change in inequality (Dastidar 2012). This study categorizes the economy into three sectors: agriculture, industry (including mining, manufacturing, utilities, and construction), and services. We also accommodate growth and poverty as explanatory variables to capture the poverty–growth–inequality triangle as many researchers also found that Gini is influenced by growth and poverty (Chen and Ravallion 1997; Easterly 1999; Dollar and Kraay 2002). This study also includes control variables for foreign direct investment (FDI), gross enrollment ratio, and government investment in infrastructure and human capital. The econometric model, then, is as follows:[5]

$$G_{it} = \alpha_i + \beta_1.X_{AGRit} + \beta_2.X_{SER\ (or\ IND)it)} + \beta_3 g_{it} + + \beta_4 pov_{it} + \delta.control_{it} + \varepsilon_{it} \quad (7)$$

where,

G	= the Gini coefficient;
X_{AGR}	= the share of agriculture in aggregate output (%);
X_{IND}	= the share of the industry sector in aggregate output (%);
X_{SVC}	= the share of the service sector in aggregate output (%);
g	= economic growth;
pov	= poverty rate;
control	= control variables, including gross participation rate of high school, FDI (in logarithm), share of infrastructure expenditure to total government expenditure, share of human capital expenditure (health and education) to total government expenditure;
i	= province, i = 1,..., 34;
t	= year t = 2000, 2001, . . . , 2013.

5 Dastidar (2012) explained that, in Equation 7, if the share of service sector in aggregate output is not included in the equation, then β_1 will be the effects of change in the share of the agriculture sector, in place of the service sector, while holding the industry sector constant. On the other hand, in Equation 7, the share of industry sector is not included in the model, which will alter the interpretation of the agriculture–industry transition. The β_1 in the second model will show the effects of increase (decrease) of the agriculture share in place of the decrease (increase) of the industrial share, while holding the service share constant.

The econometric model is estimated using a panel data set. The data include 33 provinces in Indonesia with an unequal number of observations over time for each province from 2000–2013. Most of data are taken from the latest publication of Badan Pusat Statistik (BPS), Indonesia's central statistics bureau, and datasets from the Indonesia Database for Policy and Economic Research (INDO–DAPOER) World Bank.

10.5 Results and Analysis of Structural Transformation and Inequality Decomposition

10.5.1 Static Decomposition

The decomposition of the MLD in this chapter is based on five kinds of partition: sector of occupation (agriculture, industry, and service), location (urban and rural), and employment status (formal and informal) education, and household size. The sectoral shifts in Indonesia, as in other developing countries, have jumped from the agriculture sector to the service sector, without the maturity of the industry sector. Table 10.4 shows that the share of population in the service sector increased significantly, although the industrial sector experienced a very slow growth during the last 2 decades from 16.80% (1996) to 19.72% (2015).

From 1996 to 2014, the average income in the agriculture sector was always lower than in the other sectors, which is in line with the low average income in rural, relative to urban, areas. However, the relative income shows that there was convergence among sectors, locations, and employment statuses, as the relative income of those working in the service sector, urban areas, and in formal sectors decreased.[6] The relative income in the service and industry sectors decreased from 2005 to 2014. On the other hand, the relative income of those working in the agriculture sector fell compared to the average income of society. This means that this group has not benefited much from the progress of economic development.

Decomposition of the Theil's L (MLD) and Gini Index results supports the hypotheses of Dastidar (2012) and Paul (2016), under which inequality in the agriculture sector remains lower than in the other sectors, even after structural transformation has taken place. Inequality in the service sector, as measured by the MLD and Gini index, remained high from 1996 to 2014.

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6 Convergence means that the relative income is close to 1.

Table 10.4: Descriptive Analysis of Subgroup Partition

	Population Share			Mean Income (1996 = 100)			Relative Income			Theil's Inequality			Gini Index		
	1996	2005	2014	1996	2005	2014	1996	2005	2014	1996	2005	2014	1996	2005	2014
Sector of Occupation															
Agriculture	45.37	53.75	32.38	45,844	68,196	155,869	0.68	0.80	0.68	0.127	0.192	0.168	0.276	0.340	0.322
Industry	16.80	22.69	19.72	77,696	100,029	227,724	1.16	1.17	1.00	0.271	0.238	0.261	0.407	0.381	0.400
Services	37.83	23.56	47.90	87,967	110,118	278,473	1.31	1.29	1.22	0.274	0.263	0.283	0.406	0.399	0.415
Employment Status															
Informal	63.78	68.23	64.67	56,689	72,575	193,994	0.84	0.85	0.85	0.198	0.197	0.238	0.345	0.347	0.382
Formal	36.22	31.77	35.33	85,515	112,614	292,443	1.27	1.32	1.28	0.294	0.273	0.277	0.422	0.406	0.411
Location															
Rural	66.17	56.67	50.14	49,511	60,903	167,844	0.74	0.71	0.73	0.139	0.138	0.171	0.291	0.291	0.325
Urban	33.83	43.33	49.86	101,591	117,202	290,052	1.51	1.37	1.27	0.294	0.258	0.299	0.420	0.395	0.425
Completed Education															
Not completed Formal Education	39.31	29.56	21.93	48,681	60,421	229,436	0.73	0.71	1.00	0.153	0.139	0.263	0.303	0.291	0.401
Compulsory (SD–SMP)	42.29	46.26	53.75	63,320	71,371	184,161	0.94	0.84	0.81	0.212	0.162	0.191	0.356	0.315	0.344
Secondary (SMA)	14.41	18.43	8.23	103,168	121,754	280,918	1.54	1.43	1.23	0.241	0.220	0.222	0.381	0.365	0.368
Tertiary (University)	3.99	5.75	16.10	159,108	208,227	349,337	2.37	2.44	1.53	0.347	0.337	0.400	0.454	0.448	0.482
Household Size															
<=2 HH Member	14.72	18.51	19.69	103,563	120,388	318,852	1.54	1.41	1.39	0.321	0.278	0.295	0.442	0.411	0.421
>2–<=5 HH Member	61.39	65.20	66.64	64,437	80,334	213,686	0.96	0.94	0.93	0.213	0.206	0.239	0.360	0.355	0.383
> 5 HH Member	23.89	16.29	13.67	51,607	65,276	172,537	0.77	0.77	0.75	0.212	0.236	0.263	0.358	0.379	0.402
Total	**100**	**100**	**100**	**67,129**	**85,295**	**228,772**	**1.00**	**1.00**	**1.00**	**0.253**	**0.243**	**0.272**	**0.391**	**0.385**	**0.408**

HH = household, SD = *Sekolah Dasar*/Primary School, SMP = *Sekolah Menengah Pertama*/Junior High School, SMA = *Sekolah Menengah Atas*/Senior High School.

Note: the relative income is the sectoral income divided by the average income.

Source: Authors' calculations using the National Socioeconomic Survey (SUSENAS) Dataset (1996, 2005, and 2014).

There have been two different patterns of inequality in Indonesia. In the period 1996–2005, both industry and service sectors, as well as households living in urban areas, experienced decreasing inequality, while the agriculture sector and those living in rural areas experienced a decrease in inequality measured by both the Theil index and the Gini Index.

The period 2005–2014 saw an opposite pattern of inequality because the Asian financial crisis, which hit high-income households mainly located in urban areas, reduced the income gap. On the other hand, the rupiah's depreciation during the crisis benefited export-oriented farmers, mostly located outside Java. Consequently, the agriculture sector experienced an increase in inequality. Economic recovery after the crisis initiated a growing inequality in Indonesia since the welfare of the rich (the urban and capital-intensive sector) has grown at a higher rate than that of the poor (the rural and agriculture sector).

The trend in inequality within the rural and urban areas is completely different to that discussed by Oyvat (2016) in Turkey. The Theil's L index and the Gini index show that inequality in urban areas is greater than in rural areas in Indonesia, which is in line with Kuznets' 1955 hypothesis. However, the results also show the growing disparity of income within each area. Similar trends are also found among formal and informal employees. While the formal sector has more inequality than the informal sector, each sector's "within" inequality has been increasing since 2005.

The decomposition of the Theil's L index in Table 10.5 shows that inequality within sectoral groups has been increasing rapidly because more labor moves from the agriculture sector—the sector with the least inequality—to the service and industry sectors, which have higher inequalities. This movement is in line with the decrease of "between sectoral" inequality. Kuznets (1955) argued that inequality between the agriculture and non-agriculture sectors should increase as the economy develops based on the assumption of perfect industrialization. In Indonesia's case, however, it did not happen because the economy jumped from the agriculture to the service sector, which led to an imperfect industrialization. Table 10.5 confirms that the structural transformation from the agriculture sector to either the industry or service sectors over the last 2 decades are not the main driver to the increased inequality in Indonesia, as the ratio of the "between" group is only around 18% (1996), 10% (2005), and 11% (2014).

As we have seen, Indonesia has witnessed a rather rapid urbanization, especially in the last 2 decades. "Within" location inequality also shows an increasing trend. Migration from rural to urban areas increases inequality because it has created an unequal proportion of the population.

Table 10.5: Static Decomposition of Theil's L

	Year			Change	
Partition	1996	2005	2014	1996–2005	2005–2014
Sector of Occupation					
Within group (Iw)	0.207	0.219	0.241	0.013	0.022
Between group (Ib)	0.046	0.024	0.031	–0.022	0.007
Theil index (I_0)	0.253	0.243	0.272	–0.010	0.029
Ratio (Ib/I_0) in %	18.290	9.840	11.390	–8.450	1.550
Employment Status					
Within group (Iw)	0.233	0.221	0.252	–0.011	0.031
Between group (Ib)	0.020	0.022	0.020	0.002	–0.002
Theil index (I_0)	0.253	0.243	0.272	–0.010	0.029
Ratio (Ib/I_0) in %	7.970	9.010	7.320	1.040	–1.690
Location					
Within group (Iw)	0.191	0.190	0.235	–0.001	0.045
Between group (Ib)	0.061	0.053	0.037	–0.008	–0.016
Theil index (I_0)	0.253	0.243	0.272	–0.010	0.029
Ratio (Ib/I_0) in %	24.240	21.880	13.600	–2.360	–8.280
Educational Attainment					
Within group (Iw)	0.198	0.176	0.246	–0.022	0.071
Between group (Ib)	0.055	0.067	0.025	0.013	–0.042
Theil index (I_0)	0.253	0.243	0.272	–0.010	0.029
Ratio (Ib/I_0) in %	21.630	27.710	9.370	6.090	–18.350
Household Member					
Within group (Iw)	0.229	0.224	0.253	–0.004	0.029
Between group (Ib)	0.024	0.019	0.019	–0.005	0.000
Theil index (I_0)	0.253	0.243	0.272	–0.010	0.029
Ratio (Ib/I_0) in %	9.560	7.760	6.860	–1.800	–0.900

Ib = "Theil's L index Between" group, lw = "Theil's L index Within" group.

Notes: The authors would like to thank Ananda Dellina who helped to create the Excel calculations of dynamic decomposition.

Source: Authors' calculations using the National Socioeconomic Survey (SUSENAS) Dataset (1996, 2005, and 2014).

One possible reason for the increasing "within" location inequality and thus decreasing "between" location inequality during the last 2 decades could be that the new labor arrivals from the rural to urban areas have entered the urban informal sector, in which average incomes are lower than the urban modern sector. This is confirmed by the increasing inequality within the informal sector during the last decade.

Among the partitions, location, educational attainment, and sectoral occupation are the most important factors to explain inequality, although their importance is declining. In 1996, "between" location inequality contributed up to 24.24% of total inequality, compared to the "between" sectoral inequality, which only accounted for 18.29%. However, in 2014, urban–rural inequality decreased to only 13.60%, compared to sectoral inequality of 10.48%, and employment inequality of 7.32%. Therefore, the static decomposition suggests that most inequality is due to disparities across regions (rural and urban), and therefore the policy for tackling inequality should focus on regional economic development, with special attention to helping villages.

This decomposition also confirms that both sectoral occupation and educational attainment could explain the sources of inequality in Indonesia. During the last decade, improving access to education, as shown by a decrease—from almost 40% in 1996 to around 22% in 2014—in the numbers of household heads without formal education, has reduced "between" group inequality in Indonesia. Results from the static decomposition suggest that occupation, location, and education are the three factors to which the government should pay attention to tackle inequality in Indonesia.

10.5.2 Dynamic Decomposition

Table 10.6 shows the decomposition of inequality changes from the 2 decades of 1996–2014 and from the decade of 2005–2014. Increases in inequality of as much as 0.019 (Theil's Index) or 0.017 (Gini Index) from 1996–2014 are mostly due to the pure inequality effect (unexplained effect), if we consider occupational sectors, i.e., agriculture, industry, and service, as the partition. Although inequality within the industry sector decreases, as can be observed by a decrease in the pure inequality in industry (negative 0.0017), inequality within the agriculture and service sector still increases. The negative sign of the "within sectoral" income effect during 1996–2014 suggests that the income of the subgroup has converged; however, effects from the income effect are outweighed by the effects of the increase in pure inequality, thus increasing overall inequality. A closer look reveals that the greatest contributor to the increase in income inequality during 1996–2014 was the fast growth of

Table 10.6: Structural Transformation and Dynamic Decomposition of Income Inequality

Partition	Pure Inequality	Allocation Effect on "Within Group" Component	Allocation Effect on "Between Group" Component	Income Effect
Period of 1996–2014 (Δ Theil = –0.019)				
Sectoral Occupation (Total)	0.020	0.017	–0.005	–0.010
Agriculture	0.017	–0.019	–0.138	–0.314
Industry	–0.003	0.008	0.029	0.032
Service	0.005	0.028	0.104	0.272
Location (Total)	0.022	0.022	0.004	–0.026
Rural	0.019	–0.025	–0.167	–0.389
Urban	0.003	0.047	0.171	0.363
Employment Status (Total)	0.022	–0.001	0.000	0.000
Informal	0.027	0.002	0.009	–0.251
Formal	–0.005	–0.003	–0.009	0.251
Educational Attainment (Total)	0.037	0.013	0.023	–0.046
Not Completed	0.041	–0.010	–0.050	–0.153
Compulsory (SD–SMP)	–0.007	0.006	0.029	–0.135
Secondary (SMA)	–0.002	–0.017	–0.080	0.109
Tertiary (University)	0.005	0.035	0.124	0.132
Household Size (Total)	0.024	0.003	0.001	–0.006
<=2 HH Member	–0.004	0.015	0.054	0.192
>2–<=5 HH Member	0.018	0.012	0.053	–0.087
> 5 HH Member	0.010	–0.024	–0.106	–0.112
Period of 1996–2005 (Δ Theil = –0.009)				
Sectoral Occupation (Total)	0.024	–0.010	–0.001	–0.021
Agriculture	0.033	0.013	0.087	–0.200
Industry	–0.007	0.015	0.060	0.048
Service	–0.002	–0.038	–0.148	0.131
Location (Total)	–0.013	0.013	0.003	–0.011
Rural	–0.001	–0.013	–0.099	–0.234
Urban	–0.013	0.026	0.102	0.223
Employment Status (Total)	–0.006	–0.004	–0.001	0.003
Informal	0.001	0.009	0.045	–0.144
Formal	–0.006	–0.013	–0.046	0.147

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Table 10.6 *continued*

Partition	Pure Inequality	Allocation Effect on "Within Group" Component	Allocation Effect on "Between Group" Component	Income Effect
Educational Attainment (Total)	–0.029	0.008	0.008	0.005
Not Completed	–0.005	–0.014	–0.102	–0.136
Compulsory (SD–SMP)	–0.020	0.007	0.040	–0.066
Secondary (SMA)	–0.004	0.009	0.044	0.106
Tertiary (University)	0.000	0.006	0.027	0.100
Household Size (Total)	–0.004	0.002	0.001	–0.006
<=2 HH Member	–0.007	0.011	0.041	0.105
>2–<=5 HH Member	–0.003	0.008	0.038	–0.045
> 5 HH Member	0.006	–0.017	–0.078	–0.067
Period of 2005–2014 (Δ Theil = 0.029)				
Sectoral Occupation (Total)	0.001	0.021	–0.003	0.009
Agriculture	–0.010	–0.039	–0.223	–0.100
Industry	0.004	–0.007	–0.030	0.018
Service	0.007	0.066	0.250	0.091
Location (Total)	0.037	0.008	0.000	–0.016
Rural	0.018	–0.010	–0.068	–0.168
Urban	0.019	0.018	0.068	0.152
Employment Status (Total)	0.029	0.002	0.001	–0.003
Informal	0.027	–0.008	–0.036	–0.111
Formal	0.002	0.010	0.037	0.108
Educational Attainment (Total)	0.060	0.011	0.021	–0.055
Not Completed	0.040	0.010	0.050	–0.062
Compulsory (SD–SMP)	0.014	–0.002	–0.012	–0.088
Secondary (SMA)	0.000	–0.026	–0.121	0.045
Tertiary (University)	0.006	0.029	0.103	0.049
Household Size (Total)	0.029	0.000	0.000	0.000
<=2 HH Member	0.003	0.003	0.013	0.084
>2–<=5 HH Member	0.022	0.003	0.014	–0.045
> 5 HH Member	0.004	–0.007	–0.027	–0.039

SD = Sekolah Dasar/Primary School, SMP = *Sekolah Menengah Pertama*/Junior High School, SMA = *Sekolah Menengah Atas*/Senior High School, HH = household.

Source: Authors' estimation using the National Socioeconomic Survey (SUSENAS) Dataset (1996, 2005, and 2014).

the service sector in which all components of dynamic decomposition have a positive value. While the economic transition from agriculture to other sectors in the economy has contributed to a decrease in equality, this contribution has been cancelled out by the increasing inequality in both the industry and service sectors.

If we consider a real partition, rural–urban population shifts contribute most to the increases in inequality, accounting for 0.0226 of the changes in inequality. The population shifts from rural to urban areas have caused an increase in inequality during 1996–2014. On the other hand, the employment status partition could not explain the source of the inequality increases, since the pure inequality effect is higher than the change in I_0 (*Theil's*). Even when employment shifts from the formal to the informal sector and raises income in the informal sector (which should promote convergence) the pure inequality effect is so high that it outweighs it. The education partition also confirms that the growing inequality from 1996–2014 is most likely to have been the result of a pure inequality effect. Though the growing income of households without formal education and households with compulsory education contributed to reducing inequality during this period, these contributions could not cancel out the growth of inequality due to the pure effect and allocation effect. Unfortunately, the growing income of those who completed secondary education and have a university education positively contributed to rising inequality during 1996–2014, as shown by the positive income effects (Table 10.6).

During the period 2005–2014, Indonesia experienced a substantial increase in equality as the inequality measures increased by almost 0.024 (Gini Index) and 0.029 (Theil). In sectoral partition, allocation effects contributed to 0.0197 of the increase in inequality, while area and employment status partition could powerfully explain the increase in inequality. Population shifts from rural to urban in 2005–2014 accounted for a 0.0081 increase in inequality, which overpowers the convergence effect from the income increases in the rural area.

Examining the periods 1996–2005 and 2005–2014, we observe two different patterns. Inequality decreased from 1996 to 2005 while from 2005 to 2014 it increased. Although inequality began to increase after the economic recovery of 2000–2005, the impact of a decrease in inequality as a result of the 1998 financial crisis was greater than the increase in inequality during 2000–2005. Consequently, if we look at the two points of 1996 and 2005, inequality seems to be decreasing during 1996–2005. In the context of sectoral occupation, while pure inequality (unexplained) dominated an inequality increased during 1996–2005, the allocation effect on "within" group components contributed most of the inequality increases in this period. However, the pattern would be different if we looked at the rural–urban partition and the household–member partition, as pure inequality contributed most to rising inequality from 2005–2014.

10.5.3 Regression Results

In Table 10.7, we present the main results from the estimated fixed-effects panel data models (based on the Hausman specification test). In the context of structural transformation and inequality, the econometric estimations show similar findings to Theil's L decomposition, namely that there is evidence of the relationship between structural transformation and growing inequality in Indonesia. The magnitude of coefficients from both models seems to support the idea of structural transformation leading to an increase in inequality in Indonesia.

Table 10.7 shows the results of fixed-effect estimations consisting of six models. Models 1, 2, and 3 capture the agriculture–industry transition, while models 4, 5, and 6 capture the agriculture–service transition. The significant negative sign in the agriculture share on aggregate value added in the economy and industry share shows similar results to Ghosh Datisdar (2012). The negative sign of the agriculture share means a decrease in the agriculture share, while holding industry share constant and an increase in the service sector share will increase the Gini coefficient. The negative effects of both variables persist when we use step-wise regression (see result in Models 4, 5, and 6). This might occur because the service sector has the highest inequality, compared to the agriculture and industry sectors. Thus, in the context of Indonesia, moving the business to the service sector (without the maturity of the industry sector) will increase the inequality overall.

Models 4, 5, and 6 show a decreasing agriculture share in GDP, while holding the service sector constant, which left the industry sector to increase, will also increase inequality. And increasing the share of the service sector will also significantly increase the Gini ratio, which represents increasing inequality. Thus, increasing the share of the service sector tends to increase inequality, while increasing the agriculture and industry sectors will decrease inequality. The agriculture and industry sectors in Indonesia are labor-intensive, therefore increases in both sectors will benefit the laborers, who are usually in lower-income jobs. This decreases inequality. On the other hand, the service sector employs highly skilled labor—which mainly comes from upper-middle-income families—and is relatively more capital-intensive. Consequently, increasing the service sector will benefit only a very small number of people, hence the increasing inequality.

Table 10.7: Structural Transformation and Income Inequality: Fixed Effect Estimations

Dependent Variable	Inequality					
	Agriculture–Industry Transition			Agriculture–Service Transition		
Independent Variables	(1)	(2)	(3)	(4)	(5)	(6)
Agriculture share in GDP	–1.627***	–0.784**	–0.789*	–1.436***	–0.603**	–0.408
	0.196	0.339	0.397	0.178	0.238	0.331
Industrial share in GDP				–0.571***	–0.181	–0.139
				0.082	0.117	0.155
Service share in GDP	0.689***	0.291	0.389*			
	0.100	0.188	0.221			
Economic growth		0.069*	0.086*		0.069*	0.063*
		0.036	0.043		0.037	0.036
Socio-demographic factors						
Poverty rate		–0.006***	–0.002		–0.006***	–0.004
		0.001	0.003		0.001	0.002
Senior high school net enrollment			0.001			0.001*
			0.000			0.000
Log of foreign direct investment			0.004**			0.005***
			0.002			0.002
Government factors						
Infrastructure share in expense			–0.077**			–0.073**
			0.033			0.033
Human capital share in expense			0.078			0.095
			0.092			0.109
Intercept	0.309***	0.442***	0.261**	0.873***	0.648***	0.471***
	0.039	0.069	0.103	0.064	0.077	0.119
R-square (within)	0.513	0.567	0.502	0.495	0.559	0.481
F-stat (Wald-chi)	36.64***	40.13***	22.45***	34.17***	51.01***	25.08***
No. Obs.	288	288	171	288	288	171

F-stat = a statistical measure of the fit of linear model, GDP = gross domestic product, R-square = a statistical measure of actual data proximity to the fitted regression line, Wald-chi = a statistical measure to check whether the explanatory variables in a model are significant.

Note: Figures in parentheses are t-statistics; ***, **, * indicate statistical significance at 1%, 5%, and 10% levels, respectively.

Source: Authors' estimation.

The positive and significant value of the economic growth coefficient shows the impact of increasing economic growth toward increasing inequality, as already discussed in Section 10.3.2. Similar results are found in Dastidar (2012) and Dartanto and Patunru (2016). This indicates that economic growth is not inclusive, since the rich enjoy the benefits of growth more than the poor.

The socio-demographic variables consist of poverty rates in each province, net enrollment of senior high schools in each province, and the realized FDI. The poverty rate has an insignificant and negative effect on the Gini ratio, which means that a province with a higher poverty rate tends to have a lower level of inequality. There has been no consensus on the relationship between poverty and inequality. Dartanto and Patunru (2016) found an inconclusive correlation between the Gini ratio and the poverty rate, depending on the estimation methods and control variables. We have argued that regions with a high poverty rate tend to have an equal distribution since most people have a similar standard of living.

Senior high school enrollment proved to be an insignificant positive in affecting inequality, which is similar to the results of Dartanto and Patunru (2016). Increasing senior high school enrollment increases the skilled labor force. As mentioned above, raising the skilled labor force will increase the inequality as education expands the gap of labor productivity among workers. Lipsey and Sjolhom (2004) found that FDI has benefited skilled workers more than unskilled workers in emerging economies, including Indonesia. Also, FDI can increase the inequality in other ways. This is because FDI gives more return to the capital owners than to the workers. As a result, the growth of income from capital will be higher than the growth of labor wages.

Lastly, government factor variables consist of shares of infrastructure and shares of human capital—i.e., education and health—in government expenses. While the share of human capital in government expenses does not significantly affect inequality, the infrastructure share in local government expenses significantly reduces inequality, at 95% confidence level. These findings suggest that public investment in infrastructure will contribute to a reduction in inequality in Indonesia. In combination with the positive impact of human capital investment on inequality, it is not necessarily the government's task to stop such investment, but the government should ensure that low-income groups also benefit from it. Moreover, the local government in a province with high FDI should carefully mitigate the adverse impact of FDI on inequality, by, for instance, implementing a quota for hiring local people to work in FDI companies.

10.6 Conclusion

Indonesia has experienced a pattern similar to other countries in Southeast Asia in that a substantial decrease in poverty has been accompanied by an increasing Gini index, particularly from 1996 to 2014. Many researchers have attempted to find the link between structural transformation and inequality. One of the oldest theories is the Kuznets curve. As the economy develops from an agriculture to an industry orientation, inequality will first increase before it eventually decreases as the economy moves to the service sector. The Kuznets curve assumes that the structural changes that occur in an economy follow the agriculture–industry–service transition, which has commonly been the case in developed countries. Indonesia's experience is similar to that of other developing countries, in that there has been an economic transition from an agriculture-oriented to a service-oriented economy before the industry sector has actually matured.

This chapter uses Theil's L decomposition and econometric estimation to explore the relationship between structural transformation and inequality in Indonesia. From the static and dynamic decomposition, this study concludes that (i) the root of increasing inequality in Indonesia is still "mysterious," since the pure inequality effect (the unexplained effect) still dominates the explanation of increasing inequality, especially when we consider the group partition of area, employment status, and educational attainment. Static decomposition has also confirmed a similar finding, that "between" group inequality could only explain less than 25% of inequality; (ii) population shifts from the agriculture sector to either the industry or service sectors, from rural to urban areas, and from informal to formal employment are the second contributor to the increasing levels of inequality from 1996 to 2014; (iii) improvements in educational attainment from 1996 to 2014 contributed to an increase in equality; and (iv) even though the contribution of structural transformation was canceled out, the increasing inequality was curbed by the growing income among the less educated people who work in the informal agriculture sector and live in rural areas. Fixed-effect estimations could be used to provide economic evidence that supports the notion that structural transformation leads to increases in inequality in Indonesia. The service sector's increasing share in the economy raises inequality because the service sector is capital-intensive and high-skill-intensive. Therefore, only a few people enjoy the benefits of growth in this sector compared with growth in the agriculture or industry sectors.

Elaborating on descriptive analysis, decomposition, and econometric analysis, this study recommends that because of relatively high disparities across regions (rural and urban), the policy for tackling inequality should focus on regional economic development, with special attention to helping poor villages. Moreover, econometric analysis suggests that public investment in infrastructure will contribute to a reduction in inequality in Indonesia, and provinces with high FDI should carefully mitigate the adverse impact of FDI on inequality.

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11

Structural Transformation, Growth, and Inequality: Evidence from Viet Nam

Vengadeshvaran Sarma and Saumik Paul

11.1 Introduction

Economic development and growth entail large-scale structural transformation of economies (Hnatkovska and Lahiri 2014). Many Asian and African economies are now undergoing such large-scale structural transformation—typically from agriculture to manufacturing and service sectors. Such structural transformation inevitably entails reallocation of workers from the primary sector to the manufacturing and service sectors. One of the important questions arising from such structural transformation led growth is whether such growth helps the poor. On the one hand, growth may lift people out of poverty and therefore improve living standards for everyone. On the other hand, growth may increase income inequality by benefitting the rich more than the poor. There is no consensus in the literature on whether structural transformation led growth achieves the twin goals of improving welfare for the poor and decreasing income inequality.

Viet Nam, one such developing economy, introduced a series of economic reforms in 1986—termed *Doi Moi*. These reforms enabled private lease of agricultural land (which enabled lease holders to trade land and seek rent on land), deregulated the domestic market significantly and also introduced trade liberalization measures. In particular, agricultural products were allowed to be exported, and foreign ownership of manufacturing firms was allowed. Price of agricultural goods increased as a result of trade liberalization, but it was the manufacturing sector that experienced rapid expansion over the last 3 decades. Workers have also therefore increasingly moved from agriculture to manufacturing (and to a smaller extent to services).

Structural transformation has led to sustained economic growth in Viet Nam, but at the expense of increasing income inequality. Economic growth in Viet Nam averaged 5%–6% over the last 3 decades. In particular, the 2000s saw average growth rates of about 6.4%. Gross domestic product (GDP) per capita at purchasing power parity (PPP) increased from $970 in 1990 to $6,023 in 2015. The proportion of the population living on under $3.10 a day (at 2011 PPP) decreased from 34.7% to 3.5%. However, in the same period the World Bank GINI index increased from 35.7 in 1992 to 38.7 in 2012.[1] There is also evidence that the reduction in poverty and dividends from growth were spread unevenly across Viet Nam, increasing income inequality between regions and to some extent within regions (World Bank 2013).

In this chapter, we examine how structural transformation through growth contributes to income inequality. In particular, we address the following research questions:

- Does economic growth affect income inequality?
- Is change in income inequality explained by sectoral participation within the income distribution?

We use three rounds of repeated cross-sectional Vietnamese data to analyze structural change and income inequality over an 8-year period. We use the 2002, 2006, and 2010 rounds of the Vietnam Household Living Standards Survey (VHLSS) conducted by the General Statistics Office (GSO) in Viet Nam. The VHLSS data show significant structural transformation in Viet Nam over the 8-year period. Descriptive evidence also indicates a significant increase in household income over the period emulating the increase in national GDP. Further, similar to the World Bank GINI index, our data indicate a widening income disparity in Viet Nam over the years. There is also evidence to suggest the existence of significant regional disparity in structural transformation, income growth, and income inequality.

Using growth incidence curves (GICs) and re-centered influence functions (RIFs), we identify how structural transformation maps onto the income distribution over the time periods. The data suggests that labor mobility between the agriculture and manufacturing sectors was more prominent for the 30th to 65th percentile population. Regression outcomes also indicate that participation in agriculture

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1 These statistics are downloaded from the World Bank's World Development Indicators (WDI) database.

and manufacturing yielded lower income compared to participation in the service sector, indicating negative returns to both working in agriculture and the manufacturing sectors. However, unconditional quantile RIF regression coefficients indicate that returns to agriculture and manufacturing are only negative for the poor—the returns are in fact positive for the top 20 percentile in agriculture and the top 10 percentile in manufacturing. While the returns to both agriculture and manufacturing are improving across the income distribution, there is evidence that, currently, the disparity in sectoral returns across the income distribution contribute to widening income inequality. We then apply an Oxaca–Blinder style decomposition to our RIF estimates to identify the composition and structural effects of change. About 90% of the variation in growth across the income distribution is explained by structural effects across both periods: 2002–2006 and 2006–2010. We do not find that structural transformation explains these structural effects. For those in the bottom half of the income distribution, we find that household characteristics contribute significantly in explaining structural effects.

Overall, our results indicate the need for the state to work towards improving the distribution of growth dividends across the income distribution. There is also some evidence that the poor may be concentrated in interior Viet Nam, away from the coastal regions and industrial zones—engaging in smallholder farming. Government policies may be required to ensure access to non-farm activities for such workers. Without adequate measures to address the widening income inequality, sustained growth may accelerate income inequality along geographical, and perhaps ethnic lines.

We make two key contributions to the literature. First, we add to the work of McCaig, Benjamin, and Brandt (2015) by applying RIF estimates to decompose growth effects and map those onto the income distribution. Second, we also identify how sectoral returns on participation affect individuals and households along the income distribution, thus analyzing how growth dividends are shared along the income distribution and how this contributes to income (in)equality.

This chapter proceeds as follows. In Section 11.2, we briefly discuss the literature on structural transformation and inequality with a special focus on Viet Nam. In Section 11.3, we discuss the data. Section 11.4, outlines the estimation strategy and the results. Section 11.5 concludes.

11.2 Structural Transformation and Income Inequality: The Case of Viet Nam

As Hnatkovska and Lahiri (2014) discussed, structural transformation has led to sustained economic growth in developing countries in Africa, Latin America, and especially, Asia. Such structural transformation typically entails a shift in economic activity from agriculture to manufacturing and services. This is characterized in dual economy models such as that of Lewis (1954), where agriculture, the traditional sector, has lower productivity while the modern sectors, manufacturing and services, have higher productivity.[2] Globalization and transfer of technology have helped developing countries to accelerate structural transformation (Aizenman, Lee, and Park 2012). As resources, especially labor, move from the less productive agricultural sector to the more productive manufacturing and service sectors, the economy and people's income grow (McMillian and Rodrik 2011; Rodrik 2013). Whether such growth benefits everyone in an economy is contentious.

Kuznets (1955) hypothesized an inverted U-shaped relationship between economic growth and income inequality. Kuznets argued that as economies grow, income inequality will initially worsen. This is because much of the growth is likely to reward skills and those with access to capital—exhibiting pro-rich growth. Gradually over time, as low-skilled workers move to higher productivity and income sectors, the growth is likely to be more pro-poor. The empirical literature on this topic has boomed since the publication of the Deininger and Squire (1996) inequality dataset. Many of the cross-country studies (such as Datt and Ravallion 1998; Dollar and Kraay 2002; Ravallion 2012) and country case studies (such as Ravaliio and Datt 1996; Ravallion and Chen 2007) show that economic growth in fact reduces poverty. However, as Gunatilaka and Chotikapanich (2009) and Rubin and Segal (2015) showed, growth is likely to increase income inequality and be pro-rich through two channels: (1) the rich receive larger shares of their income through wealth, which is more sensitive to growth than wage income; and (2) access to better education, infrastructure, and mobility yield better returns for the rich. There is also some evidence that the causal

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2 McMillan and Rodrik (2011) posited that the productivity gap between the traditional and modern sectors exhibit a U-shaped relationship. Initially, the productivity gap widens as productivity in the modern sectors grows with technology and reforms. As economies experience a shift in resources, especially labor, from agriculture to the modern sectors, the productivity gap between agriculture and the modern sectors is likely to decrease.

relationship flows both ways, and in fact high levels of inequality can hamper growth, and vice versa (UNRISD 2010).[3]

Viet Nam has experienced significant sustained economic growth since the economic reforms of 1986, termed *Doi Moi* (meaning: renovation). Since 1986, the Vietnamese economy has grown at average growth rates of between 5% and 6% (with exceptions during the Asian financial crisis in 1999 and the global economic crisis in 2009 [Figure 11.1]).

The economic reforms introduced private lease of agricultural land (previously all agricultural land was state owned), enabling trade and rental of such land. The reforms also introduced trade liberalization policies encouraging agricultural and manufacturing exports. The government also allowed for foreign ownership of manufacturing firms, at one point up to 100%. Prior to the reforms, almost the entire manufacturing sector was led by state-owned enterprises (SOEs). Between 1989 and 2010, however, the number of SOEs declined by as much as 75% and the labor force in SOEs shrunk by about 40% (World Bank 2011). Since the economic reforms, productivity and wages in manufacturing have increased, causing a pull factor for workers to move from agriculture to manufacturing (see Appendix, Figure A11.1 for the change in labor force participation across sectors and Figure A11.2 for change in sectoral productivity). It should, however, be noted that, opening up of the agricultural sector for exports, increased prices of agricultural products and also improved rice yield from 3.33 tons per hectare in 1992 to 4.90 in 2006 (Benjamin et al. 2009). McCaig and Pavcnik (2013), however, pointed out that this increase was still not sufficient to incentivize agricultural workers to remain in the sector. Labor productivity in Viet Nam increased by 5.1% between 1990 and 2005, and 38% of this can be attributed to structural change (McCaig and Pavcnik 2013). McCaig and Pavcnik also argued that the flexible labor force ensured that structural unemployment remained very low and only for brief periods. Rapid and sustained economic growth in Viet Nam, however, was accompanied by an increase in income inequality (Figure 11.2).

Viet Nam's structural transformation-led growth exhibits increasing income inequality—especially with regional heterogeneity. As seen in Figure 11.2, the GINI index for Viet Nam increased from 35.7 to 38.7 over the 20-year period from 1992 to 2012. Given the increase

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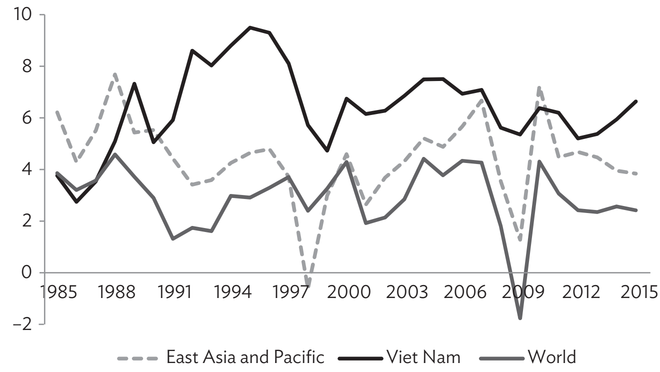
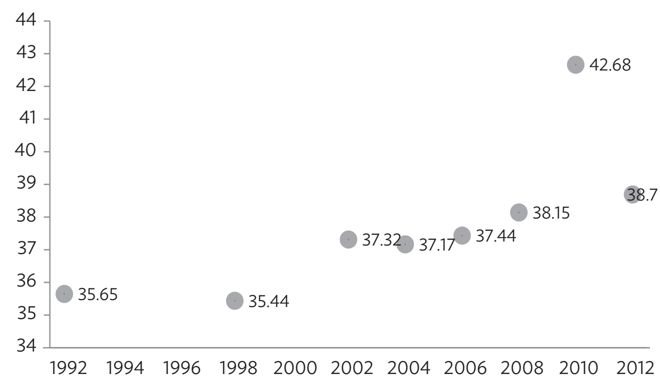
3 Similar evidence is presented in 12 studies summarized in Benabou (2000). However, Banerjee and Duflo (2003) showed that the causal relationship between income inequality and economic growth is likely to be non-linear, and any changes to income inequality (in any direction) are likely to reduce future growth.

Figure 11.1: Annual GDP Growth



GDP = gross domestic product.
Source: World Development Indicators.

Figure 11.2: Gini Index



Source: World Development Indicators.

in income inequality, Akram–Lodhi (2005) argued that Viet Nam's economic reforms were not pro-poor and in fact created a peasant class differentiation. Evidence from Table 11.1 also indicates that rising income (at the provincial level) has contributed to rising income inequality (increasing the provincial GINI). The table shows that increases in per capita household expenditure (used as a proxy for per

Table 11.1: Effect of per Capita Income on Gini—Provincial Analysis

Dep Var: Gini	(1)	(2)	(3)	(4)	(5)	(6)
Log PCHHE	0.023***	0.048***	0.057***	0.034*	0.041	0.054
	(0.004)	(0.012)	(0.015)	(0.017)	(0.033)	(0.032)
Net migration				−0.012*	−0.013	−0.013
				(0.005)	(0.009)	(0.009)
Log domestic remittance						−0.019
						(0.013)
Log foreign remittance						
Skilled agricultural worker						
Skilled manufacturing worker						
Professional						
Unskilled worker						
Year dummies	√	√	√	√	√	√
Region dummies		√	√	√	√	√
Individual and HH controls						
Constant	0.108**	−0.085	−0.131	0.041	0.033	0.055
	(0.038)	(0.120)	(0.142)	(0.168)	(0.304)	(0.307)
Number of observations	192	192	128	128	64	64
R-Squared	0.138	0.43	0.48	0.508	0.431	0.444
Dep Var: Gini	**(7)**	**(8)**	**(9)**	**(10)**	**(11)**	**(12)**
Log PCHHE	0.057***	0.063***	0.064***	0.068***	0.064***	0.076***
	(0.013)	(0.012)	(0.011)	(0.016)	(0.016)	(0.020)
Net migration						
						−0.003
Log domestic remittance	−0.016	0.000				−0.02
	(0.008)	(0.008)				
Log foreign remittance		−0.009***	−0.009***	−0.006**		
		(0.002)	(0.002)	(0.002)		
Skilled agricultural worker				39.158*	34.862	49.721*
				(18.983)	(19.588)	(23.156)
Skilled manufacturing worker				38.983*	34.676	49.399*
				(18.988)	(19.596)	(23.153)
Professional				39.377*	35.073	49.911*
				(18.988)	(19.606)	(23.176)
Unskilled worker				39.203*	34.898	49.737*
				(18.989)	(19.593)	(23.168)
Year dummies	√	√	√	√	√	√
Region dummies	√	√	√	√	√	√
Individual and HH controls				√	√	√
Constant	−0.057	−0.234*	−0.194	−0.238	−0.290	−0.499**
	(0.121)	(0.111)	(0.108)	(0.157)	(0.161)	(0.186)
Number of observations	192	192	192	192	192	128
R-Squared	0.442	0.536	0.536	0.633	0.6	0.702

Dep. Var. = dependent variable, Log PCHHE = logarithm of per capita household expenditure.

Note: *** $p<0.001$, ** $p<0.01$, * $p<0.05$. Robust standard errors in parentheses.

Source: Authors' calculations based on VHLSS 2002, 2006, and 2010.

capita income) increase the provincial Gini, and this effect is robust to alternate specifications after controlling for regional and time-fixed effects. Results from Table 11.1 also indicate that domestic migration has no statistically significant effect on income inequality—but foreign remittances reduce income inequality.

Benjamin and Brandt (2004) identified that if agricultural incomes increase (as is the case in Viet Nam) it would help reduce the inequality arising from rapidly increasing income from other sources. However, they also noted that Viet Nam's ability to grow with equity depends on access to non-agricultural opportunities. Perhaps this explains the regional heterogeneity, well documented in World Bank (2013) (see Figure 2, p. 6 of the report). The World Bank report shows that coastal regions in Viet Nam experienced almost universal declines in the poverty rate. (In fact, nationally, the proportion of the population living on under $3.10 a day (at 2011 PPP) decreased from 34.7% to 3.5%). However interior regions, the mountainous North–West, and Central Coasts, experienced lower rates of reduction in poverty. The World Bank (2013) report and McCaig, Benjamin, and Brandt (2015) highlighted that such regional variation is also a product of ethnic factors in Viet Nam. Almost half of those in poverty in Viet Nam are ethnic minorities, despite making up only 15% of the population (World Bank 2013). Another factor that helps explain this regional variation is the availability of non-farm activities.

In the north, Ha Noi dominates manufacturing, while in the south, the south east region—home to Ho Chi Minh—dominates. As seen in Figure A11.3, this causes net migration to be positive for Ho Chi Minh and Binh Duong in the south and Ha Noi in the north, but almost all other regions experience negative net migration (more people leave these provinces compared to the number of people who come in). There is also a significant shift away from agriculture in the regions in the south, more so than in the north (see Figure A11.4). The increased concentration of manufacturing firms and modern sectors in the Red River Delta, south east, and the Mekong River Delta has caused the productivity of these regions and therefore incomes in these regions tend to be much higher than in the rest of Viet Nam.

Given the non-inclusive growth that Viet Nam continues to experience across ethnic and regional lines, we identify how structural change may explain growth differences across the income distribution. In the next section, we discuss the data that we use and provide some descriptive statistics.

11.3 Data

We use three rounds of repeated cross-sectional data (the 2002, 2006, and 2010 rounds) from the Vietnamese Household Living Standards Survey (VHLSS). The surveys are conducted biennially and are based on the World Bank's Living Standard Measurement Surveys (LSMS). The VHLSSs are nationally representative (at the provincial level) and are stratified geographically. The smallest unit of geographical analysis are the communes. The communes are drawn from the 1999 census (for 2002 and 2006 VHLSS) and 2009 census (for the 2010 VHLSS). Communes make up districts, districts make up provinces. Provinces are the largest geographical unit available in the surveys. However, we could use provincial data to create regions—the highest level of geographical demarcation. Viet Nam is divided into eight regions composed of 58 provinces and 5 municipalities (which are considered to be on par with provinces).[4] The VHLSS contains information on household expenditures, employment, household and individual characteristics, among others. Our unit of analysis is the household. Household membership is defined by physical presence: individuals must eat and live with other members for at least 6 out of the past 12 months and contribute to collective income and expenses. Therefore, people, living, working, or studying outside of the household would not be part of the household unit in the data and in our analysis. For the purpose of our analysis we use consumption expenditure as a proxy for income, because consumption expenditure is likely to be more accurate in measuring welfare of households in developing countries (for a discussion on this topic, see Deaton and Zaidi 2002).[5] Table A11.1 provides descriptive statistics from the three rounds of the VHLSS.

The descriptive statistics indicate little changes across households and individual characteristics but demonstrate large changes in sectoral participation and skills. Households are getting smaller, the share of ethnic minorities is increasing, land holding is decreasing; but, most importantly, household income is increasing (proxied by household consumption). There is a large shift in the proportion of workers engaged in agriculture and manufacturing and a small increase in those engaged

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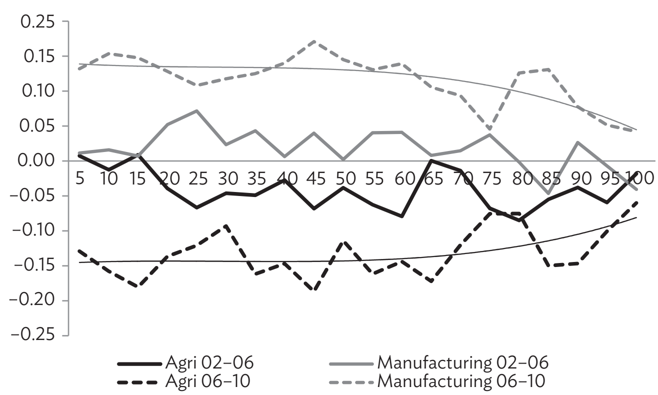
4 During the 8-year period that we refer to in our data, several provinces experienced splits or annexation, which we discuss here. The province Ha Tay was annexed into Ha Noi in 2008. The province Dien Bien was carved out of Lai Chau in 2003. The province Dak Nong was carved out of Dak Lak in 2003. The province Hau Giang was carved out of Can Tho in 2003.

5 McCaig, Benjamin, and Brandt (2015), however, using a similar dataset (with additional rounds of the VHLSS) used information on income to compute the income inequality measures rather than consumption expenditure.

in the service sector. The proportion of workers engaged in agriculture dropped 17 percentage points and that of manufacturing increased by 14 percentage points. There is also some descriptive evidence to suggest that the proportion of skilled workers in the agriculture and non-agricultural sectors has dramatically increased over the 8-year period—they have nearly doubled. The share of the population in the economically active regions—the Red River Delta, the South East, and the Mekong River Delta—marginally decrease in our data over the years; however, in comparable Vietnamese GSO data, we in fact find small marginal increases in the population in these regions.

The descriptive statistics indicate a large shift across the income distribution from agriculture to manufacturing as depicted in Figure 11.3. The non-linear trend lines for participation in agriculture and manufacturing across the two time periods indicate that the shift in participation from agriculture to manufacturing is prominent for those in the 30th to 65th percentile of the income distribution. As Phan and Coxhead (2010) pointed out, mobility constraints for the poorest may prevent them from making use of non-farm based opportunities and exasperate the income divide. Similarly, the richest whose income may be derived from returns from investments in agriculture or performance related wage income, may in fact experience increased income as agricultural productivity increases. This may dis-incentivize those at the higher quantiles of the income distribution to move towards the modern sectors (Rubin and Segal 2015).

Figure 11.3: Sectoral Participation by Income Quantile

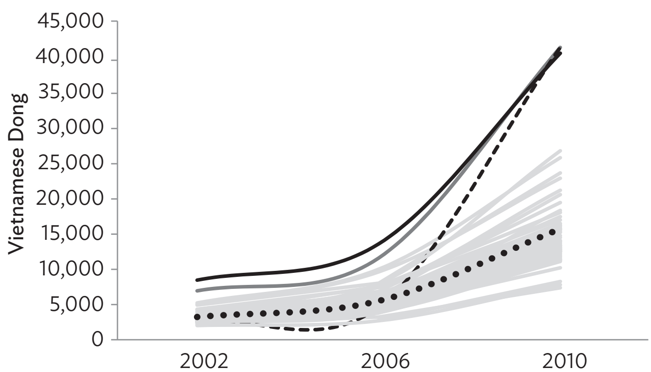


Source: World Development Indicators.

Structural transformation, however, increases income inequality and this effect is heterogeneous across regions. As we show in Figure A11.4, the rate of change from agriculture to manufacturing varies by region. The differences in structural transformation between regions affects the income inequality between the regions. As we see in Figure 11.4, the provincial GDP has widened across the provinces in the 8-year period we study. This may partly be explained by migration flows into these provinces. It may also be a function of the differences in returns to participation across sectors. From 2006–2010 we find regions and provinces with traditionally very high levels of agriculture—the north central coast and the central highlands—also experienced an increase in Gini. This may partly be explained by the migration of some households within the center of the income distribution to manufacturing-intensive regions. Such moves widen the Gini for the remaining population in a region.

Using this descriptive evidence, we build on our research questions to identify how structural transformation may help understand the differences in growth across the income distribution. For this purpose, we use a RIF-based decomposition analysis. We explain this empirical strategy in the next section.

Figure 11.4: Per Capita Gross Regional Product (local prices)



Note: The black line represents Ho Chi Minh, the grey line Ha Noi, the dashed line Ha Tay, and the large dotted line Viet Nam.

Source: Authors' calculations based on VHLSS 2002, 2006, and 2010.

11.4 Empirical Strategy and Results

Our estimation strategy relies on mapping structural transformation and growth to the income distribution. Since the seminal work of Kuznets (1955), a large body of empirical work has attempted to understand whether the inverted U-shaped relationship between growth and income inequality exists. Gallup (2012) showed that there is no consensus in the empirical literature. While several empirical studies have tried to fit the data to an inverted-U shape proposed by Kuznets (Kanbur 2000), very little is known about why an economy would fit or not fit such an inverted U-shaped curve. One channel through which an economy may be mapped onto the Kuznets curve is through population movements across time along the income distribution—which may cause pro-rich and pro-poor growth periods (Anand and Kanbur 1993). Using a dual economy framework proposed in Paul (2016) we link structural transformation to growth across time and along the income distribution.

11.4.1 Mapping Changes in Income Inequality

Similar to Paul (2016), we use Growth Incidence Curves (GICs) to measure mean growth rate in each income quantile. These GICs show gains from growth and are distributed across the income distribution (Ravallion and Chen 2003). Formally, we can denote this as:

$$g(p) = \frac{\Delta y(p)}{y_0(p)} = \frac{y_1(p)}{y_0(p)} - 1$$

Where, $g(p)$ is the growth rate in income for quantile p; y represents income.

Pro-rich growth spells will exhibit upward sloping GICs while pro-poor spells will exhibit downward sloping GICs. If the GICs are relatively flat—i.e., exhibit similar levels of growth across the income distribution—then inequality does not change much. If across two time periods GICs exhibit a pro-rich growth spell followed by a pro-poor growth spell, this is then similar to the Kuznets motion—income inequality initially widens but then narrows (Paul 2016).[6]

Over the 8-year period, the GICs demonstrate pro-rich growth. The GIC for the 2002 to 2006 period exhibits a fairly flat curve, indicating that growth rates across income quantiles were positive and fairly

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6 For a detailed discussion on the assumptions and specifications of the framework we apply here, see Paul (2016).

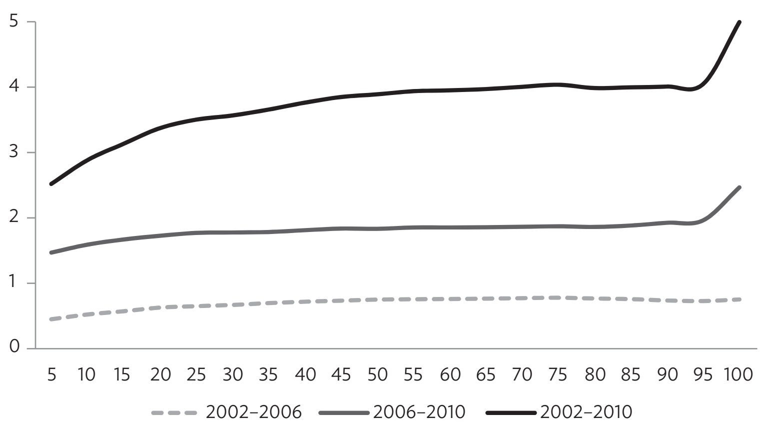
homogenous. In the 2006 to 2010 period however, the GIC depicts pro-rich growth. While there was positive growth across all income quantiles, growth income accelerated much more for the top 5th percentile and was slower for the bottom 20th percentile—widening income inequality.

Growth dividends are also ethnically polarized. As evident from Figure 11.6, the proportion of Kinh (ethnic majority) in the lowest income quantiles dropped dramatically from 2002 to 2010 and marginally increased in the highest income quantiles. More than half of those in the bottom 20th quantiles are ethnic minorities despite making up only about 15% of the population. Further, the proportion of ethnic minorities in the bottom 20th quantiles in fact increased over the 8-year period. Slower-paced structural transformation among the ethnic minorities partially explains the widening income disparity across majority Kinhs and the ethnic minorities (see Figure A11.5).

11.4.2 Returns to Sectoral Participation across Income Quantiles

We use Re-centered Influence Function (RIF) regressions to connect unconditional marginal quantiles to observable covariates (including household, structural factors, and geographical factors) based on Paul (2016) and Fortin, Lemieux, and Firpo (2010). Collecting the leading

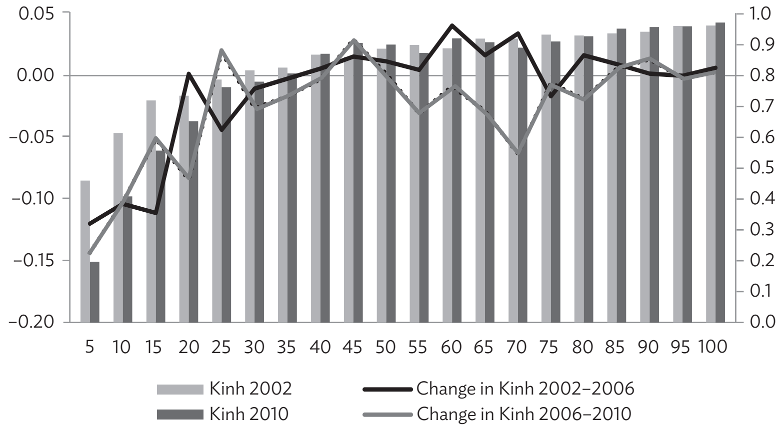
Figure 11.5: Growth Incidence Curves



HH = household.

Source: Authors' calculations based on VHLSS 2002, 2006, and 2010.

Figure 11.6: Change in Ethnic Composition across Income Quantiles



Source: Authors' calculations based on VHLSS 2002, 2006, and 2010.

terms of a Von Mises (1947) linear approximation of the associated functional, the rescaled influence function of the pth quantile of the distribution of y can be written as:

$$RIF\left(y;\, q_p\right) = q_p + IF\left(y\,; q_p\right) = q_p + \frac{\left[p - I(y \le q_p)\right]}{f_y(q_p)}$$

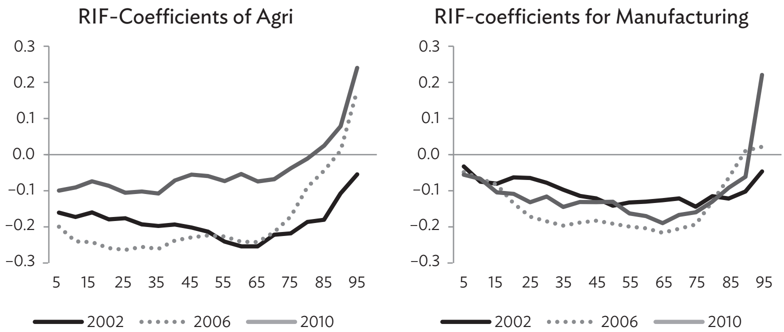
We consider movements from agriculture to manufacturing to be the main channel of structural transformation. The RIF regression for the pth quantile of the distribution of income (y) can therefore be written as:

$$RIF(y;\, q_p) = \beta_0 + \beta_1 Agri + \beta_2 MAN + X'\gamma + s$$

where the unconditional or marginal quantile is $q_p = \int E[RIF(y;\, q_p, F_y) \mid X] dF(X)$. *Agri* is a dummy for participation in agriculture, *MAN* is a dummy for participation in manufacturing, γ is a set of covariates, and ε is the error term.

We produce ordinary least square (OLS) estimations of the RIF (presented in Table A11.2) and also plot the RIF coefficients in Figure 11.7. The RIF regressions indicate negative income gains associated with participation in both agriculture and manufacturing as opposed to

Figure 11.7: Unconditional Quantile Regression Coefficients



RIF = re-centered influence function.

Note: The x-axis indicates the income quantiles.

Source: Authors' calculations based on VHLSS 2002, 2006, and 2010.

participation in the service sector. However, skilled workers across all three sectors experienced positive income returns. There is also some evidence in the regression results to suggest that agricultural land holding size adversely affects income, but this result is likely to be driven by non-agricultural high-wage employment. There is also strong evidence to suggest households in the South East had higher per capita income than the rest of the regions, the magnitude is also statistically large. This highlights the concentration of modern sector economic activity in the Ho Chi Minh province and its neighboring provinces. The RIF coefficients when plotted against the income distribution, however, illustrate an interesting narrative—returns to agriculture and manufacturing (and even services) is only positive for the rich. In 2002, returns to participation in agriculture and manufacturing are negative across the income distribution. But in 2010, returns to both agriculture and manufacturing improve for those in the top 20th percentile and top 10th percentile, respectively. These results again re-iterate a widening income disparity in Viet Nam alongside economic growth and rising incomes.

11.4.3 Structural Change and Income Inequality: Decomposition

While the evidence thus far has demonstrated a link between economic growth and widening income inequality, it is important to analyze how much of this widening income inequality is explained by structural change. We use a generalized Oaxaca–Blinder decomposition analysis (discussed in Fortin, Lemieux, and Firpo [2010] and Paul [2016]) to estimate the relative contribution of sectoral transformation on income inequality. We can denote the decomposition function as:

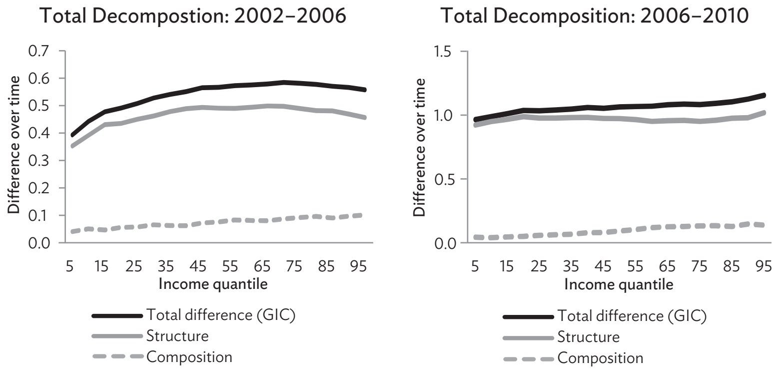
$$\Delta^{\theta}_{Overall} = E\left(X|t=1\right)(\beta^{\theta}_{1} - \beta^{\theta}_{C}) + E\left(X|t=1\right)\beta^{\theta}_{C} - E\left(X|t=0\right)\beta^{\theta}_{0}$$

Where, the linear RIF-regressions of the pth quantile of the distribution of y is estimated by replacing y with the estimated value of $\widehat{RIF}(y;\, q_p)$. The structure and composition effects can be decomposed as:

$$\text{Structure Effect} = E\left(X|t=1\right)^{T} . (\hat{\gamma}^{q_p}_{1} - \hat{\gamma}^{q_p}_{C})$$
$$\text{Composition Effect} = E\left(X|t=1\right)^{T} . \hat{\gamma}^{q_p}_{C} - E\left(X|t=0\right)^{T} . \hat{\gamma}^{q_p}_{0} .$$

The decomposed GICs in Figure 11.8 indicate that much of the variation in income growth is explained by structural effects. About 90% of the variation in growth across the income distribution is explained by structural effects across both periods: 2002–2006 and 2006–2010. The contribution of structural effects in explaining growth, however, declines for the rich, across both time periods. Composition effects have a marginally higher capacity to explain the income growth of the top 10th percentile, but yet, the contribution in explaining is very small. We then decompose the structural and composition effects by covariates, to identify which factors affect structural and composition effects. In particular, we are interested to know whether structural transformation—differences in participation rates in agriculture and manufacturing, explain the differences in growth across the income distribution. We present the decomposition of covariates' contribution to structural effects in Figure A11.6. We do not find that structural transformation explains the structural effects. Structural transformation contributes less than 1% in explaining structural effects but contributes more significantly in explaining composition effects (not presented here for brevity). Much of the structural effects are unexplained and can be attributed to unobservable factors. For those in the lowest half of the income distribution, we find that household characteristics (including ethnicity) contribute significantly in explaining structural effects. But the lack of significant contributions by sectoral covariates in the Oaxaca–Blinder decomposition indicate that while structural transformation-led growth has increased income inequality, structural transformation by itself may not sufficiently explain changes in income inequality.

Figure 11.8: Decomposition Analysis



GIC = growth incidence curve.

Source: Authors' calculations based on VHLSS 2002, 2006, and 2010.

11.5 Conclusion

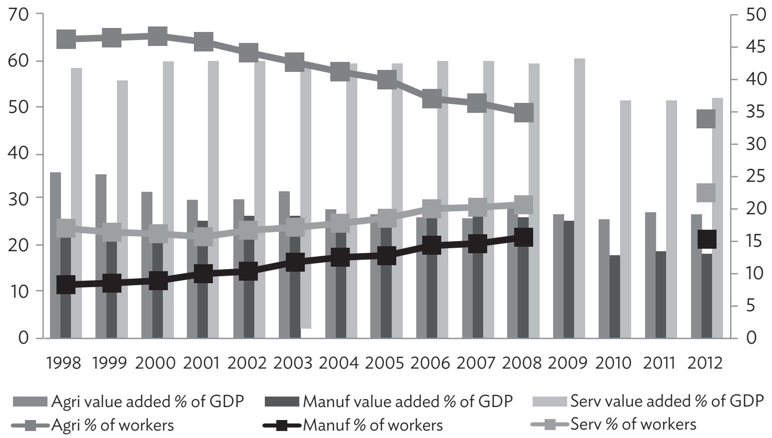
Viet Nam has experienced sustained and rapid economic growth since the *Doi Moi* economic reforms of 1986. Viet Nam's growth levels have surpassed the average growth for the East Asia and Pacific regions and the economy continues to grow at an annual average 6%. With economic growth, Viet Nam has also experienced a marginal albeit significant increase in income inequality.

Growth in Viet Nam, however, has not been entirely inclusive. The data indicate that structural transformation occurred across all income quantiles, but the shift from agriculture to manufacturing was more prominent for those at the center of the income distribution. The data also indicate that returns to agriculture and manufacturing were only positive for the top 10th to 20th percentile, exacerbating the income divide. Growth incidence curves indicate that Viet Nam's growth, especially from 2002 to 2010, has been pro-rich. Further, growth has been heterogeneous across ethnic groups and regions. In Viet Nam, ethnic concentration of regions also varies. The regions experiencing high levels of growth and modern sector activity are predominantly occupied by the Kinh ethnic group—the major ethnic group in Viet Nam. Such geographical and hence ethnic concentration of structural transformation have widened income inequality between regions and between ethnic groups. In decomposition analyses, however, we find that structural transformation does not sufficiently explain variations in income growth across the income distribution. The decomposition analysis indicates that household characteristics (including ethnicity) and unobservables explain much of the variations in growth across the income distribution.

Given the widening income inequality, government policies need to address more inclusive growth strategies. We propose three strategies to improve income equality in Viet Nam. First, improving skills acquisition for those at the lowest percentiles of the income distribution. There is strong evidence that skilled workers across the income distribution earn positive returns on their skills. Distinctions between those with and without skills—especially in the agricultural sector—widen overall income inequality. Second, as Phan and Coxhead (2010) pointed out, it is important to improve access to non-farm activities for the poor. Given that sectoral productivity and incomes are higher in the modern sectors, the poor, who are unable to move to regions with higher modern sector concentration may be left out from reaping growth dividends. Government policies aimed at increasing access to non-farm activities in regions with very high agricultural activity and poverty may help improve income equality. Third, reducing ethnic disparities in income growth. Geographical concentration of modern sector activity in the Red River Delta, the south east, and the Mekong River Delta have contributed to widening income disparities among Kinhs and the ethnic minorities, as ethnic composition in Viet Nam is highly localized across different regions. While ethnic minorities have also experienced rising income over the years, their rate of increase in income has been significantly lower than that for Kinhs. Without targeted policies aimed at reducing inter-ethnic income inequality, Viet Nam may experience widening income inequality between ethnicities, regions, and economic activities.

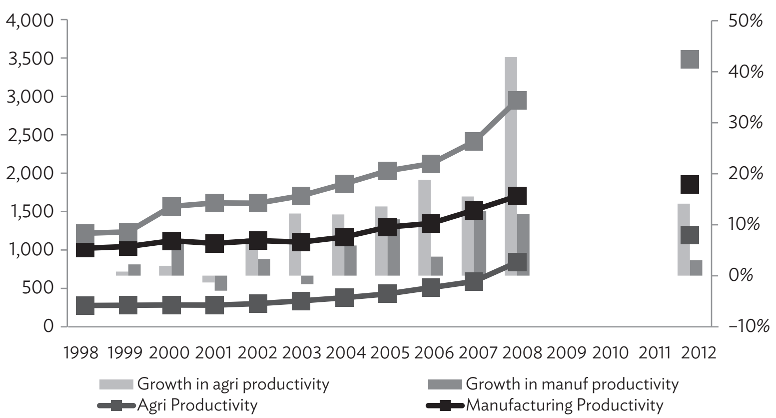
Appendix

Figure A11.1: Sectoral Contribution to GDP and Share of Labor Force *(%)*



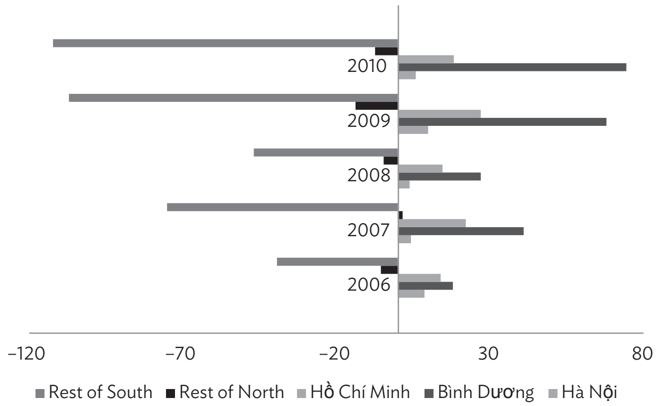
GDP = gross domestic product, Agri = agriculture, Manuf = manufacturing, Serv = services.
Source: World Development Indicators and McCaig and Pavcnick (2013).

A11.2: Sectoral Productivity (Share of GDP/Share of Employment, by Sector, $, PPP)



GDP = gross domestic product, PPP = purchasing power parity, Agri = agriculture, Manuf = manufacturing.
Source: World Development Indicators and McCaig and Pavcnick (2013).

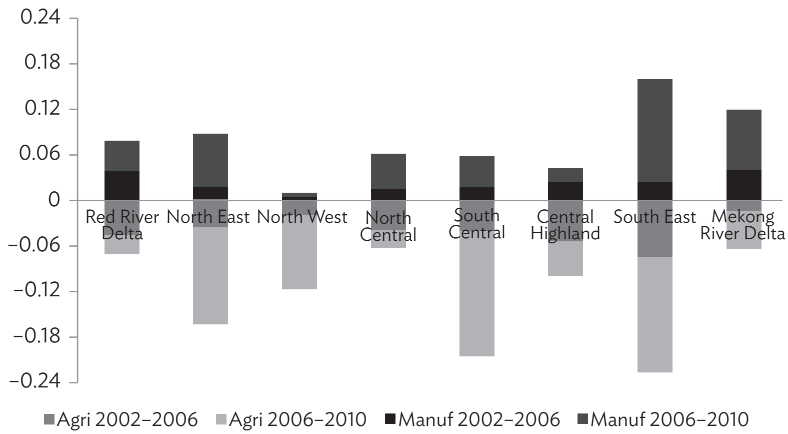
Figure A11.3: Net Migration



Note: The graph shows the net immigration by region in percentage. A negative value indicates higher emigration than immigration into the city.

Source: General Statistics Office (GSO), Viet Nam.

Figure A11.4: Change in Sectoral Participation by Region



Agri = agriculture, Manuf = manufacturing.

Source: Authors' calculations based on VHLSS 2002, 2006, and 2010.

Table A11.1: Descriptive Statistics

	2002	2006	2010
Observations	19,648	7,984	8,127
HHSize	4.506	4.294	3.975
	(1.729)	(1.631)	(1.520)
Log Land	6.174	6.304	5.864
	(3.884)	(3.741)	(3.945)
Ethnicity	2.036	2.22	2.371
	(3.724)	(4.270)	(4.343)
Age of Head	44.542	46.646	45.559
	(12.054)	(11.629)	(12.173)
Gender of Head (Male = 1)	0.8	0.789	0.79
	(0.400)	(0.408)	(0.407)
Married (Yes = 1)	0.863	0.859	0.86
	(0.344)	(0.348)	(0.347)
Secondary ed (Yes = 1)	0.42	0.427	0.419
	(0.494)	(0.495)	(0.493)
Higher ed (Yes = 1)	0.208	0.227	0.245
	(0.406)	(0.419)	(0.430)
Years of schooling of head	6.963	7.212	7.341
	(3.547)	(3.556)	(3.615)
No. of children	1.896	1.573	1.365
	(1.330)	(1.231)	(1.123)
Male adults	1.259	1.317	1.263
	(0.731)	(0.756)	(0.710)
Female adults	1.351	1.403	1.348
	(0.679)	(0.699)	(0.671)
lpchhexp	7.949	8.463	9.495
	(0.595)	(0.636)	(0.689)
Observations	19,648	7,984	8,127
Agriculture	0.605	0.566	0.434
	(0.489)	(0.496)	(0.496)
Manufacturing	0.154	0.173	0.29
	(0.361)	(0.378)	(0.454)

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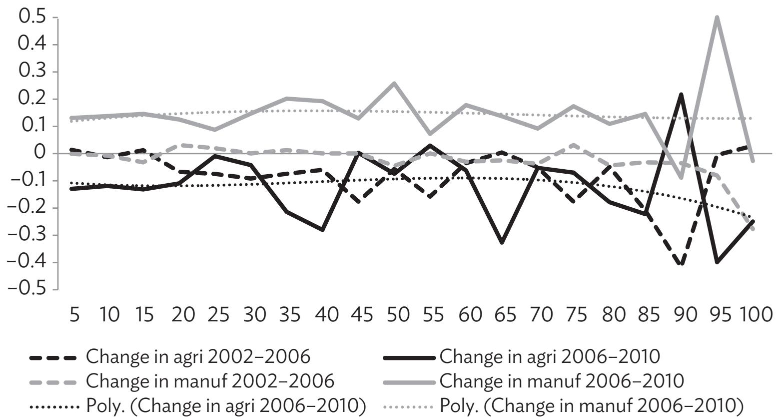
Table A11.1 *continued*

	2002	2006	2010
Wholesale, Retail, Transport	0.151	0.157	0.162
	(0.358)	(0.364)	(0.368)
Other Services	0.089	0.105	0.114
	(0.285)	(0.306)	(0.318)
Leaders	0.021	0.03	0.022
	(0.144)	(0.170)	(0.146)
Professionals	0.084	0.097	0.194
	(0.277)	(0.297)	(0.395)
Skilled agri worker	0.05	0.042	0.107
	(0.217)	(0.201)	(0.309)
Unskilled agri worker	0.546	0.518	0.397
	(0.498)	(0.500)	(0.489)
Skilled manufacturing worker	0.112	0.126	0.184
	(0.315)	(0.332)	(0.388)
Unskilled other	0.184	0.183	0.096
	(0.387)	(0.387)	(0.295)
Region–Red River Delta	0.22	0.205	0.18
	(0.414)	(0.403)	(0.384)
Region–North East	0.158	0.151	0.167
	(0.365)	(0.358)	(0.373)
Region–North West	0.037	0.052	0.076
	(0.190)	(0.222)	(0.264)
Region–North Central Coast	0.115	0.112	0.109
	(0.319)	(0.315)	(0.312)
Region–Central Highlands	0.093	0.095	0.071
	(0.290)	(0.293)	(0.257)
Region–South Central	0.059	0.068	0.09
	(0.236)	(0.252)	(0.287)
Region–South East	0.115	0.121	0.109
	(0.319)	(0.326)	(0.311)
Region–Mekong River Delta	0.202	0.196	0.199
	(0.402)	(0.397)	(0.399)

HHSize = household size, Agri = agriculture.

Source: Authors' calculations based on VHLSS 2002, 2006, and 2010.

A11.5: Structural Change among Ethnic Minorities by Income Quantile



Agri = agriculture, Manuf = manufacturing.

Source: Authors' calculations based on VHLSS 2002, 2006, and 2010.

Table A11.2: RIF Regression

Dep: lpchhexp	2002	2006	2010	Pooled
Sector–Agriculture	−0.187***	−0.175***	−0.039	−0.117***
	(0.014)	(0.018)	(0.021)	(0.011)
Sector–Manufacturing	−0.102***	−0.131***	−0.096***	−0.111***
	(0.017)	(0.021)	(0.023)	(0.013)
Skilled agriculture occupation	0.165***	0.240***	0.125***	0.134***
	(0.019)	(0.029)	(0.019)	(0.013)
Skilled manufacturing occupation	0.098***	0.082***	0.185***	0.127***
	(0.018)	(0.022)	(0.021)	(0.013)
Professional	0.234***	0.266***	0.391***	0.32***
	(0.02)	(0.023)	(0.024)	(0.014)
Log land size	−0.022***	−0.025***	−0.027***	−0.026***
	(0.001)	(0.002)	(0.002)	(0.001)
Household Size	0.017***	0.011	−0.012*	0.009**
	(0.004)	(0.006)	(0.006)	(0.003)
Married (Yes=1)	0.041*	0.034	0.048	0.035**
	(0.016)	(0.021)	(0.025)	(0.013)

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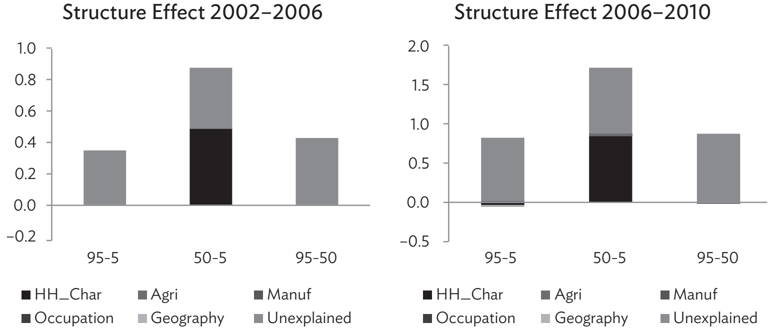
Table A11.2 *continued*

Dep: lpchhexp	2002	2006	2010	Pooled
Secondary ed. (Yes=1)	0.118***	0.197***	0.215***	0.177***
	(0.01)	(0.014)	(0.014)	(0.008)
Higher ed. (Yes=1)	0.315***	0.428***	0.433***	0.402***
	(0.014)	(0.018)	(0.019)	(0.011)
Ethnicity	0.201***	0.251***	0.455***	0.292***
	(0.014)	(0.02)	(0.019)	(0.01)
No. of children	−0.143***	−0.153***	−0.157***	−0.151***
	(0.005)	(0.007)	(0.008)	(0.004)
More than one adult male (Yes=1)	0.027	0.006	0.051	0.031
	(0.022)	(0.03)	(0.033)	(0.018)
More than one adult female (Yes=1)	−0.143***	−0.249***	−0.08	−0.146***
	(0.037)	(0.057)	(0.046)	(0.03)
Region–Red River Delta	−0.179***	−0.141***	0.302***	−0.030**
	(0.014)	(0.018)	(0.025)	(0.011)
Region–North East	−0.115***	−0.143***	0.053**	−0.051***
	(0.015)	(0.019)	(0.019)	(0.011)
Region–North West	−0.149***	−0.121***	−0.038	−0.100***
	(0.025)	(0.03)	(0.022)	(0.015)
Region–North Central Coast	−0.292***	−0.349***	−0.059**	−0.233***
	(0.015)	(0.02)	(0.02)	(0.011)
Region–Central Highlands	−0.157***	−0.116***	−0.052*	−0.104***
	(0.015)	(0.02)	(0.022)	(0.011)
Region–South Central	−0.096***	−0.010	0.190***	0.043**
	(0.019)	(0.025)	(0.023)	(0.014)
Region–South East	0.247***	0.300***	0.321***	0.291***
	(0.019)	(0.022)	(0.025)	(0.013)
Year 2006				0.456***
				(0.007)
Year 2010				1.408***
				(0.008)
Constant	8.261***	8.779***	9.167***	8.095***
	(0.045)	(0.068)	(0.056)	(0.035)
R–Squared	0.427	0.498	0.518	0.736
Observations	19,648	7,984	8,127	35,759

RIF = re-centered influence function, lpchhexp = log per capita household expenditure.

Source: Authors' calculations based on VHLSS 2002, 2006, and 2010.

Figure A11.6: Decomposition of Structure Effect



HH_Char = household characteristic, Agri = agriculture, Manuf = manufacturing.
Source: Authors' calculations based on VHLSS 2002, 2006, and 2010.

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Kuznets Beyond Kuznets

Structural Transformation and Income Inequality in the Era of Globalization in Asia

Kuznets' views about the inverted-U relationship between inequality and development and the process of structural transformation have been under the lens of researchers for a long time. Over the last 20 years, immense potential for growth in Asia has been facilitated by structural transformation. However, it remains undecided whether the contribution of structural transformation will stay as one of the crucial factors in determining potential productivity growth and income distribution. This book brings together novel conceptual frameworks and empirical evidence from country case studies on topics related to structural transformation, globalization, and income inequality.

"Structural transformation entails a change in quantities and/or a change in prices across sectors (e.g., modern/traditional, agriculture/manufacturing/services, urban/rural), demographic groups (male/female, young/prime-aged/old), and other categories. This volume is a welcome addition to thinking about economic growth and development in structural transformation terms. Much can be learned."

Gary Fields, professor of economics, Cornell University

"Global inequality is one of the most pressing challenges of our time. At the same time, structural transformation is one of the essential pre-conditions for rapid broad-based economic growth. This book provides a comprehensive account of the relationship between structural transformation and inequality, with several carefully done country case-studies. The book will be valuable to academics and policy-makers alike."

Kunal Kalyan Sen, professor, University of Manchester

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The Asian Development Bank Institute, located in Tokyo, is the think tank of the Asian Development Bank. The institute aims to identify effective strategies to improve policy and development management in Asia and the Pacific. We work with an extensive network of partners in the region and globally to influence policies on poverty reduction, inclusive growth, the environment, regional cooperation, infrastructure development, middle-income countries, and private sector development.

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