HOKKAIDO UNIVERSITY

DOCTORAL DISSERTATION

Prioritizing Economic Development for Increasing Dietary Diversity

By

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Gratitude is the parent of all virtues. As the curtain draws to these three years of herculean, yet tremendously enriching academic journey in Hokkaido University, my heart is full of joy and gratitude. I echo with Duncan in Shakespearean Macbeth “Oh my plenteous joy, wanton in its fullness, seeks to hide itself in the cockles of my heart.” I thank God immensely for His unfailing paternal solicitude within these years. May His name be ever praised.

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ABSTRACT

The article in chapter one explains how food production diversity mitigates dietary diversity against shocks-induced income variations. We construct survey-panel dataset, separate 2,336 households by their credit status, and estimate a switching regression model. Increasing vulnerability of Nigeria`s farm households to food security risks motivates this study. As Nigeria relies majorly on oil and gas rents for revenues, global shocks generate macroeconomic fluctuations. This complicates policymaker`s attempts to boost food production using agricultural transformative reforms. Households try to diversify crop production to sustain quality nutrition, but they are constrained by credit to do so. We find that credit-unconstrained households diversified food production, but credit-constrained households could not. However, diversifying crop production shows a slight mitigation to nutritional quality. Therefore, income growth remains highly important for increasing dietary diversity.

The second article, which is reported in chapter two, investigates similarities in effects of infrastructure on economic development of 130 countries over 25 years. An autoregressive distributed lag (ARDL) model is used to extract the extent of disparities in wages, income, and nutrition originating from skilled labor and infrastructure complementarity. We identify latent country groups based on unknown group structure in panel ARDL models. We find that infrastructure has group-heterogeneity of effects on economic development across countries. Most African countries fell into groups that do not reap infrastructure and skilled labor complimentary advantages for economic growth. However, infrastructure has narrow economic growth prospects in Africa because of limited industrialization. Education of labor might be more viable for Africa`s sustainable development.

The article in chapter three examines the effect of education of workers on economic growth of 102 countries over 15 years. I estimate the econometric model of the supply of and demand for educated services with macro production technologies. The results indicate a significant positive causality between educated services and economic performance. Investing in education shows optimum at three to six years of schooling where enterprise-needed skills are taught. Most developed countries maximize growth because

they have workers with ideal education and skills needed by companies. This maximum growth generates employment for unemployed workers with the enterprise-required skills. Africa`s workers show inadequate education compared with labor in advanced nations. Poor education account for the low income in Africa and effort to suggest a remedial measure led to my fourth research project as discussed in chapter four.

The chapter provides a guide on education and allocation of labor to minimize unemployment and poverty. It utilizes panel data set generated from Nigeria's general household survey (GHS) panel. A simultaneous equation model wherein equations of demand for and supply of educated labor endogenize investment in education is formulated. Slope heterogeneity of relationship between educated labor and income growth is considered. The results show that completing tertiary education is enough for educated labor to secure jobs and maximize wages through contributions to total output.

The analysis so far indicates that own saving and money transfers do not provide substantial consumption insurance against macroeconomic shocks. This information coupled with those in the previous summaries establish a conclusion that, "Economic development should be prioritized to ensure increasing dietary diversity of households." This concluding empirical fact, which remains relevant to most African countries, corresponds my doctoral dissertation theme. The economic development's importance for increasing dietary diversity is evaluated as an extended chapter to this dissertation–the chapter five.

The evaluation shows that food items and food groups consumed out of those available but unattainable by households is infinitesimal. This indicates a low economic development in Africa. Therefore, African countries should, "Prioritize economic development for increasing dietary diversity of their populace."

0.1. RESEARCH BACKGROUND AND GENERAL INTRODUCTION

In the early 1960s and late 1980s, Agriculture was Africa's primary source of revenues. Policymakers supplied farm households' inputs and financing supports to increase economic growth through agricultural commercialization. Households earned increased income from farm produce. Moreover, agricultural output met food demand and substantially increased external reserves by increasing exports of semi-processed food items. Prices of food items were low because staple crops were mostly produced locally. Food importations were minimal. Many individuals in households that did not own a farm worked for farm-owners and in non-agricultural enterprises. Unemployment and poverty rates were reduced. There was a general increase in economic growth and food security of households at that time.

However, in the 1990s, deregulation of farm support-system eliminated certain agricultural credit schemes and transformative initiatives (Kherallah et al., 2002). This was more pronounced in Sub-Saharan African (SSA) countries, where economic growth interest was shifted to natural resources. Most of the countries became resource-reliant, depending sorely on world markets` prices for economic development. This is still the situation of many SSA countries today, which has socioeconomic consequences. One of its implications is decrease in dietary diversity of households. After deregulation dismantled agricultural support systems, farm households faced inputs and credit constraints (Adjognon et al., 2017). This led to stagnant agricultural production and a substantial reduction in the domestic food supply (Kelly et al., 2003; Morris et al., 2007).

Consequently, food importations rose in response to accelerating demand for food items from rapidly increasing population (Gollin et al., 2016). This increased prices of domestically produced and imported food items. Farm households that now make small profits from sales of agricultural produce, face inflating food prices, and could purchase fewer food items. Moreover, most households consumed less preferred food items because of increase in prices of items. Accordingly, over 33.2 percent of households were malnourished at that time (FAO et al., 2018), despite the increases in food importations: mostly caloric food items, especially rice and wheat, were imported (Ecker & Hatzenbuehler, 2021), items in other food groups especially micronutrients' sources such as fruits, vegetables, pulses, nuts, and seeds, were in shortage (Jones et al., 2014; Harika et al., 2017).

Poor dietary diversity is still prevalent in Africa (Kumssa et al., 2015; FAO, 2020), and farm households are most vulnerable (Fanzo, 2018; Sibhatu & Qaim, 2017). Although households attempt to diversify food production (Jones et al., 2014), it had not ameliorated dietary inadequacy. Studies suggest that income growth is key to increasing dietary diversity (Ecker, 2018; Ecker & Hatzenbuehler, 2021). Achieving sustainable economic growth is a struggle to developing countries. This is because of limited potential for industrialization accompanied by inadequate infrastructural status. Another reason for the lack of development is complexities in diversifying crop production by each farm household.

A comparative analysis of developed and developing countries may provide an important empirical guide to economic growth policies of developing countries. It could reveal economic growth secrets of advanced nations for developing countries to learn. This dissertation attempts such an analysis, focusing on infrastructure and education because of their transformative roles in advanced countries.

Regarding structure, chapter one investigates contributions of agricultural production diversity to dietary diversity. Chapter two and chapter three present comparative studies to guide development policies. Based on country-positions in the comparison studies, a guide is provided in chapter four to help poor households liberate from poverty. Moreover, economic growth's importance for improvements in dietary diversity is assessed in chapter five. This is immediately followed by a summary of the evaluation and general conclusion of dissertation.

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CHAPTER ONE

FOOD CONSUMPTION–PRODUCTION ADJUSTMENTS TO ECONOMIC CRISES UNDER CREDIT CONSTRAINTS IN NIGERIA

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Food consumption–production adjustments to economic crises under credit constraints in Nigeria

Abstract

Poverty and inadequate dietary diversity are increasing in resource-reliant African countries like Nigeria. Policymakers have attempted using agricultural policy reforms to boost productivity and increase income. However, macroeconomic instabilities complicate agricultural transformation. Consequently, farm households try to diversify food production to mitigate shocks-induced nutrition losses. However, credit constraints disrupt planting of different crops required for adequate diets. This study, which is co-authored by Professor Shingo Takagi, investigates dietary diversity performance during Nigeria's Agricultural Transformation Agenda. It examines whether credit-constrained households adjust food consumption and production differently from credit-unconstrained families. The aim is to uncover the dietary diversity implications of the adjustments and evaluate the changes such a linkage has undergone during the commercialization initiative. While credit-unconstrained households diversified food production to mitigate dietary diversity losses, credit-constrained households were unable to do so. A policy that improves credit access for farm-input purchases appeared to increase dietary diversity. However, macroeconomic shocks disrupt smooth implementations of the policy. Policy decisions on the designation of a financial-support scheme that approves credit to households for operating off-farm enterprises must be considered. The business profits could complement farm income to improve family's dietary diversity. Part of the profits could again be plow back into farm-input needs to enhance agricultural commercialization.

Keywords

agricultural policy, agricultural transformation, consumption–production linkage, dietary diversity, credit constraint, Nigeria

JEL classification

O13; Q12; Q18

1. INTRODUCTION

1.1. Societal problems of interest

Given the growing population of farm households in SSA countries, agricultural transformation is one of the top strategies for increasing economic growth and reducing poverty. Modernizing the agricultural sector is vital to diversify the SSA economies and increase food production (McMillan et al., 2014). The growth in agricultural productivity stems from the presence of enabling structural policy reforms and agricultural sector investments (Jayne et al., 2019). Policymakers in SSA countries have prioritized inputs and financing supports for agricultural commercialization in recent years (Rodrik, 2018).

This is especially in Nigeria given its large farm households and extreme unemployment and poverty rates. Two of the most recent agricultural sector initiatives in Nigeria include the 2011–15 Agricultural Transformation Agenda (ATA) and its successor, the 2016–20 Agricultural Promotion Policy (APP) (FMARD, 2011, 2016). Implementing the policies requires fund transfers from the federal government, through the state and local governments, to the households in more rural areas of the countries. Public revenues from natural resources, particularly the oil and gas rents, which fluctuate with the prices of oil and gas in the world's market (Sibhatu et al., 2015), are used for the implementation of such policies.

This suggests that countries' macroeconomic and fiscal conditions are significant for modernizing agricultural production and commercializing crops' marketing. Transforming agricultural activities can help grow farms' income, enabling farm households to consume appropriate food items for a healthy life. The growing consumption may stimulate aggregate demand and generate pro-poor economic growth. However, specializing in a few profitable crops reduces production diversity of farms and food self-sufficiency of households (Ecker, 2018). This could have important nutritional implications.

To protect families from poor dietary diversity that results from the unfolding macroeconomic downturns, households often reduce farm specialization to maintain food production diversity (Dillon & Barrett, 2017). This is consistent with the evidence of diversifying food production for improving dietary adequacy found in SSA countries (Dillon et al., 2015; Ayenew et al., 2018). Using production diversity to mitigate dietary diversity losses is rational due to the non-separability of farm production decisions and household consumption choices consequent upon the dysfunctional markets in SSA (Poulton et al., 2010).

However, given the poverty rates in SSA countries, planting new crops may require external resources, suggesting the relevance of credit access for increasing dietary diversity of households. Additionally, macroeconomic and fiscal volatilities complicate agricultural policy reforms, with the associated food production and welfare consequences (Wossen et al., 2017). Most studies investigating the production and consumption decisions of farm households in African countries (Jones et al., 2014; Romeo et al., 2016) used cross-sectional data or short panel data of one year or two years.

Such research provided little coverage of the macroeconomic and fiscal changes surrounding households. These studies suggested income growth and food production diversification for increasing households' dietary diversity. However, existing studies have not explored how households have performed in increasing dietary diversity for their families in recent years. Did households actually remedied income losses by increasing food production diversity or they obtained loans to insure their dietary diversity losses?

Studies attempting to measure the dietary diversity performance of African farm households are limited. The work by Ecker and Hatzenbuehler (2021) is notable in this area. It documents that the beneficiaries of Nigeria's Growth Enhancement Scheme (GES) – the ATA's key initiative – witnessed improved dietary diversity during the period of ATA. Regarding pooled households, it remains unclear whether the increased dietary diversity was due to the agricultural policy program or households took loans to insure their dietary losses in periods of economic crisis. The later could be the case and this study tries to test it.

Empirical evidence from earlier studies has limited usefulness for policymakers, especially in Africa's context with random failure of the credit markets (Davis et al., 2009). To better investigate households' dietary diversity conditions, this study uses Nigeria's household panel data that span over seven years and coincide with the ATA periods. In doing it, households are separated based on their credit status to study their relative production and consumption responses to changing macroeconomic and fiscal outcomes. The empirical results may be useful for agricultural policymakers in Africa, especially countries where dietary-sensitive agricultural policy is a priority.

1.2. Questions that motivate this study

Understanding consumption and production decisions that farm households use to mitigate dietary diversity losses at any credit condition will serve agricultural policy purposes. One way to explain such non-separable decisions is to examine households` dietary changes associated with their consumption and production choices. The objective of this study is to precisely investigate such a link in Nigeria`s context. To do it, the following research questions are addressed:

1) Do farm households adjust food consumption and production alike regardless of their credit status?
2) Is there a connection between credit positions and dietary implications of such adjustments?
3) How has such linkage changed during the GES agricultural initiative?

Aside from African countries, empirical answers to these questions may be relevant to many other countries in Asia and Latin America, facing issues like lack of access to credit and high poverty rates.

1.3. Importance of conducting this study

This study has notable significance in terms of data and results. Nigeria`s farm households are ultimate beneficiaries of the work. However, its usefulness extends to households in other developing countries. Especially countries relying on natural resources for revenues, and where improving dietary diversity is a goal of agricultural policy. Therefore, this work has great usefulness to policy analysts and agricultural policymakers in developing countries. It exposes the diversity of agricultural production as households` common response to macroeconomic volatilities.

This reaction retards agricultural growth and decelerate farm commercialization, income increase, and dietary diversification. This is because crop production diversity may not be enough to account for dietary diversity losses resulting from income changes generated by macroeconomic shocks.

The originality of panel dataset used has multidisciplinary relevance in different fields, generating big returns to society. For example, the panel dataset has the potential of being used in the fields of behavioral and welfare economics to estimate the link between income inequality and consumption distribution. It can be as well used by the health scientists to establish the link between shocks to income and changes in customers' health expenditures. The panel dataset can be utilized by dietitians and nutritionists (medical scientists) to determine the optimal frequency of clients' food-intake.

Moreover, the dataset can be applied in the fields of sociology and anthropology to evaluate the role of food gifts in the social behaviors of individuals in households. Finally, the dataset has relevance in the field of education as it can be used to examine the contributions of schooling to households' living conditions.

Use of the panel dataset in the various fields allows for derivation of sound policies around welfare and behavioral economics; health; and education; including adjustments in health insurance. It also enables the designation of diets and nutritional advice and promotion of social and cultural solidarities since receiving gifts is related to the extent of interactions in society. Moreover, improvements in science and technology; industry; and good cultural and societal solidarities require good health of the people.

They supply the requisite ideas, innovations, skills, and other important human inputs. Improved health of the people through quality dietary diversity ensures the productivity of all sectors which consequently reflects in the productivity of the aggregate economy. Therefore, the importance of this research cut across almost every sector of the economy. This makes it pertinent for improved productivity, governance, entrepreneurial development, high standard of living, and the generation of efficient labor.

1.4. Geographical and content coverage of this work

This is a micro-data and Nigeria specific research. It focuses on households` diets by investigating the correlation between agricultural production diversity and dietary diversity. The gap in this literature (the effect of crop production diversity on dietary diversity) is to address issues of credit constraints, and of the performance of the ATA. Moreover, this research is the first to utilize a panel dataset newly constructed from survey-waves in accounting for credit conditions in the study of household's behaviors.

Researchers that have collected information from the same survey focused on the repeated cross-sectional data. This captures households' characteristics only at a moment in time. Gathering information from every available wave of the survey better captures the intertemporal budgets of households. This is required for a deeper understanding of households' behaviors in terms of their responses to effects on them, of the environment they live in. These gaps pose a knowledge need that necessitates this scientific inquiry. Indicators of dietary diversity, agricultural production diversity, household's income, farm households` characteristics, and household's demographics, are used.

To gain clearer understanding of this study's contributions and of the panel dataset used and their variable measures, it is important to read through the organizational directives underneath.

1.5. Location of issues contained in this study

The section describes households' credit status and its linkage with dietary diversity. Thereafter, data construction, descriptive evidence, and the estimation technique are discussed. Immediately following these are interpretations and implications of results, and then the conclusion of study.

2. POLICY ISSUES, CREDIT-STYLIZED FACTS, AND LITERATURE REVIEW

2.1. ATA and credit status of households in Nigeria

Nigeria is Africa's largest crude oil producer with oil and gas rents as its main revenue–source. The share of oil and gas in the country's GDP is volatile and hovers around 3 percent and 18 percent between 2011 and 2018 (EIA, 2019). During those periods, agriculture's share in GDP is consistently 21 percent and that in employment declined from 40.2 percent to 36.6 percent (World Bank, 2019). However, Nigeria's annual spending on food imports increased to US$6.1 billion in 2018 from US$3.2 billion in 2011 (World Bank, 2019). Nevertheless, about 86.4 million persons between 2017 and 2019 experienced poor diversity of their diets (FAO, 2020).

Consequently, the Federal Ministry of Agriculture and Rural Development (FMARD) believed that through agricultural commercialization, the locally produced food items could substitute the imported ones thereby reducing spending on food imports. Additionally, it generates foreign exchange through farm exports and increases dietary diversity by making food items accessible to the people (FMARD, 2016). The ATA was initiated in 2011 to increase farm productivity, efficiency, and effectiveness (FMARD, 2011). Prior to 2011, world's oil prices rose, and Nigeria's GDP growth increased.

However, oil prices became stable in 2011 and lower petroleum was produced, reducing oil revenues. Resultantly, Nigeria's economic growth reduced between 2011 and 2012 before it increased above 6 percent between 2013 and 2014 (EIA, 2019). During 2015–2016, oil price fell, and Nigeria's terms of trade deteriorated, leading to a decreased oil revenue. These macroeconomic fluctuations increased fiscal deficits starting from 2013 (IMF, 2017).

The GES is the ATA's primary initiative through which FMARD issued e-wallets to over 12 million farmers in 2011–2014 to buy inorganic fertilizer at subsidized cost from retailers (Wossen et al., 2017). Other fertilizer assistance to farmers accompanied the ATA; however, its implementation was reduced under the APP as macroeconomic volatilities worsened (FMARD, 2016). In addition to the increasing macroeconomic shocks at that time, several farm households had binding credit constraints.

Table 1 presents credit-questionnaire responses in the Nigeria general household survey (GHS) panel. Roughly 11.7 percent of Nigerian farm households in wave three, which increased to 27.9 percent of households in wave four, were credit constrained, as they needed a loan but did not apply for it (a-1). Additionally, the number of households that were constrained by their inability to repay loans decreased from approximately 64.5 percent in wave three to roughly 47 percent in wave four (b-1). However, the number of households that could obtain loans if they wanted to, increased from about 6.1 percent to around 9.8 percent (b-2).

TABLE 1. ———STYLIZED FACTS ON CREDIT STATUS PROVIDED BY RESPONDENTS IN THE NIGERIA'S GHS-PANEL

				Average expenditure and dietary diversity					
				wave3 ***			wave4 ***		
(a) Out of total number of households surveyed:	wave3	wave4	credit status	exp	dds	fvs	exp	dds	fvs
(a-1) Those that needed a loan but did not apply for it	0.117	0.279	constrained	5.05	8.51	16.2	5.57	8.82	17.1
(a-2) Those that did not need a loan and did not apply*	0.707	0.568							
(b-1) Out of (a-1), those that had low assets	0.645	0.470	constrained	4.88	7.83	13.9	5.62	8.28	15.3
(b-2) Those that had very high liquid assets	0.061	0.098	not constrained	5.15	8.41	15.4	5.56	8.83	17.4
(a-3) Households that applied for and received loans	0.167	0.119							
(c-1) Those that received their applied amount **	0.092	0.064	not constrained	5.04	8.69	16.0	5.79	8.59	16.2
(c-2) Those that received less than they applied for	0.076	0.055	constrained	5.16	9.03	17.5	6.00	9.66	19.0
(c-3) Those with approved but not received loans	0.009	0.005	constrained	5.20	8.00	13.8	6.02	10.2	19.4
(c-4) Households whose loans were not approved	0.012	0.022	constrained	4.95	7.98	14.4	5.60	7.89	15.6
(a-4) Households that do not own any asset	0.782	0.756	constrained	4.99	8.21	15.0	5.64	8.57	16.2
(a-5) Households that own some assets	0.218	0.244							
(f-1) Those with assets less than the mean asset	0.872	0.814	constrained	4.93	8.04	14.5	5.63	8.49	15.9
(f-2) Those with assets at least equal to the mean	0.129	0.186	not constrained	5.23	8.70	16.3	5.69	9.24	18.6

* partly self-selected due to inability of paying back the potential amount of loans ** partly reporting enough amount of loan due to self-selection *** sample average expenditure (exp), dietary diversity score (dds), and food variety score (fvs) for the various credit classification of households

The credit-constrained households spent less than the credit-unconstrained households in the third wave; however, the increase in the expenditure of the former was more than that of the latter in the fourth wave.

Furthermore, roughly 6.4 percent of households in wave four, which fell from 9.2percent in wave three, witnessed less difficulty in obtaining loans (c-1). Moreover, about 7.6 percent of households received lesser loan amount than requested in wave three compared to 5.5 percent in wave four (c-2). Households that managed to get the entire loan amount sanctioned to them were not credit constrained unlike those that received lesser amount than they had applied for. The credit-constrained households spent more than those that were credit unconstrained and better diversified their diets. Additionally, roughly 0.9 percent and 0.5 percent of households in wave three and wave four, respectively, got approval but were yet to receive loans (c-3).

Moreover, about 1.1 percent of households in wave three and roughly 2.2 percent in wave four were denied loans (c-4). These indicate that around 6.34 percent of households were not credit constrained, whereas about 8.9 percent of households were credit constrained based on the past three-year information from the household survey.

Inadequate collateral prevented most households from applying for a loan (NBS, 2016a, 2016b). Compared to 2018, there was a decrease in the value of guaranteed loans provided by the agricultural credit guarantee scheme fund (ACGSF) to the extent of NGA ₦307,594 in 2019 (CBN, 2020). Following Kumar et al. (2013) and Ali et al. (2014), self-selected households and those that were denied loans are defined as credit constrained. However, credit status of households who declared no need of loans for having sufficient income was defined on the basis of their liquid assets (b-1; b-2), in line with Zeldes (1989). (Some households might become credit-constrained if they witness income shocks.)

Notice that Table 1 shows credit information in wave three and wave four because the two waves provide better coverage of credit data due to upgrades in the survey-questionnaires (NBS, 2018).

2.2. Dietary diversity and credit constraint's linkage

Several studies in Africa's context explain dietary diversity's linkage with income changes and food production diversity. Jones et al. (2014) focused on Malawi; Sibhatu et al. (2015) on Ethiopia, Malawi, and a few other countries; and Romeo et al. (2016) on Kenya. Studies by Hirvonen and Hoddinott (2017) on Ethiopia; Carletto et al. (2017) on Malawi, Tanzania, and Uganda; and Dillon et al. (2015), Ayenew et al. (2018), and Sani and Miklas (2022) on Nigeria are notable.

Dillon et al. (2015) estimated Nigeria GHS-Panel data to find that producing 10 percent more crops led to 2.4 percent more diverse foods consumed. Using the same database and fixed effects (FE) method, Ayenew et al. (2018) confirmed that dietary diversity increased by roughly 0.019 units consequent upon one additional crop produced. These studies used cross-section data, reflecting inadequate coverage of changes in the environments that households live in. However, Ecker (2018) on Ghana and Ecker and Hatzenbuehler (2021) on Nigeria are notable exceptions, as these studies utilized panel data of over seven years.

Ecker and Hatzenbuehler (2021) estimated FE models with three dietary diversity's indicators, namely – the dietary diversity score (DDS), food variety score (FVS), and per capita calorie intake. Similarly, planted food crops and crop groups are indicators of crop production diversity, with per capita expenditure as a surrogate for income. Their study reported that a 10 percent increase in income resulted in a 0.24-unit increase in food items consumed and 0.09-unit increase in food groups consumed. An additional crop planted increased food items consumed by roughly 0.11-units and food groups consumed by about 0.09-units.

The coefficient estimates of 0.11 increase in food items consumed mirrors the result produced by Ecker (2018), which used combined data from 2005-06 and 2012-13 from Ghana living standard survey (LSS) to analyze FE model. Ecker and Hatzenbuehler (2021) found that any additional food consumed out of a diversified crop produced was reduced by the related income variability.

However, food production-consumption evidence for Africa remains mixed. For instance, after FE estimation of Tanzanian data, Habtemriam et al. (2021) found insignificant association between crop production indicator of crop species count and the dietary diversity measure of food consumption score. Similar result was found by Sinyolo et al. (2021) between crop production and micronutrient consumption.

Another subset of research found that access to credit markets diversifies diets more than crop production diversity. Using the instrumental variable (IV) method and Ghana LSS dataset, Annim and Frempong (2018) found that aside from income, positive association also occurs between access to credit and dietary diversity. The work by Ali et al. (2014) classified households by their credit status and analyzed Rwandan dataset. Similarly, Lukwa et al. (2022) emphasized how water and energy are inter-related to increase dietary diversity of households in SSA countries.

They found that credit-unconstrained households had roughly 17 percent average growth in farm output. Moreover, credit-constrained households had approximately 6.3 percent lesser chance of operating non-agricultural businesses, suggesting that credit constraints affect households' income. This corroborates evidence by Kumar et al. (2013), which revealed that consumption choices and production decisions are adversely affected by credit constraints. Results from the switching regression model by Mukasa et al. (2017) predicted about 60 percent growth in output of reducing credit constraints in Ethiopia.

2.2.1. Gaps in the empirical literature reviewed.

The first subset of the literature reviewed studies the correlations amongst crop production diversity, households' income, and dietary diversity (Jones et al., 2014; Ayenew et al., 2018; etc.). The second subset of studies emphasizes the extent that binding credit constraints affect dietary diversity of households (Annim & Frempong, 2018; etc.). Moreover, the third subset of work presents how credit constraints affect income and agricultural productivity (Kumar et al., 2013; Mukasa et al., 2017; etc.).

Clearly, there is a knowledge gap in-between, going through channels of income and production to dietary diversification. Could this be part of reasons for the mixed results that were previously pointed out?

(See, e.g., Habtemariam et al., 2021; Sinyolo et al., 2021). Moreover, how do farm households' decisions vary with their credit positions? Also, is there a link between credit status of households and dietary implications of such decisions? The empirical analyses below emphasize these issues.

3. DATA DESCRIPTION

3.1. Data construction

This study used the Nigeria GHS-Panel as the database for empirical analyses (NBS, 2018). Data were collected from roughly 4,167 households that mostly farm small areas of land, after planting periods and following harvest. The aim was to incorporate crop planting and harvest information within an agricultural year (NBS & World Bank, 2016a). There are, presently, four panel waves: Wave one, 2010-11; wave two, 2012-13; wave three, 2015-16; and wave four, 2018-19.

However, only 1,507 households among those originally interviewed in wave one through wave three were assessed in wave four because of insecurities in some regions at that time (NBS, 2018). To investigate this study's hypotheses and simplify comparison with related studies especially Ecker and Hatzenbuehler (2021), the first three waves were focused on.

Farm households, defined as those that produce crops, rear livestock, and undertake other agricultural activities (NBS & World Bank, 2016a) were the broad focus of analyses. Following Ecker and Hatzenbuehler (2021), this wider sample was narrowed to include households that cultivated farmlands and consumed food items at home. This gave a balanced panel sample of 2,336 households, amounting to 56.1 percent of the complete balanced panel sample.

While 727 households were credit-constrained by their inability to obtain loans, 825 households received the full amount of loans they requested and so were not credit constrained. These gave a panel data of 1,552 households in the loan-application classification.

Moreover, 88 households that partly received loans and 322 households with no loan-application had low assets and were credit constrained.

TABLE 2. ——CLASSIFICATION OF HOUSEHOLDS USING LOAN-APPLICATION QUESTIONNAIRE AND LIQUID ASSETS

	Refused	Accepted		why no application?		Total
		Partly	fully	Satisfied	self-selected	
applying for loans	727	980				1,707
		155	825			
not applying for loans				629		629
				435	194	
	constrained HHs			not constrained HHs		
		value of assets per capita		value of assets per capita		
		less than mean	not less than mean	less than average	not less than average	
		88	67	322	307	
Total		constrained HHs	not constrained HHs	constrained HHs	not constrained HHs	2,336

Note: There are 727 households that were refused loans and so were credit-constrained and 825 households that received full amount of loans they requested and then were credit-unconstrained. Again, 88 households out of those that partly received loans and 322 households among those that had no need of additional income had low liquid assets and belong to the credit-constrained group. Similarly, 67 households with partial loan-receipt and 307 non-participants in the credit market owned sufficiently high liquid assets and so had unbinding credit constraint.

Adding these to the previously credit-constrained households gave a balanced panel of 1,137 households with binding credit constraints in the joint classification. Likewise, 307 self-selected households and 67 households with incomplete loan receipts, had substantial liquid assets. These, together with the previous credit-unconstrained households, constituted the 1,199 households with unbinding credit constraints in the mixed separation. Table 2 summarizes the sample classifications.

Data were constructed for dietary diversity indicators and the calorie intake indicator. Similar to other studies (Ecker, 2018; Ayenew et al., 2018), the dietary indicators used were FVS and DDS, with calorie intake per capita as the calorie indicator. In predicting dietary quality and measuring food security, dietary diversity was used (Ruel, 2003). To construct dietary indicators, food items and food groups consumed in the consumption modules were counted.

Before the counting of FVS, the same food in various product forms was unified. Food grouping by Swindale and Bilinsky (2006) was adopted for DDS. In line with Dillon et al. (2015) and Jones et al. (2014), food crop variety (FCV) and food crop group (FCG) were used as indicators for food production diversity. Similar to FVS and DDS, food crops and crop groups planted in the agricultural modules were counted as measures for FCV and FCG, respectively.

For the income variable which was proxy by amount of expenditure per capita, food and non-food expenditure of households were aggregated, following Deaton and Zaidi (2002). The income data were from the post-planting and post-harvest survey-rounds. Data on food consumption and households' characteristic variables were from the post-harvest survey-rounds. Moreover, the food production data were gathered from the post-planting survey-rounds.

3.2. Descriptive evidence

Table 3 presents descriptive analyses of key variables in the mixed classification. Average dietary diversity increased over the survey periods as FVS and DDS show.

TABLE 3. ———DESCRIPTION OF MAJOR VARIABLES USED IN THIS STUDY AND THEIR SUMMARY STATISTICS

	W1: 2010-11		W2: 2012-13		W3: 2015-16		Compounded annual growth rate for all waves: 2010-16		
	Mean	SD	Mean	SD	Mean	SD	w1-w2	w2-w3	w1-w3
PANEL A: Credit-constrained households:									
Food variety score (FVS) (max.=60)	13.2	4.35	14.0	4.62	15.1	4.90	1.48	1.52	1.94
Dietary diversity score (DDS) (max.=12)	7.69	1.96	7.93	1.93	8.24	1.87	0.77	0.77	0.99
Calorie intake per capita (CIC) (kcal/day; log)	6.90	0.93	6.29	1.13	7.57	0.72	—2.29	3.77	1.33
Expenditure per capita (EXP) (₦/day; log)	5.02	0.70	4.92	0.70	4.98	0.65	—0.50	0.24	—0.11
Food crop variety (FCV) (max.=41)	3.34	1.61	3.43	1.56	3.37	1.53	0.67	—0.35	0.13
Food crop groups (FCG) (max.=7)	2.24	0.96	2.28	0.95	2.19	0.87	0.44	—0.80	—0.32
PANEL B: Credit-unconstrained households:									
Food variety score (FVS) (max.=60)	12.9	4.30	13.7	5.08	14.8	4.88	1.52	1.56	1.98
Dietary diversity score (DDS) (max.=12)	7.57	1.97	7.83	2.03	8.18	1.89	0.85	0.88	1.11
Calorie intake per capita (CIC) (kcal/day; log)	6.90	0.74	6.39	1.16	7.57	0.72	—1.90	3.45	1.33
Expenditure per capita (EXP) (₦/day; log)	5.00	0.71	4.96	0.71	5.00	0.67	—0.20	0.16	0.00
Food crop variety (FCV) (max.=41)	3.27	1.57	3.43	1.52	3.42	1.53	1.20	—0.06	0.64
Food crop groups (FCG) (max.=7)	2.15	0.90	2.23	0.88	2.19	0.87	0.92	—0.36	0.26

Note: There are 1,137 credit-constrained households and 1,199 credit-unconstrained households per wave. Again, calorie intake per capita has 1,030 credit-constrained households and 1,082 credit-unconstrained households. In each panel, the first three variables are dietary diversity indicators and the last two the food production indicators. The expenditure is then an income variable.

Credit-constrained households earned a little more income and consumed more food items and food groups than the credit- unconstrained households in wave one. In wave two, income of the credit-constrained households fell lower than that of the credit-unconstrained households.

Meanwhile, the former allowed calorie consumption to fall below that of the latter but maintained an increase in dietary diversification. Income of the credit-constrained households rose in wave three but was lower than that of the credit-unconstrained households. The former increased both calorie consumption and food diversity more than the latter in wave three.

Contrarily, credit-unconstrained households increased food items and food groups consumed by almost the same annual rate throughout the survey years as the compounded annual growth rate (CAGR) for FVS and DDS show. However, a decline in income caused credit-constrained households to increase food items consumed at a slower rate between wave one and wave two.

When income rose, credit-constrained households maintained the same increment in food variety as the credit-unconstrained households between wave two and wave three. However, both the credit-categories of households increased food groups consumed by almost the same rate. The summary statistics for other variables used are in the appendix, Table E1.

4. ESTIMATION MODELS AND METHODS USED

4.1. Empirical model adopted

Consider a dietary diversity FE model developed by Ecker and Hatzenbuehler (2021):

$$y_{hast} = \alpha_{h|a|s} + \beta_1 x_{hast} + \beta_2 d_{hast} + \beta_3 d_{hast} \times x_{hast} + F'_{hast}\gamma + Z'_{hast}\delta + \emptyset_t + \varepsilon_{hast},$$

where subscripts h, a, s, and t index the household, the local government area, the state, and the time, respectively. This relates dietary diversity (y_{hast}) to household income (x_{hast}); food production diversity (d_{hast}); association between food production diversity and income growth ($d_{hast} \times x_{hast}$); household farm characteristics (F_{hast}); and household demographics (Z_{hast}). Table 3 provides the details of the main variables.

In addition, the FE model allows for the presence of two-ways fixed effects ($\alpha_{h|a|s}$ and $\emptyset_t$) to capture a heterogeneity specific to a household and a time effect across households.

4.1.1. Limitations of the Ecker and Hatzenbuehler (2021)'s model

In the FE model of section 4.1., it is assumed that farm production decisions and household consumption decisions have homogeneous effects on dietary diversity across households. This hypothesis, in Africa's context, especially Nigeria with idiosyncratic failure of credit markets (Adjognon et al., 2017), is severely restrictive. As originally presented (in Table 1), some households experienced income declines but were unable to use credit over the sample periods (NBS, 2018). The adverse effect of credit constraints on consumption-compositions is well documented (Kumar et al., 2013).

Differences in dietary diversities consequent upon heterogenous production-consumption reactions are expected between households that are credit constrained and those that are not. In addition, the FE model captures genuine unobservables by enabling fixed effects but does not control for contingent unobservables due to potential omitted variables. For example, conflicts between herdsmen and farmers, which can lead to destruction of planted food crops and death of farm animals, can influence dietary diversity. However, past evidence has shown that endogeneity is not a serious problem in this area of study, particularly on Nigeria's data (Ecker & Hatzenbuehler, 2021; Ayenew et al., 2018). This is because studies that used IVs and those that employed FE obtained closely related results in terms of direction and magnitude of coefficient estimates. It could be that data generation process used in earlier studies which is followed in this work substantially eliminates the potential endogeneity of selecting agricultural plants.

Besides, instrumenting for endogenous credit separation of households further minimizes endogeneity problem in our case. Welfare loss due to types of accidents (such as the herders–farmers clash) could be insured if credit markets function properly. However, without well-working credit markets, such unobservables are sources of creating credit constraints, which leads to correlations between welfare (proxied by dietary diversity) and credit constraint status (captured by the error term in the FE model) of a household.

Therefore, the FE model developed by Ecker and Hatzenbuehler (2021) requires modifications. One of the transformations is to heterogenize the association between food production diversity and dietary diversity, and that between households' income and dietary diversity. Section 4.2. considers these issues.

4.2. Econometric modifications of the FE model in section 4.1.

The possible presence of credit constraints for some households leads to the modified FE model, the switching regression model (Wooldridge, 2015). This can control for the heterogeneity and endogenous classifications of households in the consumption-production relations due to credit constraints. The switching regression model consists of the following three equations:

$$d_{it} = 1\{z'_{it}\gamma + c_{d,i} + v_{it} > 0\}, \quad (1)$$

$$y_{1,it} = x'_{it}\beta_1 + c_{1,i} + u_{1,it}, \quad (2)$$

$$y_{0,it} = x'_{it}\beta_0 + c_{0,i} + u_{0,it}, \quad (3)$$

where *i* represents a household at a local government area in a state (the triple subscript in Ecker and Hatzenbuehler (2021) is reduced to a single subscript for simplicity), and *t* represents time. The first equation is the selection equation; if a household is classified into the credit-constrained group, the dependent variable d_{it} takes the value of one. Otherwise, it is assigned a value of zero. The variable z'_{it} includes observable determinants of households' credit status, which includes the liquid asset information. The construction of the dependent variable d_{it} was discussed in Section 2. $c_{d,i}$ is a fixed effect and v_{it} is the error term in this equation.

The second and third equation represents production-consumption relations for the credit-constrained households and the credit-unconstrained households, respectively. The dependent variables, $y_{1,it}$ and $y_{0,it}$, are latent variables of dietary diversity for each credit status' group, x'_{it} is a vector of explanatory variables, which includes household income, food production diversity, association between food production diversity and income growth, household farm characteristics, and household demographics. $c_{1,i}$ *and* $c_{0,i}$ are fixed effects, and $u_{1,it}$ and $u_{0,it}$ are error terms in equation (2) and (3), respectively.

The difference between coefficient vectors β_1 and β_0 captures heterogeneous production-consumption relations across credit status' groups. Recall that the error term v_{it} in (1), $u_{1,it}$ in (2), or $u_{0,it}$ in (3) may be correlated due to uninsured occasional welfare loss events, which leads to correlation between credit status and household dietary diversity through observed and unobserved factors in these equations.

Multazashvili and Wooldridge (2016) proposed an estimation method of the above switching regression model with fixed effects using a control function (CF) approach. The observed dependent variable is given as:

$$\begin{aligned} y_{it} &= d_{it} y_{1,it} + (1 - d_{it}) y_{0,it} \\ &= d_{it}\left(x'_{it}\beta_1 + c_{1,i} + u_{1,it}\right) + (1 - d_{it})\left(x'_{it}\beta_0 + c_{0,i} + u_{0,it}\right) \\ &= x'_{it}\beta_0 + d_{it}x'_{it}(\beta_1 - \beta_0) + p_{it} + d_{it}q_{it}, \end{aligned}$$

where $p_{it} \equiv c_{0,i} + u_{0,it}$ and $q_{it} \equiv c_{1,i} - c_{0,i} + u_{1,it} - u_{0,it}$. When these compounded error terms are projected onto the space spanned by all explanatory variables over the sample period, they consist of two terms: the correlated part with all explanatory variables and the uncorrelated one. Furthermore, following the Mundlak approach adopted by Multazashvili and Wooldridge (2016), the correlated parts are assumed to be linear functions of the sample averages of all explanatory variables, $p_{it} = \bar{x}'_i\theta_p + \varepsilon_{p,it}$ and $q_{it} = \bar{x}'_i\theta_q + \varepsilon_{q,it}$, where the standard deviation of $\varepsilon_{p,it}$ ($\varepsilon_{q,it}$) is σ_p (σ_q). Therefore, the above observed dependent variable can be written as follows:

$$\begin{aligned} y_{it} &= x'_{it}\beta_0 + d_{it}x'_{it}(\beta_1 - \beta_0) + \left(\bar{x}'_i\theta_p + \varepsilon_{p,it}\right) + d_{it}\left(\bar{x}'_i\theta_q + \varepsilon_{q,it}\right) \\ &= x'_{it}\beta_0 + d_{it}x'_{it}(\beta_1 - \beta_0) + \bar{x}'_i\theta_p + d_{it}\bar{x}'_i\theta_q + \left(\varepsilon_{p,it} + d_{it}\varepsilon_{q,it}\right) \quad (4) \end{aligned}$$

Similarly, when we assume that the compound error term in the selection equation (1) can be decomposed into the correlated and the uncorrelated parts with all explanatory variables, and that the correlated part can be summarized as the Mundlak type of linear function, the compound error term is approximated as $c_{d,i} + v_{it} = \bar{z}_i\theta_r + \varepsilon_{r,it}$ (the standard deviation of $\varepsilon_{r,it}$ is normalized to one for identification) and the selection equation with a fixed effect can be rewritten as follows:

$$d_{it} = 1\{z_{it}'\gamma + \bar{z}_i\theta_r + \varepsilon_{r,it} > 0\}. \qquad (5)$$

Next, assuming that there is joint normality of the error terms, $\varepsilon_{p,it}$ and $\varepsilon_{r,it}$ ($\varepsilon_{q,it}$ and $\varepsilon_{r,it}$) with a correlation coefficient ρ_p (ρ_q) and all error terms are independent of $x_{i1},\ldots,x_{iT}$ and $z_{i1},\ldots,z_{iT}$, the control functions for the equation (4), or the generalized residual in (4) is given as, using the results $E[\varepsilon_{p,it}|d_{it}] = \rho_p\sigma_p h_{it}$ and $E[\varepsilon_{q,it}|d_{it}] = \rho_q\sigma_q h_{it}$,

$$E[\varepsilon_{p,it} + d_{it}\varepsilon_{q,it}|d_{it}] = \rho_p\sigma_p h_{it} + \rho_q\sigma_q d_{it}h_{it}, \quad (6)$$

where $h_{it} \equiv h(d_{it}) = d_{it}\frac{\phi(z_{it}'\gamma+\bar{z}_i\theta_r)}{\Phi(z_{it}'\gamma+\bar{z}_i\theta_r)} - (1-d_{it})\frac{\phi(z_{it}'\gamma+\bar{z}_i\theta_r)}{1-\Phi(z_{it}'\gamma+\bar{z}_i\theta_r)}$

Finally, combining (4) with (6),

$$y_{it} = x_{it}'\beta_0 + d_{it}x_{it}'(\beta_1-\beta_0) + \bar{x}_i'\theta_p + d_{it}\bar{x}_i'\theta_q + \rho_p\sigma_p h_{it} + \rho_q\sigma_q d_{it}h_{it}$$

$$+(\varepsilon_{p,it} + d_{it}\varepsilon_{q,it}) - E[(\varepsilon_{p,it} + d_{it}\varepsilon_{p,it})|d_{it}]$$

To make the estimation of this equation feasible, we first estimate γ *and* θ_r using the probit model and construct the fitted value of h_{it}, $\hat{h}_{it} \equiv d_{it}\frac{\phi(z_{it}'\hat{\gamma}+\bar{z}_i\hat{\theta}_r)}{\Phi(z_{it}'\hat{\gamma}+\bar{z}_i\hat{\theta}_r)} - (1-d_{it})\frac{\phi(z_{it}'\hat{\gamma}+\bar{z}_i\hat{\theta}_r)}{1-\Phi(z_{it}'\hat{\gamma}+\bar{z}_i\hat{\theta}_r)}$. Then, we run a linear regression model to obtain the coefficient estimates,

$$y_{it} = x_{it}'\delta_1 + d_{it}x_{it}'\delta_2 + \bar{x}_i'\delta_3 + d_{it}\bar{x}_i'\delta_4 + \delta_5\hat{h}_{it} + \delta_6 d_{it}\hat{h}_{it} + error \quad (7)$$

Therefore, to reproduce the coefficient of the unconstrained group, β_0, we know $\beta_0 = \delta_1$. The coefficient of the constrained group is $\beta_1 = \delta_1 + \delta_2$. The significance of δ_5 *and* δ_6 is corresponding to the exogeneity test of the selection equation. In the following estimation results, heteroskedasticity-robust standard error estimates are used.

5. COEFFICIENT ESTIMATES AND INTERPRETATION

5.1. Pooled and "exogenous classification" results

Equations (2) and (3) were estimated by the FE method, and results on FVS and DDS are reported in Table 4 and Table 5, respectively. In the tables, columns (i)–(iii) used loan-classification panel dataset, and columns (iv)–(vi) estimated loan-and-asset classification. Clearly, column (i) and column (iv) do not account for credit constraints and pooled households in the relevant classifications. However, column (ii) and column (v) show results for credit-unconstrained households. Moreover, column (iii) and column (vi) report results for households with binding credit constraints. Results are robust across the specifications. As expected, crop production diversity has a positive and significant relation with dietary diversity.

As Table 4 shows, households that produced one additional crop consumed an average of about 0.20 more food items, irrespective of credit status. This suggests that households transfer farm produce as seeds across agricultural seasons, enabling additional crop-production even in periods of binding credit constraints. For credit-unconstrained households, one more crop produced led to, on average, about 0.23 improved quality of diets (column ii, panel A). The size of this estimate is larger than that of Ecker and Hatzenbuehler (2021), but mirrors result by Dillon et al. (2015).

Accounting for farm characteristics' variables in Table 5 shows that producing one new crop enabled credit-unconstrained households to consume an average of roughly 0.09 increased food groups (columns ii and v, panel E). This is consistent with the result found by Ecker and Hatzenbuehler (2021) and approximates results by Ecker (2018). Consequently, ignoring credit constraints while investigating the effect of diversifying food production on dietary diversity is consistent with estimating the effect for households that are not credit constrained.

Accordingly, one new crop produced is as good as approximately 0.10 increased consumption of food groups by credit-unconstrained households (columns ii and v), just as it is by the pooled households (columns i and iv) [Table 5, panels (D)–(E)]. However, for credit-constrained households, producing a new crop increased food groups consumed by, on average, roughly 0.20 (columns iii and vi).

TABLE 4. ——RESULTS OF THE FIXED EFFECTS MODEL FOR DIETARY DIVERSITY [a]

	Food variety score (FVS)					
	Classification based on loans			Loan and assets' classification		
Model specifications	(i)	(ii)	(iii)	(iv)	(v)	(vi)
Panel A						
Food crop variety	0.212***	0.227***	0.214***	0.170***	0.168***	0.183***
	(0.045)	(0.063)	(0.066)	(0.038)	(0.053)	(0.053)
Expenditure per capita (log)	2.576***	2.176***	3.100***	2.598***	2.287***	2.950***
	(0.119)	(0.152)	(0.189)	(0.099)	(0.133)	(0.146)
Panel B						
Food crop variety	0.188***	0.198***	0.195***	0.152***	0.149***	0.165***
	(0.046)	(0.064)	(0.067)	(0.038)	(0.055)	(0.054)
Expenditure per capita (log)	2.556***	2.165***	3.081***	2.586***	2.279***	2.927***
	(0.119)	(0.151)	(0.190)	(0.099)	(0.133)	(0.146)
Panel C						
Food crop variety	0.474*	0.586	0.440	0.698***	1.047***	0.412
	(0.288)	(0.392)	(0.428)	(0.239)	(0.346)	(0.333)
Expenditure per capita (log)	2.749***	2.425***	3.249***	2.952***	2.876***	3.093***
	(0.226)	(0.300)	(0.347)	(0.186)	(0.263)	(0.266)
Food variety × expenditure	—0.057	—0.079	—0.049	—0.110**	—0.181***	—0.050
	(0.057)	(0.079)	(0.084)	(0.048)	(0.069)	(0.066)

[a] The sample has 1,552 pooled households [column (i)], 825 credit-unconstrained households [column (ii)], and 727 credit-constrained households [column (iii)] per survey wave in the loan classification. There are 2,336 households [column (iv)], 1,199 households with unbinding credit constraints [column (v)], and 1,137 households with binding credit constraints [column (vi)] per wave in the loan and asset classification. Each regression accounts for household demographics and household and time fixed effects. Estimation in Panel B further controls for farm characteristics, and Panel C incorporates the association between food production diversity and household income. Standard errors (in parentheses) are clustered at the household level.
***, **, * Coefficient is statistically significant at the 1%, 5%, and 10% level, respectively.

TABLE 5. ———RESULTS OF FIXED EFFECTS MODEL FOR DIETARY DIVERSITY [b]

	Dietary diversity score (DDS)					
	Classification based on loans			Loan and assets' classification		
Model specifications	(i)	(ii)	(iii)	(iv)	(v)	(vi)
Panel D						
Food crop groups	0.142***	0.120**	0.166***	0.133***	0.110**	0.159***
	(0.035)	(0.052)	(0.048)	(0.030)	(0.043)	(0.042)
Expenditure per capita (log)	1.017***	0.874***	1.211***	1.048***	0.898***	1.219***
	(0.052)	(0.070)	(0.080)	(0.044)	(0.060)	(0.064)
Panel E						
Food crop groups	0.124***	0.088*	0.157***	0.116***	0.087**	0.148***
	(0.036)	(0.053)	(0.050)	(0.030)	(0.044)	(0.042)
Expenditure per capita (log)	1.008***	0.873***	1.208***	1.042***	0.897***	1.212***
	(0.052)	(0.069)	(0.080)	(0.044)	(0.060)	(0.065)
Panel F						
Food crop groups	0.587***	0.478	0.798***	0.663***	0.565**	0.780***
	(0.217)	(0.314)	(0.305)	(0.183)	(0.268)	(0.252)
Expenditure per capita (log)	1.214***	1.042***	1.505***	1.282***	1.102***	1.495***
	(0.109)	(0.151)	(0.161)	(0.090)	(0.128)	(0.128)
Food groups × expenditure	—0.093**	—0.079	—0.127**	—0.110***	—0.096*	—0.127**
	(0.043)	(0.063)	(0.060)	(0.036)	(0.053)	(0.050)

[b] The sample has 1,552 total households (model 1), 825 credit-unconstrained households (model 2), and 727 credit-constrained households (model 3) per survey wave in the loan classification. There are 2,336 sampled-households (model 4), 1,199 households with unbinding credit constraints (model 5), and 1,137 households with binding credit constraints (model 6) per wave in the loan and asset classification. Each regression accounts for household demographics and household and time fixed effects. Estimation in Panel B further controls for farm characteristics with Panel C additionally incorporating the association between food production diversity and household income. Standard errors (in parentheses) are clustered at the household level.

***, **, * Coefficient is statistically significant at the 1%, 5%, and 10% level, respectively.

Moreover, income–dietary diversity's estimate follows "a priori" expectation of a positive and significant relationship. This suggests that income changes generate the same direction of changes in dietary diversity. As Table 4 presents, a 10 percent increase (decrease) in income of households that had unbinding credit constraints led to roughly [2.425×ln(100+10)/100] or 0.23 average increase (decrease) in the food items consumed (column ii, panel C).

This is consistent with the result by Ecker and Hatzenbuehler (2021). However, it is shown that the same percentage point change in income of the credit-constrained households generates approximately 0.31 average change in the food items consumed (column iii, panel C).

This is clearly larger than the effect for the credit-unconstrained group, and this result remained unchanged after verifying it with the mixed classified panel dataset [columns (iv)–(vi)]. It is again shown that income has an average mitigation effect of roughly 0.01 and about 0.02 for every positive association between crop production diversity and dietary diversity of the pooled households and credit-unconstrained households, respectively [columns (iv)–(v)].

This result, which is consistent with Ecker and Hatzenbuehler (2021), does not hold for households with binding credit constraints (column vi). Ignoring credit constraints produces results that lie in-between estimates for the two credit-groups but are closer to the result for the unconstrained credit-group than that of the constrained credit-group.

The effect of income on DDS is shown in Table 5. While households without difficulty in accessing credit markets were consuming an average of roughly 0.08 more food groups for a 10 percent income growth (column ii, panel E), those with difficulty were eating about 0.12 more food groups, on average (column iii). The percentage points change yielded roughly 0.10 improvement in the quality of diets consumed by the pooled households (column i). The coefficient estimates for the credit-unconstrained households again mirrors result by Ecker and Hatzenbuehler (2021).

By implication, binding credit constraints affect dietary diversity of households. This suggests that ignoring credit constraints while investigating the association between income and dietary diversity yields misleading evidence for households with binding credit constraints. While such results retain relevance for households that do not face binding credit constraints, this study further produces empirical evidence for the credit-constrained households.

Clearly, a vast majority of credit-constrained households were hand-to-mouth and impatient in their consumption decisions. When income grew, they likely spent much of the increase on consumption. In periods of income decline, they consumed fewer food items and food groups. In line with Aguiar et al. (2020), credit-constrained households adjusted spending to a larger degree through food items and food groups consumed. Any credit-constrained household was, by implication, at a kink of the intertemporal budget constraint and its marginal utilities coincided with intertemporal-food prices as slack conditions (Attanasio & Weber, 2010).

Conversely, credit-unconstrained households increased (decreased) food items and food groups consumed by a smaller margin than credit-constrained households when income increased (decreased). This is consistent with the precautionary saving behavior because it appears that credit-unconstrained households consumed more food items and food groups when income increased, but still saved part of the increased income for later consumption.

5.2. The "endogenous classification" results

Note that error terms in equation (2) and (3) reflect neglected heterogeneity, which likely includes factors that are correlated with credit status. With such correlated factors, endogenous classification is required. This is why the endogenous switching regression (ESR) equation (7) was estimated, and results reported in Table 6 and Table 7. Column (i) and column (iv) control for households' demographics' variables, while column (ii) and column (v) account for farm characteristics' variables. Column (iii) and column (vi) then test for mitigation effect.

Meanwhile, panel *G* and panel *I* report main results and panel *H* and panel *J* present credit constrained-induced behaviors. Table 6 reports that, on average, households ate roughly 0.26 more food items for any

TABLE 6. —SWITCHING REGRESSION MODEL'S RESULTS FOR DIETARY DIVERSITY [c]

	Food variety score (FVS)					
	Classification based on loans			Loan and assets' classification		
Model specifications	(i)	(ii)	(iii)	(iv)	(v)	(vi)
Panel G						
Food crop variety	0.258^{***}	0.222^{***}	0.513	0.181^{***}	0.156^{**}	0.970^{**}
	(0.079)	(0.079)	(0.524)	(0.069)	(0.068)	(0.459)
Expenditure per capita (log)	2.310^{***}	2.291^{***}	2.487^{***}	2.359^{***}	2.349^{***}	2.892^{***}
	(0.225)	(0.221)	(0.439)	(0.197)	(0.193)	(0.383)
Food variety × expenditure			—0.059			$—0.164^{*}$
			(0.109)			(0.094)
Panel H						
Credit: food crop variety	—0.068	—0.051	—0.036	—0.001	0.005	—0.527
	(0.114)	(0.112)	(0.744)	(0.096)	(0.095)	(0.616)
Credit: expenditure	0.970^{***}	0.967^{***}	0.982	0.693^{**}	0.677^{**}	0.326
	(0.326)	(0.321)	(0.614)	(0.272)	(0.266)	(0.509)
Credit: (crop variety ×			—0.001			—0.107
expenditure)			(0.153)			(0.126)
Additional considerations:						
Farm characteristics?	No	Yes	Yes	No	Yes	Yes
Correlated effects?	Yes	Yes	Yes	Yes	Yes	Yes

[c] The sample has 825 credit-unconstrained households and 727 credit-constrained households per survey wave in the loan classification of column (i), (ii), and (iii). There are 1,199 households with unbinding credit constraints and 1,137 households with binding credit constraints per wave in the loan and asset classification: Column (iv), (v), and (vi). Each regression accounts for household demographics and household and time fixed effects. Standard errors (in parentheses) are clustered at the household level. ***, **, * Coefficient is statistically significant at the 1%, 5%, and 10% level, respectively.

TABLE 7. —SWITCHING REGRESSION MODEL'SLTS FOR DIETARY DIVERSITY [d]

	Dietary diversity score (DDS)					
	Classification based on loans			Loan and assets' classification		
Model specifications	(i)	(ii)	(iii)	(iv)	(v)	(vi)
Panel I						
Food crop groups	0.127***	0.090	0.436	0.113**	0.086	0.543
	(0.061)	(0.063)	(0.448)	(0.052)	(0.052)	(0.357)
Expenditure per capita (log)	0.914***	0.910***	1.061***	0.910***	0.909***	1.106***
	(0.102)	(0.102)	(0.221)	(0.085)	(0.085)	(0.179)
Food groups × expenditure			—0.070			—0.092*
			(0.093)			(0.073)
Panel J						
Credit: food crop groups	0.022	0.051	0.371	0.040	0.054	0.261
	(0.084)	(0.084)	(0.566)	(0.070)	(0.070)	(0.451)
Credit: expenditure	0.336***	0.337**	0.496*	0.319***	0.313***	0.414*
	(0.141)	(0.140)	(0.291)	(0.115)	(0.114)	(0.233)
Credit: (crop groups × expenditure)			—0.062			—0.041
			(0.116)			(0.091)
Additional considerations:						
Farm characteristics?	No	Yes	Yes	No	Yes	Yes
Correlated effects?	Yes	Yes	Yes	Yes	Yes	Yes

[d] The sample has 825 credit-unconstrained households and 727 credit-constrained households per survey wave in the loan classification [column (i), (ii), and (iii)]. There are 1,199 households with unbinding credit constraints and 1,137 households with binding credit constraints per wave in the loan and asset classification: Column (iv), (v), and (vi). Each regression accounts for household demographics and household and time fixed effects. Standard errors (in parentheses) are clustered at the household level. ***, **, * Coefficient is statistically significant at the 1%, 5%, and 10% level, respectively.

additional crop produced (column i, Panel G). Moreover, Table 7 shows that producing one new crop enabled households to consume approximately 0.13 increased food groups, on average (column i, Panel I). The results on FVS mirror Dillon et al. (2015)'s results, and those on DDS echoed Ecker and Hatzenbuehler (2021)'s results.

Table 6 shows that regardless of credit status, households that witnessed a 10 percent income change made about 0.22 adjustments in food items they consumed (column i, Panel G). Aside from this, credit-constrained households consumed about 0.09 additional food items (column i, Panel H). Likewise in Table 7, the percentage point change yielded roughly 0.09 change in food groups (column i, Panel I), on the sample average. Additionally, credit-constrained households consumed about 0.03 more food groups than the credit-unconstrained ones (column i, Panel J).

Unlike the FEs, results from CF show that mitigation effects do not hold. Moreover, some FE coefficients lost significance in the CF. Generally, the results of the CF estimation of the ESR model are closer to the results of previous studies than the FEs. This is likely because of correlated effects across the specifications. However, results from both methods are somewhat similar, suggesting that effects of endogenous selection should not be ignored but the extent is not so severe.

Note that similar relationships are found on calorie consumption per capita. To avoid repeating similar discussions, the subsection on calorie consumption is left in the appendix.

5.3. The GES assessment

To evaluate the GES, farm households that received e-wallet or assistance for inorganic fertilizer they used were differentiated from those that did not. Table 8 shows the descriptive statistics of the beneficiaries versus the non–beneficiaries over the ATA's periods. In the table, credit-constrained farm households (upper panel) were separated from the credit-unconstrained households (lower panel). As the mean FCV and FCG show, GES recipients had insignificant food production diversity, whether credit-constrained or not.

TABLE 8. ———DESCRIPTIVE STATISTICS OF THE GES BENEFICIARIES AND NON-BENEFICIARIES BETWEEN 2010-16.

	GES beneficiaries					GES non-beneficiaries				
	Wave 1 (2010-2011)		Wave 3 (2012-2016)		Percentage point	Wave 1 (2010-2011)		Wave 3 (2010-2016)		Percentage point
Variables	Mean	SD	Mean	SD	difference	Mean	SD	Mean	SD	difference
Food variety score (FVS)	12.5	5.09	13.9	3.68	11.9%**	13.0	4.31	14.8	4.71	14.1%***
Dietary diversity score (DDS)	7.11	2.05	7.80	1.70	9.7%**	7.60	1.99	8.16	1.88	7.4%***
Expenditure per capita (₦/day; log)	4.94	0.65	4.77	0.53	−3.4%*	4.98	0.69	4.94	0.63	−0.8%
Food crop variety (FCV)	3.40	1.73	3.46	1.46	1.7%	3.44	1.55	3.43	1.44	−0.1%
Food crop groups (FCG)	2.07	0.89	2.11	0.77	1.9%	2.22	0.91	2.13	0.78	−4.1%**
Food variety score (FVS)	11.8	3.91	13.5	4.76	13.9%**	12.9	4.19	14.5	4.65	12.9%***
Dietary diversity score (DDS)	7.02	1.93	7.75	2.05	10.74**	7.49	1.95	8.12	1.82	8.4%***
Expenditure per capita (₦/day; log)	5.16	0.64	4.87	0.63	−5.4%**	5.00	0.69	4.98	0.64	−0.4%
Food crop variety (FCV)	3.25	1.46	3.41	1.00	4.6%	3.34	1.57	3.49	1.45	4.5%**
Food crop groups (FCG)	1.92	0.70	2.03	0.64	6.3%	2.10	0.87	2.12	0.78	1.0%

Note: ***, **, * The mean difference is statistically significant per a two-sided *t*-test, at 1%, 5%, and 10% level, respectively. The top panel is for the credit-constrained households while the bottom part is for the credit-unconstrained households. There are 70 credit-constrained and 59 credit-unconstrained beneficiaries, amounting to 129 beneficiaries per wave. Likewise, there are 739 credit-constrained and 804 credit-unconstrained non-beneficiaries, which gives 1,543 households per wave.

This is in accordance with Wossen et al. (2017)'s conclusion that households who benefited from the policy reform had increased maize harvest and revenues, suggesting that they planted a few profitable crops. Credit-unconstrained non-beneficiaries of GES clearly produced more crops as the mean FCV shows. This indicates that the reduction in the new crops produced by the credit-constrained non-recipients shown by the mean FCG was due to binding credit constraints.

The statistics suggest that GES beneficiaries adjusted land area devoted for non-staple crop production to produce increased profitable crops. It is also shown that GES recipients and non-recipients had similar dietary diversity's increase as the mean FVS and DDS show.

Table 9 presents regression results of the switching regression models with the dietary diversity indicators and income and food production diversity indicators. Food production diversity had insignificant association with dietary diversity among GES beneficiaries, regardless of their credit status. This suggests that households that benefited from the agricultural policy specialized in production of a few profitable crops, supporting Pingali and Rosegrant (1995)'s conclusion.

However, GES non-recipients that produced one more crop consumed about 0.24 increased food items, on average (column iv, top panel). Likewise, producing a new crop was associated with consuming an average of roughly 0.20 more food groups (column iv, bottom panel).

This point estimate mirrors that of Ecker and Hatzenbuehler (2021) for farm households in non-adopter states of the agricultural policy reform. The results suggest a stronger food consumption–production connection among GES non-recipients than the beneficiaries. Clearly, GES enabled beneficiaries to remain positioned for agricultural commercialization goal.

However, recipients of the agricultural policy faced more dietary diversity consequences than the non-beneficiaries especially the credit-constrained households. This is because the policy recipients were less food self-sufficient and relied more on dysfunctional markets for dietary diversification as they produced more of a few profitable crops.

TABLE 9. —SWITCHING REGRESSION MODEL'S RESULTS FOR GES EVALUATION [e]

	GES beneficiaries			GES non-beneficiaries		
	(i)	(ii)	(iii)	(iv)	(v)	(vi)
Food variety score (FVS):						
Food crop variety	—0.141	—0.262	0.606	0.235***	0.231***	0.551
	(0.354)	(0.394)	(2.254)	(0.082)	(0.082)	(0.545)
Expenditure per capita (log)	2.084**	2.176**	1.914	2.413***	2.413***	2.632***
	(0.951)	(0.886)	(1.792)	(0.211)	(0.207)	(0.432)
Credit: expenditure	1.573	1.442	0.957	0.770**	0.765***	0.917
	(1.361)	(1.326)	(3.063)	(0.313)	(0.305)	(0.611)
Dietary diversity score (DDS):						
Food crop groups	0.284	0.195	—1.645	0.195***	0.183**	0.218
	(0.340)	(0.382)	(1.804)	(0.064)	(0.065)	(0.389)
Expenditure per capita (log)	0.877***	0.877**	0.088	0.960***	0.965***	0.980***
	(0.428)	(0.434)	(0.932)	(0.093)	(0.092)	(0.195)
Credit: expenditure	0.760	0.744	1.788	0.364***	0.358***	0.609**
	(0.561)	(0.578)	(1.377)	(0.133)	(0.131)	(0.276)
Additional considerations:						
Farm characteristics?	No	Yes	Yes	No	Yes	Yes
Correlated effects?	Yes	Yes	Yes	Yes	Yes	Yes

[e] The sample has 70 credit-constrained households and 59 credit-unconstrained households per wave in the beneficiaries' column (i), (ii), and (iii). There are 739 households with binding credit constraints and 804 households with unbinding credit constraints per wave in the non-beneficiaries: Column (iv), (v), and (vi). Each regression accounts for household demographics and household and time fixed effects. Standard errors (in parentheses) are clustered at the household level. The estimated coefficient on the interaction term between income and food production diversity is insignificant and excluded in the table.

***, **, * Coefficient is statistically significant at the 1%, 5%, and 10% level, respectively.

For example, income per capita of the credit-constrained beneficiaries decreased from ($e^{4.94}$) or about NGA ₦139.8 per day in wave one to roughly NGA ₦117.9 per day in wave three. This amounted to a percentage point difference of 3.4 percent per day over the ATA's period (Table 8, top panel). Consequently, they had [(2.084+1.573)×ln(100+3.4)/100] or roughly 0.12 average decrease in the food items consumed (column i, top panel), and [(0.877+0.760)×ln(100+3.4)/100] or about 0.05 reduction in the food groups consumed (column i, bottom panel).

It is likely that households that benefited from GES relied on other sources such as food gifts or monetary assistance from friends and relatives to attain the increase in their dietary diversity shown by the mean FVS and DDS in Table 8. Similarly, credit-unconstrained recipients of GES were supposed to have 0.19 (0.09) decrease in food items (food groups) consumed but might have used credit to maintain their dietary diversification. The magnitude of estimates on FVS and DDS for GES benefited, and non-benefited households approximate the ones obtained by Ecker and Hatzenbuehler (2021) for families in the adopter and non-adopter states, respectively.

In sum, the descriptive evidence and estimation results in this GES assessment indicate that farm households that benefited from ATA separated production and consumption decisions better than the non-participants. The agricultural policy reform that allowed households access to increased farm inputs enabled families to be less dependent on food self-sufficiency against dietary diversity losses from adverse macroeconomic changes.

However, specializing in profitable crop production made credit-constrained recipients more vulnerable to economic shocks as they had not adequately diversified their food production to protect their families' dietary diversity from severe macroeconomic shocks.

5.4. Observed evidence and implications

It is now clear that food production diversity, income, and credit constraints affect dietary diversity of households. An example is used below to illustrate how these variables affect dietary adequacy. Credit-unconstrained households had an increase in crop production diversity from about 3.230 crops in wave one to roughly 3.444 crops in wave three (see Table 10). This amounts to a 0.999 percent CAGR in food items consumed over the 7-year periods. Using 0.258 effect of crop production diversity on food items consumed (see Table 6), a compounded annual growth effect of 0.264 percent was calculated (see Table 10 again).

This implies that producing more crops led to about 0.26 percent more food items consumed annually. Moreover, food items consumed by credit-unconstrained households grew at a CAGR of approximately 2.228 percent (see Table 10 once again). This altogether implies that [0.264/2.228] or roughly 11.85 percent growth in the consumed food items can be attributed to food production diversity. Similarly, [0.077/1.273] or approximately 6.05 percent increase in food groups consumed can be linked to production of new crops (see Table 10). Additionally, around 0.16 percent growth in food groups consumed is attributable to income growth (see Table 10).

Table 10 also reports that per capita income of credit-constrained households declined from NGA ₦203.9 per day in wave one to NGA ₦192.4 per day in wave three, amounting to about 0.83 percent compounded annual decline rate over the period. Using the 0.0328 estimate on income (Table 6), the compounded annual decline rate was computed to be roughly 0.026 percent (Table 10). As food items consumed grew at a CAGR of about 2.037 percent (Table 10), it can be inferred that a decrease in income reduced food items consumed by roughly 1.28 percent annually. In this order, [0.010/1.113] or 0.90 percent decline in food groups consumed can be due to the income decrease.

It is likely that credit-unconstrained households also experienced reduced income but obtained loans to maintain their dietary diversity. Unfortunately, credit-constrained households did not have sufficient access to loans. Binding credit constraints again affected dietary diversity of credit-constrained households through the channel of food production diversity.

This is due to the negative association between credit constraints and crop production diversity (Guirkinger & Boucher, 2008). For example, about 2.26 percent and roughly 5.75 percent reduction in food items and food groups consumed, respectively, can be due to less diverse food produced (Table 10).

TABLE 10. PRODUCTION DIVERSITY AND INCOME'S EFFECTS ON DIETARY DIVERSITY [e]

	Survey wave 1 to wave 3			Compounded annual growth rate for all the survey waves			
	W1	W2	W3	W1-W2	W2-W3	W1-W3	Effects
Panel K							
Food variety score	12.34	13.17	14.40	1.629	1.808	2.228	β_0=(.)
Food crop variety	3.230	3.444	3.463	1.612	0.112	0.999	0.264
Expenditure per capita	181.9	180.4	184.0	—0.203	0.396	0.166	0.004
Food variety × expenditure	591.4	596.6	629.9	0.221	1.090	0.904	—0.002
Dietary diversity score	7.343	7.633	8.023	0.972	1.002	1.273	β_0=(.)
Food crop groups	2.125	2.219	2.215	1.094	—0.044	0.592	0.077
Expenditure per capita	181.9	180.4	184.0	—0.203	0.396	0.166	0.002
Food groups × expenditure	394.3	396.3	410.1	0.127	0.687	0.563	—0.001
Panel L							
Food variety score	13.43	14.21	15.46	1.419	1.711	2.037	β_1=(.)
Food crop variety	3.436	3.503	3.393	0.487	—0.636	—0.178	—0.046
Expenditure per capita	203.9	186.2	192.4	—2.251	0.656	—0.830	—0.026
Food variety × expenditure	689.5	618.7	632.2	—2.672	0.435	—1.230	0.002
Dietary diversity score	7.752	8.022	8.377	0.858	0.870	1.113	β_1=(.)
Food crop groups	2.316	2.341	2.234	0.266	—0.934	—0.517	—0.064
Expenditure per capita	203.9	186.2	192.4	—2.251	0.656	—0.830	—0.010
Food groups × expenditure	475.5	428.9	431.2	—2.544	0.103	—1.389	0.002

[f] Panel K represents credit-unconstrained households and panel L credit-constrained households for loan classification's panel dataset. The compounded annual growth effect of any explanatory variable on any dietary diversity indicator is calculated using the endogenous switching regression (ESR) coefficient estimates on the relevant variable, $\hat{\beta}_1$, for credit-constrained households and $\hat{\beta}_0$ for credit-unconstrained households. The ESR results that control for farm characteristics were used.
The compounded annual growth effect can be calculated as

$$\left\{\left(\frac{x_{w3}-x_{w1}}{x_{w1}}\right)\hat{\beta}_j+1\right\}^{1/7} \forall j \in \{0\ 1\}; x=(exp, fcv, fcg, fcv\_exp, fcg\_exp)'$$

here w denotes survey wave and $\hat{\beta}_j$ is the interpreted endogenous switching regression (ESR) estimate of $\hat{\beta}_1$ for the credit-constrained households and $\hat{\beta}_0$ for the credit-unconstrained households.

In sum, credit-constrained households might improve dietary diversity like their credit-unconstrained counterparts, if a significant reduction in credit constraints is achieved.

Policy implications of results above are manifold. First, the income increase of credit-unconstrained households is consistent with Nigeria's ATA–and agricultural policies of other African countries–aimed at farm commercialization. The associated improved dietary diversity implies that agricultural transformation policies improve dietary diversity through farm profits.

Second, credit-unconstrained households diversified food production throughout the sample-periods to secure dietary diversity in periods of income losses. Even though this shocks-mitigating strategy does not complement agricultural commercialization efforts, it remains a common reaction for coping with income shocks. This suggests that to realize commercialization goals, households' reactions to macroeconomic changes must be incorporated into agricultural policies. Third, the decline in income of credit-constrained households implies that binding credit-constraints decelerate progress toward agricultural transformation and dietary diversity.

Moreover, the diminished diverse food produced indicates that credit-constrained households were unable to remain positioned for dietary diversification in periods of deteriorating macroeconomic conditions due to income constraints for seed acquisitions. To simultaneously achieve agricultural transformation and increase in households' dietary diversity, policymakers must use credit policies as a necessary complement to agricultural policies.

Note that off-farm job plays significant role in input purchase decisions (Adjognon et al., 2017), and it was found to improve dietary diversity in this study. These suggest that households use nonfarm income to diversify diets and settle farm-input needs. There is a policy need for interventions that allow households access to loans for nonfarm enterprises. This will enable households plow back cash partly into farm input needs, thereby improving dietary diversity.

It again allows households to produce profitable crops and thus promotes agricultural commercialization. This is consistent with the dietary-sensitive agricultural interventions suggested by Fraval et al. (2019) for increasing income, generating non-agricultural income opportunities, and diversifying food production. Rather than recommending Heumesser and Kray (2019)'s pathways as Fraval and his coauthors did, we suggest reconciling the specialization and diversification odds by creating access to credits for nonfarm businesses.

This is because binding credit constraints affect income diversification into high return off-farm activities (Woldenhanna & Oskam, 2001), which are critical avenues out of poverty (Ali et al., 2014). Nonfarm income may serve as an important complement to agricultural income, allowing for a balance between farm commercialization and dietary diversification targets during economic crises.

6. RECOMMENDATIONS AND CONCLUSION

6.1. Summary of results

This study investigates the relationship between food production diversity as well as households' income growth and their dietary diversity. Nigeria's three-wave survey panel dataset that coincides with the ATA's periods was used. Dietary diversity of every household increased during the ATA periods. However, credit-unconstrained households had a larger increase than credit-constrained households.

Moreover, food production diversity and income of credit-unconstrained households increased, while those of credit-constrained households decreased. This suggests that credit-unconstrained households used credit resources to mitigate dietary diversity losses in periods of economic shocks, unlike credit-constrained households. Households prioritized use of loans for maintaining families' dietary diversity in periods of economic crisis over agricultural transformation goals.

With dysfunctional credit markets, food production diversification does not insure families against income-induced dietary losses. Binding credit constraints decelerate farm commercialization progress because of discontinuities of the implementations of agricultural policies during deteriorating macroeconomic and fiscal conditions.

Moreover, food production diversity and dietary diversity's positive association found in this study validates results obtained by Dillon et al. (2015), Ayenew et al. (2018), and Ecker and Hatzenbuehler (2021). However, endogenizing credit-classification shows that the production–income mitigation effect found by Ecker and Hatzenbuehler (2021) does not hold. This suggests that diversifying food production to mitigate dietary diversity losses from income shocks is ineffective with binding credit constraints. An additional novelty of this study's results is that income changes affect dietary diversity of credit-constrained households more than that of the credit-unconstrained households.

This suggests that macroeconomic shocks adversely affect dietary diversity of the former more than that of the latter. An original panel dataset that is newly constructed from a household survey was used to produce these results. It appears that credit constraints do not just impede households from diversifying diets for their families through food production diversity, but also pull them out of agricultural transformation agenda during economic downturn.

6.2. Policy recommendations

This work has great real-world's applicability. The results call for policy reforms not just in Nigeria but in other resource-reliant countries. Such reforms could trigger improved dietary diversity of households. This section extends previous implications for policy recommendations. It does this by calculating what the coefficient estimates imply for dietary diversity. To start with, it is shown that households had 60 food items and 12 food groups that they could consume from (Table 3). The estimated effect of EXP on FVS and DDS for credit-unconstrained households is 2.310 and 0.914, respectively (Table 6). This shows that households that witnessed a 10 percent income growth consumed ($2.310\ln(1.1) \times 60$) or about 13.2 more food items. This amounted to a roughly 1.05 increased food groups.

However, most households could not reap these dietary diversity benefits because their income (EXP) remained unchanged (Table 3). This could be part of reasons dietary diversity is poor in Nigeria, just as it is in many other developing countries. To ameliorate this situation, policymakers should prioritize national income growth since that is the major determinant of dietary diversity. Aside from natural resources, national economic growth sources should be diversified by pursuing increase in industrialization and modernizing the agricultural sector.

Furthermore, the estimated effect of EXP on FVS and DDS for the credit-constrained households is (2.310+0.970) or about 3.28 and (0.914+0.336) or roughly 1.25, respectively (Table 7). Over the sample periods, income (EXP) of households decreased, and families consumed about 14.1 food items and roughly 7.95 food groups (Table 3). Having a 10 percent income decrease was consistent with consuming ($3.28\ln(1.1) \times 14.1$) or about 4.41 less food items and roughly 0.95 reduced food groups. Increased provisions of credit access to farm households are recommended. Additionally, policymakers may design new consumption insurance programs that compensate households against unfavorable macroeconomic changes.

Moreover, income shocks generated greater crop production diversity. However, results show that crop production diversity does not reasonably offset shocks-associated dietary losses. For example, households that planted 10 more (new) crops consumed about 2.58 (1.27) increased food items (food groups), on average. Accordingly, a 10 percent income decrease reduces dietary diversity by about 13.2 items and increasing crop production diversity by 10 units ameliorates the dietary losses just by roughly 2.58 items.

Clearly, crop production diversity is not enough to maintain dietary diversity of households during shocks to their income. This empirical finding should be explained to Nigeria's farm households especially given their low educational and literacy levels. Doing so could re-position farm households for the agricultural commercialization objective.

6.3. Suggestions for future research

In the presence of binding credit constraints, future studies should investigate other consumption insurance against economic shocks. I am currently conducting related study, focusing on funds transferred to households as assistants from friends or relatives and the personal savings. As this study has not been completed, I could not include it to this chapter as I planned. Another suggestion is to explore how misclassifications of credit status could alter the dietary diversity's effects of income and crop production diversity.

Moreover, effects of changing food prices on dietary diversity may serve important policy purposes. It is suggestive to investigate the effect of food prices through the medium of combinations of food items purchased (quantities) on dietary diversity. Doing so could produce important insights on improving dietary diversity of households, especially given the rapidly increasing prices of food items in recent years.

6.4. Conclusion of study

To mitigate dietary diversity losses and increase agricultural growth, granting households credit access for operating non-farm businesses should complement agricultural input supports. Farm households can use business profits to reduce dietary losses due to economic shocks. Households may as well plow back profits into agricultural input needs. Expectedly, this would reposition farm households for the agricultural commercialization targets and, as well, improve their dietary diversity.

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7. SUPPORTING INFORMATION

7.1. Table of contents

7.2. Interpretation of the estimated coefficients on calorie consumption

Tables C1–C3 report the FE estimation results of the relationship between food production diversity as well as household income and total calorie intake per capita. The estimated coefficients are robust to any choice of the two credit-classifications, and any specification of the econometric models. As suspected, the calorie intake per capita is positively and significantly related to food production diversity.

Specifically, the estimate in the loan classification show that adding one crop to the portfolio of farm crops increased average per capita calorie intake by roughly ($e^{0.06}$) or about 6.18 percent (column i, Table C1). This estimate mirrors the statistically significant relationship between Simpson production diversity index (SPDI) and total calorie consumption per capita found by Ecker and Hatzenbuehler (2021). The percentage point increase in calorie intake per capita slightly reduced to roughly 4.60 percent in the mixed classification.

These results imply that households that diversified their food production consumed similar diets irrespective of having binding credit constraints or not. The results further imply that households diversified diets as observed on FVS and DDS with the aim of achieving balanced diets. This estimated effect remained unchanged after investigated it by the CF (see Table D3). However, results from the mixture of loan-and-asset classification slightly reduced in magnitude [columns (iv)–(v), Table D3].

Moreover, the estimated coefficient for the per capita income is positive and significant. This suggests that an increase in income of each household-member generates significant increase in the per capita calorie consumption. Table C2 shows that the point estimate of the elasticity for the estimation that controls for farm characteristics equals 0.311 (column ii). This implies that a 10 percent increase in income increases per capita calorie consumption of the credit-unconstrained households by, on average, roughly 31.1 percent.

However, the percentage point change increases average calorie consumption per capita of the credit-constrained households by roughly 41.6 percent (column iii). The elasticity for the estimation that neglects the presence of credit constraints is roughly 36 percent (column i), which lies in the middle of the previous elasticities that were observed on dietary diversity indicators. This time, however, estimate for the credit-constrained households is closer in magnitude to the point estimate reported by Ecker and Hatzenbuehler (2021) for the pooled households, unlike in the case of dietary diversity indicators.

This suggests that stratifying households according to their credit situations is important for improved precision of results for any choice of the household-groups selected for investigations. Results from examination that neglects credit constraints and run a pooled panel dataset appear to be relatively less precise than if households were differentiated by their credit conditions. However, this does not contradict the soundness of findings in the existing studies because there are severe measurement errors in the calorie consumption indicator (NBS & World Bank, 2016a, 2016b). This might have seriously affected the estimated coefficients on the per capita calorie consumption.

As Table D3 shows, after controlling for the correlated effects due to credit constraints, the income elasticities became 0.44 for the credit-unconstrained households and 0.62 (=0.437+0.186) for the credit-constrained households (column ii). Similar to results on dietary diversity indicators, credit-constrained households appear to be hand-to-mount given the elasticity of calorie consumption with respect to income. Table D3 specifically reports that credit-constrained households were consuming about 18.6 percent more calorie per capita than their counterpart credit-unconstrained households for every 10 percent increased per capita income earned (see credit: expenditure, column ii). While credit-constrained households remained impatient, credit-unconstrained households were smoothing consumption as previously observed on FVS and DDS.

As Ecker and Hatzenbuehler (2021) noted, results on total calorie consumption should be used with caution. This is because food consumption quantities in the GHS-Panel, from where the per capita calorie consumption indicator was constructed, have serious measurement errors. The errors of measurement were correlated with the inconsistencies in the documentation of food quantities that were reported in nonstandard units such as bowl, heap, piece, and bunch (NBS, 2018).

TABLE A1. —RESULTS OF THE FIXED EFFECTS MODEL FOR DIETARY DIVESITY [g]

	Food variety score (FVS)					
	Classification based on loans			Loan and assets' classification		
Model specifications	(i)	(ii)	(iii)	(iv)	(v)	(vi)
Income & crop production diversity						
Food crop variety	0.212***	0.227***	0.214***	0.170***	0.168***	0.183***
	(0.045)	(0.063)	(0.066)	(0.038)	(0.053)	(0.053)
Expenditure per capita (log)	2.576***	2.176***	3.100***	2.598***	2.287***	2.950***
	(0.119)	(0.152)	(0.189)	(0.099)	(0.133)	(0.146)
Household demographics						
Age of the household head	-0.004	-0.008	-0.004	-0.003*	-0.005	-0.003
	(0.003)	(0.012)	(0.003)	(0.002)	(0.010)	(0.002)
Household head's education	-0.002	0.012	-0.017	-0.023	-0.024	-0.021
	(0.018)	(0.024)	(0.028)	(0.015)	(0.021)	(0.022)
Sex of the household head				5.975		6.076
				(3.898)		(3.968)
Household size	0.338***	0.340***	0.355***	0.386***	0.378***	0.401***
	(0.064)	(0.081)	(0.104)	(0.051)	(0.071)	(0.072)
Observations	4,656	2,475	2,181	7,008	3,597	3,411
Adjusted R-squared	0.139	0.123	0.163	0.135	0.116	0.157
Overall R-squared	-0.294	-0.321	-0.261	-0.299	-0.329	-0.268

[a] The sample has 1,552 pooled households [column (i)], 825 credit-unconstrained households [column (ii)], and 727 credit-constrained households [column (iii)] per wave in the loan classification. There are 2,336 total households [column (iv)], 1,199 credit-unconstrained households [column (v)], and 1,137 credit-constrained households [column (vi)] per wave in the loan and asset classification. Standard errors (in parentheses) are clustered at the household level. ***, **, * Coefficient is statistically significant at the 1%, 5%, and 10% level, respectively.

***, **, * Coefficient is statistically significant at the 1%, 5%, and 10% level, respectively.

TABLE A2. —RESULTS OF THE FIXED EFFECTS MODEL FOR DIETARY DIVERSITY [b]

	Food variety score (FVS)					
	Classification based on loans			Loan and assets' classification		
Model specifications	(i)	(ii)	(iii)	(iv)	(v)	(vi)
Income & crop production diversity						
Food crop variety	0.188***	0.198***	0.195***	0.152***	0.149***	0.165***
	(0.046)	(0.064)	(0.067)	(0.038)	(0.055)	(0.054)
Expenditure per capita (log)	2.556***	2.165***	3.081***	2.586***	2.279***	2.927***
	(0.119)	(0.151)	(0.190)	(0.099)	(0.133)	(0.146)
Farm household characteristics						
Off-farm employment	0.338**	0.164	0.449**	0.329***	0.185	0.437**
	(0.147)	(0.195)	(0.222)	(0.121)	(0.168)	(0.175)
Farm size (acres)	0.034*	0.029	0.040	0.025*	0.018	0.032
	(0.018)	(0.023)	(0.030)	(0.015)	(0.020)	(0.022)
Cash crop production	0.266	0.009	0.395	0.163	-0.151	0.389
	(0.264)	(0.384)	(0.366)	(0.212)	(0.311)	(0.292)
Poultry ownership	0.240*	0.567***	-0.163	0.186*	0.427***	-0.087
	(0.137)	(0.177)	(0.214)	(0.113)	(0.153)	(0.167)
Cattel ownership	0.223	0.437	-0.144	0.204	0.310	0.088
	(0.217)	(0.273)	(0.350)	(0.179)	(0.238)	(0.270)
Sheep or goat ownership	0.023	0.072	-0.066	-0.023	0.049	-0.114
	(0.151)	(0.195)	(0.235)	(0.125)	(0.170)	(0.183)

TABLE A2. Continued

	Food variety score (FVS)					
	Classification based on loans			Loan and assets' classification		
Model specifications	(i)	(ii)	(iii)	(iv)	(v)	(vi)
Household demographics						
Age of the household head	-0.004	-0.006	-0.004	-0.003*	-0.003	-0.003
	(0.003)	(0.012)	(0.003)	(0.002)	(0.010)	(0.002)
Household head's education	-0.001	0.013	-0.014	-0.023	-0.023	-0.022
	(0.018)	(0.024)	(0.028)	(0.015)	(0.021)	(0.022)
Sex of the household head				5.801		5.738
				(3.897)		(3.969)
Household size	0.320***	0.310***	0.357***	0.375***	0.352***	0.397***
	(0.064)	(0.081)	(0.104)	(0.051)	(0.071)	(0.072)
Observations	4,656	2,475	2,181	7,008	3,597	3,411
Adjusted R-squared	0.143	0.133	0.168	0.138	0.122	0.162
Overall R-squared	-0.290	-0.310	-0.259	-0.296	-0.324	-0.265

[b] An extension of the model specification that produced estimation results in Table A1. That is, results of using farm household variables and the demographic variables as estimation control variables.

TABLE A3. —RESULTS OF THE FIXED EFFECTS MODEL FOR DIETARY DIVERSITY [c]

	Food variety score (FVS)					
	Classification based on loans			Loan and assets' classification		
Model specifications	(i)	(ii)	(iii)	(iv)	(v)	(vi)
Income & crop production diversity						
Food crop variety	0.474*	0.586	0.440	0.698***	1.047***	0.412
	(0.288)	(0.392)	(0.428)	(0.239)	(0.346)	(0.333)
Expenditure per capita (log)	2.749***	2.425***	3.249***	2.952***	2.876***	3.093***
	(0.226)	(0.300)	(0.347)	(0.186)	(0.263)	(0.266)
Food variety × expenditure	-0.057	-0.079	-0.049	-0.110**	-0.181***	-0.050
	(0.057)	(0.079)	(0.084)	(0.048)	(0.069)	(0.066)
Farm household characteristics						
Off-farm employment	0.333**	0.157	0.445**	0.323***	0.176	0.434**
	(0.147)	(0.195)	(0.222)	(0.121)	(0.167)	(0.176)
Farm size (acres)	0.033*	0.029	0.039	0.024*	0.018	0.031
	(0.018)	(0.023)	(0.030)	(0.015)	(0.020)	(0.022)
Cash crop production	0.283	0.017	0.415	0.187	-0.138	0.405
	(0.264)	(0.384)	(0.368)	(0.213)	(0.311)	(0.293)
Poultry ownership	0.239*	0.561***	-0.160	0.186*	0.415***	-0.084
	(0.137)	(0.177)	(0.214)	(0.113)	(0.153)	(0.167)
Cattel ownership	0.224	0.433	-0.138	0.207	0.296	0.095
	(0.217)	(0.273)	(0.351)	(0.179)	(0.238)	(0.270)
Sheep or goat ownership	0.022	0.076	-0.072	-0.025	0.059	-0.119
	(0.151)	(0.195)	(0.235)	(0.125)	(0.170)	(0.183)

TABLE A3. Continued

	Food variety score (FVS)					
	Classification based on loans			Loan and assets' classification		
Model specifications	(i)	(ii)	(iii)	(iv)	(v)	(vi)
Household demographics						
Age of the household head	-0.004	-0.006	-0.004	-0.003*	-0.004	-0.003
	(0.003)	(0.012)	(0.003)	(0.002)	(0.010)	(0.002)
Household head's education	-0.0004	0.014	-0.014	-0.023	-0.022	-0.022
	(0.018)	(0.024)	(0.028)	(0.015)	(0.021)	(0.022)
Sex of the household head				5.804		5.735
				(3.895)		(3.969)
Household size	0.318***	0.305***	0.356***	0.372***	0.343***	0.397***
	(0.064)	(0.081)	(0.104)	(0.051)	(0.071)	(0.072)
Observations	4,656	2,475	2,181	7,008	3,597	3,411
Adjusted R-squared	0.144	0.133	0.168	0.139	0.124	0.162
Overall R-squared	-0.290	-0.310	-0.260	-0.295	-0.321	-0.265

[c] Expanding the model specification that yielded estimation results in Table A2: Results from incorporating the interaction term between income and food production diversity.

TABLE B1. ———RESULTS OF FIXED EFFECTS MODEL FOR DIETARY DIVERSITY [d]

	Dietary diversity score (DDS)					
	Classification based on loans			Loan and assets' classification		
Model specifications	(i)	(ii)	(iii)	(iv)	(v)	(vi)
Income & crop production diversity						
Food crop groups	0.142***	0.120**	0.166***	0.133***	0.110**	0.159***
	(0.035)	(0.052)	(0.048)	(0.030)	(0.043)	(0.042)
Expenditure per capita (log)	1.017***	0.874***	1.211***	1.048***	0.898***	1.219***
	(0.052)	(0.070)	(0.080)	(0.044)	(0.060)	(0.064)
Household demographics						
Age of the household head	-0.001	-0.0001	-0.001	-0.001	-0.001	-0.001
	(0.001)	(0.005)	(0.001)	(0.001)	(0.005)	(0.001)
Household head's education	0.007	0.006	-0.009	0.0003	-0.002	-0.002
	(0.008)	(0.011)	(0.012)	(0.007)	(0.009)	(0.010)
Sex of the household head				3.948**		4.026**
				(1.731)		(1.752)
Household size	0.143***	0.129***	0.168***	0.173***	0.151***	0.199***
	(0.028)	(0.037)	(0.044)	(0.023)	(0.032)	(0.032)
Observations	4,656	2,475	2,181	7,008	3,597	3,411
Adjusted R-squared	0.114	0.093	0.143	0.116	0.092	0.144
Overall R-squared	-0.332	-0.366	-0.291	-0.329	-0.366	-0.289

[d] Each wave has 1,552 total households [column (i)], 825 credit-unconstrained households [column (ii)], and 727 credit-constrained households [column (iii)] in the loan classification. There are 2,336 pooled households [column (i)], 1,199 households with unbinding credit constraints [column (ii)], and 1,137 households with binding credit constraints [column (iii)] per wave in the mixed classification. Standard errors (in parentheses) are clustered at the household level.

***, **, * Coefficient is statistically significant at the 1%, 5%, and 10% level, respectively.

TABLE B2. —RESULTS OF THE FIXED EFFECTS MODEL FOR DIETARY DIVERSITY [e]

	Dietary diversity score (DDS)					
	Classification based on loans			Loan and assets' classification		
Model specifications	(i)	(ii)	(iii)	(iv)	(v)	(vi)
Income & crop production diversity						
Food crop groups	0.124***	0.088*	0.157***	0.116***	0.087**	0.148***
	(0.036)	(0.053)	(0.050)	(0.030)	(0.044)	(0.042)
Expenditure per capita (log)	1.008***	0.873***	1.208***	1.042***	0.897***	1.212***
	(0.052)	(0.069)	(0.080)	(0.044)	(0.060)	(0.065)
Farm household characteristics						
Off-farm employment	0.163**	0.105	0.190**	0.136***	0.105	0.150**
	(0.065)	(0.089)	(0.094)	(0.054)	(0.075)	(0.078)
Farm size (acres)	0.015*	0.014	0.019	0.014*	0.011	0.016
	(0.008)	(0.011)	(0.013)	(0.007)	(0.009)	(0.010)
Cash crop production	0.146	0.293*	0.012	0.148	0.166	0.110
	(0.117)	(0.177)	(0.156)	(0.095)	(0.139)	(0.130)
Poultry ownership	0.085	0.213***	-0.078	0.058	0.141**	-0.038
	(0.061)	(0.081)	(0.091)	(0.050)	(0.068)	(0.074)
Cattel ownership	0.205**	0.342***	-0.014	0.110	0.176*	0.037
	(0.096)	(0.125)	(0.148)	(0.079)	(0.106)	(0.119)
Sheep or goat ownership	-0.059	-0.015	-0.113	-0.015	0.032	-0.066
	(0.066)	(0.089)	(0.099)	(0.055)	(0.076)	(0.081)

TABLE B2. Continued

	Dietary diversity score (DDS)					
	Classification based on loans			Loan and assets' classification		
Model specifications	(i)	(ii)	(iii)	(iv)	(v)	(vi)
Household demographics						
Age of the household head	-0.001	0.0003	-0.001	-0.001	-0.0001	-0.001
	(0.001)	(0.005)	(0.001)	(0.001)	(0.005)	(0.001)
Household head's education	0.007	0.006	0.009	-0.0004	-0.001	0.002
	(0.008)	(0.011)	(0.012)	(0.007)	(0.009)	(0.010)
Sex of the household head				3.874**		3.886**
				(1.730)		(1.754)
Household size	0.136***	0.118***	0.171***	0.169***	0.142***	0.197***
	(0.028)	(0.037)	(0.044)	(0.023)	(0.032)	(0.032)
Observations	4,656	2,475	2,181	7,008	3,597	3,411
Adjusted R-squared	0.120	0.106	0.149	0.119	0.097	0.147
Overall R-squared	-0.326	-0.351	-0.288	-0.325	-0.361	-0.287

[e] An extension of the model specification that produced estimation results in Table B1. That is, results from estimation that controls for farm household characteristics and the households demographics.

TABLE B3. —RESULTS OF THE FIXED EFFECTS MODEL FOR DIETARY DIVERSITY [f]

	Dietary diversity score (DDS)					
	Classification based on loans			Loan and assets' classification		
Model specifications	(i)	(ii)	(iii)	(iv)	(v)	(vi)
Income & crop production diversity						
Food crop groups	0.587***	0.478	0.798***	0.663***	0.565**	0.780***
	(0.217)	(0.314)	(0.305)	(0.183)	(0.268)	(0.252)
Expenditure per capita (log)	1.214***	1.042***	1.505***	1.282***	1.102***	1.495***
	(0.109)	(0.151)	(0.161)	(0.090)	(0.128)	(0.128)
Food groups × expenditure	-0.093**	-0.079	-0.127**	-0.110***	-0.096*	-0.127**
	(0.043)	(0.063)	(0.060)	(0.036)	(0.053)	(0.050)
Farm household characteristics						
Off-farm employment	0.160**	0.104	0.184*	0.135**	0.106	0.146*
	(0.065)	(0.089)	(0.094)	(0.054)	(0.075)	(0.077)
Farm size (acres)	0.015*	0.014	0.018	0.013**	0.012	0.014
	(0.008)	(0.011)	(0.013)	(0.007)	(0.009)	(0.010)
Cash crop production	0.161	0.300*	0.039	0.160*	0.167	0.135
	(0.117)	(0.177)	(0.156)	(0.095)	(0.139)	(0.130)
Poultry ownership	0.085	0.211***	-0.075	0.058	0.139**	-0.036
	(0.061)	(0.081)	(0.091)	(0.050)	(0.068)	(0.074)
Cattel ownership	0.206**	0.341***	-0.012	0.110	0.171	0.044
	(0.096)	(0.125)	(0.148)	(0.079)	(0.106)	(0.119)
Sheep or goat ownership	-0.057	-0.011	-0.114	-0.013	0.036	-0.067
	(0.066)	(0.089)	(0.099)	(0.055)	(0.076)	(0.081)

TABLE B3. Continued

	Dietary diversity score (DDS)					
	Classification based on loans			Loan and assets' classification		
Model specifications	(i)	(ii)	(iii)	(iv)	(v)	(vi)
Household demographics						
Age of the household head	-0.001	0.0004	-0.001	-0.001	-0.0003	-0.001
	(0.001)	(0.005)	(0.001)	(0.001)	(0.005)	(0.001)
Household head's education	0.007	0.006	0.009	-0.0004	-0.001	0.002
	(0.008)	(0.011)	(0.012)	(0.007)	(0.009)	(0.010)
Sex of the household head				3.877**		3.889**
				(1.729)		(1.752)
Household size	0.135***	0.117***	0.171***	0.168***	0.141***	0.197***
	(0.028)	(0.037)	(0.044)	(0.023)	(0.032)	(0.032)
Observations	4,656	2,475	2,181	7,008	3,597	3,411
Adjusted R-squared	0.121	0.107	0.151	0.121	0.099	0.149
Overall R-squared	-0.324	-0.351	-0.285	-0.323	-0.359	-0.284

[f] Expanding the model specification that produced estimation results in Table B2: Results from including the interaction between household income and food production diversity.

TABLE C1. RESULTS OF THE FIXED EFFECTS MODEL FOR CALORIE INTAKE [g]

	Calorie intake per capita (CIC)					
	Classification based on loans			Loan and assets' classification		
Model specifications	(i)	(ii)	(iii)	(iv)	(v)	(vi)
Income & crop production diversity						
Food crop variety	0.060***	0.062***	0.059***	0.045***	0.045***	0.047***
	(0.012)	(0.017)	(0.017)	(0.010)	(0.014)	(0.014)
Expenditure per capita (log)	0.358***	0.310***	0.418***	0.352***	0.289***	0.422***
	(0.031)	(0.041)	(0.048)	(0.026)	(0.035)	(0.038)
Household demographics						
Age of the household head	-0.0005	-0.002	-0.0004	-0.0001	-0.002	0.00002
	(0.001)	(0.003)	(0.001)	(0.0005)	(0.003)	(0.001)
Household head's education	-0.0001	-0.003	0.003	0.002	0.001	0.002
	(0.005)	(0.006)	(0.007)	(0.004)	(0.005)	(0.006)
Sex of the household head				0.272		0.287
				(0.959)		(0.975)
Household size	-0.092***	-0.123***	-0.045***	-0.088***	-0.127***	-0.050***
	(0.017)	(0.022)	(0.026)	(0.013)	(0.019)	(0.019)
Observations	4,173	2,211	1,962	6,336	3,246	3,090
Adjusted R-squared	0.075	0.078	0.074	0.066	0.065	0.071
Overall R-squared	-0.391	-0.389	-0.395	-0.404	-0.406	-0.398

[g] There are 1,391 pooled households [column (i)], 737 credit-unconstrained households [column (ii)], and 654 credit-constrained households [column (iii)] per wave in the loan classification. There are 2,112 total households [column (iv)], 1,082 credit-unconstrained households [column (v)], and 1,030 credit-constrained households [column (vi)] per wave in the loan and asset classification. Standard errors (in parentheses) are clustered at the household level. ***, **, * Coefficient is statistically significant at the 1%, 5%, and 10% level, respectively.

TABLE C2. RESULTS OF THE FIXED EFFECTS MODEL FOR CALORIE INTAKE [h]

	Calorie intake per capita (CIC)					
	Classification based on loans			Loan and assets' classification		
Model specifications	(i)	(ii)	(iii)	(iv)	(v)	(vi)
Income & crop production diversity						
Food crop variety	0.062^{***}	0.065^{***}	0.061^{***}	0.047^{***}	0.048^{***}	0.048^{***}
	(0.012)	(0.017)	(0.017)	(0.010)	(0.014)	(0.014)
Expenditure per capita (log)	0.360^{***}	0.311^{***}	0.416^{***}	0.351^{***}	0.285^{***}	0.423^{***}
	(0.031)	(0.041)	(0.048)	(0.026)	(0.035)	(0.038)
Farm household characteristics						
Off-farm employment	-0.001	-0.010	0.012	0.056^{*}	-0.063	-0.051
	(0.039)	(0.054)	(0.057)	(0.032)	(0.044)	(0.046)
Farm size (acres)	0.001	0.001	0.001	0.003	0.002	0.004
	(0.005)	(0.006)	(0.008)	(0.004)	(0.005)	(0.006)
Cash crop production	-0.032	-0.003	-0.062	-0.074	-0.095	-0.071
	(0.070)	(0.107)	(0.094)	(0.056)	(0.083)	(0.076)
Poultry ownership	0.019	0.005	0.032	0.042	0.032	0.054
	(0.036)	(0.048)	(0.054)	(0.029)	(0.040)	(0.043)
Cattel ownership	-0.001	-0.026	0.029	0.003	-0.023	0.030
	(0.057)	(0.074)	(0.089)	(0.047)	(0.062)	(0.071)
Sheep or goat ownership	0.069^{*}	-0.127^{**}	-0.004	-0.044	-0.061	-0.024
	(0.039)	(0.053)	(0.059)	(0.032)	(0.044)	(0.047)

TABLE C2. Continued

	Calorie intake per capita (CIC)					
	Classification based on loans			Loan and assets' classification		
Model specifications	(i)	(ii)	(iii)	(iv)	(v)	(vi)
Household demographics						
Age of the household head	-0.0005	-0.003	-0.0004	-0.0001	-0.002	0.00003
	(0.001)	(0.003)	(0.001)	(0.0005)	(0.003)	(0.001)
Household head's education	-0.00005	-0.003	0.003	0.002	0.001	0.002
	(0.005)	(0.007)	(0.007)	(0.004)	(0.005)	(0.006)
Sex of the household head				0.259		0.293
				(0.960)		(0.977)
Household size	-0.092***	-0.121***	-0.046*	-0.089***	-0.127***	-0.052***
	(0.017)	(0.022)	(0.026)	(0.013)	(0.019)	(0.019)
Observations	4,173	2,211	1,962	6,336	3,246	3,090
Adjusted R-squared	0.076	0.082	0.075	0.067	0.068	0.073
Overall R-squared	-0.392	-0.388	-0.401	-0.403	-0.407	-0.399

[h] An extension of the model specification that produced estimation results in Table C1. That is, results of the estimation with both the farm household variables and household demographic variables.

TABLE C3. RESULTS OF THE FIXED EFFECTS MODEL FOR CALORIE INTAKE [i]

	Calorie intake per capita (CIC)					
	Classification based on loans			Loan and assets' classification		
Model specifications	(i)	(ii)	(iii)	(iv)	(v)	(vi)
Income & crop production diversity						
Food crop variety	0.166**	0.313***	0.036	0.107***	0.278***	0.017
	(0.076)	(0.106)	(0.109)	(0.062)	(0.091)	(0.087)
Expenditure per capita (log)	2.429***	0.477***	0.400***	0.391***	0.438***	0.378***
	(0.059)	(0.082)	(0.088)	(0.049)	(0.069)	(0.069)
Food variety × expenditure	-0.021	-0.051**	0.005	-0.012	-0.046**	0.013
	(0.015)	(0.021)	(0.021	(0.012)	(0.018)	(0.017)
Farm household characteristics						
Off-farm employment	-0.003	-0.013	0.012	-0.057*	-0.064	-0.050
	(0.039)	(0.054)	(0.057)	(0.032)	(0.044)	(0.046)
Farm size (acres)	0.0004	0.001	0.001	0.003	0.002	0.004
	(0.005)	(0.006)	(0.008)	(0.004)	(0.005)	(0.006)
Cash crop production	-0.025	0.001	-0.064	-0.071	-0.093	-0.076
	(0.070)	(0.107)	(0.094)	(0.056)	(0.083)	(0.077)
Poultry ownership	0.019	0.002	0.032	0.042	0.030	0.053
	(0.036)	(0.048)	(0.054)	(0.029)	(0.039)	(0.043)
Cattel ownership	-0.0003	-0.028	0.029	0.003	-0.025	0.028
	(0.057)	(0.074)	(0.090)	(0.047)	(0.062)	(0.071)
Sheep or goat ownership	-0.068*	-0.124**	-0.003	-0.044	-0.059	-0.023
	(0.039)	(0.053)	(0.059)	(0.032)	(0.044)	(0.047)

TABLE C3. Continued

	Calorie intake per capita (CIC)					
	Classification based on loans			Loan and assets' classification		
Model specifications	(i)	(ii)	(iii)	(iv)	(v)	(vi)
Household demographics						
Age of the household head	-0.0005	-0.003	-0.0004	-0.0001	-0.003	0.00004
	(0.001)	(0.003)	(0.001)	(0.0005)	(0.003)	(0.001)
Household head's education	0.00004	-0.003	0.003	0.002	0.001	0.002
	(0.005)	(0.007)	(0.007)	(0.004)	(0.005)	(0.006)
Sex of the household head				0.260		0.293
				(0.960)		(0.977)
Household size	-0.093***	-0.125***	0.046*	-0.090***	-0.130***	-0.052***
	(0.017)	(0.022)	(0.026)	(0.013)	(0.019)	(0.019)
Observations	4,173	2,211	1,962	6,336	3,246	3,090
Adjusted R-squared	0.077	0.086	0.075	0.068	0.070	0.073
Overall R-squared	-0.392	-0.384	-0.402	-0.403	-0.403	-0.400

[i] Expanding the model specification that yielded estimation results in Table C2: Results from incorporating the interaction term between income and food production diversity.

TABLE D1. SWITCHING REGRESSION MODEL'S RESULTS FOR DIETARY DIVERSITY [j]

	Food variety score (FVS)					
	Classification based on loans			Loan and assets' classification		
model specifications	(i)	(ii)	(iii)	(iv)	(v)	(vi)
Income & crop production diversity						
Food crop variety	0.258^{***}	0.222^{***}	0.513	0.181^{***}	0.156^{**}	0.970^{**}
	(0.079)	(0.079)	(0.524)	(0.069)	(0.068)	(0.459)
Expenditure per capita (log)	2.310^{***}	2.291^{***}	2.487^{***}	2.359^{***}	2.349^{***}	2.892^{***}
	(0.225)	(0.221)	(0.439)	(0.197)	(0.193)	(0.383)
Food variety × expenditure			-0.059			-0.164^{*}
			(0.109)			(0.094)
Farm household characteristics						
Farm size (acres)		0.017	0.017		0.006	0.006
		(0.032)	(0.032)		(0.027)	(0.027)
Cash crop production		0.219	0.225		0.080	0.093
		(0.542)	(0.544)		(0.429)	(0.430)
Poultry ownership		0.673^{***}	0.669^{***}		0.452^{**}	0.442^{**}
		(0.226)	(0.226)		(0.193)	(0.193)
Cattle ownership		0.330	0.327		0.205	0.192
		(0.313)	(0.313)		(0.268)	(0.268)
Sheep or goat ownership		0.154	0.158		0.165	0.174
		(0.243)	(0.243)		(0.213)	(0.213)

TABLE D1. continued.

	Food variety score (FVS)					
	Classification based on loans			Loan and assets' classification		
Model specifications	(i)	(ii)	(iii)	(iv)	(v)	(vi)
Household demographics						
Age of the household head	0.012	0.014	0.014	0.018	0.019	0.019
	(0.015)	(0.015)	(0.015)	(0.013)	(0.013)	(0.013)
Household head's education	0.017	0.017	0.017	-0.012	-0.012	-0.011
	(0.030)	(0.030)	(0.030)	(0.026)	(0.026)	(0.026)
Sex of the household head	-1.377***	-0.963***	-0.966***	6.909	6.799	6.792
	(0.300)	(0.303)	(0.304)	(11.954)	(13.293)	(13.340)
Household size	0.754***	0.698***	0.696***	0.733***	0.702***	0.698***
	(0.083)	(0.085)	(0.085)	(0.070)	(0.071)	(0.071)
Constraints' induced behavior						
Credit: food crop groups	-0.068	-0.051	-0.036	-0.001	0.005	-0.527
	(0.114)	(0.112)	(0.744)	(0.096)	(0.095)	(0.616)
Credit: expenditure	0.970***	0.967***	0.982	0.693**	0.677**	0.326
	(0.326)	(0.321)	(0.614)	(0.272)	(0.266)	(0.509)
Credit: [crop groups × expenditure]			-0.001			0.107
			(0.153)			(0.126)
Correlated effects?	Yes	Yes	Yes	Yes	Yes	Yes
Observations	4,656	4,656	4,656	7,008	7,008	7,008
Overall R-squared	0.295	0.336	0.336	0.281	0.326	0.326
Adjusted R-squared	0.291	0.328	0.328	0.278	0.321	0.321

[j] The sample has 825 credit-unconstrained households and 727 credit-constrained households per wave in the loan classification. There are 1,199 credit-unconstrained households and 1,137 credit-constrained households per wave in the loan and asset classification. ***, **, * Coefficient is significant at the 1%, 5%, and 10% level, respectively.

TABLE D2. SWITCHING REGRESSION MODEL'S RESULTS FOR DIETARY DIVERSITY [k]

	Dietary diversity score (DDS)					
	Classification based on loans			Loan and assets' classification		
model specifications	(i)	(ii)	(iii)	(iv)	(v)	(vi)
Income & crop production diversity						
Food crop groups	0.127^{***}	0.090	0.436	0.113^{**}	0.086	0.543
	(0.061)	(0.063)	(0.448)	(0.052)	(0.052)	(0.357)
Expenditure per capita (log)	0.914^{***}	0.910^{***}	1.061^{***}	0.910^{***}	0.909^{***}	1.106^{***}
	(0.102)	(0.102)	(0.221)	(0.085)	(0.085)	(0.179)
Food groups × expenditure			-0.070			-0.092^{*}
			(0.093)			(0.073)
Farm household characteristics						
Farm size (acres)		0.010	0.010		0.007	0.008
		(0.015)	(0.015)		(0.012)	(0.012)
Cash crop production		0.366^{*}	0.372^{*}		0.239	0.240
		(0.204)	(0.205)		(0.161)	(0.161)
Poultry ownership		0.248^{**}	0.246^{**}		0.145^{*}	0.143^{*}
		(0.101)	(0.101)		(0.084)	(0.084)
Cattle ownership		0.306^{**}	0.305^{**}		0.143	0.138
		(0.148)	(0.148)		(0.128)	(0.128)
Sheep or goat ownership		0.010	0.014		0.068	0.071
		(0.108)	(0.108)		(0.093)	(0.093)

TABLE D2. continued.

	Dietary diversity score (DDS)					
	Classification based on loans			Loan and assets' classification		
Model specifications	(i)	(ii)	(iii)	(iv)	(v)	(vi)
Household demographics						
Age of the household head	0.006	0.007	0.007	0.006	0.006	0.006
	(0.007)	(0.006)	(0.007)	(0.006)	(0.006)	(0.006)
Household head's education	0.006	0.006	0.006	0.002	0.002	0.002
	(0.013)	(0.013)	(0.013)	(0.011)	(0.011)	(0.011)
Sex of the household head	-0.454***	-0.340***	-0.331***	4.146	4.058	4.075
	(0.114)	(0.117)	(0.119)	(7.544)	(8.101)	(8.070)
Household size	0.263***	0.242***	0.241***	0.250***	0.238***	0.238***
	(0.036)	(0.036)	(0.036)	(0.029)	(0.030)	(0.030)
Constraints' induced behavior						
Credit: food crop groups	0.022	0.051	0.371	0.040	0.054	0.261
	(0.084)	(0.084)	(0.566)	(0.070)	(0.070)	(0.451)
Credit: expenditure	0.336***	0.337**	0.496*	0.319***	0.313***	0.414*
	(0.141)	(0.140)	(0.291)	(0.115)	(0.114)	(0.233)
Credit: [crop groups × expenditure]			-0.062			-0.041
			(0.116)			(0.091)
Correlated effects?	Yes	Yes	Yes	Yes	Yes	Yes
Observations	4,656	4,656	4,656	7,008	7,008	7,008
Overall R-squared	0.288	0.315	0.326	0.275	0.303	0.304
Adjusted R-squared	0.285	0.308	0.308	0.273	0.298	0.299

[k] The sample has 825 credit-unconstrained households and 727 credit-constrained households per wave in the loan classification. There are 1,199 credit-unconstrained households and 1,137 credit-constrained households per wave in the loan and asset classification. ***, **, * Coefficient is significant at the 1%, 5%, and 10% level, respectively.

TABLE D3. SWITCHING REGRESSION RESULTS FOR CALORIE INTAKE [1]

	Calorie intake per capita (CIC)					
	Classification based on loans			Loan and assets' classification		
model specifications	(i)	(ii)	(iii)	(iv)	(v)	(vi)
Income & crop production diversity						
Food crop variety	0.063***	0.060***	0.075	0.035**	0.032**	0.061
	(0.019)	(0.019)	(0.120)	(0.015)	(0.016)	(0.103)
Expenditure per capita (log)	0.436***	0.437***	0.447***	0.400***	0.397***	0.416***
	(0.046)	(0.046)	(0.090)	(0.039)	(0.040)	(0.076)
Food variety × expenditure			-0.003			-0.006
			(0.024)			(0.020)
Farm household characteristics						
Farm size (acres)		0.001	0.001		0.002	0.002
		(0.008)	(0.008)		(0.007)	(0.007)
Cash crop production		0.174	0.175		0.097	0.097
		(0.149)	(0.149)		(0.113)	(0.114)
Poultry ownership		0.055	0.055		0.046	0.046
		(0.056)	(0.056)		(0.047)	(0.047)
Cattle ownership		-0.091	-0.091		-0.077	-0.078
		(0.063)	(0.063)		(0.053)	(0.053)
Sheep or goat ownership		-0.131**	-0.131**		-0.064	-0.064
		(0.060)	(0.060)		(0.052)	(0.052)

TABLE D3. continued.

	Calorie intake per capita (CIC)					
	Classification based on loans			Loan and assets' classification		
Model specifications	(i)	(ii)	(iii)	(iv)	(v)	(vi)
Household demographics						
Age of the household head	0.003	0.003	0.003	0.004	0.004	0.004
	(0.004)	(0.004)	(0.004)	(0.003)	(0.003)	(0.003)
Household head's education	0.001	-0.0003	-0.0003	0.005	0.005	0.005
	(0.008)	(0.008)	(0.008)	(0.006)	(0.006)	(0.006)
Sex of the household head	0.149^{*}	0.089	0.088	1.360	1.405	1.400
	(0.080)	(0.080)	(0.080)	(1.947)	(1.608)	(1.577)
Household size	0.140^{***}	0.143^{***}	0.143^{***}	0.144^{***}	0.144^{***}	0.144^{***}
	(0.017)	(0.017)	(0.017)	(0.014)	(0.014)	(0.014)
Constraints' induced behavior						
Credit: food crop variety	-0.023	-0.020	-0.220	-0.001	0.005	-0.238
	(0.028)	(0.028)	(0.181)	(0.023)	(0.023)	(0.149)
Credit: expenditure	0.190^{***}	0.186^{**}	0.050	0.204^{***}	0.212^{***}	0.047
	(0.074)	(0.074)	(0.140)	(0.061)	(0.061)	(0.114)
Credit: [crop variety ×			0.040			0.049^{*}
expenditure]			(0.036)			(0.030)
Correlated effects?	Yes	Yes	Yes	Yes	Yes	Yes
Observations	4,173	4,173	4,173	6,336	6,336	6,336
Overall R-squared	0.213	0.233	0.233	0.212	0.231	0.232
Adjusted R-squared	0.208	0.224	0.224	0.209	0.225	0.226

[1] The sample has 737 credit-unconstrained households and 654 credit-constrained households per wave in the loan classification. There are 1,082 credit-unconstrained households and 1,030 credit-constrained households per wave in the loan and asset classification. ***, **, * Coefficient is significant at the 1%, 5%, and 10% level, respectively.

TABLE E1. ——DESCRIPTION OF THE CONTROL VARIABLES USED IN THIS STUDY AND THEIR SUMMARY STATISTICS

	W1: 2010-11		W2: 2012-13		W3: 2015-16		Compounded annual growth rate for all waves: 2010-16		
	Mean	SD	Mean	SD	mean	SD	w1-w2	w2-w3	w1-w3
PANEL A: Credit-constrained households:									
Farm household characteristics:									
Off-farm employment (OFE) (1=yes, 0=no)	0.51	0.50	0.49	0.50	0.46	0.50	-1.00	-1.26	-1.46
Farm size (FS) (acres)	2.54	4.21	2.26	3.49	2.19	3.21	-2.88	-0.63	-2.10
Cash crop production (CCP) (1=yes, 0=no)	0.08	0.26	0.10	0.30	0.09	0.28	5.74	-2.09	1.70
Poultry ownership (PWN) (1=yes, 0=no)	0.42	0.49	0.47	0.50	0.48	0.50	2.85	0.42	1.93
Cattle ownership (CWN) (1=yes, 0=no)	0.15	0.35	0.16	0.36	0.16	0.36	1.63	0.00	0.93
Sheep/goat ownership (SGN) (1=yes, 0=no)	0.40	0.49	0.45	0.50	0.47	0.50	2.99	0.87	2.33
Household demographics:									
Household size (HSIZE)	6.50	3.11	7.07	3.33	7.88	3.59	2.12	2.19	2.79
Age of the household head (AGE) (years)	54.0	58.1	53.3	14.7	54.3	14.0	-0.33	0.37	0.08
Education of household head (EDC) (years)	11.9	3.73	12.2	3.89	12.6	3.65	0.62	0.65	0.82
Family-head sex (SEX) (1=male, 0=female)	0.89	0.31	0.89	0.31	0.89	0.31	0.00	0.00	0.00
PANEL B: Credit-unconstrained households:									
Farm household characteristics:									
Off-farm employment (OFE) (1=yes, 0=no)	0.56	0.50	0.52	0.50	0.51	0.50	-1.84	-1.39	-1.33
Farm size (FS) (acres)	2.79	4.52	2.56	3.40	2.57	3.48	-2.12	0.08	-1.17
Cash crop production (CCP) (1=yes, 0=no)	0.05	0.22	0.07	0.26	0.09	0.28	8.78	5.15	8.76
Poultry ownership (PWN) (1=yes, 0=no)	0.42	0.49	0.48	0.50	0.53	0.50	3.39	2.00	3.38
Cattle ownership (CWN) (1=yes, 0=no)	0.22	0.41	0.22	0.41	0.22	0.41	0.00	0.00	0.00
Sheep/goat ownership (SGN) (1=yes, 0=no)	0.45	0.50	0.52	0.50	0.55	0.50	3.68	1.13	2.91
Household demographics:									
Household size (HSIZE)	6.40	3.06	6.91	3.17	7.80	3.51	1.94	2.45	2.87
Age of the household head (AGE) (years)	49.5	14.7	52.2	14.5	53.8	14.2	1.34	0.61	1.20
Education of household head (EDC) (years)	12.1	3.76	12.5	3.75	12.7	3.65	1.34	0.32	0.69
Family-head sex (SEX) (1=male, 0=female)	0.91	0.29	0.91	0.29	0.91	0.29	0.00	0.00	0.00

Note: There are 1,137 credit-constrained households and 1,199 credit-unconstrained households per wave

TABLE F1. —SWITCHING REGRESSION RESULTS FOR GES ASSESSMENT ON FVS [m]

	Food variety score (FVS)					
	GES beneficiaries			GES non-beneficiaries		
Model specifications	(i)	(ii)	(iii)	(iv)	(v)	(vi)
Income & crop production diversity						
Food crop variety	-0.141	-0.262	0.606	0.235***	0.231***	0.551
	(0.354)	(0.394)	(2.254)	(0.082)	(0.082)	(0.545)
Expenditure per capita (log)	2.084**	2.176**	1.914	2.413***	2.413***	2.632***
	(0.951)	(0.886)	(1.792)	(0.211)	(0.207)	(0.432)
Food variety × expenditure			0.074			-0.065
			(0.480)			(0.112)
Credit induced behaviors						
Credit: food crop variety	0.520	0.633	-0.041	-0.049	-0.043	0.144
	(0.426)	(0.473)	(3.602)	(0.117)	(0.115)	(0.748)
Credit: expenditure	1.573	1.442	0.957	0.770**	0.765***	0.917
	(1.361)	(1.326)	(3.063)	(0.313)	(0.305)	(0.611)
Credit: [crop variety ×			0.141			-0.039
expenditure]			(0.749)			(0.156)
Farm characteristics?	No	Yes	Yes	No	Yes	Yes

[m] The sample has 70 credit-constrained households and 59 credit-unconstrained households per wave in the beneficiaries' column (i), (ii), and (iii). There are 739 households with binding credit constraints and 804 households with unbinding credit constraints per wave in the non-beneficiaries: Column (iv), (v), and (vi). Each regression accounts for household demographics and household and time fixed effects. Standard errors (in parentheses) are clustered at the household level.

***, **, * Coefficient is statistically significant at the 1%, 5%, and 10% level, respectively.

TABLE F2. —SWITCHING REGRESSION RESULTS FOR GES ASSESSMENT ON DDS [n]

	Dietary diversity score (DDS)					
	GES beneficiaries			GES non-beneficiaries		
model specifications	(i)	(ii)	(iii)	(iv)	(v)	(vi)
Income & crop production diversity						
Food crop groups	0.284	0.195	-1.645	0.195***	0.183**	0.218
	(0.340)	(0.382)	(1.804)	(0.064)	(0.065)	(0.389)
Expenditure per capita (log)	0.877***	0.877**	0.088	0.960***	0.965***	0.980***
	(0.428)	(0.434)	(0.932)	(0.093)	(0.092)	(0.195)
Food groups × expenditure			0.387			-0.007
			(0.396)			(0.078)
Credit induced behaviors						
Credit: food crop groups	-0.038	0.029	-0.052	-0.052	-0.040	0.503
	(0.410)	(0.446)	(0.089)	(0.089)	(0.089)	(0.503)
Credit: expenditure	0.760	0.744	1.788	0.364***	0.358***	0.609**
	(0.561)	(0.578)	(1.377)	(0.133)	(0.131)	(0.276)
Credit: [crop groups ×			-0.505			-0.109
expenditure]			(0.581)			(0.106)
Farm characteristics?	No	Yes	Yes	No	Yes	Yes

[n] The sample has 70 credit-constrained households and 59 credit-unconstrained households per wave in the beneficiaries' column (i), (ii), and (iii). There are 739 households with binding credit constraints and 804 households with unbinding credit constraints per wave in the non-beneficiaries: Column (iv), (v), and (vi). Each regression accounts for household demographics and household and time fixed effects. Standard errors (in parentheses) are clustered at the household level.

***, **, * Coefficient is statistically significant at the 1%, 5%, and 10% level, respectively.

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CHAPTER TWO

AN EMPIRICAL EXAMINATION OF THE EFFECT OF INFRASTRUCTURE ON ECONOMIC DEVELOPMENT: A LARGE AND HETEROGENEOUS PANEL DATA ANALYSIS

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An empirical examination of the effect of infrastructure on economic development: A large and heterogeneous panel data analysis

Abstract

Infrastructure drives economic development. This study investigates to what extent infrastructure and skilled labor affect aggregate output. It analyzes large heterogeneous panel data of 130 countries over two decades. Professor Shingo Takagi is a co-author to this paper. We implement an autoregressive distributed lag (ARDL) model to extract the long-run production technology relationship among economic growth, infrastructure, and skilled labor. The complementarity of skilled labor and infrastructure is conducive to skill-biased economic growth. Skill differences account for disparities among workers' wages worldwide, thereby widening inequalities in income and consequently, living standards. Previous studies, such as Calderón et al. (2015), used frameworks that assumes production function homogeneity across countries. Contrarily, we propose a methodology to identify latent country groups based on the long-run production technology embedded in the ARDL model, using the estimation procedure of Liu et al. (2020). We select the optimal number of groups by implementing a new information criterion under multiple nuisance parameters and estimate the coefficients of the production functions for each country group. Based on the complementarity estimates of country groups and the estimated country classifications, we find that the effects of infrastructure generated grouped heterogeneity of growth span across countries in estimated production relationships.

Keywords

identifying latent groups, heterogeneous large panel data, complementarity, infrastructure

JEL classification

C23, D24, I30

1. INTRODUCTION

1.1. Overview and problems of study

Infrastructure is one of the foundations of social and economic life because it contributes to economic growth and improvements in quality of life. Starting from the road and water supply networks of Ancient Rome to the recent information and communications technology networks, infrastructure has been crucial to the maintenance and improvement of the productivity of commerce, agriculture, and industry. Many scholars and policymakers have studied the effects of infrastructure on economic growth and welfare, as well as its underlying mechanisms (Jimenez, 1995).

The primary purpose of this study is to investigate to what extent infrastructure and other related inputs affect aggregate output, using large heterogeneous panel data of 130 countries over a period of two decades. In previous theoretical and empirical studies, most macroeconometric models assume that physical capital (possibly including infrastructure) is the key input of a production function that generates aggregate output. This implies that public and private capital are perfect substitutes for each other. However, empirical evidence does exist against the 'perfect substitutability' theory, in that public and private capital can be complementary inputs of production (An et al., 2019). Therefore, it is important to separate infrastructure from other forms of physical capital while measuring returns to production inputs.

Another important factor to consider regarding the specification of production function is the productive effect of capital-labor complementarity, which has received overwhelming attention in the literature (Krusell et al., 2000; Maliar et al., 2020; Na et al., 2020). Although some studies have found empirical evidence against capital-skill complementarity (Duffy et al., 2004), most evidence continues to favor the hypothesis of capital-skill complementarity (Correa et al., 2019; Tyers & Yang, 2000). Previous studies have also examined the theoretical and empirical implications of capital-skill complementarity on economic inequality, the wage-gap between skilled and nonskilled labor, and the productivity gaps among economic sectors (Krusell et al., 2000; Maliar et al., 2020).

Following the same reasoning of capital-skill complementarity, infrastructure (which is deemed as a part of physical capital) should be considered a complementary or substitute input to skilled labor in macroeconomic production technology. Furthermore, since building infrastructure implies vast expenditure, policymakers are often concerned, not only with its direct effects (such as those that are growth enhancing), but also its indirect effects (including income redistribution). The precise assessment and understanding of the contributions of infrastructure to the global economy are important issues in economics.

A topic that is yet to be fully explored in the assessment of the economic effects of infrastructure is the treatment of heterogeneity across units (Calderón & Servén, 2014). The effect of infrastructure on total output may vary across units and over sample points due to various reasons. One of such reasons is the heterogeneous features of infrastructure or production technology. Although several previous empirical studies have attempted to use panel data to control unobserved heterogeneity (represented by fixed effects), as in Eberhardt et al. (2013), the assumption of poolability (except the constant term across cross sectional units) is generally restrictive and may yield biased estimates. Additionally, estimating the effect of infrastructure on the output of each country using time-series data may suffer from efficiency loss.

To balance the possibility of bias with that of efficiency loss while considering heterogeneity, various econometric methods have been developed to endogenously find and classify latent groups in large panel data settings (Su et al., 2016; Liu et al., 2020). Accordingly, this study classifies 130 developed and developing countries in our panel dataset into finite groups in terms of the features of estimated production function. Subsequently, we present the group-wise production functions to be estimated. The classification algorithm (which is detailed in Section 3) is based on the work of Liu et al. (2020).

Our main contribution to the literature is relating heterogeneity in parameters of production function with the classification of countries in terms of the marginal effect of production inputs, especially between infrastructure and skilled labor. This has important implications for domestic income inequalities across countries. Given an increase in infrastructure investment, income inequality may increase in countries with infrastructure-skill complementarity in terms of wage increases for skilled labor. However, income inequality could decrease in countries with substitutable inputs between infrastructure and skilled labor arising from the wage reduction for skilled labor. We examine the relationship between complementarity and income inequality based on our estimation results.

1.2. Questions we asked before conducting this study

This scientific accomplishment is intended to address the following questions:

1) To what extent do infrastructure and skilled labor affect economic development of countries?
2) Does infrastructure complement skilled labor in production technology relationships?
3) Is there a grouped heterogeneity of econometric relationships in large panel data of countries?
4) What countries reap infrastructure-skill complementary advantages to economic development?
5) Does infrastructure-skill complementarity imply increasing income inequality?

1.3. Reasons for proceeding with this work after the questions in 1.2.

We believe that this study is worth conducting because of its significance. This work enables policymakers in developing countries to modify development policies following those of developed nations. It provides researchers with the state-of-art econometric methodology to classify countries into unknown groups. As originally explained, country-groups are based on similarities in the relationship between infrastructure and economic development. This could reveal the extent infrastructure contributes to the economic development success of developed nations for developing countries to learn and possibly adopt.

The methodology as well enables developing countries to identify developed nations to look up to and learn from. This could be achieved by establishing the optimal number of groups using the information criterion proposed here. For consistency, increase the group number to produce new country-groups and check if they are subsets of original groups. If they are, then, the selected group number is, indeed, optimal.

At this stage, estimate relationships of interest for each group. It is recommendable for a country to imitate another nation that share group-membership with it.

1.4. Regions of the world and section of economy covered in this study

This is a macro-level study on developing and developed countries. It investigates an unknown relatedness among 130 countries in terms of correlations between infrastructure and aggregate economic output. It contributes to knowledge by presenting an original econometric methodology to extract (latent) groups in large panel data of countries. In doing so, it incorporates the complementary advantages of infrastructure and skilled labor for economic growth and development. The variables used include measures of the aggregate economic growth, physical capital, and secondary schooling. Additional variables include indicators for constructing synthesis of infrastructural index. A directory for tracking data descriptions and empirical analysis and their implications is provided underneath.

1.5. How this research is structured

Section two reviews similar studies and exposes gaps in empirical literature. Section three describes the dataset used, whereas section four presents the basic econometric model and the estimation procedure. Section five reports the estimation results and discusses their empirical implications. Section six makes recommendations and concludes the study.

2. REVIEW OF RELATED STUDIES

2.1. Studies on the capital-skill complementarity

During the past two decades, labor-force trend has shown increase in high-skilled than low-skilled workers (Krusell et al., 2000). Income inequality, defined as income of high-skilled workers relative to that of low-skilled workers, has significantly also increased (Papageorgiou & Chmelarova, 2005). What are, then, sources of the inequalities? Griliches (1969), interpreted income inequality as implications of capital-skill complementarity, defined as smaller elasticity of substitution between capital and high-skilled workers than that between capital and low-skilled workers.

Numerous studies have since then concluded that capital-skill complementarity is the significant source of the increase in income inequalities. Krusell et al. (2000), Lindquist (2005), Papageorgiou and Chmelarova (2005), Parro (2013), and Dolado et al. (2018) are typical to this empirical conclusion.

By estimating a structural vector autoregression (SVAR), Dolado et al. (2018) found that capital-skill complementarity significantly increases income inequalities due to monetary innovations. They used a production technology with capital-skill complementarity and asymmetric search and matching frictions across high-skilled and low-skilled workers. Variables utilized include log of industrial production, unemployment rate, log of skill premium, and employment rates of skilled and unskilled workers.

Other variables include the consumer price index inflation and federal funds rate. An unanticipated monetary expansion was found to increase capital and high-skilled workers' demands. Since high-skilled workers have smaller matching frictions, the increased demand for high-skilled workers increases their income. Because high-skilled workers are more complementary to capital than substitutable low-skilled workers, the increased capital demand amplifies the relative income divergence.

This result is consistent with the discovery by Anna (2020), which estimated SVAR also, using US quarterly data from 1979q1-2018q4. Anna built a dynamic new Keynesian technology that separates the production responsibilities of high-skilled workers from those of low-skilled workers by incorporating capital-skill complementarity. Anna's results are reminiscence of those obtained by Dolado et al. (2018), showing a clear divergent in relative incomes of high-skilled workers to that of low-skilled workers caused by shocks due to uncertainty, which Anna interpreted as recessionary.

Krusell et al. (2000), focused on explaining income inequality in terms of observable variables for the US economy from 1963-1992. They utilized a production technology that is Cobb-Douglas in capital structure and constant elasticity of substitution (CES) over capital equipment, and the high-skilled and low-skilled workers. The technology was benchmarked to a nonlinear state-space model, and estimation procedure of two-step simulated pseudo-maximum likelihood (SPML) utilized to solve for possible endogeneity-problem.

Changes in the observed factor inputs were found to explain large inequalities in income through capital-skill complementarity. Similar and even greater estimates were obtained by Polgreen and Silos (2008), which recalibrated Krusell et al. (2000)'s model with new data and the proximate capital-equipment variables in the early work of Greenwood et al. (1997). Unfortunately, Polgreen and Silos' results turn to be unlikely to Greenwood et al.'s findings.

In addition to skill-biased technology that is embodied with capital goods, Parro (2013) recognized that capital goods are traded worldwide. He explained that, apart from skill-biased technological change, trade change is skill-biased also, and might likely cause income inequalities across globe. Estimated variables included: capital goods, noncapital manufacturing tradable and nonmanufacturing tradable goods, and nontradable goods. Capital-skill complementarity was introduced to a nested CES production technology, and a counterfactual estimation exercise was implemented. Parro concluded that trade is advantageous to both high-skilled workers and low-skilled workers, and that the magnitude of the benefits determines the extent of differences in income between 1990 and 2007.

Using data for 52 countries, and the ordinary least squares (OLS) procedure, Papageorgiou and Chmelarova (2005), found consistent but more powerful estimates than Duffy et al. (2004), who find weak capital–skill complementarity evidence in a panel dataset of 73 countries over 25 years. However, when the estimation was conducted separately for the OECD and non-OECD subsamples, no capital–skill complementarity evidence was found for the OECD subsample. This is reminiscence of the results by Ruiz-Arranz (2002), that recognize skill-biased technological change for increasing income inequality.

The result is important also to studies that attempt to examine implications of capital-skill complementarity to increasing income inequality in the U.S. and other advanced economies (see, e.g. Krusell et al., 2000). In addition, the second result suggests that there are important group effects.

Several other studies have estimated capital-skill complementarity hypothesis (see, e.g., Taniguchi & Yamada, 2019; Akermannet al. 2015; Henderson, 2009; Strobel, 2014; Wingender, 2015; Juan et al. 2014; Lindquist, 2004, 2005). Capital-skill complementarity has economic growth implications also (see, e.g., Yasar & Morrison, 2008; Maliar & Maliar, 2011; Tsaurai & Ndou, 2019). Maliar and Maliar (2011) re-specified Krusell et al. (2000)'s CES production technology in the form of a balanced growth model and empirically re-gauged how it explains Krusell at al.'s US data.

Rather than SPML of Krusell at al., Maliar and Maliar utilized a simulation-rooted parameterized expectations algorithm (PEA) proposed by den Haan and Marcet (1990). Moreover, Maliar and Maliar (2011) bounded the simulated series on initial iterations as in Maliar and Maliar (2003b), to guarantee that estimates converge toward the balanced-growth-path values. Results showed underestimation of the increase in the relative incomes of the high-skilled workers to that of low-skilled workers, and so lack of capital-skill complementarity explanations for the income inequality of the US macro-economy.

A fraction of these studies focusses on complementarity analytical frameworks: Sato (1967); Anderson and Moroney (1994); Acemoglu (2002); Donglan and Dequn (2014); and Henningsen et al. (2019) emphasize importance of and ways of nesting CES production function in complementarity analyses.

2.1.1.Knowledge gaps in the studies reviewed in 2.1.

Neither Duffy et al. (2004), nor, in fact, the entire reviewed studies, considered the grouped slope heterogeneity of the observed capital-skill complementarity variable. We make this methodological contribution. Additionally, citations in other sections show several studies on the effect of infrastructure on economic development. The same applies to skilled labor and economic growth as in the next chapter.

If capital, skilled labor, and infrastructure separately affect aggregate productivity. And if the first two factors complement each other in production, the last two forces could, as well, have complementary economic growth effect. This line of study has not been considered, at least, to our knowledge at this moment. We, therefore, attempt to fill this important gap in literature.

Moreover, almost all studies reviewed focus on homogenous groups such as the OECD countries. To allow developing countries to lean from developed nations, heterogenous panel of countries may be gathered for an empirical investigation. When considering it, an endogenous identification of country-groups should be undertaken. This study provides such an econometric approach.

3. DATA SOURCES AND DEFINITIONS OF VARIABLES

As previously mentioned, this study investigates to what extent infrastructure and skilled labor affect aggregate output. It is based on the analysis of large heterogeneous panel data of 130 countries over two decades (the sample period being 1990-2015). As summarized in Table 1, the data generated are defined as follows: output-side real gross domestic product (GDP) at chained purchasing power parities (PPPs) (in million 2011 US \$), a measure of aggregate output shown as *Y*, and capital stock at constant 2011 national prices (in million 2011 US \$) shown as *K*.

Table 1. Summary statistics: Output and inputs from 1990-2015

	Mean	SD	Min.	Max.	Units
Output-side GDP	0.0309	0.0312	0.0007	0.2248	2011 US dollars
Physical capital	0.1394	0.1453	0.0011	1.1420	2011 US dollars
Secondary education	2.6276	1.5897	0.0600	8.6500	Years
Electricity	0.0019	0.0022	0.0000	0.0143	Gigawatts
Main phone lines	0.4085	0.3860	0.0004	1.4906	Number of lines
Road networks	0.0165	0.0181	0.0004	0.1393	Kilometers

Note: Each variable, except the secondary variable, is transformed in per worker terms. The basic summary statistics were calculated over a sample of 130 countries from 1990-2015.

The data on *Y* and *K* are generated from the Penn World Table (PWT) 9.1 (Feenstra et al., 2015). Data on average years of secondary schooling were collected from the Barro and Lee (2013) database. The average years of secondary schooling of the population is depicted as *s*, which represents skilled labor (labor effectiveness), that is defined by $S = \exp\{s\}$. Although years of secondary education is used, S is a surrogate for skills from schooling, including tertiary education. The choice of secondary schooling as well as its empirical treatment is in ccordance with related studies especially work by Calderón et al. (2015).

Additional data include the total length of the road network (TROADS; in kilometers), obtained from the World Road Statistics; power generation capacity (EGC; in megawatts), collected from the United Nations Energy Statistics; and the total number of main telephone lines (MLINES) and labor force (LWDI), both collected from the World Development Indicator 2019. The variables enter production technologies as per person (divided by total labor force), except for the education-based skills, S. Infrastructure variables are each defined as per person before construction of the synthesis of infrastructure index.

The MLINES, EGC, and TROADS are used to construct the infrastructure index. Following Calderón et al. (2015), a principal component method is applied to the three series to construct an index for infrastructure. The first main component of these three infrastructure availability services captures the synthesis of the infrastructure index[1].

4. ECONOMETRIC METHODOLOGY

4.1. Estimation and model selection

Our primary goal was to estimate the long-run relationship between the output and input variables, allowing for heterogeneity in coefficients. However, unrestricted heterogeneity in coefficients can cause under-identification or efficiency loss. When using the framework of the autoregressive distributed lag (ARDL) model to capture the dynamics of the variables in it, ARDL(P, Q), the model is

$$\sum_{p=0}^{P} \lambda_{i,p}\, y_{i,t-p} = \sum_{q=0}^{Q} f'_{i,t-q}\beta_{i,q} + \mu_i + u_{i,t},$$

[1] The synthesized infrastructure index is given as $0.3654331 \log\left(\frac{\text{TROADS}}{\text{LWDI}}\right) + 0.3719091 \log\left(\frac{\text{EGC}}{\text{LWDI}}\right) + 0.2626578 \log\left(\frac{\text{MLINES}}{\text{LWDI}}\right)$, which explains approximately 84% of the focused dimensions' variation.

where all coefficients are assumed to be heterogeneous across countries. A country-specific intercept term (i.e. a fixed effect term), μ_i, is included, and the error term $u_{i,t}$ is assumed to be idiosyncratic with a constant variance σ^2. The sample size of the cross-sectional dimension is shown as N and that of the time-series dimension as T. An error-correction model (ECM) representation of the ARDL(P, Q)[2 3] model is given as follows:

$$\Delta y_{it} = \phi_i\left(y_{i,t-1} - f'_{i,t-1}\theta_i\right) + \sum_{p=1}^{P-1} \lambda_{i,p}\, \Delta y_{i,t-p} + \sum_{q=0}^{Q-1} \underbrace{\Delta f'_{i,t-q}}_{1\times k}\, \delta_{i,q} + \mu_i + \epsilon_{i,t} \tag{1}$$

$$= \phi_i \xi_{i,t-1}(\theta_i) + \left(\Delta y_{it-1} \cdots \Delta y_{it-p+1}\ \Delta f'_{i,t} \cdots \Delta f'_{i,t-q+1}\ 1\right)\begin{pmatrix}\lambda_i\\ \delta_i\\ \mu_i\end{pmatrix} + \epsilon_{i,t},\ \xi_{i,t-1}(\theta_i) \equiv y_{i,t-1} - f'_{i,t-1}\theta_i$$

$$= \phi_i \xi_{i,t-1}(\theta_i) + W_i \eta_i + \epsilon_{i,t} \tag{2}$$

The error correction term, $\xi_{i,t-1}(\theta_i)$, captures the stable, long-run relationships between relevant variables. In this case, it is interpreted as the production function ($y_{i,t}$: output, $\mathbf{f}_{i,t} = (k_{i,t}, z_{i,t}, s_{i,t}, z_{i,t}s_{i,t})'$: physical capital, infrastructure, skilled labor, and the cross-term of the last two production inputs. Further details are described in Section 2).

$$y_{i,t-1} - f'_{i,t-1}\theta_i = y_{i,t-1} - \beta_{k,i}k_{i,t-1} - \beta_{z,i}z_{i,t} - \beta_{s,i}s_{i,t} - \beta_{zs,i}z_{i,t}s_{i,t} \tag{3}$$

Although Calderón et al. (2015) assumes the homogeneity of the coefficients on $\mathbf{f}_{i,t}$, that is, $\theta_i = \theta = (\beta_k,\beta_z,\beta_s,\beta_{zs})$ for any i, this is a somewhat restrictive assumption. All countries would have similar production technologies and the differences would only be attributed to those in input quantity. Allowing for country-wise coefficients would result in a serious efficiency loss during estimation. Therefore, we allow for group-wise coefficients, but the membership is unrestricted and estimated from the data. Consistently, we assume

[2] The selection of P and Q is based on the method by Calderón et al., 2015, where the Akaike information criterion (AIC) is used to determine the lag lengths of the ARDL model. Both lag lengths are selected by country, using the AIC. The lengths are confined to 2. Due to the lag-length selection strategy, the length of the in-sample time period is 24, even though the dataset included 26 years' information.

[3] In addition, Calderón et al., 2015 apply the filtration to the original variables to remove the aggregate effects and time effects in the sample; they subtract the cross section means of the variables from the original variables for this purpose. We also adopt their filtration.

the presence of group-wise, long-run relationships for the country groups: G1, G2, ..., GG. Each country belongs to one of the G groups,

$$\xi_{i,t-1}(\theta^{(1)}) = y_{i,t-1} - f'_{i,t-1}\theta^{(1)} = y_{i,t-1} - \beta_k^{(1)} k_{i,t-1} - \beta_z^{(1)} z_{i,t} - \beta_s^{(1)} s_{i,t} - \beta_{zs}^{(1)} z_{i,t} s_{i,t}, \;\; if \quad i \in \mathcal{G}_1$$

$$\xi_{i,t-1}(\theta^{(2)}) = y_{i,t-1} - f'_{i,t-1}\theta^{(2)} = y_{i,t-1} - \beta_k^{(2)} k_{i,t-1} - \beta_z^{(2)} z_{i,t} - \beta_s^{(2)} s_{i,t} - \beta_{zs}^{(2)} z_{i,t} s_{i,t}, \;\; if \quad i \in \mathcal{G}_2$$

$$\vdots$$

$$\xi_{i,t-1}(\theta^{(G)}) = y_{i,t-1} - f'_{i,t-1}\theta^{(G)} = y_{i,t-1} - \beta_k^{(G)} k_{i,t-1} - \beta_z^{(G)} z_{i,t} - \beta_s^{(G)} s_{i,t} - \beta_{zs}^{(G)} z_{i,t} s_{i,t}, \;\; if \quad i \in \mathcal{G}_{\mathcal{G}}$$

We also assume that the short-run dynamics, driven by coefficient parameters, ϕ_i and η_i, are heterogeneous across countries. Country-specific, unrestricted coefficients are used in the model. Under the assumption of homogeneous long-run coefficients, Pesaran et al. (1999) propose the 'Pooled Mean Group' estimation method. In this study, we extend this model with homogeneous long-run coefficients among all countries to that with heterogeneous coefficients across a finite number of country groups. There are a small number of groups that show similar patterns of production function. Under this set up, there are $kG + N[(p - 1) + kq + 3]$ parameters in the model $\left(\{\theta^{(g)}\}_{g=1}^{G}, \{\lambda_i, \delta_i, \mu_i, \phi_i, \sigma_i^2\}_{i=1}^{N}\right)$.

4.2. Estimation of grouped coefficients

Here, we introduce the group membership variable g_i, which takes a value of $\{1,2,...,G\}$ according to the group to which the country i belongs. The concentrated log-likelihood function of model (2), after concentrating the parameters $\{\lambda_i, \delta_i, \mu_i\}_{i=1}^{N}$, is given as follows: by using $Q_{W,i} \equiv I_T - W_i(W_i'\boldsymbol{W_i})^{-1}\boldsymbol{W_i'}$: define as $\theta_i \equiv \theta^{(g_i)}$,

$$\begin{aligned}
\ln L\left(\{\boldsymbol{\theta}^{(g)}\}_{g=1}^{G}, \{\phi_i, \sigma_i^2\}_{i=1}^{N}\right) &= \sum_{i=1}^{N}\sum_{t=1}^{T} \ell_{it}(\boldsymbol{\theta}_i, \phi_i, \sigma_i^2) \\
&= \sum_{i=1}^{N}\left\{\sum_{t=1}^{T} \frac{-1}{2}\left(\log(2\pi) + \log\sigma_i^2 + \frac{(\Delta\mathbf{y}_i - \phi_i \cdot \boldsymbol{\xi}_i(\boldsymbol{\theta}_i))'\,\mathbf{Q}_{W,i}\,(\Delta\mathbf{y}_i - \phi_i \cdot \boldsymbol{\xi}_i(\boldsymbol{\theta}_i))}{\sigma_i^2}\right)\right\} \\
&= -\frac{NT}{2}\log(2\pi) + \sum_{i=1}^{N}\left(-\frac{T}{2}\log\sigma_i^2 - \frac{(\Delta\mathbf{y}_i - \phi_i \cdot \boldsymbol{\xi}_i(\boldsymbol{\theta}_i))'\,\mathbf{Q}_{W,i}\,(\Delta\mathbf{y}_i - \phi_i \cdot \boldsymbol{\xi}_i(\boldsymbol{\theta}_i))}{2\sigma_i^2}\right)
\end{aligned}$$

The estimation algorithm is given as follows (see Liu et al., 2020):

1) Given the number of groups G and an initial value of the long-run parameter[4] $\theta = \left(\theta^{(1)}, \theta^{(2)}, \ldots, \theta^{(G)}\right)$ and $\theta_i \equiv \theta^{(g_i)}$, estimate the parameters of the short-run dynamics, $\left\{\hat{\phi}_i, \hat{\sigma}_i^2\right\}_{i=1}^{N}$, and the error correction term $\xi_i(\theta_i)$ as follows:

$$\hat{\phi}_i = \left(\xi_i(\theta_i)' Q_{W,i} \xi_i(\theta_i)\right)^{-1} \xi_i(\theta_i)' Q_{W,i} \Delta y_i \hat{\sigma}_i^2$$

$$= T^{-1}(\Delta y_i - \phi_i . \xi_i(\theta_i))' Q_{W,i}(\Delta y_i - \phi_i . \xi_i(\theta_i))$$

$$\xi_i(\theta_i) = y_{i,t-1} - f_{i,-1}\theta_{i,}\, \theta_{i,} \equiv \theta(g_i)$$

$$\hat{\phi}_i = \left(\xi_i(\theta_i)' Q_{W,i} \xi_i(\theta_i)\right)^{-1} \xi_i(\theta_i)' Q_{W,i} \Delta y_i$$

$$\hat{\sigma}_i^2 = T^{-1}\left(\Delta y_i - \phi_i \cdot \xi_i(\theta_i)\right)' Q_{W,i}\left(\Delta y_i - \phi_i \cdot \xi_i(\theta_i)\right)$$

$$\xi_i(\theta_i) = y_{i,-1} - f_{i,-1}\theta_i,\ \theta_i \equiv \theta(g_i)$$

for each i, $1 \le i \le N$.

2) Select the optimal group for the i-th country as

$$g_i^* = \arg\min_{1 \le g \le G} \left\{ -\frac{T}{2} \log \hat{\sigma}_i^2 \, \frac{\left(\Delta \boldsymbol{y_i} - \hat{\phi}_\iota \cdot \boldsymbol{\xi_i}\left(\boldsymbol{\theta}^{(g)}\right)\right)' \boldsymbol{Q_{W,i}} \left(\Delta \boldsymbol{y_i} - \hat{\phi}_\iota \cdot \boldsymbol{\xi_i}\left(\boldsymbol{\theta}^{(g)}\right)\right)}{2\hat{\sigma}_i^2} \right\},$$

for each i, $1 \le i \le N$. Then, we obtain the optimal membership as $\mathcal{G}^* = (g_1^*, g_2^*, \cdots, g_N^*)$ at this step.

3) Update the long-run parameter given the membership $\mathcal{G}^* = (g_1^*, g_2^*, \cdots, g_N^*)$ as ($\mathcal{G}_g^* \equiv \{\ i \mid g$_{i}^{* } $= g,\ 1 \le i \le N\ \}$),

$$\widehat{\boldsymbol{\theta}}_1 = \left\{ \sum_{i \in \mathcal{G}_1^*} \frac{(\phi_i)^2}{\sigma_i^2} \cdot \left(F_{i,-1}\right)' Q_{W,i}\left(F_{i,-1}\right) \right\}^{-1} \sum_{i \in \mathcal{G}_1^*} \frac{\phi_i}{\sigma_i^2} \cdot \left(F_{i,-1}\right)' Q_{W,i}\left(\Delta y_i - \phi_i \cdot y_{i,-1}\right)$$

[4] The criterion function has multiple optima; the optimal value is sensitive to initial values. After attempting several initial parameters, we select the one reaching the maximum.

$$\widehat{\boldsymbol{\theta}}_2 = \left\{\sum_{i\in\mathcal{G}_2^*} \frac{(\phi_i)^2}{\sigma_i^2} \cdot \left(F_{i,-1}\right)' Q_{W,i}\left(F_{i,-1}\right)\right\}^{-1} \sum_{i\in\mathcal{G}_2^*} \frac{\phi_i}{\sigma_i^2} \cdot \left(F_{i,-1}\right)' Q_{W,i}\left(\Delta y_i - \phi_i \cdot y_{i,-1}\right) \vdots$$

$$\widehat{\theta_G} = \left\{\sum_{i\in\mathcal{G}_\mathcal{G}^*} \frac{(\phi_i)^2}{\sigma_i^2} \cdot \left(F_{i,-1}\right)' Q_{W,i}\left(F_{i,-1}\right)\right\}^{-1} \sum_{i\in\mathcal{G}_\mathcal{G}^*} \frac{\phi_i}{\sigma_i^2} \cdot \left(F_{i,-1}\right)' Q_{W,i}\left(\Delta y_i - \phi_i \cdot y_{i,-1}\right)$$

4) Repeat steps 1-3 until convergence.

The asymptotic properties of the coefficient estimator and the group membership were established by Liu et al. (2020). Details of the results are shown in the Appendix.

4.3. Model selection

Information criteria for model selection under the presence of incidental parameters are proposed in Lee and Phillips (2015). They established conditions for the consistency of model selection, where the selected model is asymptotically true. We slightly modify their Bayesian-like information criterion, using the modified profile likelihood contribution, $\ell_{it}(\theta_i,\hat{\alpha}_i(\theta_i))$ and the correction term. The information criterion is defined as

$$IC(g) = -\frac{2}{NT}\sum_{i=1}^{N}\left\{\sum_{t=1}^{T} \ell_{it}\left(\theta^{(g_i)}, \widehat{\boldsymbol{\alpha}}_i(\theta_i)\right) - M_i\left(\theta^{(g_i)}\right)\right\} + \frac{h(NT)}{NT} \times gK,\ 1 \le g_i \le g, \qquad (4)$$

$$M_i(\theta) = \frac{1}{2}\left\{-E_T\left[\frac{\partial^2 \ell_{it}\left(\theta, \widehat{\boldsymbol{\alpha}}_i(\theta)\right)}{\partial\alpha_i\,\partial\alpha_i'}\right]\right\}^{-1}\left\{E_T\left[\frac{\partial \ell_{it}\left(\theta, \widehat{\boldsymbol{\alpha}}_i(\theta)\right)}{\partial\alpha_i}\frac{\partial \ell_{it}\left(\theta, \widehat{\boldsymbol{\alpha}}_i(\theta)\right)}{\partial\alpha_i'}\right]\right\}.$$

The requirement for the consistency is just that $h(NT)$ is a non-decreasing function of NT. After attempting some candidates, we ultimately choose $h(NT) = (NT)^{3/8}$ since $\ln(NT)$ is too loose and $(NT)^{1/2}$ is too severe to pick up moderate group sizes. The results of model selection by the information criterion, defined in (4), and by the criterion proposed by Liu et al. (2020), are shown in Table 2.

Table 2. Model selection based on information criteria

Number of Groups	G=1	G=2	G=3	G=4	G=5
IC in (4)	-3.631	-3.695	-3.721	-3.742	-3.743*
IC from Liu et al. (2020)	-1.855	-1.889	-1.904	-1.919	-1.922*

Number of Groups	G=6	G=7	G=8	G=9	G=10
IC in (4)	-3.735	-3.720	-3.724	-3.715	-3.696
IC from Liu et al. (2020)	-1.921	-1.917	-1.921	-1.919	-1.913

Note: The asterisk (*) shows the minimum value among the candidate models.
Both information criteria show that the model with five groups is the optimal model.

Both information criteria show that the optimally selected model is the one with five groups (G = 5). In the estimation results section, we use those from the model with G = 4, G = 5 and G = 6 to reduce the risk of false selection. Further research examining the validity of our choice for the information criterion is ongoing.

The classification result of the model with 5 groups and the coefficient estimates of the models with 4, 5, and 6 groups are summarized in Table 3 and Table 4. The results and interpretations are discussed in the following section.

Table 3. Country Classification List (G = 5)

Name	Code	Name	Code	Name	Code	Name	Code	Name	Code
Group1		**Group2**		**Group3**		**Group4**		**Group5**	
36 countries		21 countries		28 countries		29 countries		16 countries	
Bangladesh	BGD	Colombia	COL	Kyrgyz	KGZ	Niger	NER	Tajikistan	TJK
Sudan	SDN	Finland	FIN	Jordan	JOR	Morocco	MAR	Poland	POL
Lithuania	LTU	Cyprus	CYP	Chile	CHL	Switzerland	CHE	Slovak Rep.	SVK
Philippines	PHL	Israel	ISR	Peru	PER	Iceland	ISL	New Zealand	NZL
Latvia	LVA	South Africa	ZAF	France	FRA	Zimbabwe	ZWE	Bulgaria	BGR
Korea	KOR	Croatia	HRV	Greece	GRC	Syria	SYR	Guatemala	GTM
Mozambique	MOZ	Sri Lanka	LKA	Spain	ESP	Paraguay	PRY	Nepal	NPL
Togo	TGO	Portugal	PRT	Slovenia	SVN	Ireland	IRL	Dominica	DOM
Czech Rep.	CZE	Indonesia	IDN	Germany	DEU	Italy	ITA	Australia	AUS
Benin	BEN	Mali	MLI	Cameroon	CMR	Maldives	MDV	Belgium	BEL
Uganda	UGA	Panama	PAN	Austria	AUT	Iraq	IRQ	Lesotho	LSO
Senegal	SEN	Argentina	ARG	Zambia	ZMB	Russia	RUS	Ecuador	ECU
Sweden	SWE	Netherlands	NLD	Ukraine	UKR	Mauritius	MUS	Pakistan	PAK
Egypt	EGY	Kenya	KEN	Tunisia	TUN	Serbia	SRB	Ghana	GHA
Burundi	BDI	Belize	BLZ	Gambia	GMB	Hungary	HUN	Jamaica	JAM
Romania	ROU	Namibia	NAM	Turkey	TUR	Haiti	HTI	Malta	MLT
India	IND	United Arab Emirates	ARE	Costa Rica	CRI	Yemen	YEM		
Estonia	EST	Canada	CAN	Algeria	DZA	Brunei Darussalam	BRN		
Cambodia	KHM	Albania	ALB	Brazil	BRA	United States	USA		
Gabon	GAB	Norway	NOR	Iran	IRN	Trinidad and Tobago	TTO		
Denmark	DNK	Thailand	THA	United Kingdom	GBR	Saudi Arabia	SAU		
Myanmar	MMR			Congo, Rep.	COG	Bolivia	BOL		
Qatar	QAT			Botswana	BWA	Japan	JPN		
Cote d'Ivoire	CIV			Barbados	BRB	Luxembourg	LUX		
Honduras	HND			Kazakhstan	KAZ	Liberia	LBR		
China	CHN			Uruguay	URY	Kuwait	KWT		
Lao PDR	LAO			Mexico	MEX	Vietnam	VNM		
Central Africa	CAF			Nicaragua	NIC	Moldova	MDA		
El Salvador	SLV					Malaysia	MYS		
Sierra Leone	SLE								
Fiji	FJI								
Mongolia	MNG								
Rwanda	RWA								
Malawi	MWI								
Venezuela	VEN								
Mauritania	MRT								

Note: There are a total of 130 countries, and each column reports the names and initials of country-membership of the groups.

Table 4. Coefficient Estimates

	Group1		**Group2**		**Group3**		**Group4**		**Group5**		**Group6**	
G=4												
	Estimat	**S.E.**	**Estimat**	**S.E.**	**Estimat**	**S.E.**	**Estimat**	**S.E.**	**Estimat**	**S.E.**	**Estimat**	**S.E.**
β_k	0.7998	0.0523	0.5853	0.0547	0.3971	0.0414	-0.4348	0.0511				
β_z	-0.2964	0.0409	0.5782	0.0482	-1.1913	0.1041	0.1961	0.0328				
β_s	0.1723	0.0239	-0.1295	0.0311	-1.2690	0.1077	-0.0131	0.0179				
β_{zs}	-0.0422	0.0119	0.4113	0.0422	0.9166	0.0754	-0.0205	0.0125				
G=5												
	Estimate	S.E.	Estimate	S.E.	Estimate	S.E.	Estimate	S.E.	Estimate	S.E.	Estimate	S.E.
β_k	0.8549	0.0566	0.5410	0.0699	0.4431	0.0555	-0.4369	0.0553	0.3831	0.0175		
β_z	-0.3359	0.0436	0.6167	0.0516	-1.3017	0.1499	0.2364	0.0335	-0.1039	0.0401		
β_s	0.1625	0.0267	-0.1302	0.0347	-1.1192	0.1047	-0.0098	0.0197	-0.1055	0.0290		
β_{zs}	-0.0376	0.0142	0.4305	0.0449	0.7743	0.0734	-0.0196	0.0134	0.2130	0.0303		
G=6												
	Estimate	S.E.	Estimate	S.E.	Estimate	S.E.	Estimate	S.E.	Estimate	S.E.	Estimate	S.E.
β_k	0.9857	0.0638	0.5466	0.0662	0.4456	0.0575	-0.4476	0.0508	0.3779	0.0176	0.1969	0.0419
β_z	-0.4239	0.0480	0.6111	0.0491	-1.3157	0.1571	0.2540	0.0376	-0.0530	0.0352	-0.0841	0.0480
β_s	0.1238	0.0306	-0.1339	0.0336	-1.1220	0.1040	-0.0138	0.0185	-0.1203	0.0331	0.1928	0.0122
β_{zs}	-0.0013	0.0215	0.4336	0.0446	0.7766	0.0726	-0.0143	0.0143	0.2116	0.0319	-0.0361	0.0103

Note: Information criterion selected five as the optimum groups existing in the panel dataset (G=5). The point estimates from G=4 (under-selection) and G=6 (over-selection) are presented to clearly show how the methodology used consistently classified countries in the panel dataset.

5. ESTIMATION RESULTS AND INTERPRETATION

5.1. Results' discussion guide

The model we investigate is the production function of the following form,

$$Y = K^{\beta_k} Z^{\beta_z} S^{\beta_s} \exp\{\beta_{zs} \log Z \log S\} \tag{5}$$

where Y is the output per worker, K is the physical capital stock per worker, Z is the infrastructure service per worker (the geometric average of telecommunication stock, road stock, and electricity-generating stock, defined in the footnote of page 4), and S is the skilled labor (defined as the exponential of the average years of secondary education in the population). This is an extended version of a Cobb-Douglas production function with an interaction term (Na et al., 2020).

In the logarithm form, the estimated model is given as a linear-in-parameters model with an interaction term,

$$\log Y = \beta_k \log K + \beta_z \log Z + \beta_s \log S + \beta_{zs} \log Z \log S.$$

From this setup, the marginal product of infrastructure is

$$\frac{\partial Y}{\partial Z} = (\beta_z + \beta_{zs} \log S)\frac{Y}{Z},$$

and the marginal product of the skilled labor is

$$\frac{\partial Y}{\partial S} = (\beta_s + \beta_{zs} \log Z)\frac{Y}{S}.$$

The term (β_z+β_{zs} log$S$) represents the total contribution of infrastructure to aggregate output, and (β_s+β_{zs} log$Z$) is similarly defined for skilled labor. They are interpreted as the effect of each input on the output. The cross derivative of Y with respect to Z and S is given as:

$$\frac{\partial^2 Y}{\partial S\, \partial Z} = \{\beta_{ZS} + (\beta_Z + \beta_{zs} \log S)(\beta_S + \beta_{zs} \log Z)\}\frac{Y}{ZS}.$$

The sign of the cross derivative is related to the concept of complementarity or substitutability in the definition by Milgrom and Roberts (1990), which is determined by $\beta_s + \beta_{zs}$ log$Z$, $\beta_z + \beta_{zs}$ log$S$, and β_{zs}. When infrastructure and skilled labor are complementary, as infrastructure investment increases, the marginal product of skilled labor rises. Subsequently, wages paid to skilled labor increase, which will widen the wage gap between skilled and nonskilled workers. This wage increase would manifest in the Gini coefficient of the economy, leading to a rise in the coefficient. This possible rise in income inequality is, however, significant only in countries with large number of low-skilled labor compared with the number of high-skilled labor.

Conversely, when infrastructure and skilled labor are substitutable inputs, increases in infrastructure will reduce the marginal product of skilled labor and the payment to the latter will decrease. This interpretation can help us understand the narrowing mechanism of the income gap. Thus, the substitution between S and Z could lead to decrease in the Gini coefficient of the economy. Similar to the case of complementarity, income inequality could reduce just for countries with smaller high-skilled labor relative to low-skilled labor.

5.2. Classification results

In this subsection, we discuss classification results in terms of the signs of the estimated marginal product of skilled labor ($\partial Y/\partial S$), infrastructure ($\partial Y/\partial Z$), and the cross derivative of the production function with respect to both inputs ($\partial^2 Y/\partial S\partial Z$). In Table 5, we show the estimated signs of the groups with the feature of substitution between S and Z ($\partial^2 Y/\partial S\partial Z < 0$). The numbers between the parentheses denote the positive and negative estimates of the parameters for the corresponding model. For example, **Group1** of the model with the number of groups $G = 4$ contains 40 countries.

Table 5. Signs of estimated parameters: substitute technology

	Group1	**Group4**	**Group6**
the number of groups in the estimated model is four ($G = 4$)			
$\frac{\partial Y}{\partial S}$	(960 , 0)	(0 , 792)	
$\frac{\partial Y}{\partial Z}$	(0 , 960)	(792 , 0)	
$\frac{\partial^2 Y}{\partial S\partial Z}$	(0 , 960)	(0 792)	
the number of groups I in the estimated model is five (G =5)			
$\frac{\partial Y}{\partial S}$	(864 , 0)	(13 , 683)	
$\frac{\partial Y}{\partial Z}$	(0 , 864)	(696 , 0)	
$\frac{\partial^2 Y}{\partial S\partial Z}$	(0 , 864)	(48 648)	
the number of groups in the estimated model is six ($G = 6$)			
$\frac{\partial Y}{\partial S}$	(648 , 0)	(0 , 624)	(384 , 0)
$\frac{\partial Y}{\partial Z}$	(0 , 648)	(624 , 0)	(0 , 384)
$\frac{\partial^2 Y}{\partial S\partial Z}$	(0 , 648)	(24 , 600)	(24 , 360)

Note: The entry (A, B) shows that the number of positive estimates is A and the number of negative estimates is B. The average cross derivative estimates are -0.0933 ($G = 4$), -0.0922 ($G = 5$), -0.0538 ($G = 6$) for Group1, -0.0231 ($G = 4$), 0.0209 ($G = 5$), 0.0131 ($G = 6$) for Group4, and 0.0271 ($G = 6$) for Group6, where G is the number of groups in the estimated model

The sample period used for the estimation is 24 years; therefore, there are 960 = 40 × 24 observations in this category. The table shows (960,0), (0,960), and (0,960) for $\partial Y/\partial S$, $\partial Y/\partial Z$, and $\partial^2 Y/\partial S\partial Z$ respectively, which reveal that all estimated $\partial Y/\partial S$ in this category are positive. Likewise, all estimated $\partial Y/\partial Z$ and $\partial^2 Y/\partial S\partial Z$ are negative. This sign pattern is common to one of the models with $G = 5$ and $G = 6$. **Group1** is characterized by a positive marginal product of skilled labor, a negative marginal product of infrastructure, and a negative cross derivative with respect to both inputs. The negative marginal product of infrastructure does not conform with apriori expectation. This result is a methodological weakness, and its detailed causes are beyond the scope of this study. Results on cross derivatives are focus of discussion for countries having such a negative infrastructural growth effect.

Group6 has the same sign pattern as **Group1**: this is closely related to the grouping process; a large percentage of the countries in **Group6** is separated from **Group1**. **Group4** also has negative cross-derivative estimates. However, the sign pattern of marginal products is the opposite, namely, the one of skilled labor is negative and that of infrastructure is positive. Interpretations of these results and their statistical significance are discussed in the following subsection.

In Table 6, **Group2** and **Group3** show positive cross-derivative estimates, while **Group5** shows a mixed-sign result of cross-derivative estimates.[5]

Table 6. Signs of estimated parameters: complementary technology

	Group2	**Group3**	**Group5**
the number of groups in the estimated model is four (G = 4)			
$\frac{\partial Y}{\partial S}$	(30 , 546)	(0 , 792)	
$\frac{\partial Y}{\partial Z}$	(576 , 0)	(0 , 792)	
$\frac{\partial^2 Y}{\partial S \partial Z}$	(576 , 0)	(792 0)	
the numbe r of groups in the estimated model is five (G = 5)			
$\frac{\partial Y}{\partial S}$	(19 , 485)	(19 , 653)	(6 , 378)
$\frac{\partial Y}{\partial Z}$	(504 , 0)	(0 , 672)	(1 , 383)
$\frac{\partial^2 Y}{\partial S \partial Z}$	(480 , 24)	(672 0)	(193 , 191)
the number of groups in the estimated model is six (G = 6)			
$\frac{\partial Y}{\partial S}$	(25 , 479)	(0 , 672)	(4 , 284)
$\frac{\partial Y}{\partial Z}$	(504 , 0)	(0 , 672)	(17 , 271)
$\frac{\partial^2 Y}{\partial S \partial Z}$	(504 , 0)	(672 , 0)	(192 , 96)

Note: The entry (A,B) shows that the number of positive estimates is A and the number of negative estimates is B. The cross derivative estimates are 0.3363 (G = 4), 0.3454 (G = 5), 0.3679 (G = 6) for Group2, 2.4239 (G = 4), 2.1891 (G = 5), 2.2106 (G = 6) for Group3, and 0.3201 (G = 5), 0.3685 (G = 6) for Group5, where G is the number of groups in the estimated model.

[5] The cross-derivative estimates of **Group5** are concentrated on just three points: 50% (42%) of estimates are just approximately zero, 19% (25%) are approximately 0.44, and 31% (33%) are approximately 0.78 for the model with five (six) groups: the feature of this group is that almost half of estimates are approximately zero, and the remaining are positive.

Group2 is clearly characterized by a negative sign for the marginal product of skilled labor and a positive sign for that of infrastructure. **Group3** and **Group5** have negative marginal products.

From these tables, it is clear that all the groups are classified in terms of the signs of marginal products and cross derivatives, except for the cross-derivative estimates of **Group5**. We emphasize that our grouping method can find and classify the different coefficient patterns in the macro production function.

Accordingly, Canada and Netherlands in **Group2**, Germany and the United Kingdom in **Group3**, and other countries in the respective groups (see Table 3) clearly show skill-infrastructure complementarity. Some countries in **Group5** that Australia and New Zealand fell into (see Table 3 again), similarly had a complementary production technology. These results are consistent with those in Taniguchi and Yamada (2022), Michaels et al. (2014), and Krusell et al. (2000). Given that the above listed countries are mostly Organisation for Economic Cooperation and Development (OECD) countries, our results clearly expand the work of Taniguchi and Yamada (2022).

This suggests that infrastructure-induced technical advancement in the countries raises skilled-labor contributions to aggregate economic output, favoring skill premium. It appears that access to adequate infrastructure enables skilled workers to create new production formula and disseminate the innovative approaches across enterprises in the countries. Additionally, skilled workers diffuse the new production processes in industries that adopt them. These aspects increase the marginal productivity of skilled labor and its remunerations in the form of take-home wages.

Importantly, Burundi, Uganda, and many other African countries fell into **Group1** that is characterized by substitutable skill-infrastructure production technology. Bangladesh and Mongolia in Asia, Romania in Europe, and El Salvador in America also fell into this group. Increasing infrastructure investment in these counties reduces skill premium, implying that it decreases marginal product and wages of the skilled workers. Countries in **Group6**, which are a subset of those in **Group1**, have a similar outcome of technical changes. In Japan, the United States, and some other countries in **Group4**, increasing infrastructure investment and skill acquisitions leave skill premium unchanged in the statistical sense.

Overall, infrastructure and skill as complementary production technologies enhance the productivity of skilled labor and increase its wages relative to that of unskilled workers. The reverse is the case for a substitutable infrasrtcure and skilled labor production technology. However, whether the associating wage changes could increase or decrease income inequality depends on the size of skilled labor relative to unskilled labor. This implies that the wage increases found for skilled labor in Germany may not increase income inequality because the country is made up of mostly high-skilled workers, each of which benefits from the wage increases. Contrarily, the wage reduction found for skilled labor in Burindi could decrease income inequality because the country is a dominant of unskilled workers. The magnitude and statistical significance of the production factors are further discussed and additional countries with complementary technologies are enlisted.

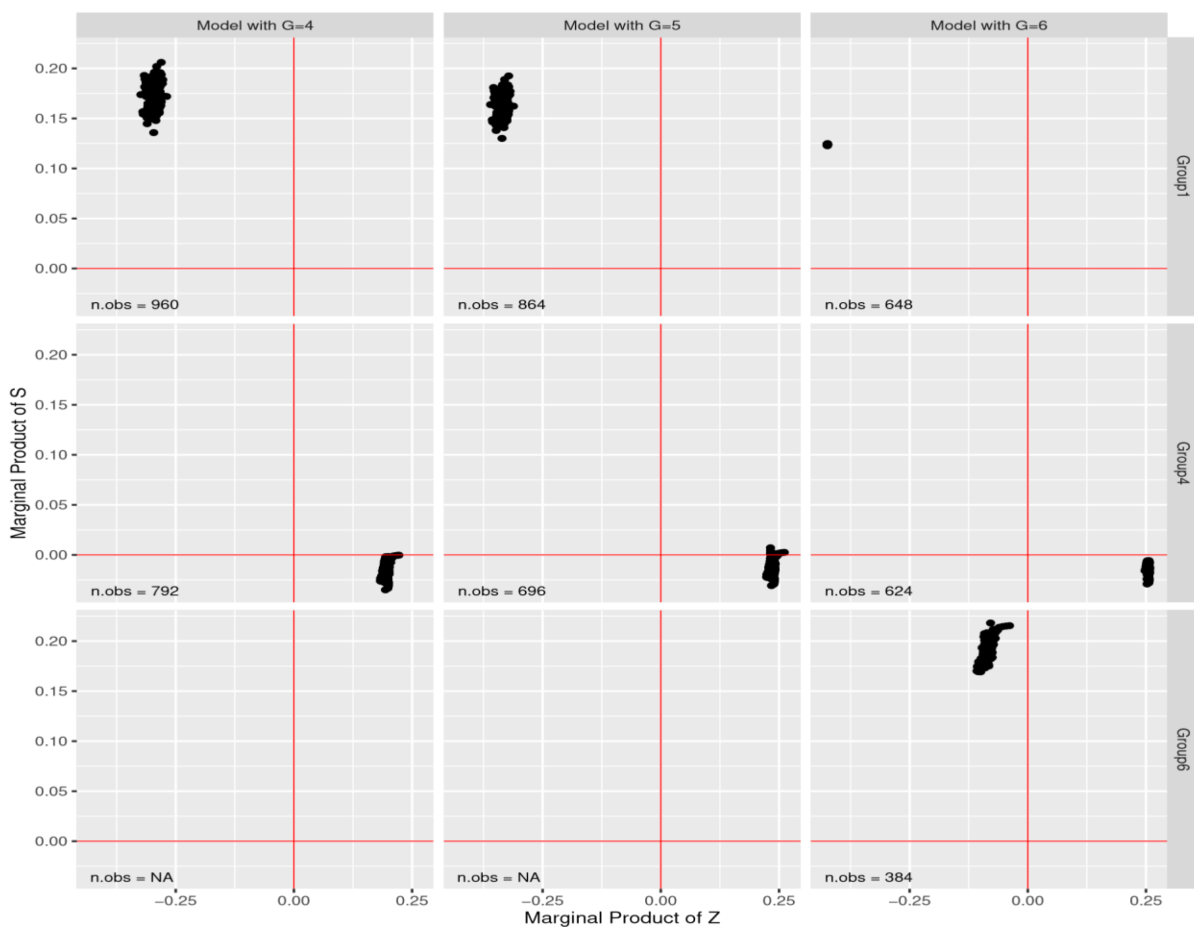
5.3. Negative marginal product of infrastructure, positive marginal product of skilled labor

For the first country group (**Group1**), the direct effect of infrastructure on output per worker is negative and significant. The point estimate in Table 4 is -0.296 (s.e.=0.04), -0.336 (s.e.=0.04), and -0.424 (s.e.=0.05) when G = 4, G = 5, and G = 6, respectively. This negative effect can be due to data aggregations and the network characteristic of infrastructure. For example, infrastructural (e.g., transport) investment has an output reallocation effect (Melo et al., 2013). By classifying countries into groups, the effect can be negative if infrastructure redistributes output to the winning locations. With network externalities, nonlinearity in infrastructure-output relations implies that a positive effect is feasible when a critical network mass is reached (e.g., the universal penetration rate for telephones).

The negative point estimate of infrastructure does not always indicate that infrastructure is irrelevant. Since infrastructure capital is already included in the physical capital stock, this implies that infrastructure has the normal productivity effect of capital as a whole. This explains the very large effect we find for physical capital. We find that the elasticity of output with respect to the physical capital stock amount to approximately 0.80, 0.86, and 0.99, holding infrastructure and skilled labor constant. This implies a large effect from increasing the physical capital stock and removing an equal amount of investment in infrastructure capital. This suggests that there is large network externality to physical capital.

The estimated output effects of skilled labor, log *S*, are 0.172 (s.e.=0.02), 0.163 (s.e.=0.03), and 0.124 (s.e=0.03) when $G = 4$, $G = 5$, and $G = 6$, respectively. This implies that if other forces are held constant, the (average) increases in output per worker resulting from a 1 percent increase in skilled labor are roughly 17.2 percent, 16.3 percent, and 12.4percent, for $G = 4$, $G = 5$, and $G = 6$, respectively. For the coefficient of the interaction term between infrastructure and skilled labor, log*Z* log*S*, the estimated effect is negative and significant, except for the estimate with six groups ($G = 6$). The point estimates of the coefficient on the interaction term are-0.042 (s.e.=0.01), -0.038 (s.e.=0.01), and -0.001 (s.e.=0.02), for $G = 4$, $G = 5$, and $G = 6$, respectively. The estimated total effects (the marginal products) are depicted in Figure 1.

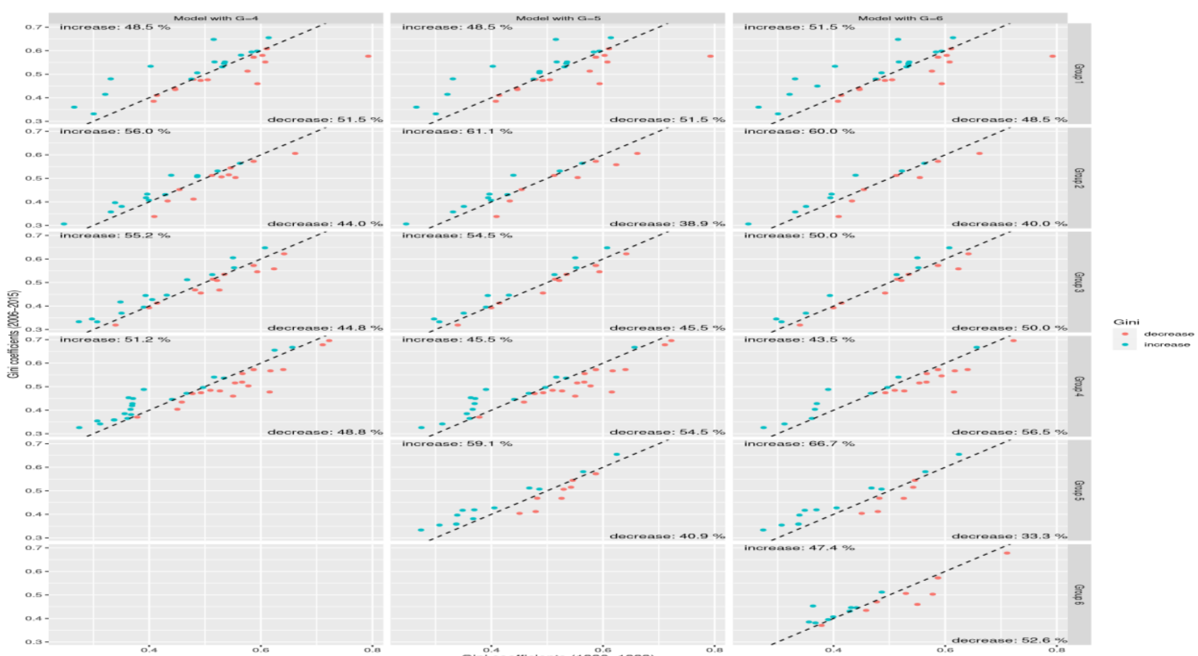
Figure 1. Marginal Products of *S* and *Z*: Group1, Group4, and Group6



These estimates reveal the substitutability between skilled labor and infrastructure and could result in a reduction in income inequality. In this case, an increase in infrastructure causes income to flow from skilled labor to nonskilled labor, indicating that the production sector using the latter input requires relatively more intensive infrastructure services. With increases in infrastructure, the wages of skilled labor decline and those of nonskilled labor increase, reducing wage inequality.

As evidence of this income gap reduction effect, we refer to Figure 2, which contains Gini coefficient estimates of the last 10 years (2006-2015) and those of the first 10 years (1990-1999) of the sample period with a 45-degree line.[6] Points above (below) 45-degree lines indicate that the Gini coefficients increased (decreased) in the last 10 years of the sample period. Figure 2 shows that the Gini coefficient estimates of **Group2**, **Group3**, and **Group5** (**Group1**, **Group4**, and **Group6**) are relatively increasing (or decreasing, as the case may be) at the end of the sample period.

Figure 2. Changes in Gini coefficient estimates from the first 10 years to the last 10 years.



Note: The graph is reported vertically, starting from $G = 4$ in the first column through to $G = 6$ in the third column. In each of the columns, the uppermost graph is for Group1, followed by Group2 in that order towards the last country-groups.

[6] The Gini coefficient estimates are calculated from Top 10% share, Bottom 50% share, and Top 1% share, taken from the website of the World Inequality Database (https://wid.world/). Except Fiji and Balbados, all countries and almost all sample periods are covered by available Gini coefficient estimates.

The panels in the middle columns of Figure 2 are based on the country classification using the five-groups model, and the top panel is the one for **Group1**. The ratio of the points (51.5 percent) below the 45-degree line is relatively larger than that (48.5 percent) above the line, which implies that a relatively large number of countries exhibit downward trends in their Gini coefficients over the sample period. Although some large deviations above the line are found for some **Group1** countries with lower Gini coefficients at the beginning of the sample period, a relatively large number of countries are consistent with the above income gap reduction reasoning. Since some countries in **Group1** with the five-groups model are classified into **Group6** with the six-groups model, the income gap reduction effects in **Group1** are mitigated.

The sign pattern of the marginal products of Z and S in **Group6** is similar to that in **Group1**, but the significance and effects of Z are less than those in **Group1** (see Figure 1). The substitution effect between Z and S (the cross-derivative estimate) in **Group6** is also negative but close to zero (see the note below Table 5). This similarity in estimates between **Group1** and **Group6** is partly due to the over-specification of the number of groups. Information criteria lead to five being selected as the optimal number of groups. As a result, adding another group (the sixth group) yields estimates like those of the first group, suggesting that the sixth is a subgroup of the first one, as predicted when the consistency of the grouping was established by Liu et al. (2020).

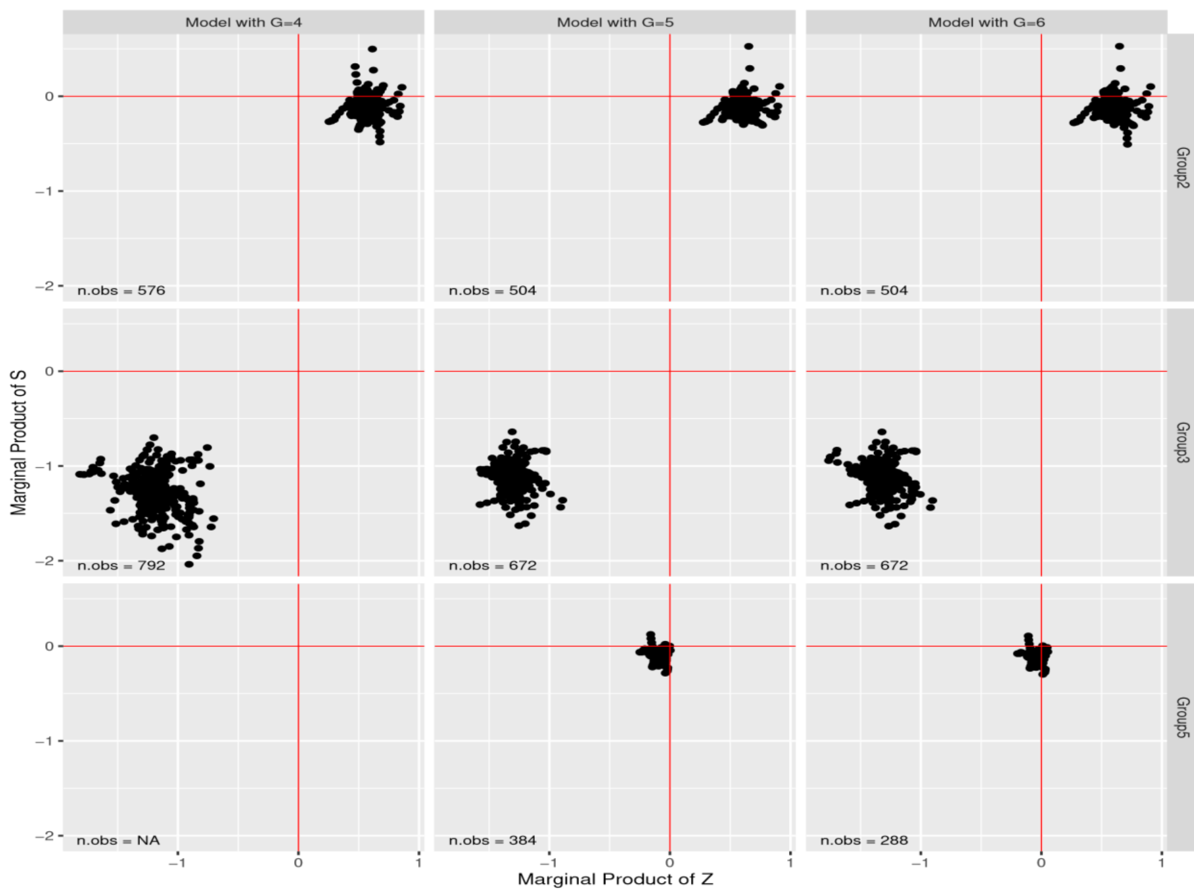
5.4. Positive marginal product of infrastructure, negative marginal product of skilled labor

Next, we consider estimation results of the second country group (**Group2**). Infrastructure has a positive and significant direct effect on output per worker. From Table 4, the estimated coefficients are 0.578 (s.e.=0.05), 0.617 (s.e.=0.05), and 0.611 (s.e.=0.05), when $G = 4$, $G = 5$, and $G = 6$, respectively. This indicates that infrastructure is an important and robust production factor across models with $G = 4$, $G = 5$, and $G = 6$. As an example of growth-promoting infrastructure, we can consider road infrastructure, which can link markets and cause an increase in competition.

In addition, communication systems can increase the rate of diffusion of technology, increasing output. The increases in output with respect to a 10 percent increase in infrastructure investments, on average, are 5.8 percent, 6.2 percent, and 6.1 percent for $G = 4$, $G = 5$, and $G = 6$, respectively.

For the coefficient of the interaction term log Z log S, the point estimates are 0.411 (s.e.=0.04), 0.431 (s.e.=0.04), and 0.434 (s.e.=0.04) for $G = 4$, $G = 5$, and $G = 6$, respectively. This indicates that, aside from the direct increasing effect on output, an increase in the volume of infrastructure services raises output indirectly by *crowding-in* skilled labor leading to a consequent rise in the marginal products of skilled labor (see the top panels in Figure 3 for the total effect of infrastructure). Infrastructure provision can improve health and education outcomes and enhance skilled labor. Similarly, improved access to electricity may raise educational attainment and reduce the cost of skill acquisition. Generally, infrastructure provision could increase overall economic output and performance.

Figure 3. Marginal Products of S and Z: Group2, Group3, and Group5



Therefore, infrastructure raises the marginal product and remuneration of skilled labor. Income flows from nonskilled labor to skilled labor, increasing their wage premium, and consequently, the wage gap between the two. As evidence of the mechanism, the Gini coefficients in this category tend to be upward: the relative frequencies above the 45-degree line (increase in Gini coefficients) in the plot of **Group2** are larger than those below the line (decrease) in Figure 2.

If other forces are held constant, skilled labor earns roughly 4 percent more than unskilled labor for every 10 percent increase in infrastructure provision. The total contribution of infrastructure to economic growth and development is calculated as its direct marginal product in addition to its indirect marginal economic growth contribution through the channel of skilled labor. This depends largely on how efficiently skilled labor uses infrastructure in the production process.

Skilled labor is estimated to have a negative and significant relationship with productivity performance. The estimated coefficients are -0.130 (s.e.=0.03), -0.130 (s.e.=0.03), and -0.134 (s.e.=0.03) for $G = 4$, $G = 5$, and $G = 6$, respectively. Although part of the estimated marginal product of skilled labor is distributed at approximately zero (see the note below Table 5), the negative estimates show that the suggestion to invest in schooling to raise output does not hold in the data. Pritchett (2001) also pointed out the case where education for skill-acquisition is not effective.

The second group (**Group2**) and fourth group (**Group4**) are similar in terms of the signs of the marginal product of infrastructure and skilled labor; the former is positive and significant, and the latter is negative and less significant (see Table 4, the top panels of Figure 3 for **Group2**, and the middle panels of Figure 1 for **Group4**). The extent of the direct effect of both S and Z on economic output (measured by β_s and β_z) in **Group2** is larger than that in **Group4**, and the total effect of infrastructure on aggregate output is generally positive, whereas the total effect of skilled labor is generally close to zero.

The cross derivatives in **Group4** tend to be negative but they are also distributed around zero (see the note below Table 5), except for a few points. Interestingly, these negative cross derivatives in **Group4** might lead a relatively large number of member countries to smaller Gini coefficients in the last period of the sample (see the panels of **Group4** in Figure 2). The second group and fourth group are similar in terms of the marginal products, but the substitutability and the complementarity between S and Z result in the different patterns of income distribution.

5.5. Other cases

Finally, the third group (**Group3**) and fifth group (**Group5**) are similar in the sign patterns of coefficient estimates; both *Z* and *S* are negative and significant (see Figure 3) and the coefficient on the interaction term is positive (or negative but almost zero in **Group5**, see the note below Table 6) and significant: the difference between the two groups is in the relative magnitude of the coefficient on the interaction term. It is difficult to explain why both marginal products were negative, but large and positive cross-derivative estimates highlight the strong complementarity of infrastructure and skilled labor and the importance of their joint use as a determinant of output in these categories.

6. RECOMMENDATIONS AND CONCLUSION

6.1. Summary of results

In this study, we examined the effect of infrastructure on economic development. We estimated an extended Cobb-Douglas production technology embedded in an autoregressive distributed lag (ARDL) model with grouped coefficients and possible inputs' complementarity. Nuisance parameters were controlled for, and an asymptotically optimal model was selected using the Bayesian-like information criterion, which is based on a modified profile likelihood. We found that the effects of infrastructure generated grouped heterogeneity of growth across countries in the estimated production relationships.

Another interesting finding is that our method is stable and consistent in classifying countries into groups. While some estimated groups were only subsets of true groups, none were a mixture of elements from multiple true groups. For example, **Group1** exhibits a positive marginal product of skilled labor, a negative marginal product of infrastructure, and a negative cross derivative with respect to both inputs.

Group6 also exhibits the same sign pattern as **Group1**, suggesting that a large part of country members in **Group6** is separated from **Group1**. Since infrastructure capital is somewhat included in the physical capital stock, the negative marginal product of infrastructure suggests that it had the normal productivity effect of capital, implying a large network externality to physical capital stock. Similarly, the negative cross derivative of inputs suggests that infrastructure and skilled labor are close substitutes in the production process. This has a reduction implication to income inequality of countries in **Group1** and **Group6** in terms of wage redistribution from skilled labor to nonskilled one.

Similarly, **Group2** has a negative marginal product of skilled labor and positive marginal product of infrastructure and of the cross derivative. The positive cross derivative of inputs indicates that infrastructure crowds in skilled labor in production, leading to a rise in its marginal products. Marginal products, which equal rewards to inputs, imply that infrastructure raises the wages paid to skilled labor. Income flows from unskilled labor to skilled labor, thus increasing their wage premium and the wage gap between them. **Group2** and **Group4** are similar in terms of the signs of the marginal product of infrastructure and skilled labor. However, they are different in terms of the complementarity between infrastructure and skilled labor, which lead to different patterns of income distribution.

6.2. Practical implications of results and recommendation

It is shown that infrastructure play a “direct” and an “indirect” role on the economic development of most developed countries. The significant effect of infrastructure on economic growth exemplifies the direct role. While this direct effect holds in some developing countries, it is more pronounced in developed countries. Therefore, developing countries (especially African countries) should intensify provisions of infrastructure for sustainable economic growth and development. In doing this, the countries should look up to infrastructural status in Japan and other like-minded countries.

The indirect development’s role of infrastructure is measured as its crowding-in economic growth effect of the skilled labor. This economic growth-effect of infrastructure appears to be realizable mostly in developed countries. For most developing countries to reasonably harness the infrastructural development potentials, policymakers should take the volume of infrastructural services in, for example, Germany as a "desired level" to pursue. This has to be accompanied by provisions of, for example, scholarships, fellowships, and other initiatives that encourage educational attainment. It is the adequacy of skills in people that transform infrastructural advantages into significantly measurable development figures.

Infrastructure-skill complementarity does not always imply increasing income inequality in a country dominated by skilled workers. While complementarity between infrastructure and skilled labor generates extra development opportunities in the United Kingdom, for example, it may not widen income inequality. However, the substitution between infrastructure and skilled labor decreases economic growth and reduces income inequality in Uganda that has a few skilled workers and a dominant of unskilled labor. It is, therefore, a recommendation that developing countries should adopt some infrastructure-and-skill development policies of certain economically successful nations of the world.

6.3. Limitations of this study

One finding that is difficult to explain is why both **Group3** and **Group5** have negative marginal products of the two inputs. However, their large and positive cross-derivative estimates highlight the strong complementarity between infrastructure and skilled labor, as well as the importance of their joint use as a determinant of total output. Our model could partially explain these counter-intuitive findings, but it might be too simple to capture the entire features of the macro production function across countries.

To obtain estimation results that are more intuitively appealing, more elaborate input variables may be required (Duffy et al., 2004). A more refined specifications of production function, such as nested constant-elasticity-of-substitution production functions (Sato, 1967) or a semiparametric parsimonious flexible functional form (Coppejans, 2003), may be required too. Such extensions comprise our future research.

6.4. Conclusion

Infrastructure and skilled labor exhibit development transformative power in most developed countries. Resultantly, a comparative analysis of developed and developing countries is important. It provides the later countries with sound policy guide in terms of lists of developed countries to look up to and learn from. An econometric methodology of finding latent groups and a criterion of selecting an optimal number of country-group make this possible. Once an optimal group number is chosen and estimation conducted, it is advisable for a country to learn from another successful country that fell its own estimated group. A country in one group adopting development policy of a successful country in another group may be disastrous. This is because they do not share a common nature of the relationships of interest.

An important question, however, is why do most developing countries appear not to reap the complementary benefits of infrastructure and skilled labor on economic growth? In addition to infrastructural inadequacy, do most developing countries have inefficient development of human capital? What is the position of especially African countries around the world in terms of their investment in human capital? These important questions motivate research presented in the subsequent chapter.

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7. APPENDIX

7.1. Asymptotic properties of the estimator

We introduce some notations frequently used in large panel data literature, including Hahn and Kuersteiner (2011). The short-run parameters (nuisance parameters) are shown as $\alpha_i \equiv (\phi_i, \sigma_i^2)'$and derivatives of the likelihood contribution with respect to θ and α as (note that $E_T[X_t] = T^{-1}\sum_{t=1}^{T} X_t$ and $\overline{\mathrm{E}}_T[X_t X_s]$ is an estimate of the long-run covariance matrix between X_t and Y_s):

$$U_{it} = \frac{\partial \ell_{it}(\boldsymbol{\theta_i}, \boldsymbol{\alpha_i})}{\partial \theta_i}, V_{it} = \frac{\partial \ell_{it}(\theta_i, \alpha_i)}{\partial \alpha_i},$$

$$U_{\alpha,it} = \frac{\partial^2 \ell_{it}(\boldsymbol{\theta_i}, \boldsymbol{\alpha_i})}{\partial \theta_i\, \partial \alpha_i'}, U_{\alpha\alpha,it} = \frac{\partial^3 \ell_{it}(\boldsymbol{\theta_i}, \boldsymbol{\alpha_i})}{\partial \theta_i(\partial \alpha_i \otimes \partial \alpha_i)'}, V_{\alpha,it} = \frac{\partial^2 \ell_{it}(\boldsymbol{\theta_i}, \boldsymbol{\alpha_i})}{\partial \alpha_i\, \partial \alpha_i'}, V_{\alpha\alpha,it}$$

$$= \frac{\partial^3 \ell_{it}(\boldsymbol{\theta_i}, \boldsymbol{\alpha_i})}{\partial \alpha_i(\partial \alpha_i \otimes \partial \alpha_i)'}$$

where $(\partial\alpha_i \otimes \partial\alpha_i)' = \left(\left(\partial\phi_i, \partial\sigma_i^2\right)' \otimes \left(\partial\phi_i, \partial\sigma_i^2\right)'\right)' = \left((\partial\phi_i)^2, \partial\phi_i\, \partial\sigma_i^2, \partial\sigma_i^2\, \partial\phi_i, \left(\partial\sigma_i^2\right)^2\right)$, and

$$\Psi_{it} = \left\{E_T\left[V_{\alpha,it}\right]\right\}^{-1} V_{it},\ \widetilde{U}_{it} = U_{it} - \Xi_i V_{it},\ \widetilde{U}_{\alpha,it} = U_{\alpha,it} - \Xi_i V_{\alpha,it},\ \widetilde{U}_{\alpha\alpha,it} = U_{\alpha\alpha,it} - \Xi_i V_{\alpha\alpha,it}$$

where $\Xi_i = E_T[U_{\alpha,it}]\{E_T[V_{\alpha,it}]\}^{-1}$. Liu et al. [2020] proved that the asymptotic distribution of the estimator is given as follows:

$$\sqrt{\mathrm{NT}}(\hat{\boldsymbol{\theta}}^{(\mathrm{g})} - \boldsymbol{\theta}^{(\mathrm{g})}) \longrightarrow \mathrm{N}\left(\kappa \mathcal{I}_{\mathrm{g}}^{-1}\boldsymbol{d}_g, \frac{\mathbf{1}}{\boldsymbol{\pi}_g}\mathcal{I}_g^{-1}\mathcal{D}_g\ \mathcal{I}_g^{-1}\right), \quad g = 1,2,\dots,G\ (\geq G_0),$$

where$\kappa = \lim_{N,T\to\infty}\sqrt{\frac{N}{T}}, \pi_g = \lim_{N,T\to\infty}\frac{N_g}{N}$, and N_g is the number of

countries in g,

$$\mathcal{I}_{g} = \frac{1}{N_g}\sum_{i\in\mathcal{G}_{g}}\left(-E_T\left[\frac{\partial U_{it}}{\partial \theta_i'}\right] + E_T\left[\frac{\partial V_{it}'}{\partial \theta_i}\right]\left\{E_T\left[\frac{\partial V_{it}}{\partial \alpha_i}\right]\right\}^{-1} \cdot E_T\left[\frac{\partial V_{it}}{\partial \theta_i'}\right]\right)$$

$$\mathcal{D}_{g} = \frac{1}{N_g}\sum_{i\in\mathcal{G}_{g}}\bar{E}_T[\tilde{U}_{it}\tilde{U}_{is}']$$

$$\boldsymbol{d}_g = \frac{1}{N_g}\sum_{i\in\mathcal{G}_{g}}\left\{\bar{E}_T[\tilde{U}_{is}']\bar{E}_T[\tilde{U}_{\alpha,it}\boldsymbol{\psi_{is}}] + \frac{1}{2}E_T[\tilde{U}_{\alpha\alpha,it}]vec(\bar{E}_T[\boldsymbol{\psi_{it}\psi_{is}}])\right\}$$

The bias-corrected estimator is defined as $\tilde{\boldsymbol{\theta}}^{(g)} = \hat{\boldsymbol{\theta}}^{(g)} - T^{-1}\mathcal{I}_{g}^{-1}\boldsymbol{d}_{g}$, which we report as the estimation results.

Liu et al. (2020) established not only the consistency and the asymptotic normality of the long-run coefficient parameter, but also the consistency of the group classification. This consistency implies that all estimated groups are surely included in a certain true group if their numbers in the estimated mode (G) are greater than or equal to the true number of groups (G_0): $G \geq G_0$. Some estimated groups are only subsets of true groups if $G \geq G_0$, but the appropriate combination of estimated groups can reproduce the true groups with probability one as the sample size goes to infinity.

The important point is that, asymptotically, none of the estimated groups become a mixture of elements from multiple true groups. Of course, when $G = G_0$, the estimated group memberships are expected to be identical to true group memberships. In this sense, the selection of the number of groups is especially important in our research.

CHAPTER THREE

A NEW WAY TO LOOK AT OLD ISSUES: WORKER EDUCATION AND REGIONAL ECONOMIC GROWTH

FEBRUARY 2023

A new way to look at old issues: Worker education and regional economic growth

Abstract

Education-based skills can improve economic growth in various ways. Nevertheless, existing studies have found that investing in education produces minimal returns. However, their results may have been affected by attenuation bias after the application of particular assessment adjustments. In addition, there is no evidence of causality in several studies. Accordingly, this study investigates the effects of workers' education on economic growth. Data of 102 nations from 2000 to 2015 are used to discern the yearly effects on the development of services provided by educated workers. Micro-models of the supply of and demand for the services provided by educated workers are estimated with macro production technologies. The findings indicate a significant positive causality between the services provided by educated workers and economic performance, particularly when there is optimal education investment. Investment in education appears to be ideal at roughly three to six number of years of education in fields where enterprise-required skills are taught. Economies in which average workers have attained this educational level and possess the skills needed by companies in the relevant locations maximize economic growth. As a result of the economic growth, employment increases for unemployed workers with the enterprise-required skills.

Keywords

Education investment, services of educated workers, economic growth, optimum education, maximum growth effect, regional economic growth

JEL classification

O47, O57, I25, I29

1. INTRODUCTION

1.1. Statement of problem

Researchers have long endeavored to understand the impact of workers' education on overall economic growth, producing a significant body of research (Barro, 1991, 2001; Benos & Zotou, 2014; Breton, 2013; Hanushek & Woessmann, 2012; Hendricks, 2002; Jones, 2002a; Vandenbussche et al., 2006). The relevance of this topic continues to grow because of evolving and innovative approaches to output production (Acemoglu et al., 2018; Chatterjee & González-Rivera, 2018; Toivanen & Väänänen, 2016).

This study re-evaluates how investing in education affects economic growth. Specifically, it uncovers certain relatedness existing among groups of countries in terms of their commitment to investing in education for economic growth.

The study contributes to the literature by finding latent groups of related economies and the effects of education investment on economic growth for each group. It presents a new intuitive approach to determining group heterogeneity in the effect of education investment on economic growth. The study also investigates whether the effect of workers' education on economic growth is correlated with the rising demand for services provided by educated workers triggered by increased economic growth. The findings in this regard contribute to the literature on the relationship between education investment and employment creation.

Historical data of 102 countries from the period 2000–2015 are used to explore the effects of investing in education on economic growth. Education investments can improve economic growth in various ways. First, investing in education generates economic growth because the outcomes—ideas, information, and competencies—increase the demand for the inputs used in their production. In economies where workers have only basic capabilities, innovative approaches to production are restricted, and industrial growth is limited (Squicciarini & Voigtländer, 2015). In such economies, operational costs are high, and sales are minimal (Restuccia & Rogerson, 2017).

The acquisition of skills by workers reduces these costs and increases sales. Investing in education can enhance the workers' skills (Bell et al., 2019), leading to the adoption of new production approaches and the spread of innovative ideas across enterprises (Freire-Serén, 2001). Firms capable of establishing and diffusing new processes realize increased benefits (Bertrand & Schoar, 2003; Bloom et al., 2013). In general, education investments generate externalities and demonstrate a spillover effect (Acemoglu & Angrist, 2000; Belenzon & Schankerman, 2013).

Nevertheless, existing studies have found that investing in education produces minimal returns (Krueger & Lindahl, 2001; Portela et al., 2004). However, their results appeared to have been affected by the attenuation bias after the application of particular assessment adjustments (Acemoglu & Autor, 2012). Hanushek and Woessmann (2008), and Oreopoulos and Salvanes (2011) used various assessment adjustments to derive comparative results. Fuente and Doménech (2006), and Cohen and Soto (2007) further attempted to overcome the problems of measurement in the Barro and Lee (2001) data in terms of educational attainment.

In addition, there is no evidence of causality in several studies (Bils & Klenow, 2000); an exception is the study by Sianesi and Van Reenen (2000), which found reverse causation between investment in education and economic growth. Reverse causation suggests that an increase in economic growth can result from education investments, and economic growth increases can increase the demand for the services of educated workers. This identifies a simultaneity problem between the services of educated workers and economic growth.

However, most approaches for finding group heterogeneity of an economic relationship do not adequately account for endogeneity, such as the approach by Liu et al. (2020). This study presents a new intuitive approach that first demonstrates how severe the effects of endogeneity and unobserved heterogeneity are in the relationship between education investments and economic growth. The next step is to select an estimator that sensibly accounts for the aforementioned problems to track the latent groups of related economies in terms of the effect that the services provided by educated workers exert on economic growth.

Education investments can work in conjunction with other growth-enhancing elements such as investment in infrastructure or unobserved components such as social dispositions toward work and business and the robustness of property rights. In this study, I used country-specific fixed effects to control for potentially spurious relationships. The spillover effects suggest nonlinearities in the output effect of investments in education (Kalaitzidakis et al., 2001; Kijek & Kijek, 2020). It indicates that the size of the economic growth impact caused by education investment depends on reaching a critical investment threshold. This result suggests that a positive economic growth effect can impose a threshold on a country's education investment.

This study investigates the existence of these nonlinearities in the economic growth effect of education investments and the extent of the investments' threshold. The findings have consequences for public policy in terms of the optimum level of education investment that maximizes output growth.

1.2. Questions asked in this research.

The following specific questions are addressed in this research:

1) Does education investment generate employment opportunity for the educated unemployed?
2) What is the economic growth rate that sustains a low and stable rate of unemployment?
3) Do nonlinearities exist in the economic growth effect of education investment?
4) Is an economic growth effect of workers' education dependent on an investment threshold?
5) What is education investment's threshold that produces a positive economic growth effect?

1.3. In what ways is this study significant?

The econometric model developed in this study has eminent growth significance. It assists labor economists in establishing the hourly wage rate that equilibrates the demand for and supply of educated services. The rationale behind the model is that every individual that possesses skills that move businesses forward is hired at this wage rate. And, while in employment, it maximizes the marginal contribution of the educated service to performances of enterprises that hired it.

When enterprises recruit, they look forward to hiring workers with similar skills to those of their best educated workers. Therefore, the model suggested could be used to track the skill composition of workers that businesses often employ. Further research on the background of workers that make highest feasible marginal contributions to performances of businesses could help in upgrading the educational curricula of countries.

The study provides a comparative analysis of countries in terms of the relationship between education investments and economic growth. This helps countries to assess the educational and skill levels of their workers relative to those of their competitive nations. In doing this, the model enables empirical comparisons of the extent that workers` education increases economic growth across countries. It further allows for discovering the degree of differences at which education of workers contributes to employment generation around the globe.

This could guide countries in adopting educational laws of nations where workers` education has substantially improved economic growth and employment. This may be particularly useful to developing countries that may be interested in improving their educational curricula to speed up their development pace.

1.4. Land and sector coverage

This work uses macro-data and has global coverage. It studies the importance of educating workers for economic growth of developed and developing countries. Notwithstanding the significant policy implications, only a limited number of studies have investigated whether the effect that education investments have on economic growth is correlated with a rising demand for educated services triggered by increased economic growth. This is a matter of econometric identification.

Furthermore, the decision of the family unit to invest resources to provide educated services to businesses and whether the enterprises decide to recruit the services provided are dependent on price estimations. It is very challenging to differentiate the micro-forces of the supply of and demand for services of educated workers from the aggregate economic output. Although human capital theory makes important linkages, they have not been sufficiently explored from an empirical perspective.

1.5. Research organizations

This study adopts the following structure. Section two presents a brief discussion on extant studies, whereas section three describes the data and provides important linkages. Section four expands the econometric model and empirical method, while the coefficient estimates are reviewed in section five. The conclusion of study is provided in section six.

2. LITERATURE REVIEW AND KNOWLEDGE GAPS

2.1. Existing similar studies

Early empirical evidence indicates that investment in education is correlated with economic growth (Benhabib & Spiegel, 1994). However, this does not imply a feedback causality. Resultantly, policy proposals about employment-generating potential of education investment based on this evidence may be largely inconsequential. This section reviews related literature.

In doing so, it considers Barro (1991) that investigates whether service of an educated worker has an impact on economic growth. Using data from a panel of countries for the period between 1960 and 1985, Barro estimated GDP per capita on the 1960 GDP per capita, the primary school enrolment rate, and the secondary school enrolment rate. The standard least squares' regression approach is used. He finds that workers' education has a significant impact on the GDP per capita, adjusting the average rate of economic growth at approximately 3 percent. However, there was no evidence that a bidirectional causality exists between the two variables.

Based on data sourced from approximately 100 countries for the periods: 1965-1995 and 1960-1990, Barro (2001) investigates the effect of education of workers on the rate of real per capita GDP growth. The study considers law and order as well as different macroeconomic aspects as estimation control variables. He finds that service of an educated worker has a positive and significant impact on GDP per capita growth rate. The point estimate on the workers' educational measure is 0.004. Barro explains that the significant relationship may not prove reverse causality but suggests innovation disseminations.

The work of Krueger and Lindahl (2001) and Portela et al. (2004) produced similar minimal impact of educated service on economic growth. Using annualized data and a pooled OLS approach, these studies determined that service of an educated worker essentially makes an annual contribution of about 0.3 percent and roughly 0.4 percent to economic growth, respectively.

Importantly, these empirical results have satisfied public policy demands. Nevertheless, some more recent evidence indicates that those earlier results may have been affected by attenuation problems. Acemoglu and Autor (2012) determined that it is possible to considerably reduce this problem by estimating a full-scaled Mincerian equation. They propose assessment of the relationship between workers' education and economic growth over an extended period. Their findings indicate that commitment for improvement of education-based skills contributes roughly 7.2 percent to per capita income.

By using various assessment adjustments, Hanushek and Woessmann (2008), and Oreopoulos and Salvanes (2011) derived comparative results. Hanushek and Woessmann find that investment in education (where years in education is used as a proxy) made an average contribution of about 36.9 percent to the growth rate of per capita GDP. This estimation has significance from a statistical perspective. It leads to a question of whether the originally reviewed results were attenuated. Fuente and Doménech (2006), and Cohen and Soto (2007) attempted to overcome the problems of measurement encountered in the previous data of Barro-Lee.

Clearly, consistent evidence on workers' education appears to indicate that the minimal returns previously reviewed do not hold after different econometric corrections were made. However, some work that control errors of measurements in the educational-skill measures appear to overestimate the returns on investing in education. Although the importance of investing in education for economic growth cannot be overemphasized, the previously reviewed estimate of 0.369 may be too large. One explanation analyzed below is that a contemporaneous relationship could exist, suggesting the use of an adjusted cross-sectional model.

Regarding spurious relationship, the work by Mankiw et al. (1992) and Barro and Sala-I-Martin (1995) have an important insight. They investigate how workers' education impacts economic growth using data from about 98 non-oil producing countries between 1960 and 1985. Mankiw et at. estimated log-differenced GDP per working-age person on the mean percentage of the working-age population in secondary education (human capital proxy). Additional variables include log GDP per working-age person in 1960 as well as log per capita investment.

After obtaining results for the 98 countries, they further estimated 22 OECD countries to find that the effect of workers' education on GDP growth is significantly lower for the later countries than it is for the former. An explanation for these findings could be that there were considerable differences in education of workers as well as its effects among groups of countries around the world. This study attempts to find such a group-heterogeneity of effects existing between education investments and economic growth.

2.1.1. Existing gaps in literature

The reviewed studies offer evidence that investing in education has a positive impact on total output. Fundamentally, the studies used single-equation modelling. This could not allow for evidence on the extent of employment of educated workers that accompanies national income growth. A micro-equation of the demand for and supply of services of educated workers is important to endogenize education investments. This study aligns such a micro-condition with the model of aggregate production. Additionally, reviewed studies consider a homogenous collection of countries. Therefore, research involving a heterogenous group of countries is necessary. The empirical analysis below accounts for the heterogeneity of workers' education across countries.

3. DATA

3.1. Data sources and variable definitions

This section examines the association between investments in education and economic growth. Data are sourced from 102 developed and developing countries for the period 2000–2015. Considering developed and developing countries provide a better coverage of the regional economies that is necessary in examining the effect of worker education on economic growth around the world. The 2000–2015-time frame is used because of incomplete data for some variables such as road networks.

As it was initially explained, the aim of this study is to re-evaluate how investing in education has affected regional economic growth in the recent decade. The data examined include the real gross domestic product (GDP), capital stock (K), total stock of workers (TSW), number of persons employed (NPE), and the overall population (POP).

Additional data include the average years of secondary education (SEC), price of educational services (PES), real deterioration of educational services (RDE), and contributing family workers (HS). They also include measures of infrastructure services: main telephone lines (MTL), total road networks (TRN), and electricity generating capacity (EGC). The education variable can be observed at five-year intervals. Table 1 shows the variables used in the analysis and the specific rundown measurements; data sources are provided as footnotes.

The country-specific data was used to generate all missing information regarding years of investments in education via the exponential growth procedure (EGP), in which the growth rate remains constant over a certain period. Starting from the education investment in 2000, the growth rate is applied to the total initial investments, along with any changes in the growth rate.

TABLE 1. ———DESCRIPTION OF STUDY VARIABLES AND SUMMARY STATISTICS

Variables	Description	Mean	Standard deviation	Minimum	Maximum
K [a]	Real capital stock at current prices in millions United States' dollar $	2701.504	7350.058	4.055	86485.090
RDH [a]	Deterioration of human capital, proxy by real depreciation rate	0.043	0.011	0.023	0.101
NPE [a]	Number of persons employed as a measure of raw labor in millions	23.951	89.702	0.122	791.770
GDP [a]	Real GDP at constant prices in millions US$, a proxy for output	717.046	1977.265	2.731	17126.860
PHC [a]	Price of human capital services, proxy by price of capital services	0.859	0.443	0.061	3.241
POP [a]	Populations in millions	52.218	178.218	0.270	1397.029
HS [b]	Household size, proxy by the total contributing family workers in %	7.111	8.966	0.013	48.473
TSW [b]	Total stock of workers, proxy by total labor force in million	2470.505	8946.493	14.499	78707.32
MTL [b]	Main telephone lines	10624.020	33505.940	0.800	367786
TRN [c]	Total road network in kilometres	293.239	847.677	1.230	6586.623
EGC [d]	Electricity generating capacity in megawatts	43.362	139.818	0.007	1628.711
SEC [e]	Durations of secondary schooling, a measure of human capital stock	3.302	1.563	0.130	8.410
USA	Dummy variable for United States	0.010	0.099	0	1
LOW	Dummy variable: 1 if SEC < 2.5	0.335	0.472	0	1
MHIGH	Dummy: 1 if 2.5 < SEC ≤ 5.5	0.586	0.493	0	1
VHIGH	Dummy variable: 1 if SEC > 5.5	0.079	0.270	0	1

Sources: [a] Penn World Table 9.1 (Feenstra et al. 2015); [b] World Development Indicators 2019; [c] the World Road Statistics; [d] the United Nations Energy Statistics; and [e] Barro and Lee (2013). % Stands for percent, and $ is a symbol for the United States' dollar.

Points are then computed using the R software for the periods 2000–2005, 2005–2010, and 2010–2015, taking the predicted education investment for 2015 into account. Investments in education occurs every year, causing an exponential growth. The infrastructure measure is constructed as a geometric mean of the MTL, TRN, and EGC, in accordance with Calderón et al. (2015).

3.2. Descriptive statistics

Before commencing the modeling process, various broad midpoints are arranged, and the fundamental linkages are analyzed. Table 1 reveals the increase in education investment along with the calculated average real GDP for the 102 countries for 2000–2015. Real GDP increased from approximately US$ 3 million to about US$ 17,127 million, which amounts to a mean growth of roughly US$ 717 million over the 15-year period. This economic growth can be partially attributed to an increase in the education investment from roughly 0.13 years to around 8.41 years with a mean of about 3.30 years over the 2000–2015 periods.

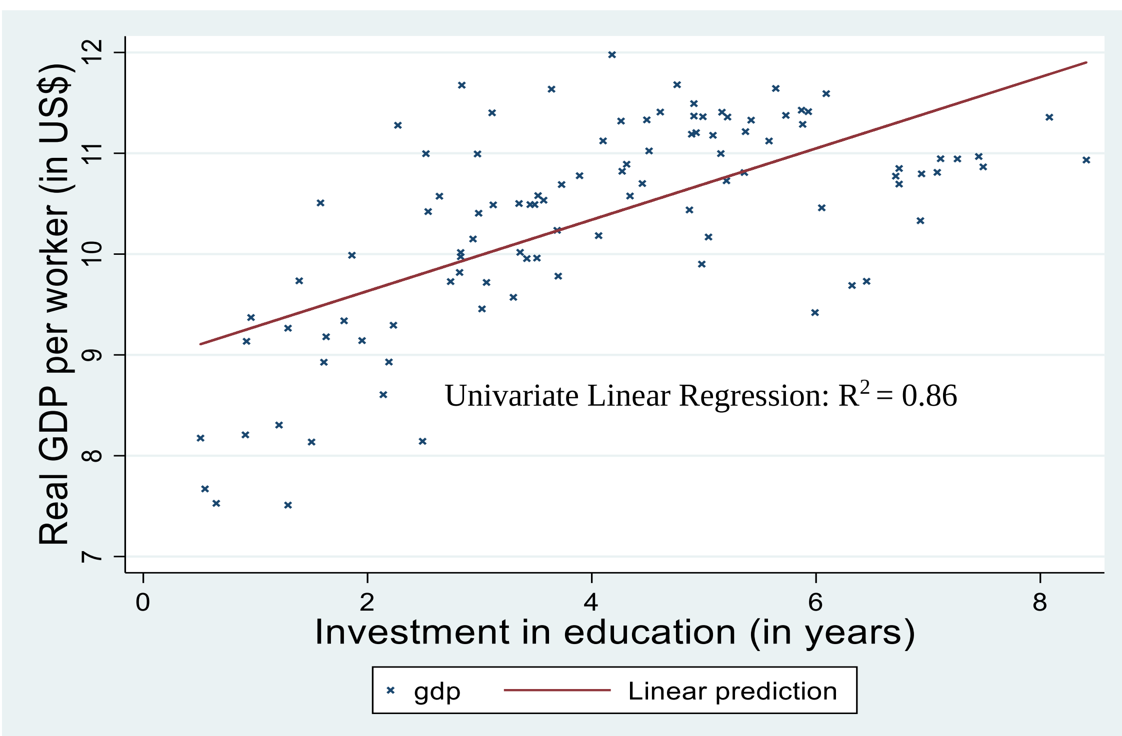

Figure 1. Investment in education and real GDP per worker for 102 countries

A total of 1,632 observations were used, and the summary statistics for other variables are also shown in Table 1. Overall, it can be concluded that there is a strong and positive association between education investment and economic growth, with a correlation coefficient of about 0.64. This robust relationship correlates with the significant effects identified when aggregate output is regressed on education investment.

Figure 1 shows the relationship between education investment and GDP per worker for a single year, 2015. A univariate cross-country regression of investment in education clarifies that it is responsible for approximately 86 percent of the variations in aggregate economic output. Investment in education appears to be a major contributor to the overall output growth.

4. RESEARCH METHODOLOGY

4.1. The Röller and Waverman (2001)'s model

Consider a structural model of telecommunication investment used by Röller and Waverman (2001):

$$\log(GDP_{it}) = a_{0i} + a_1 \log(K_{it}) + a_2 \log(TLF_{it}) + a_3 \log(PEN_{it}) + a_4 t + \varepsilon_{it}^1 \quad (1)$$

$$\log(PEN_{it} + WL_{it}) = b_0 + b_1 \log(GDP_{it}/POP_{it}) + b_2 \log(TELP_{it}) + \varepsilon_{it}^2 \quad (2)$$

$$\begin{aligned} \mathrm{Log}(TTI_{it}) = {} & c_0 + c_1 \log(GA_{it}) + c_2 GD_{it} + c_3 (1 - USCAN).WL_{it} \\ & + c_4 (1 - USCAN) \log(TELP_{it}) + c_5 (USCAN).\log(TELP_{it}) + \varepsilon_{it}^3 \end{aligned} \quad (3)$$

$$\log\left(PEN_{it}/PEN_{i,t-1}\right) = d_0 + d_1 \log(TTI_{it}) + d_2 \log(GA_{it}) + \varepsilon_{it}^4 \quad (4)$$

where equation (1) specifies aggregate production as functions of physical capital stock (K); total labor force (TLF), a proxy for human capital stock; telecommunication stock, proxied by telephone penetration rate (PEN); and a linear time trend (t). It enables for country-specific fixed effects. Similarly, equation (2) presents real GDP per capita and telephone service price (TELP) as factors determining effective demand for telephone mainlines per capita, which is measured as telephone mainlines per capita plus waiting list per capita (WL). Waiting list per capita is combined with the penetration rate to capture telecommunication services' market-clearing.

This is because the service price of telephone cannot explain the available number of telephones mainlines at any moment in time. It is believed that there may be excess of telephone mainlines in some countries. Again, the reduced-form equation (3) postulates that telecommunication infrastructure investment (TTI) is a function of country geographic area (GA), government real deficit (GD), the waiting list and price of telephone service. The *USCAN* is a dummy variable for the United States and Canada with respect to their supply-side reaction to waiting line and prices. In addition, equation (4) defines telecommunication infrastructure investment as the variation in the telecommunication infrastructure stock.

With the presence of the micromodel of demand for and supply of telecommunication infrastructure in system (1)–(4), the telecommunications infrastructure is endogenized (Röller & Waverman, 2001). That is, because equations (2), (3), and (4) includes the supply of and demand for telecommunication infrastructure, the telecommunications sector is endogenized. Importantly, note that equation (2) reflects the elasticity of telecommunication-service demand with respect to income growth.

4.2. Röller and Waverman (2001)'s model adapted for educated services and growth.

The aim of this study is to endogenize education investment similar to the endogenous telecommunication infrastructure in the system of equations (1)–(4). To do it, a structural model is envisaged within a production function framework in which investment in education is endogenized. A micromodel showing the supply of and demand for educated service, which is evaluated using macro production models, is specified. In this approach, investment in education is endogenized and the previously identified reverse causality is controlled.

Country-specific fixed effects are added to solve the aforementioned spurious associations. Equation (1) is modified so that the macro activity of a nation is interfaced with its stock of capital (K), infrastructure index (INFR), the number of persons in employment (NPE), and services of educatedworkers. Educated workers' services, rather than investment in education, enters the aggregate output production function because individual companies demand educated services, instead of investment in education. However, demand for the services of educated workers by enterprises is feasible when there is a supply of educated services by families, which is possible through households' investment in education.

The following dynamic simultaneous equations that relates to equations (1)–(4) is specified to explain economic growth with endogenous investment in education:

$$\log(GDP_{it}) = a_{i0} + \sum_{j=0}^{4} a_{1j} \log\left(K_{i,t-j}\right) + \sum_{j=0}^{4} a_{2j} \log\left(INFR_{it-j}\right)$$

$$+a_3(SEC_{it}) + \sum_{j=1}^{3} \theta_j \log\left(GDP_{i,t-j}\right) + \varepsilon_{it}^1 \qquad (1')$$

$$\log(SEC_{it}/SEC_{i,t-1}) = b_{i0} + \sum_{j=0}^{1} b_{1j} \log\left(K_{i,t-j}\right) + \sum_{j=0}^{1} b_{2j} \log\left(RDE_{i,t-j}\right)$$

$$+\sum_{j=0}^{1} b_{3j} \log(TSW_{it}) + \gamma \log(SEC_{it-1}/SEC_{i,t-2}) + \varepsilon_{it}^2 \qquad (2')$$

$$\log(SEC_{it}) = c_{i0} + \sum_{j=0}^{1} c_{1j} \log\left(PES_{i,t-j}\right) + \sum_{j=0}^{1} c_{2j} \log\left(\frac{GDP}{POP}\right)_{it-j} + \sum_{j=0}^{1} c_{3j} \log\left(LA_{i,t-j}\right)$$

$$+\delta \log\left(SEC_{i,t-1}\right) + \varepsilon_{it}^3 \qquad (3')$$

$$\log(TSW_{it}) = d_{i0} + \sum_{j=0}^{1} d_{1j} \log\left(HS_{i,t-j}\right) + \varphi \log\left(TSW_{i,t-1}\right)$$

$$+\sum_{j=0}^{1} d_{3j} \,(1-USA).\log\left(PES_{i,t-j}\right) + \varepsilon_{it}^4 \qquad (4')$$

where definitions of the variables are provided in Table 1.

SEC is average years of secondary education, which is used as a proxy for educated services (Barro, 2001). Although this measure of educated services is better than the other measures grounded in investment amounts (Kalaitzidakis et al., 2001), it is not reflective of the variances in the quality of education in different countries and different periods. The educated services used by enterprises is a determinant of the total output in equation (1'). As a result of the previously identified econometric complexities, country-fixed effects are allowed in the total output equation (1').

Equation (4') presents the supply of educated services as the overall stock of labor within a country. Based on this available stock of labor, firms recruit an optimal SEC amount of educated services, which determines the overall productivity in the output equation (1'). The educated services is embodied in the entire workforce in an economy. From this total supply, firms recruit the SEC. The supply of educated services at a given time cannot be clarified using the price of an educated service. There could be an overabundance of supply in some countries based on this price, meaning that a certain proportion of educated workers could lack employment for an extended period prior to finding a job.

Unfortunately, the price of an educated service for all the countries being considered could not be accessed. The measure utilized is the capital service price level. Furthermore, a dummy for the United States is used because of the country's reaction to prices on the supply side. As suppliers of educated services in the United States are predominantly driven by private markets, the price elasticity of supply is expected to be different. The capital service price level for the United States differs from that of other nations (see, e.g., Feenstra et al., 2015 for an in-depth explanation of the data). Similarly, the size of the household, *HS*, affects the supply of educated services.

Differences in market characteristics and functions of company managers around nations render it challenging to clearly demonstrate the demand side of educated services in economies. It is logical to develop an operational model for educated services' demand. Since the activities of businesses fundamentally differ among nations, the potential to conceive a specific model remains limited. One approach could be to recognize enterprises' optimal production methods and accept that the volume of educated service that yields outputs at the least cost is fully explicated by the price of an educated service, *PES*; the income per capita, *GDP/POP*; the country land area, *LA*, as well as the volume of educated services employed in the previous year, SEC_{t-1}. This is shown in equation (3'). (Incorporating additional variables affecting the demand for services of educated workers may strengthen the identification of equation (3') as a "demand" function.)

Equation (2') shows investments in education in the form of a production equation, in which production of education-based skills is determined by the input of physical capital, *K*; the input of labor stock, *TSW*; the rate at which educated service deteriorates, *RDE*; and past education investments, (SEC_{t-1}/SEC_{t-2}). It is individuals that invest certain number of years in education. In making a decision of where to study, they consider the adequacy of capital equipments that are availability for their learning as well as the types of human labor that would mentor them.

The supply and demand conditions in equations (2')–(4') cause the education investment to be endogenized, similar to the case of telecommunications infrastructure investment. The generalized method of moments (GMM) approach was used to obtain estimations of equations (1')–(4') for the 102 nations. Table 2 shows the numerical estimations. Note that "The focus of the empirical analysis is not on the estimation of demand and supply relationships in the telecommunications industry" (Röller & Waverman, 2001 p. 918). As equation (1') is a modified version of the original equation (1), to implement this study's hypotheses, equations (2), (3), and (4) in the startup model are abstracted from.

5. PRESENTATIONS OF RESULTS AND INTERPRETATION

5.1. Results and interpretation

Table 2 shows the results of the regression of services of educated workers on economic growth. The ordinary least squares (OLS) method is used in Column 1, which does not account for country-specific fixed effects and reverse causality. In Column 2, the least squares dummy variable (LSDV) approach is used, which controls for country-specific fixed effects but not feedback causality. Additionally, the GMM process is employed in Column 3, which solves for fixed effects as well as simultaneity.

The capital variable, *K*, is introduced into the structure log (capital per worker). It has profound significance for the economic growth regression: the estimated coefficient is 0.299 (t-statistic of 3.03), whereas the OLS mean estimate is 0.350 (t-statistic of 6.59). This indicates that the capital per worker is robustly and positively correlated with the GDP per worker.

TABLE 2. —EDUCATION AND GDP PER WORKER: ESTIMATES OF EQUATIONS (1')–(4') [a]

	Column1		Column2		Column3 [b]		Column4 [b]	
	Estimate	*T*-value	Estimate	*T*-value	Estimate	*T*-value	Estimate	*T*-value
Output equation								
K	0.350	6.59	0.371	6.58	0.299	3.03	0.312	4.02
INFR	0.087	2.73	0.082	2.41	0.095	3.06	0.091	2.75
SEC	0.002	1.15	0.004	0.65	0.021	2.08	——	——
LOW × *SEC*	——	——	——	——	——	——	0.018	0.99
MHIGH × *SEC*	——	——	——	——	——	——	0.037	2.02
VHIGH × *SEC*	——	——	——	——	——	——	0.031	2.16
GDP_{t-1}	1.003	13.70	0.793	9.49	0.909	8.90	0.919	10.47
Demand equation								
GDP / POP	0.041	1.22	0,009	0.26	0.216	2.27	0.216	2.27
PES	—0.036	—1.57	—0.009	—0.50	—0.410	—2.72	—0.410	—2.72
LA	—1.240	—0.43	—1.449	—1.16	28.65	1.14	28.65	1.14
SEC_{t-1}	1.021	116.64	1.147	37.24	1.039	26.48	1.039	26.48
Supply equation								
HS	0.004	1.74	0.006	2.66	0.006	2.28	0.006	2.28
(1-USA) × *PES*	—0.010	—1.99	—0.001	—0.28	0.025	2.13	0.035	2.13
TSW_{t-1}	0.998	1199.38	0.983	138.84	0.983	84.69	0.983	84.69
Investment equation								
K	0.005	084	0.004	0.59	0.052	2.04	0.052	2.04
RDE	—0.027	—0.68	—0.070	—1.38	—0.781	—4.14	—0.781	—4.14
TSW	—0.045	—3.04	—0.018	—0.87	0.117	2.02	0.117	2.02
SEC / SEC_{t-1}	0.914	42.10	0.811	34.71	0.614	6.92	0.614	6.92

[a] Columns 1 and 2 report estimates from OLS and LSDV sequentially, and Columns 3 and 4 present GMM estimates. [b] The number of instruments is 63 and 87 for Columns 3 and 4, respectively, which include the exogenous and first-order predetermined variables in the equations; lag of the dependent variable was not used as instrument in a particular equation. The forward orthogonal demeaning (FOD) transformation was used (Hsiao & Zhou, 2017).

The estimations produced by these methods are, to a certain extent, similar to the result of Romer (1990) that "in many countries, the portion of income paid to capital is around 33 percent" (p.25), implying that these estimations are not to be ignored (see also Gollin, 2002).

NFR, the infrastructure variable, is included in the output regression to reflect the extent to which infrastructure services can be accessed, in line with Calderón et al. (2015). The estimated coefficient on the synthesis of infrastructure index is fundamentally positive at 0.095 (t-statistic = 3.06) and representative of economic growth regressions. In the OLS method, the mean *INFR* was calculated at 0.087 (t-statistic = 2.73). This indicates a significant and positive relationship between the rise in infrastructure services and the output per worker. For example, the coefficient size implies that if infrastructure services increase by 10 percent, there will be approximately 1 percent rise in GDP per worker annually. Such elasticities replicate the returns to infrastructure, as demonstrated by Calderón et al. (2015).

Furthermore, the regressions include a specific relationship connecting previous and present economic growth for long-term horizons. For example, the GDP_{t-1} denotes the output per worker in the previous year. The estimated coefficient for the previous economic growth is 0.909 (t-statistic = 8.90). In Column 1 (the OLS results), the estimate is 1.003 (t-statistic = 13.70). Although these results suggest divergent economic growth, the estimates for the GMM estimator are considerably superior to those of the OLS estimator. The estimate for past economic growth fell from 1.003 in the OLS method to 0.793 in the LSDV technique (see Columns 1 and 2). The GMM estimate for the previous GDP per worker lies between these estimates. It makes, in line with Bond (2002), the estimator superior to the former two estimators.

The results of the education variable (*SEC*) are provided in Column 1. The economic growth elasticity is estimated to be 0.002 (t-statistic = 1.15), which is, as expected, insignificant but positive. The estimated value of 0.002 (for the OLS) and the LSDV estimate of 0.004 mirror the findings of previous research that did not consider endogeneity seriously while investigating the effect of educated services on economic growth (Krueger & Lindahl, 2001; Portela et al., 2004).

While educated services do not necessarily have a very large impact on output per worker, this estimated value is not sufficient according to the "growth power" predicted by Romer (1990, pp.18–21). This could possibly be because the attenuation bias remains unaddressed. Another potential factor could be the presence of misleading relationships, requiring a fixed-effects estimation. The ambiguous evidence of previous economic growth (GDP_{t-1} in Column1) further implies spurious correlations.

5.2. Results on the demand for, supply of, and investment in, education

The results in Table 2 are also estimations of investments in education and the associated supply and demand. Although they are not the main focus of this research, efforts were made to control for them, as would be considered sensible. The results exhibit relative robustness, but the results in Column 3 are the key focus. Educated services' demand has a significant inverse relationship with the price of an educated service (*PES*), and size of the point estimate suggests that the demand is not elastic. Real GDP per capita, *GDP/POP*, is positive and significantly affects the demand for the services of educated workers.

This income effect confirms the hypothesized existence of feedback causality between services of educated workers and economic growth. It implies that investing in education generates employment for unemployed workers that possess the education-based skills required by enterprises, but not for all types of unemployed workers. It is shown that the country land areas is a positive but insignificant determining factor of the demand for educated services. The demand in the previous year, SEC_{t-1}, is positively and significantly correlated with that in the current year.

The price and supply of an educated service are significantly and directly related. The point estimate is less than unity, which suggests that the supply is not elastic across nations. In the United States, the supply exhibits perfect inelasticity as the price remains constant. Household size, *HS*, is significant in explaining the supply of educated services, and the supply in the previous year is positively associated with educated services' supply in the current period. Again, capital *K* leads to growth in the production of education-based skills.

However, the rate at which educated service deteriorates, *RDE*, significantly and negatively affects the production of education-based skills. Furthermore, an increase in the labor stock, *TSW*, leads to increases in the production of education-based skills, which confirms that education investment makes services of educated workers available for hire for enterprises. Moreover, previous education investments (SEC_{t-1}/SEC_{t-2}) lead to a considerable increase in the production of education-based skills in the current time.

5.3. Controlling for fixed effects and endogeneity

To investigate whether there is any change in the estimated effect of an educated service on output per worker after controlling for spurious relationships and endogeneity, Equation$(1')$ was re-evaluated, taking into account country-specific fixed effects; the results are shown in Column 3. The determined effect of commitment to investing in education to output per worker is fundamentally transformed.

The estimated elasticity increases to 0.021 (t-statistic = 2.08), suggesting economic growth effects that are considerably more plausible than previous estimations. This indicates that an additional year of schooling yields a considerable average increase in GDP per worker. In particular, if all other factors remain constant and simultaneity and country-specific fixed effects are considered, the mean growth in GDP per worker due to an additional year spent in education is 2.1 percent per annum.

In general, more plausible estimations were obtained by addressing the issue of simultaneity as well as misleading relationships. Overall, the GMM outcomes show an increased economic growth effect of education, similar to previous studies that applied varying corrections (Acemoglu & Autor, 2012; Hanushek & Woessmann, 2008; Oreopoulos & Salvanes, 2011). In addition, Colclough et al. (2010) explain the differences in related estimation results. The representation of country-specific fixed effects with no reverse causality does not solve the assessment bias (see Column 2). An increased impact is identified when controlling for simultaneity as well as country-specific fixed effects.

5.4. Testing for nonlinearity in education and growth's relationship

The key focus of this study is to assess the effect of investing in education on economic growth, and to examine whether the economic growth equation is nonlinear. To investigate whether the increased economic growth effects are associated with a restriction on the investments in education of a public economy, the overall output equation (1') is reformulated as follows:

$$\log(GDP_{it}) = a_{i0} + \sum_{j=0}^{4} a_{1j} \log\left(K_{i,t-j}\right) + \sum_{j=0}^{4} a_{2j} \log\left(INFR_{i,t-j}\right) + \sum_{j=1}^{3} \theta_j \log\left(GDP_{i,t-j}\right)$$
$$+(a_3 LOW_{it} + a_4 MHIGH + a_5 VHIGH_{it}).SEC_{it} + \varepsilon_{it}^{1} \qquad (1'')$$

where *LOW*, *MHIGH*, and *VHIGH* are dummy variables associated with low, moderately high, and very high investments in education, respectively (Table 1). The mean investment in education made by the 102 nations is approximately 3 years (see Table 1). Investment in education that fall below this mean are categorized in the low range (investment in education between the mean and medium investments, which forms roughly 33.5 percent of the panel data sample).

The years of investment in education that is above the mean are categorized in the high range (i.e., investment in education between the mean and maximum investments). It is possible to further categorize increased investments in education in the moderately high range (an investment that moves from the mean toward the midpoint to the maximum, accounting for about 58.6 percent of the sample). The remaining 7.9 percent of the panel data sample until the highest education investments' of 8.410 years is categorized as being extraordinarily high (a precise definition is provided in Table 1).

The country-specific fixed effect is considered in Equation (1"). No base is provided, because the focus is on evaluating the actual economic growth effects of education investments; in other words, the significance and signs of a_3, a_4, and a_5. For example, when a_3 is positive and significant, but a_4 and a_5 are negative, a "diminishing returns" hypothesis is supported. However, if the signs are reversed (i.e., $a_4 > 0$ and $a_5 > 0$), the evidence supports an "ideal investment" hypothesis, in that the impact might be relatively insignificant for low investment levels. Ideal education investment is defined as years of schooling the is enough to equip workers with skills that make highest attainable average contribution to economic growth. In this study, such optimum years of schooling is assumed to exclude years of compulsory education. It is instructive to state that education investment in this context reflects the number of years spent acquiring the right types of skills required by enterprises. Once there is a mismatch between the skill composition of workers and the skills companies require in an economy, the services of such workers become insignificant for maximizing economic growth.

In Table 2, segment 4 shows the evaluation results of Equations (1"), (2'), through to (4'). The point estimations for real capital, *K*; infrastructure, *INFR*; as well as previous economic growth, GDP_{t-1}, retain significance and are within the sizes formally deemed to be satisfactory. Significantly, a worker who has made a considerable investment in education and has been educated (or trained) to possess the right types of skills needed by enterprises within a nation yields an annual output of 3.7 percent (t-statistic = 2.02), which is significantly greater than the previously mentioned average output effect of 2.1 percent. By contrast, a worker whose investment in education is lacking produces 1.8 percent (t-statistic = 0.99) of economic output, which is below that of a worker that makes high investments in education.

However, the extra GDP per worker obtained disappears when the investment in education exceeds the optimal amount required to produce the highest economic growth. For example, the findings indicate that a worker with a very high education investment contributes about 3.1 percent (t-statistic = 2.16) annually to GDP growth in the long term. This is less than that of a worker with moderate investment in education. It implies that the economic growth effect of educated services rises at a constant annual rate when there is less than three years of educational investment; at an increasing annual rate for roughly three to six years of educational investment; and at a diminishing annual rate for around eight years.

This indicates that the annual contribution of educated services to economic growth is greater in a nation whose workers have, on average, at least a minimum of roughly three number of years of education and a maximum of close to eight years of education in the curriculum wherein the right skills needed most for production in that location are taught. A comparison of such economic growth advantages is considered.

5.5. Comparative analysis of the grouped results

The findings so far clearly reveal that the effect of educated services on economic growth for a moderately high level of education investment is greater than twice that with a low level of investment in education. In particular, education investments can reach an "optimum level." In this study, this optimum level equates to a mean investment of three to six years, which incorporates the mean investment in education for countries in Group 2 of Table 3. The mean investment in education for countries in Group 3 roughly exceeds the ideal education investments, and that for countries in Group 1 is generally below the threshold education investment level (see Table 3).

In this case, the findings indicate that an expansion of education investments by Group 1 countries yields a greater effect on overall economic growth. Therefore, Africa and other countries in Group 1 can grow their economies by investing in education, similar to China, Japan, and other countries in Group 2, assuming that education-based skills is significantly improved. In the United States and other countries in Group 3, education investment generates a diminishing economic growth effect. This does not imply that countries in Group 2 have grown larger than countries in other groups. It only implies that education has contributed more to the economic growth of the former countries than it has to the economic growth in the latter countries over the past one and a half decade.

Overall, Table 3 groups countries according to similarities among them with respect to the relationship between investments in education and economic growth. This illustrates the importance of group heterogeneity in the effect of investing in education on economic growth.

TABLE 3. ——GROUP-WISE ESTIMATION RESULTS

Country	Mean	Country	Mean	Country	Mean
GROUP 1	**0.018**	**GROUP 2**	**0.037**	Denmark	4.870
African countries = 17		African countries = 6		Estonia	5.017
Benin	1.576	Botswana	3.147	Finland	3.806
Burundi	0.461	Egypt	2.807	France	5.014
Cameroon	1.742	Gabon	3.090	Greece	3.610
Central African Rep	1.078	Mauritius	3.382	Hungary	3.894
Cote d'Ivoire	1.272	South Africa	2.969	Iceland	4.127
Kenya	1.441	Tunisia	2.507	Ireland	3.977
Lesotho	1.326	American countries = 10		Israel	4.514
Mauritania	0.814	Argentina	2.660	Italy	4.548
Morocco	1.711	Barbados	3.375	Latvia	5.057
Mozambique	0.278	Canada	4.982	Lithuania	5.074
Namibia	1.329	Chile	3.764	Luxembourg	4.268
Niger	0.392	Colombia	3.111	Netherlands	4.531
Rwanda	0.617	Jamaica	3.751	Norway	4.482
Senegal	0.555	Mexico	3,101	Poland	3.415
Sierra Leone	1.157	Panama	3.272	Romania	3.971
Togo	1.854	Peru	3.225	Russian Fed	4.968
Zimbabwe	1.966	Venezuela	2.571	Serbia	4.138
American countries = 10		Asian countries = 12		Slovak Rep	4.373
Bolivia	2.398	China	2.740	Slovenia	4.994
Brazil	2.264	India	2.569	Spain	3.899
Costa Rica	2.198	Iran	3.649	Sweden	5.091
Dominican Rep.	2.474	Japan	4.658	Switzerland	4.929
Ecuador	2.327	Jordan	3.739	United Kingdom	4.929
Guatemala	0.980	Korea, Rep	4.971	Oceania countries = 3	
Honduras	1.554	Kuwait	3.020	Australia	4.727
Nicaragua	1.894	Malaysia	4.399	Fiji	3.181
Paraguay	2.269	Mongolia	4.918	New Zealand	3.900
Uruguay	2.353	Qatar	2.794	**GROUP 3**	**0.031**
Asian countries = 5		Saudi Arabia	2.950	American Countries = 1	
Indonesia	1.937	Sri Lanka	4.050	United States	5.506
Iraq	2.199	European countries = 31		Asian countries = 3	
Lao PDR	1.372	Austria	5.218	Kazakhstan	6.637
Philippines	2.491	Belgium	4.236	Kyrgyz Rep	5.872
Thailand	2.086	Bulgaria	4.267	Tajikistan	6.180
European countries = 2		Croatia	4.168	European countries = 2	
Portugal	2.417	Cyprus	4.043	Germany	6.413
Turkey	2.094	Czech Rep	4.870	Moldova	5.730

[a] The mean for each country-group is the effect of investing in education on economic growth. For a specific country, it is the sample mean of education investment. Groups 1_3 are for low, moderately high, and very high levels of education investments, respectively. The total number of countries is 102.

6. RECOMMENDATIONS AND CONCLUSION

6.1. Summary of results

This study aimed to investigate the relationship between education investment and economic performance. A model was estimated in which education investment is endogenized by developing a micro model that shows the demand for and supply of educated services. To observe the effects across economies, macro production technology was used to assess the micro model.

After controlling for simultaneity and country-specific fixed effects, a causal relationship was observed between services of educated workers and the overall economic output. Given the three levels of education investments, a threshold level is reached, indicating that the highest returns on education are achieved at moderately high levels of investment. This implies that increased investments in education have a greater effect on aggregate economic growth in only a certain group of economies.

6.2. Practical example of results

The overwhelming growth of the Chinese economy, which is traceable to the 1999 Chinese educational policy, can serve as a practical example to the results obtained in this study. The policy massively increased higher education attendance in that year and the high annual rate of education attainment continued for over fifteen years. Coupled with the fact that Chinese higher institutions have a track record of teaching students the hard skills, there was a large influx of educated workers into the Chinese labor market, which is one of the secrets for Chinese economic growth in recent times.

As a result of such economic growth, employment has increased for Chinese graduates from technical or quantitative majors, but not for graduates who lack hard as well as soft skills–strong communication, analytical and managerial skills–that are required by companies (Tsang, 2000; McKinsey, 2013).

6.3. Policy recommendation

As it has been explained, this study's results have important real-world applicability. Accordingly, it is recommended that other nations especially the developing countries should adopt policies that strongly encourage higher education attendance and curricula that can appropriately match workers' skills with the types of skills enterprises require. This would expand aggregate economic growth of nations and substantially increase employment of workers.

6.4. Limitations of this study

This study could not address certain important issues. For example, identifying the most suitable group number for the obtained returns to education is important. However, it was not considered in this research. Accounting for it would help better understand the economic growth effects of the services of educated workers and consistency of country-group memberships. An educational curriculum that would better match workers' skills with the types of skills needed by companies was also not examined. Doing so would again clarify the presence of economic growth effects of education investments.

6.5. Conclusion of study

There is a threshold of education investment that produces a positive and significant effect on aggregate economic growth. Many African countries belong to a group that has not reached this critical education investment's benchmark. Additionally, almost all West African countries studied fell below this education investment's limit. This suggests that the extreme and increasing rate of poverty in most African countries could be partly traceable to low education of the people.

It also associates with the high and rising unemployment rate in the countries because any significant income growth is shown to generate employment opportunity. This establishes a conclusion that majority of poor households in Africa appear to be those having inadequate education of their labor. It is important to investigate the economic positions of African households on the basis of the education of their labor. Such an empirical examination is considered immediately following references to this chapter.

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CHAPTER FOUR

POOR AFRICA: A GUIDE TO BREAKTHROUGH POVERTY

FEBRUARY 2023

Poor Africa: A guide to breakthrough poverty

Abstract

The rising terrorism, kidnapping, and fraud in Africa are big threat to life and property. They originate partly from hopeless and frustrated people caused by extreme poverty and unemployment. To reduce poverty-generated crimes, households should be saved of hunger, starvation, and malnutrition. These poverty-indicators contribute to families` ill-health when they lack resources to pay medical bills. This study provides a guide on education and allocation of labor to minimize unemployment and poverty. To realize this goal, production formula that secure jobs and maximize wages should be acquired. Completing tertiary education was found to be consistent with having these production ideas.

Keywords

poverty, unemployment, educated labor, optimum schooling, maximum income growth.

JEL classification

I25, I32, J22.

1. INTRODUCTION

1.1. Problems of unemployment and poverty

Two major Africa`s problems, from where other issues originate, are extreme unemployment and poverty. This paper asks the following questions. I. How could African households liberate from poverty that they have lived-in for decades? II. What could be the cause of high unemployment of their labor? III. Are there solutions to these societal challenges? Answering these questions is a fight against world`s poverty. This is the primary goal of the World Bank, International Monetary Fund (IMF), and African Development Bank (AFDB). These public issues have continuously been discussed in famous media regarding provisions of their remedial measures.

Reputable economists have researched these economic concerns. For example, Banerjee and Duflo (2007, 2012**)** notably explain lives of the poor and provide antipoverty insights. Moreover, alleviating poverty has received interdisciplinary recognition. For example, Troller-Renfree et at. (2022) show that poverty alleviation improves infant brain functioning and adaptive cognitive skills. The authors and organizations call for the rethinking of practical ideas on combating global poverty and resuscitating poor economies. Obediently, this paper reveals one of the ways poor families could have better existence. In doing so, it bases its facts on data obtained from Nigeria general household survey (GHS) panel (NBS & World Bank, 2018).

One of the major causes of high poverty rate in Africa is that households do not adequately diversify their income source partly away from the primarily agricultural base, despite being small farm holders. African households have large members, and labor of a few individuals contributes significantly to family`s agricultural work. Most households are into subsistence farming and produce crop diversity that is required to meet family`s nutritional needs. This is rationalized by the unfolding economic shocks that redistribute family`s income farther into poverty. To expand household income, labor and work hours of individuals that are inactive in doing family`s farm work could be diversified into wage jobs and operating non-agricultural businesses. This helps to, going by Blundell et al. (2016), adjust shocks-induced income changes.

However, households could not engage in salary work or running non-farm enterprises because they lacked employment and start-up capital for businesses. In every honesty, however, households poorly educated their labor. Therefore, families constituted of individuals that lacked competencies that enterprises looked forward to hiring. Majority of households invested only years of compulsory schooling in education of their labor. This has resulted in non-employability of several individuals because of improperly designed educational curricula in Africa relative to those in the advanced world. Even those in employment were not adequately skillful and could not lead enterprises that hired their labor into expansions. Resultantly, businesses reluctantly employed additional labor because they operated almost at break-even points.

Therefore, the source of high poverty and unemployment rate in Africa is traceable to inadequate education of labor and low literacy of the people that live in the continent. To breakthrough poverty, households should self-select into education as Carneiro et al. (2011) reveal. While schooling, families should attain optimal education of labor that maximizes their income growth. Acemoglu et al. (2018), for example, suggest the acquisition of innovative skills for economic growth and welfare of nations. Similarly, Toivanen and Väänänen (2016) emphasize the role of education for innovating. These suggest the need to develop in individuals the production ideas that elevate countries into sustainable and pro-poor economic growth and development.

This study contributes to the literature in four major ways. First, it reveals that to gain employment, labor should possess skills that match job-vacancies in companies and other business establishments. Second, it prescribes optimum years of education of labor that maximizes wages and liberate families from poverty. Third, it constructs a new panel dataset and an original policy-oriented structural model to investigate for the first time, the importance of diversifying family labor for achieving a pro-poor economic growth and development. Additionally, it designs new educational, financing, and economic growth and development policies.

Policymakers in Africa have attempted transforming the agricultural sector for boosting national income growth. However, natural resources that generate major revenues for most countries are volatile to global shocks. Hence, farm commercialization agenda had not proved any success because of implementation cuts. Rather than profitable crops, families diversify their farm production against fiscal and macroeconomic fluctuations. Resultantly, alternate practical approach of solving the big problems is required, and this study provides one.

1.2. Objectives to be achieved

The aim of this study in its broadest sense is to, therefore, help households optimize their schooling investments and diversify their labor as a guide to breakthrough poverty. To accomplish this task, it is important to do the following.

1) Prescribe the optimal education of labor that maximizes income growth,
2) Develop a methodology and construct a new panel series to implement the expanding roles of achieving the ideal improvements of labor on income and employment creation,
3) Measure the magnitude at which poverty could be reduced and unemployment minimized through applicability of this guide, and
4) Design national policies to take Africa into pro-poor economic growth and development.

1.3. Societal importance of this study

This research is significant to households, especially those residing in Nigeria. It teaches the households that sharing their labor and hours of work amongst family agricultural work, own businesses, and wage employment could liberate them from poverty. It suggests that if two to three household members could, for example, complete a family`s agricultural work, the remainder individuals should be engaged with salary jobs and running of own enterprise. The idea is that every individual in a household that is within the working age should generate income for family`s consumption.

To enable this, households should educate their labor in schooling curricula that inculcate into people the productive skills needed by companies. This equips labor for employment and maximizes its marginal product at work. It subsequently creates employment for additional educated labor that possesses businesses-required skills. Therefore, empirical findings of this work could potentially assist policy decisions around employment generation.

This study further suggests that cost of educating labor may hinder the degree at which households acquire new skills and develop their inborn abilities. This could provide government with an empirical basis for subsidizing schooling and designing new educational financing. It could as well motivate households for effective education of their labor, which contributes to poverty alleviation.

The importance of this work extends to researchers and data analysts in Africa. It provides Nigeria`s policymakers with new panel dataset on non-existing policy variables such as literacy and unemployment rates. Additionally, this study teaches labor economists in developing countries the data generation processes of several policy-important variables including wage rate and hours of work for the labor in employment. The product of these two variables, which constitutes a part of the costs of operating businesses, could be utilized in minimizing costs for enterprises. The significant of this study is inexhaustible. It also provides researchers around the world with an original policy-oriented structural model and a pro-poor measure of income per capita.

1.4. Scope of this study

As the title shows (Poor Africa: A guide to breakthrough poverty), this is Africa`s specific research. The study provides a lead out of poverty for African households especially families that reside in Nigeria. It is an aggregate-level of empirical analysis that is built from a micro-foundation. Three major contributions of the study are to suggest ways of fighting poverty, and unemployment, and then, provide applicable policies. In doing this, it formulates an original structural model and construct a new panel dataset.

Some major variables of interest include measures of income growth as well as the demand for and supply of educated labor. For a clearer understanding of the research issues, read through the organizational directories that is provided beneath.

1.5. How this research is structured

Certain stylized facts that provide general overview of the research problem are presented. It specifically illustrates how diversifying family labor could lead to poverty reduction. Immediately following this is data descriptions and model specifications. The last two parts then discusses estimation results and provides a conclusion of the study.

2. OVERVIEW OF THE PROBLEMS

2.1. Diversifying family labor for poverty reduction

To measure poverty, food and non-food expenditures from Nigeria GHS panel were aggregated. Total expenditure of households was divided by the number of individuals that lived in families to turn it to per capita, and by seven to convert it to daily expenses.

Table 1 shows that in 2010, households lived on a per capita expenditure of about 263.9 naira a day, on average (a_1), where 'naira' is Nigeria`s currency. Nigeria`s exchange rate with the United States in 2010 is roughly 150.30 naira to one dollar (Feenstra et al., 2015). This indicates that the 1.90-dollar poverty line amounted to 150.30 × 1.90 or about 285.6 naira at that time, where '×' is multiplication. This suggests that many households were poor because they lived below the international poverty standard.

Similar calculations and comparisons were made on every household to observe that about 67.8 percent of families were poor in 2010 (Table 1, a_2). The number of poor households increased to roughly 75.8 percent in 2012 and about 82.9 percent in 2015, averaging to roughly 75.5 percent over the periods (a_2). (The exchange rates of 157.5 naira to one dollar in 2012 and 192.4 naira to a dollar in 2015 (Feenstra et al., 2015), were used for this assessment.) It appears that poverty rate was very high, and it was increasing.

TABLE 1. ——ALLOCATION OF HOUSEHOLD'S LABOR AND HOURS OF WORK [a]

Survey-wave:	W1[b]	W2	W3	Avg. [c]
(a_1) Consumption expenditure per capita	263.9	234.1	244.6	247.5
(a_2) Families that lived below poverty line	0.678	0.758	0.829	0.755
(b_1) Families that did wage (or salary) job	0.078	0.056	0.045	0.060
(b_2) Families that worked in their agriculture	0.344	0.260	0.311	0.305
(b_3) Families that owned non-farm business	0.214	0.177	0.178	0.190
(c_1) Individuals that worked in their own farm	2.480	2.510	2.920	2.637
(c_2) Weekly hours of individuals in farm work	91.60	84.10	86.10	87.53
(d) Individuals that lived in a family at that time	5.510	5.780	5.820	5.703
(e_1) Individuals that engaged in wage work	1.400	1.350	1.300	1.350
(e_2) Hours worked by individuals in wage work	72.10	71.10	52.10	65.10
(e_3) Hourly wage received from salary work	28.24	39.93	102.3	56.82
(f_1) Individuals that worked on own business	2.580	1.720	1.860	2.053
(f_2) Hours spent doing non-farm businesses	71.00	65.30	65.20	67.17

[a] Data were sourced from Nigeria general household survey (GHS) panel, post planting round.
[b] Wave one is in 2010-11, wave two in 2012-13, and wave three in 2015-16. [c] Avg. stands for average.

Part of the sources of the high poverty rate can be trackable to the allocations of family`s labor and hours of work. From the labor market participation module of the GHS panel, it can be calculated that only about 7.8 percent of families engaged in salary work in 2010 (b_1). Households that had wage job were even smaller in 2015, where roughly 4.5 percent of families worked for payment (b_1).

Agriculture was the primary source of households` income, where about 30.5 percent of families worked during the periods, on average (Table 1, b_2). While roughly 19 percent of households operated non-agricultural businesses (b_2), occupations of the remainder families were not documented, and they are excluded from this evaluation. It was observed from the GHS panel that households do not appropriately diversify their labor and working time to expand their income.

Labor diversity is defined as sharing of services and working hours of individuals in households between family agricultural work and wage employment or non-farm businesses. The aim is to diversify the earning source of households from the predominant agricultural base to a wage employment and off-farm profitable ventures for family income growth. Many individuals that worked in their family`s farm never operated non-agricultural enterprises nor involved in a wage work, and vice versa.

It was observed that most farm households were smallholders, and that labor of about three individuals was enough to complete many family`s agricultural job, on average (Table 1, c_1). Each of the individuals worked an average of about 87.5 hours in their family`s farm every week (c_2). If 8 hours × 7 days or roughly 56 hours is required for a healthy sleep in a week, for example, about 24.5 hours of leisure per week may not be small for an individual trying to liberate from poverty. It was again revealed in the survey that about six individuals lived in most families (d). However, a few households diversified labor of their members that were not significantly active in doing agricultural work.

On average, about one individual was hired from households that supplied labor for payment (Table 1, e_2). Every individual worked about 65.1 hours a week (e_2) and was paid an hourly wage of roughly 56.8 naira (e_3). Therefore, any individual that did wage work earned about 3,697.7 naira a week. This suggests that income of every individual in the households increased by 3697.7 / 7 days / 6 persons or about 88 naira a day, where '/' is division.

Notice that expenditure of individuals averaged roughly 247.5 naira a day (a_1), which is less than 166.7 × 1.90 or about 316.7-naira poverty line at that time. (The 166.7 is the average of naira to dollar exchange rates that were previously reported.) It appears that households wherein its member did wage work consumed 247.5 + 88 or about 335.5 naira a day. Clearly, most households that diversified their labor and hours of work into paid employment were not poor during the periods considered. Therefore, poor families that did not supply part of their labor for a wage should do so to escape from poverty.

As it was initially explained, however, households that searched for wage employment had only one of its members hired. It appears that unemployment constrained many families from adequately diversifying their labor. Consistently, unemployment rate in Nigeria was 21.1 percent in 2010 and it increased to 33.3 percent in 2020 (CBN, 2021). (The unemployment issue will be revisited shortly.) It was further calculated from the GHS panel that few households involved in non-agricultural self-employment.

On average, labor of about two individuals were used to operate off-farm family businesses (Table 1, f_1), where one person worked about 67.2 hours a week (f_2). If these individuals were paid the same hourly wage received by those in salary job, families they lived-in earned income of $56.8 \times 67.2 \times 2$ or about 7,633.9 naira a week. Repeating previous calculations shows that individuals in the households lived on about 429.3 naira a day. Therefore, the households had expenditures above the poverty line and cannot be considered poor, too.

If most households had diversified their labor as a few families did, they would have all lived above the global poverty benchmark, even without external interventions. However, high unemployment rate and lack of start-up capital for non-farm enterprise may have prevented families from diversifying their labor. To ease these challenging forces, individuals should develop their abilities and acquire productive skills through education (and training) as previously cited studies suggest.

Beyond this, however, they should optimize their acquisitions of unharnessed production formula through adequate education in curricula that inculcate skills that expand businesses. This could result into wage maximization, and unemployment and poverty minimization. A correctly designed educational curriculum impacts into individuals the skills required by enterprises.

Optimizing the acquisitions of production skills increases not only the employment of educated labor, but its marginal productivity when it is hired. If labor is paid value of its marginal products, wages of employed educated individuals increase even above the one that was previously reported. Consequently, income and savings of households where the employed individuals live will grow.

Resultantly, self-employment will be created through opening of non-farm businesses using savings from the increased wages. Consistently, about 52.9 percent of households that owned non-agricultural businesses used their savings as source of start-up capital in 2011 (NBS & World Bank, 2018). From the same source, families that started non-farm enterprises using their savings increased to roughly 56.7 percent in 2016. Therefore, optimizing years of education of labor creates jobs.

Moreover, an increase in the contributions of employed educated individuals to productivity could lead to better performances of enterprises that hired their labor. This could result into substantial expansions of businesses, and consequently the employment of additional educated individuals with the required skills by the enterprises. This is another channel through which ideal education of labor could reduce unemployment rate.

3. DATA GENERATION

3.1. A new panel dataset

To suggest ways households could fight poverty and unemployment, a new panel series were constructed from wave one to wave three of the GHS panel. The expenditure per capita, which its construction has earlier been explained, is a measure of income. Capital stock, which affects income, is calculated as the market worth of business equipment. Most businesses that hire labor are owned or co-owned by families. Expenditures on electricity, communication (postal and telephone), and transportation were aggregated as a surrogate for infrastructure investment. These indicators are important for enterprising.

Educated labor, wherein its importance for income growth is emphasized throughout this study, is computed as the average years of schooling of individuals in households. The highest educational level completed by individuals, which ranges from no schooling to higher degree and beyond, are recorded in the GHS panel. By learning from Barro and Lee (2013), eight years of schooling was assigned to an individual that completed primary education. This is because the individual had completed two years of nursery education plus six years of primary schooling.

The schooling investment of every individual was allocated, and average was taken within households. As this capture solely the quantity of labor education, fraction of individuals that can read and write in indigenous language in each household was calculated, as a measure of schooling quality. This improvement of labor, which plays significant role in doing businesses, can be interchangeably interpreted as literacy or knowledge. Parents` years of education were again averaged for every family. The natural logarithm of its ratio with that of households was calculated to proxy for the relationship between education investments and changes in the development of labor.

Investing in schooling and acquiring knowledge involve costs–the cost of educating labor–and it was calculated as individual`s expenditure on tuition, fares, and other spending. However, skills acquired through schooling yields benefits in the form of wages received by employed educated individuals, which is termed the price of educated labor. The labor employed is defined as an individual that either worked on family`s farm, did a wage job, or operated a non-agricultural business.

If employed and unemployed persons are added up in a household, it gives the stock of that family`s labor. This is because any individual that is below the working age was omitted. It again amounts to the average number of persons that lived in that family, which measures the mean size of that household. Distance from family houses to schools, measured as time taken by individuals to places of learning, was calculated. To generate unemployment rate, labor that is not hired was divided by the total labor of households and multiplied by 100 to convert it to percent.

Demographic variables such as sex and age of the household-head were also gathered. Additionally, household farm characteristic variables, such as farm size, non-agricultural employment, and ownership of cattle and goat, sheep, and poultry were again generated. These are majorly dummy variables that are used as analysis` controls. As originally mentioned, a few individuals engaged in a salary work, especially in wave three. This reduces the sample to 1,206 households per wave, that amounts to a balanced panel sample of about 26.3 percent of the complete 4,591 families that were interviewed.

3.2. Summary evidence

In Table 2, main variables are described alongside their summary statistics. It is again shown in the table that many households lived below the standard poverty threshold, as expenditure per capita averages $e^{5.003}$

or about 148.9 naira a day (a_1). The capital stock appreciated from $e^{5.686}$ or roughly 294.7 naira per day in 2010-11 to about 671.8 naira a day in 2015-16, averaging 445.4 naira daily over the years (a_2). Moreover, every individual spent roughly 165.7 naira a day on infrastructure services (a_3).

Importantly, investment in the education of labor averages roughly 11 years (Table 2, a_4), including the two years of pre-primary schooling that were incorporated into the constructed investment measure. It is evident, therefore, that most individuals withdrew from schooling after completing nine years of compulsory education. Such years of educating labor is lower than that in the United States, where children remain in schools between five years to 18 years of their age (Stephens & Yang, 2013). Consistently, literacy rate calculated from the GHS panel averages about 64.2 percent between 2010 and 2016 (a_5). This is below the adult literacy rate in most developed countries.

It is instructive to work through an example in illustrating the importance of diversifying educated labor from agriculture partly into salary employment for income growth. Taking education investment as a business venture, an individual named *"i"* that lived in household "j" faced an objective of maximizing profits: $\pi_i(edc_i^*) = TR(edc_i^*) - TC(edc_i^*)$, where π denotes profit, edc_i^* is the optimal schooling investment that maximizes i`s income growth, and TR and TC stand for total revenue and total cost, respectively. Because the ideal education investment is yet to be established from data, the amount of profit that *i* earns is evaluated at suboptimal years of schooling.

Notice that an average of 0.642 × 7 or around four individuals that were literate in most families correspond to roughly four persons that were employed in households (Table 2, b_1). This indicates that most educated individuals that supplied labor for wages were hired as they possessed skills needed by enterprises. It is, therefore, possible that the unemployed individuals, which average about three persons in most households (b_2), were not hired because they lacked requisite competence to significantly contribute to productivity growth.

Returning to the demonstration, it costs individual *i* an average of $e^{4.604}$ or about 99.9 naira a day through roughly 11 years of its education investment (Table 2, b_3).

TABLE 2. ———DESCRIPTION OF MAJOR VARIABLES USED IN THIS STUDY AND THEIR SUMMARY STATISTICS [a]

Variables with abbreviations (in parenthesis)	W1:2010-11		W2:2012-13		W3:2015-16		All:2010-16	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD
(a_1) Expenditure per capita (EXP) (₦ / day; log) [d]	5.005	0.712	4.943	0.717	5.061	0.660	5.003	0.698
(a_2) Capita stock per capita (K) (₦ / day; log)	5.686	1.370	6.101	1.245	6.510	1.237	6.099	1.328
(a_3) Infrastructure per capita (INFR) (₦ / day; log)	4.858	2.270	5.188	1.843	5.284	1.787	5.110	1.986
(a_4) Educated labor (EDL) (in years)	10.96	3.246	11.95	3.832	12.40	3.730	11.09	3.247
(a_5) Literacy rate (LITR), literates / family size	0.609	0.273	0.794	0.870	0.754	0.855	0.642	0.273
(b_1) Employed individuals in a household (LP)	3.532	2.016	3.531	1.927	3.683	2.055	3.582	2.000
(b_2) Unemployed individuals in a family (UP)	3.124	2.226	3.434	2.428	3.012	2.244	3.190	2.307
(b_3) Cost of educating labor (CEDL) (₦ / day; log)	4.391	1.683	4.490	1.696	4.933	1.632	4.604	1.686
(b_4) Hours of work in wage job per week (HWL)	45.72	13.28	43.77	14.76	43.06	15.65	44.18	14.63
(b_5) Price of educated labor (PEDL) (₦ / day; log)	3.393	1.535	2.821	1.583	3.163	1.660	2.792	1.624
(b_6) Household size (HHS), persons in a family	6.657	2.868	6.965	3.016	6.695	3.106	6.772	3.001
(b_7) Distance to schools (DST) (in minutes)	23.96	18.54	23.03	16.99	22.59	15.28	23.19	16.99
(b_8) Investments related to labor changes (IEDL)	1.072	0.660	1.029	0.522	1.026	0.584	1.043	0.591
(c_1) Dummy variable: 1 if EDL ≤ 11 years (LOW)	0.539	0.498	0.470	0.499	0.425	0.495	0.531	0.499
(c_2) Dummy: 1 if 11 < EDL ≤ 15 years (MEDIUM)	0.371	0.483	0.261	0.439	0.250	0.433	0.373	0.484
(c_3) Dummy variable: if EDL > 15 years (HIGH)	0.090	0.286	0.269	0.443	0,325	0.469	0.096	0.295

[a] Data were collected from the Nigeria general household survey (GHS) panel, from wave one (W1) to wave three (W3). [d] ₦ is naira, Nigeria's currency.

When it entered labor markets and was employed, it worked an average of about 44.2 hours a week at a price of $e^{2.792}$ or roughly 16.3 naira per hour (b_4 and b_5, respectively). It appears that *i*`s revenues amounted to (16.3 × 44.2) / 7 days or approximately 104.1 naira a day. This suggests a profit of 104.1 - 99.9 or about 4.2 naira daily plus promotions for over 30 years of its working life; '- 'is subtraction.

Recall that household "*j*" had about four literate employed members, and profits they earned impacted on consumption of every individual that lived in that family, whether employed or not. To demonstrate it, family "*j*" spent 99.9 × 4 or about 399.6 naira a day on the schooling of labor. Because roughly seven individuals lived in the household (b_6), 399.9 / 7 or around 57.1-naira amount of consumption per day was forgone by every individual that lived in the family to educate labor.

However, household "*j*" earned an income of 104.1 × 4 or about 416.4 naira a day from family labor that was supplied and hired for a payment. This implies that consumption of every member of the family increased by 59.5 naira every day. This increase continues through years of active service of the educated employed individuals. Given that profits from educating labor have been evaluated at suboptimal years of investments, attaining the standard threshold of schooling investments maximizes income growth.

This has implication for smoothing consumption throughout the household`s lifetime, as it saves for retirement age from the increased income during its working years. Distances to studying canters, which averages about 23 minutes from family houses (b_7), reduced fares. The relationship between investments in schooling and variations in educated labor is positive but small (b_8). This confirms that majority of families education labor minimally.

In search of the optimal years of schooling that maximizes income growth, investments in education made by households were classified into three. Households that invested at most 11 years in education are considered to have had low schooling. Between 2010 and 2016, an average of roughly 53.1 percent of families fell into this investment category (Table 2, c_1). Similarly, households that made schooling investments of over 11 years to 15 years are taken to have had medium investments. Over the periods, approximately 37.3 percent of households were in this group (c_2).

Moreover, spending over 15 years in schooling is regarded as high investments in education, and about 9.6 percent of households fell in this class (c_3). To have a rough idea of what the optimal years of education could be, a graph of the correlation between schooling investment and expenditure per capita for the most recent year, 2016, was plotted. As figure 1 shows, households that invested over 11 years to about 15 years in education of labor (medium investment) appear to have earned highest attainable income growth. A simple linear regression of expenditure per capita on years of education of labor shows that it is accountable for roughly 91.8 percent of changes in income of households. This is consistent with the previous emphasis that optimizing investments in education is an important maximiser of household`s income growth.

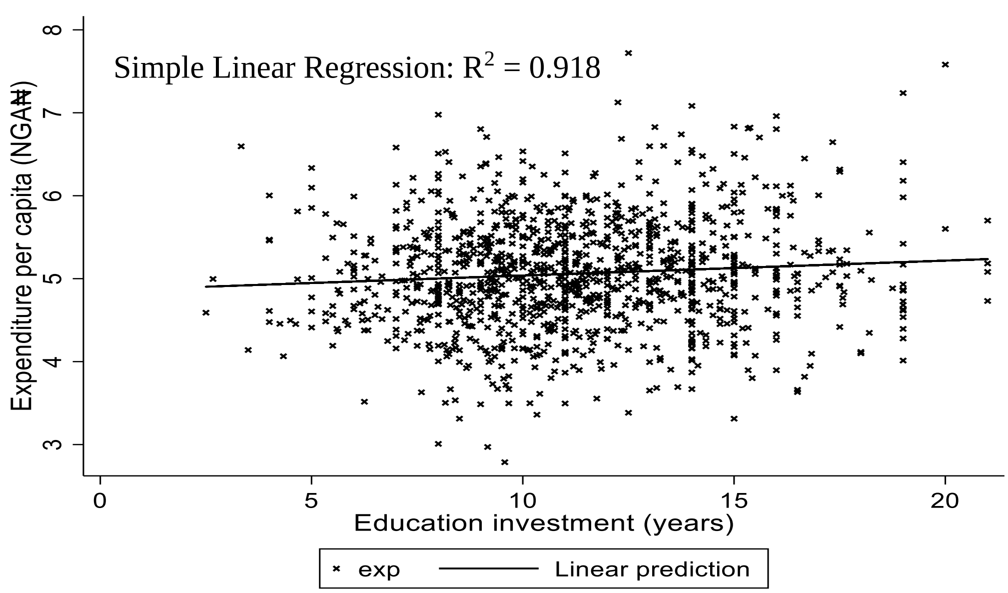

FIGURE 1. EDUCATION INVESTMENT AND EXPENDITURE, 1206 FAMILIES

The descriptive statistics of most control variables were excluded from Table 2 for lack of space. While unemployment rate averages roughly 47.7 percent, area of farmlands has a mean of about 2.28 acres. Similarly, age and sex of household-heads averages about 54.3 years and roughly 0.857, respectively. It implies that there was approximately nine male-head in every 10 families. Additionally, dummy variables for cash crop production and non-agricultural employment have the sample mean of 0.086 and 0.465, respectively.

These suggests that about nine families in any 100 households produced crops for sales, and roughly five households out of every 10 families supplied labor for wages or involved in off-farm own accounts. It is further shown that ownerships of sheep and goat, poultry, and cattle average about 0.428, 0.490, and 0.130, respectively. These imply that out of any 10 families. roughly four households had goat and sheep, about five households owned poultry farms, and approximately one family reared cattle.

4. RESEARCH METHODOLOGY

4.1. A model of educated labor diversity and income growth

Consider a structural utility function: $U_{it} = g(C_{it}, L_{it}, F_{it}, H_{it})$. It describes satisfaction that a household named *"j"* derives from consumption (C_{it}) and leisure (L_{it}). The household faces bounding constraints of its financial wealth (F_{it}) and human wealth (H_{it}). As it was previously explained, food consumption dominates households` budgets. Therefore, even if family "j" chooses leisure over work, it prefers consumption to leisure because it consumes at its leisure time. Therefore, consumption serves as a proxy for utility.

The household aim at establishing an optimal path for consumption that maximizes its lifetime (latent) utility given its effective wealth (F_{it} plus H_{it}). If the household lives during periods $t \in \{0, 1, \dots \tau\}$ for some finite $\tau \geq 1$, it faces an intertemporal budget constraint merely on its consumption sequence $\{C_t\}_{t=0}^{\tau}$, not on its saving and borrowing path $\{A_{t+1}\}_{t=0}^{\tau}$.

As the household goes from the set of per-period budgets to intertemporal budget constraint, it reduces out the saving and borrowing path to a mere feasibility instrument to optimizing its lifespan consumption. However, the household plans on recovering the saving and borrowing path once the optimal consumption sequence is attained. This is to ensure that the per-period budgets are as well always fulfilled. Given the idiosyncratic frictions in Africa`s credit markets, household "j" may be unable to borrow at some periods that $A_{t+1} < 0$.

Therefore, its consumption in those periods can be optimized using income of the same periods. Hence, the household chooses to maximize its labor income at every moment through the aggregate production technology of the national economy.

4.1.1.Functional (technology) relationships

The economy itself targets to produce the highest feasible aggregate output (EXP_{it}) at the lowest possible costs of inputs. The factors of production include the physical capita (K_{it}), infrastructure service ($INFR_{it}$), educated labor (EDL_{it}), hours of work for the labor employed (HWL), and other exogenous economic variables (Z_{it}). The Z_{it}-variables include age and sex of the household-head and a dummy variable for non-farm ownership. The costs of these factors constrain the actualization of the target output. A structural (technology) production function that links the macroeconomic activity to cost-constraining inputs is specified in the relationship (1) below:

$$(1) \qquad EXP_{it} = f(K_{it},\ INFR_{it},\ EDL_{it},\ HWL_{it},\ Z_{it}),$$

where f(.) denotes a function and variables are as defined in Table 2. The stock of educated labor is required (instead of schooling investments). This is because enterprises demand educated services for production, rather than the investment per se. In accordance with Barro (2001), the years of schooling of families was employed. This helps to, as it would be introduced shortly, establish the optimal education of labor that could take the national economy to a balanced growth.

Thereafter, household`s literacy ($LITR_{it}$), which measures schooling quality and acquired knowledge from education, would be hired, too. The coefficient on EDL_{it} in equation (1) estimates the return to educated labor for its contributions to economic output. Every educated individual strives to maximize its marginal product, which approximates its monthly take-home salary.

To participate in the national economic activity, labor should be hired by enterprises or becomes self-employed by running own businesses. A structural demand function used here relates quantity of labor demanded (EDL_{it}) to its constraining price ($PEDL_{it}$), per capita expenditure (EXP_{it}), and hours of work for the labor employed (HWL_{it}):

$$EDL_{it} = f(PEDL_{it},\ EXP_{it},\ HWL_{it}), \tag{2}$$

where variable measures are described in Table 2. Expenditure per capita is an important variable determining the quantity of labor employed. This is because changes in aggregate demand for goods and services lead to variations in business sales and expansions. The parameter on EXP_{it} in equation (2) estimates the one-way causal relationship running from economic growth to the demand for educated labor. This is the income elasticity of demand for educated service.

Notice that the coefficient on EDL_{it} in equation (1) measures a direct causal association flowing from educated labor to aggregate output–the impact of EDL_{it} on EXP_{it}. These effects represent reverse causality between economic growth and educated labor.

For there be employment, the type of educated labor demanded by enterprises should be supplied to labor markets by families. A measure of education supply is, therefore, needed to model both the demand for and supply of educated labor.

The structural supply function of educated labor is defined in equation (3) below:

$$(3) \qquad (LP_{it} + LU_{it}) = f(PEDL_{it},\ (EDH_{it} - EDP_{it}),\ W_{it}),$$

where (EDH_{it} – EDP_{it}) = $IEDL_{it}$ in Table 2; other variables are as defined in the table. Because of high unemployment rate in Africa as it was initially reported, total supply of educated service equals the labor employed (LP_{it}) plus unemployed (LU_{it}). When supplying labor, households consider the price of its educated service ($PEDL_{it}$), the improvements to its labor $IEDL_{it}$, and some exogenous forces determining supply (W_{it}).

The W_{it} includes sex of the head of a household, farm size, and cattle ownerships. As it was originally introduced, most households were poor. Therefore, costs of educating labor constrains families from developing their skills and supplying educated services. Given the high rate of unemployment, however, households do all they could to adequately improve their labor. Generally, supplying adequately educated labor helps families to be hired as they possess skills that match competencies required by enterprises for production purposes.

A structural function that describes the relationship between investment in education and the changes in the stock of educated labor is given by:

$$(4) \qquad EDH_{it} - EDP_{it} = f(CEDL_{it},\ EXP_{it},\ (LP_{it} + LU_{it}),\ DST_{it},\ UMPR_{it}).$$

To measure development of labor, average education of parents (EDP_{it}) is subtracted from the mean schooling of the whole household (EDH_{it}). Therefore, any family having a single individual is excluded from this study. In improving labor, households consider the costs of educating labor ($CEDL_{it}$), the family`s income (EXP_{it}), and size (LE_{it} + LU_{it}), proximity to places of learning from homes (DST_{it}), and unemployment rate ($UMPR_{it}$).

It is instructive to state that equations (2), (3), and (4) endogenize educated labor, because these three equations include the demand for and supply of educated service. The magnitude of employment of additional educated labor resulting from increases in the aggregate economic growth is provided for in equation (2).

4.2. Empirical equations

The econometric specification equivalent to the foregoing model (1)–(4) is as follows:

$$(1') \quad \log(EXP_{it}) = a_{i0} + a_1 \log(K_{it}) + a_2 \log(INFR_{it}) + a_3 EDL_{it} + a_4 Z_{it} + a_5 \log(HWL_{it}) + \varepsilon_{it}^1;$$

$$(2') \quad \log(EDL_{it}) = b_{i0} + b_1 \log(PEDL_{it}) + b_2 \log(EXP_{it}) + b_3 \log(HWL_{it}) + \varepsilon_{it}^2 \quad ;$$

$$(3') \quad \log(LP_{it} + LU_{it}) = c_{i0} + c_1 \log(PEDL_{it}) + c_2 \log(EDH_{it}/EDP_{it}) + c_3 W_{it} + \varepsilon_{it}^3;$$

$$(4') \quad \log(EDH_{it}/EDP_{it}) = d_{i0} + d_1 \log(CEDL_{it}) + d_2 \log(EXP_{it}) + d_3 \log(LP_{it} + LU_{it}) + d_4 \log(DST_{it}) + d_5 \log(UMPR_{it}) + \varepsilon_{it}^4.$$

The aggregate production equation (1') relates expenditure per capita (EXP_{it}) to physical capita stock (K_{it}), infrastructure service ($INFR_{it}$), educated labor (EDL_{it}), hours of work for the labor employed (HWL_{it}), and a vector of exogenous controls (Z_{it}) that have been listed. To maximize EXP_{it}, enterprises hire EDL_{it} at the "demand price" of $PEDL_{it}$ from labor markets. They pay the total cost on EDL_{it} of $PEDL_{it} \times HWL_{it}$, where the last term is again the hours of work for the labor employed. Importantly, businesses employ the type of EDL_{it} that best matches their vacancies to earn highest possible profits. They maximize gains through greater sales of their products made possible by increasing aggregate expenditure on goods and services. Therefore, EXP_{it} is an important factor in the equation of demand for educated labor (2').

To enable complete functioning of the economy, families supply labor for hire by enterprises. They charge the "supply price" of $PEDL_{it}$. This price cannot guarantee employment of all stock of educated labor made available for hiring. Therefore, labor unemployed (LU_{it}) is added to the labor employed (LP_{it}), constituting the total labor supply. The variety of educated services to supply depends on improvements to labor (EDH_{it} / EDP_{it}) made by households. It is also a function of some exogenous factors (W_{it}) that have been enlisted. These describe the equation of supply of educated labor (3').

One fact is that households cannot provide what they do not have. This means that they had to educate their labor at the cost of $CEDL_{it}$. They consider their income (EXP_{it}) and the quantity (and quality) of labor to supply (LP_{it} + LU_{it}). They also think of the closeness of schools to their homes (DST_{it}) and the rate of unemployment ($UMPR_{it}$). Equation (4') relates schooling investment to variations in the development of labor. The logarithm of (LP_{it} + LU_{it}) and (EDH_{it} / EDP_{it}) is consistent with the logarithmic transformation in Roller and Waverman (2001). (See also the model in chapter three, subsection 4.1.)

Endogenous variables in the equations include expenditure per capita (EXP_{it}) and educated labor (EDL_{it}). They additionally include total labor force (LP_{it} + LU_{it}) and a measure linking schooling investment to changes in improvement of labor–the ratio of educated labor of households to that of parents (EDH_{it} / EDP_{it}). Table 2 defines the variables. To investigate the ideal education of labor that could yield highest feasible aggregate income, equation (1') is re-specified in the form of equation (1") below:

$$(1'') \qquad \log(EXP_{it}) = a_{i0} + a_1 \log(K_{it}) + a_2 \log(INFR_{it}) + a_3 Z_{it} + a_4 \log(HWL_{it}) \\ +(a_5 LOW_{it} + a_6 MEDIUM_{it} + a_7 HIGH_{it}) \, . \; EDL_{it} + \varepsilon_{it}^1,$$

where all variables are again as defined in Table 2. Notice that each equation controls for individual-specific fixed effects. Model (1')–(4') is similar to that in Roller and Waverman (2001). Roller and Waverman's equations endogenize infrastructure investment just like model (1')–(4') does to educated labor. It is important to note again that error terms $\varepsilon_{it}^n \; \forall \, n \in \{1, 2, \dots, 4\}$ are correlated just like in the conventional simultaneous equations as it is explained underneath.

4.3. Identification and estimation approach

The aggregate output equation (1') excludes two endogenous variables: The total labor supply (LP_{it} + LU_{it}) and proxy that links investments in education to increase in skillful labor (EDH_{it} / EDP_{it}). It also omits five exogenous variables namely, price of educated labor $PEDL_{it}$, the vector of economic forces W_{it}, cost of educating labor $CEDL_{it}$, distance to places of learning DST_{it}, and the unemployment rate $UMPR_{it}$. Going by the order condition, 2 + 5 > 4 – 1, where the latter term is endogenous variables in the model less one. Therefore, output equation is overidentified, satisfying the necessary condition for identification. Clearly, there are 7 – 3 or four degrees of overidentification for the national income equation.

For the labor demand equation (2'), it omits the same endogenous variables that the output equation excludes. However, it excludes more exogenous variables than the income equation does. Specifically, the exogenous variables that the demand equation omits include all that the first equation excludes except the price of educated labor $PEDL_{it}$. In addition, it omits the physical capital stock K_{it}, infrastructure service $INFR_{it}$, and the Z_{it} vector of forces. Resultantly, the order condition for identification can be verified as 2 + 7 > 4 – 1, showing that the equation of demand for educated labor is also overidentified.

The supply equation (3') excludes the expenditure and educated labor endogenous variables. Similarly, it omits every exogenous variable that the demand equation excludes other than the W_{it} vector of variables. In place of later variables, it omits the hour of work for the labor in employment, HWL_{it}. For the education investment`s equation (4'), it omits only one endogenous variable–the educated labor EDL_{it}. The exogenous variables that it excludes are the physical capital stock K_{it}, infrastructure service $INFR_{it}$, price of labor $PEDL_{it}$, hour of work HWL_{it}, and the vectors of variables Z_{it} and W_{it}. Therefore, equation (3') as well as equation (4') fulfils the order condition for identification because each of them is overidentified.

It is important to check for the rank condition of identification, which gives sufficient information for possible estimation of model (1')–(4'). In doing so, elements of matrix B were taken to those of matrix A in equation (5) below. Thereafter, a (4–1) or 3 × 3 non-zero determinant was calculated from variables excluded in any equation but included in model (1')–(4'). (Recall that there are four endogenous variables in the equations.) A non-singular 3 × 3 matrix was obtained for each of the equations. This implies that model (1')–(4') meets the rank criterion for identification, and that it can be estimated. However, endogenous explanatory variables in the model cannot be estimated directly.

To differentiate endogenous variables from exogenous independent variables, the matrix form of model (1')–(4') can be presented as below:

$$\begin{pmatrix} 1 & -a_3 & 0 & 0 \\ -b_2 & 1 & 0 & 0 \\ 0 & 0 & 1 & -c_2 \\ -d_2 & 0 & -d_3 & 1 \end{pmatrix} \begin{pmatrix} EXP_{it} \\ EDL_{it} \\ (LP_{it} + LU_{it}) \\ (EDH_{it}/EDP_{it}) \end{pmatrix}$$

$$= \begin{pmatrix} a_{i0} \\ b_{i0} \\ c_{i0} \\ d_{i0} \end{pmatrix} + \begin{pmatrix} a_1 & a_2 & a_4 & 0 & a_5 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & b_1 & b_3 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & c_1 & 0 & c_3 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & d_1 & d_4 & d_5 \end{pmatrix} \begin{pmatrix} K_{it} \\ INFR_{it} \\ Z_{it} \\ PEDL_{it} \\ HWL_{it} \\ W_{it} \\ CEDL_{it} \\ DST_{it} \\ UMPR_{it} \end{pmatrix} + \begin{pmatrix} \varepsilon_{it}^1 \\ \varepsilon_{it}^2 \\ \varepsilon_{it}^3 \\ \varepsilon_{it}^4 \end{pmatrix},$$

which could be represented in the form of equation (5) as follow:

(5) $$AY_{it} = A_{i0} + BX_{it} + U_{it} \Leftrightarrow Y_{it} = A^{-1}A_{i0} + A^{-1}BX_{it} + A^{-1}U_{it}.$$

Notice that logarithms have been omitted for simplicity. To recover structural parameters in model (1')–(4'), inverse of matrix $A_{(4\times4)}$ is required, wherein its determinant can be calculated as $(1 - c_2d_3) - a_3b_2 + a_3b_2c_2d_3$. The last term: $a_3b_2c_2d_3$ shows relationships among endogenous variables in model (1')–(4'). It indicates that the system errors are correlated just like in the traditional simultaneous equations. The determinant of $A_{(4\times4)}$ could be reduced to $(1 - a_3b_2)(1 - c_2d_3)$.

The term a_3b_2 represents the association between educated labor in the income equation (1') and expenditure in the labor demand equation (2'). This indicates the reverse causality between income and educated labor. The term c_2d_3 shows similar feedback causality between supply of educated service in the labor development equation (4') and the improvement of labor in the supply equation (3').

Importantly, each of these terms are subtracted from one before getting the numerical determinant. This implies that simultaneity in the system should be controlled to consistently estimate model (1')–(4'). Using the correlation coefficients calculated from data, for example, $|A| = (1 - 0.043)(1 - (-0.102)) \cong 1$. This implies that model (1')–(4') is employment preserving such that any hired labor remains important to the enterprise until its retirement age.

One important assumption of model (1')–(4') is that any region has workers that are mobile and decide where to reside to maximize their utility. Equilibrium requires that utility is equal across regions, like in the Roback (1982)'s framework. If a higher utility is attainable in any state, labor migrates to that region. By doing so, wages fall because of increased labor supply in the state. This cycle repeats until utility across regions is equalized.

Using the previous utility function, equilibrium involves a set of moment conditions $U_A = U_A{}' = \bar{y}$ for all region A, A' and some (arbitrary) constant $\bar{y}$. Consistent to this moment criteria is the equilibrium of the demand for and supply of labor in model (1')–(4'). At this equilibrium, the educated labor supplied equals the employed desired amount of labor that elevates the economy to a balanced growth. On this balanced growth of the economy, every variable of model (1')–(4') is constant at its desired level.

The challenge is that these equilibrium levels of variables are unknown and are to be estimated from observed data. To do it, the desired (latent) EDL_{it} can be taken to be constant in equation (1') to generate a proxy for the (unknown) optimum EXP_{it}. This could be done by regressing expenditure on exogenous variables in the model, where endogenous regressors are fixed at their optimum. This is because explanatory variables in equation (4') affects (LP_{it} + LU_{it}) through (EDH_{it} / EDP_{it}). Together with those in equation (3') they affect EXP_{it} through equality of (LP_{it} + LU_{it}) and EDL_{it} from the moment restriction.

Similarly, the (unknown) desired EXP_{it} is assumed to be constant in equation (2') to predict the optimum EDL_{it} by estimating it on all exogenous independent variables in the model. This routine, which is repeated for the remainder endogenous variables–(LP_{it} +LU_{it}) and (EDH_{it} / EDP_{it})–is consistent with the popular ‘reduced-form’ approach. (Assuming an endogenous regressor to be constant in an equation reduces it to a constant term.)

The predicted values of endogenous variables were used as proxies for endogenous regressors, and a single-by-single estimation of each equation was undertaken. This is consistent with estimating the aggregate expenditure equation (1') by using exogenous variables in it as included instruments for EDL_{it} and those in equations (2'), (3'), and (4') as excluded instruments. Similar routine was taken when estimating equations of the demand for, supply of, and investments in, educated labor.

The model is estimated by the two-stage least squares (2SLS) method using the African panel dataset. Table 3 reports the coefficient estimates for the different specifications of model (1')–(4').

5. ESTIMATION RESULTS AND DISCUSSIONS

5.1. Results and interpretation

The first estimation of model (1')–(4'), wherein the results are presented in the first column of Table 3, employed years of schooling of households as a measure of educated labor. The estimated coefficients for the macro-expenditure equation reveal that the physical capital stock and infrastructure service are positive and significantly related with national economic output. The point estimate for physical capital stock equals 0.331 (see a_1). This is consistent with the word of Romer (2019) that one-third of total output goes to capital in most countries. The elasticity of output with respect to infrastructure service is 0.049 (a_2). This approximates the results obtained by Roller and Waverman (2001).

When literacy was hired by businesses, the results obtained are recorded in the second column of Table 3. The estimates for physical capital stock and infrastructure service remained within economically reasonable magnitudes. Interestingly, parameters on the years of education of labor and literacy in the aggregate output equation are positive and significant. These indicate that hiring more of educated labor produces significant aggregate economic growth. The point estimates on the years of schooling of labor and literacy are roughly 0.014 and about 0.016, respectively (Table 3, a_3).

TABLE 3. ———EDUCATED LABOR AND ECONOMIC GROWTH: AFRICA—–2SLS ESTIMATES OF EQUATIONS (!')–(4') [a]

	Column (1)		Column (2)		Column (3) [e]		Column (4)	
	Estimate	(SE)	Estimate	(SE)	Estimate	(SE)	Estimate	(SE)
(a) Aggregate output equation:								
(a_1) Physical capital stock (K)	0.331	(0.030)	0.454	(0.025)	0.547	(0.128)	0.621	(10.051)
(a_2) Infrastructure service (INFR)	0.049	(0.019)	0.057	(0.021)	0.071	(0.030)	0.127	(0.036)
(a_3) Educated labor (EDL)	0.014	(0.001)	0.016	(0.002)	—	—	—	—
(a_4) Low labor's education (LOW.EDL)	—	—	—	—	0.015	(0.008)	0.015	(0.007)
(a_5) Medium education (MEDIUM.EDL)	—	—	—	—	0.021	(0.004)	0.016	(0.007)
(a_6) High education (HIGH.EDL)	—	—	—	—	0.018	(0.004)	0.032	(0.006)
(b) Labor demand equation:								
(b_1) Expenditure per capita (EXP)	1.288	(0.069)	1.288	(0.069)	1.288	(0.069)	1.288	(0.069)
(b_2) Price of educated labor (PEDL)	−0.043	(0.018)	−0.043	(0.018)	−0.043	(0.018)	−0.043	(0.018)
(c) Labor supply equation:								
(c_1) Improvement of labor (IEDL)	2.476	(0.434)	2.476	(0.434)	2.476	(0.434)	2.476	(0.434)
(c_2) Price of educated labor (PEDL)	0.045	(0.022)	0.045	(0.022)	0.045	(0.022)	0.045	(0.022)
(d) Labor improvement equation:								
(d_1) Expenditure per capita (EXP)	0.088	(0.032)	0.088	(0.032)	0.088	(0.032)	0.088	(0.032)
(d_2) Cost of educating labor (CEDL)	0.020	(0.009)	0.020	(0.009)	0.020	(0.009)	0.020	(0.009)

[a] Column (1) and column (2) employed years of education; Column (2) and column (4) hired literacy. [e] Column (3)–(4) estimates (1")–(4').

These conform with the previous point that enterprises require educated service rather than investment in schooling. However, both indicators yielded close contributions to aggregate output. The estimates, which reflect the marginal products of educated service, represent shares of national income that goes to labor. Summing the EXP variable as it was used for estimation produces a total of about 18,100.56 naira per day. Therefore, the estimated coefficient on the years of schooling measure of educated labor suggests that a daily income of $0.014 \times 18{,}100.56$ or about 253.4 naira goes to any employed educated individual for its contributions to aggregate economic output.

Using the point estimate on literacy, the income shares of educated labor amounts to roughly 289.6 naira a day, on average. Recall that expenditure of an individual averaged about 148.9 naira a day (Table 2, a_1). And that, despite having approximately seven members in a household (b_6), labor of roughly four persons was hired by employers (b_1). These indicate that any hired individual earned income of $(148.9 \times 7) / 4$ or roughly 260.6 naira per day. It corresponds to $260.6 / 18{,}100.56$ or about 0.014 estimate obtained for educated labor. This is consistent with the marginal effect in Blundell et al. (2013).

Besides, coefficient estimates obtained for educated labor are consistent with one of the policy relevant estimates produced by Carneiro et al. (2011). The estimation results again average the 1.5 percent increase in wages from schooling in Duflo (2001)'s study. Moreover, the estimated labor income is close to that calculated from raw data when differences in education is not considered. To account for heterogeneity in the education of labor, equation (1') was replaced with equation (1") to estimate model (1")–(4'). This was done to provide solutions to the societal problems that were initially mentioned. To do it, the pooled estimates are used as reference points and discussions start with the problem of poverty.

5.1.1. Poverty reduction

The estimation results in the third column of Table 3 reports the aggregate economic output that is obtainable when enterprises hire individuals based on the completed years of schooling recorded in their curriculum vitae (CV). Clearly, an employed individual that had a low education of labor received a return of about 1.5 percent of total output (Table 3, a_4). This was its rewards for participating in the national production. Using the previously reported total expenditure per day, the individual`s income amounted to 0.015 × 18,100.56 or about 271.5 naira a day. To allow for the natural unemployment rate, one person is assumed to remain unemployed in every household even after education of labor.

This is consistent with reducing unemployment from its current rate of 33.3 percent to 1 / 7 or about 14.3 percent. Therefore, about six individuals are supposed to be now employed in most families because of improvements in their labor. Any household that had six employed individuals with low schooling lived on expenditure per capita of (271.5 × 6) / 7 or roughly 232.7 naira every day. This expenditure is lower than the average of 316.7-naira global poverty benchmark that was earlier calculated. It indicates that most families that had a low education of labor were poor during the sample periods considered.

Similarly, an employed individual that invested medium years in education of labor was paid a daily income of 0.021 × 18,100.56 or about 380.1 naira (Table 3, a_5). Therefore, every household that got six of such educated labor employed had expenditure per capita of (380.1 × 6) / 7 or about 325.8 naira per day. This labor income is clearly greater than the poverty line of 316.7 naira that was originally calculated. It suggests that the families lived above the globally acceptable standard of living.

This is consistent with emphasis in the previously cited studies that properly developing labor generates significant economic growth. However, as it is presented in the third column of Table 3, a highly educated labor produced income-return of 0.018 × 18,100.56 or roughly 325.8 naira a day (a_6). By repeating the previous example of six employed individuals, this labor income amounted to (325.8 × 6) / 7 or about 279.3-naira per capita expenditure a day. Therefore, the families appear to be poor.

A new knowledge in this regard is that investing adequate years in education of labor is important for achieving economic development. However, time spent schooling should not be excessive. This is because there are lower and upper education investment`s corridors below and above which educated labor makes suboptimal contributions to national economic output. Any duration of schooling in-between these bounds represent an optimal education of labor that maximizes output growth. Based on the definition in Table 2, optimal schooling corresponds to educating labor up to a higher institution. This is consistent with completing polytechnics, colleges of education, teachers` training, and the university schooling.

Notice that households that joined labor markets after their higher institution education constituted of roughly 37.3 percent (see Table 2, c_2). It suggests that over 60 percent of families were poor rightly as it was depicted in Table 1. Recall that poverty is associated with poor nutrition, poor health, and high mortality. Therefore, this finding is consistent with that of Tamura (2006) that schooling reduces mortality.

The results do not say that individuals in the academic and research institutions, most of which invested about seven more years in masters` and doctoral education, were poor. As it was originally explained, adequate education enhances employability of labor. A family of highly educated individuals wherein all persons was in employment lived on 325.8-naira expenditure per capita a day. Therefore, they cannot be considered poor. In addition, results in column four of Table 3 suggest that as highly knowledgeable as labor becomes (measured as literacy), the greater the economic growth. Using the example of even six individuals in a wage job, households with the highest (employed) literate members lived on a daily expenditure per capita of $0.032 \times 18{,}100.56$ or about 579.2 naira a day (a_6).

Interestingly, among the richest people in Africa are highly knowledgeable individuals. They are experienced in their various business endeavors, not limited to academia. Therefore, results obtained here imply that having a university education, for example, is enough to empower labor for optimum national productivity. Experiences are to be gained at work as labor learn by doing. Even for those in academia and institutions, the major determinant of their productivity are experiences and knowledge they have gathered as they also learn by doing. Therefore, if about 80 percent of families with low schooling had optimally educated their labor, poverty rate could have reduced to a less than 20 percent in the periods considered. This would have generated many jobs and substantially reduced unemployment rate.

5.1.2. Job creation / unemployment minimization

The income elasticity of demand for educated labor is, as reported in the labor demand equation of Table 3, roughly 1.288 percent (see b_1). This indicates that demand for educated labor is income elastic. Therefore, an increase in economic growth leads to a more than proportionate employment generation, ceteris paribus. Going by the originally calculated labor income there was an increment in the national output of 271.5–253.4 or roughly 18.1 naira from hiring inadequately improved labor.

Recall that there is a total of 1,206 households in the sample used, and about 53.1 percent of families had low development of labor (Table 2, c_1). This implies that a total of 0.531 × 1,206 or about 640.4 households ineffectively educated their labor. Because about four persons were employed in most households (b_1), 4 × 640.4 or roughly 2,561.6 hired labor had low education. Therefore, aggregate expenditure on goods and services increased by 18.1 × 2,561.6 or about 46,365 naira.

Using the 1.288 estimated elasticity there was employment of additional (1.288 / 100) × 46,365 or about 597.2 educated labor. Total individuals in the sample are 7 × 1,206 or about 8,442 persons. Therefore, increasing economic growth through hiring of lowly educated labor created employment of 597.2 / 8,442 or roughly 7.07 percent over the sample coverage.

To find out the education of labor that generated the greatest possible employment opportunities, similar calculations for employed mediumly educated individuals were repeated. In doing so, economic growth increased by 380.1 - 253.4 or approximately 126.7 naira because of hiring optimally educated labor. A fraction of 0.373 households mediumly educated their labor (Table 2, b_2). Using the total families in the sample there were 0.373 × 1,206 or roughly 449.8 households with ideally educated labor.

This suggests that 4 × 449.8 or about 1,799.2 mediumly educated individuals were in employment. Resultantly, national income increased by 126.7 × 1,799.2 or roughly 227,958.6 naira. This resulted to employment of additional 0.013 × 227,958.6 or about 2,963.5 educated labor. Therefore, increase in aggregate economic output due to hiring optimally educated labor led to unemployment reduction of 2,963.5 / 8,422 or roughly 35.1 percent.

Going through related calculations for the highly educated labor produces employment creation of about 5.16 percent. Therefore, attainment of optimal education of labor generates highest feasible employment through economic growth maximization. Because optimizing the education of labor also achieved the highest attainable poverty reduction, then it minimizes income inequality consistently as Fleisher et al. (2010) found. If one-half of households that inadequately educated their labor had additionally attained optimum schooling, unemployment would have reduced by over 60 percent. Therefore, the importance of optimizing education of labor goes beyond combating poverty to reducing unemployment.

In this context, inadequately educated individuals might only gain employment and liberate from poverty through investment in schooling like their ideally educated counterparts, if a significant development of their labor is attained.

5.1.3. Other estimated coefficients

In the demand panel of Table 3 (see b), an inverse and significant relationship between demand for and price of educated labor is reported. The price elasticity of demand for educated labor is computed at -0.043 (b_2), which is smaller than one, indicating inelastic demand. This is consistent with the previous emphasis that even when price of educated labor decreased, businesses could not substantially hire more labor because they had not substantially expanded. It is again shown in the supply panel (c) that improvement of labor led to about 2.48 percent more supply of educated service (c_1).

Moreover, supply and price of educated labor are directly and significantly related. The estimated elasticity of supply of educated labor is 0.045 (c_2) and it is clearly less than one. It corresponds to the earlier comment that the price of educated labor alone cannot ensure market clearing. This further justifies the reason for accounting for the unemployed labor in the supply equation.

Notice that the estimated coefficient of the “demand price” of educated labor roughly equals that of the “supply price.” (The last five in the latter price was by approximation.) This is consistent with the equality of the prices on which the equilibrium condition was based. In panel (d) of Table 3, the elasticity of increment in skills with respect to income and cost of educating labor are 0.09 (see d_1) and 0.02 (d_2), respectively.

Most of control variables were not presented in Table 3 because of space. One of such factors in the output equation is the dummy variable for non-agricultural employment. It has point estimate of 0.351 (SE.=.069), where 'SE' stands for standard error. This says that households that used part of their labor in paid jobs and own off-farm businesses earned average income of about 35.1 percent higher than those that did not. This buttresses the earlier point that diversifying family labor reduces poverty. The estimated parameter on the dummy for sex is 0.425 (SE.=.067). This suggests that male-headed households had income of roughly 42.5 percent greater than their female-headed counterparts.

It is instructive to note that an hour of work for the labor employed has coefficient estimates of 0.013 (SE.=.001) when labor was hired by years of education. An hour of work also has a point estimate of 0.018 (SE.=.002) when literacy determines the employment of labor. These estimates are reasonably close to coefficient estimates on years of education and literacy that was initially reported. It appears that hours of work for the labor in employment can serve as additional productivity measure of educated labor. Because income growth effects of years of education and literacy measures of educated labor reflect that of the hour of work, there may not be a need to further emphasize on estimate of the later measure.

Additionally, hour of work for the hired labor is estimated to decrease demand by about 1.1 percent (SE.=.003). This agrees with the original emphasis that low education of labor hinders employment. Lastly, rising rate of unemployment reduced years of investments in education by roughly 0.2 percent (SE.=.0004). It appears that being out of employment affects households` affordability of education costs.

6. RECOMMENDATIONS AND CONCLUSION

6.1. Summary of results

In Africa as at 2010, the cumulative 80 percent of families had about 20.8 percent share in national income (NBS & World Bank, 2018). That of the top 20 percent of households amounted to roughly 79.2 percent.

By 2016, income share of the former had declined to roughly 16.4 percent and that of the latter risen to about 83.6 percent. Clearly, Africa`s economic growth is not pro-poor, as almost 80 percent of national income goes to the richest 20 percent of households. The use of aggregate-data evidence for informing public policy in Africa might be, therefore, misleading.

Over the periods, many families became poor, and the poor went poorer. This is consistent with the extreme and rising rate of poverty that is recorded in Table 1. The abject poverty of most families coupled with over 33 percent unemployment of their labor, posse big problems to Africa, and the world. For example, Africa faces huge insecurity from hungry youths. People in other continent of the world had as well been defrauded and media had repeatedly enlisted many Africans amongst perpetrators of the crimes.

It is important to, therefore, ease the frustrating situations of African households. This study is set to solve these serious problems through diversity of family`s educated labor. It specifies a micro-model of demand for and supply of educated labor and estimated them with the aggregate production equation. This methodology endogenizes educated labor and enables for empirical implementation of job creation implications of reverse causality.

The estimation results show that the use of educated labor in production generates significant economic growth, consistent with the originally cited papers. However, maximizing economic growth and substantially minimizing poverty and unemployment require optimality in the acquisitions of production innovations. Improvement of labor through tertiary institutions was found to ideally equip people for this purpose.

6.2. Practical applicability of results and recommendations

The estimation results that have been interpreted above have three major practical applicability. One is in the national education policy. It is compulsory for a child in most African countries to complete six years of primary schooling and three years of junior secondary education. Results obtained suggest that this should incorporate three years of senior secondary education and about four years of higher education. This is consistent with the educational law in the United States. Most children in the United States starts schooling at age five and could quit at the age of 18 years, covering at least 13 years of education.

Moreover, it is necessary to design a credit medium in African countries that grants students' loan for schooling. This loan could be deductible from salaries during their working time. Providing such a financing vehicle could lead to success of extending years of mandatory schooling.

Another applicability of this study`s results is the economic growth and development policy. The educational system in most African countries is dilapidating because of poor funding. This has metamorphosed into unfolding striking of teachers for several months in every academic year. The findings of this research show that the economic impacts of increasing public budgets on education for poverty and unemployment reduction are too substantial for African countries to neglect.

6.3. Limitations of study

This study could not address certain significant questions. For example, what educational curricula might be suited best to appropriate these returns to educated labor? Because the findings reflect the educational law in the United States, their curricula could be adopted. However, adopted curricula should be reasonably modified to accommodate Africa`s ways of life. This is important because economic growth and development as well as poverty and unemployment reduction depend on the skills and knowledge that able people acquire, not only the years they spent educating their labor.

Another matter of importance that was not considered is the relationship between educated labor and inequality minimization. Moreover, previous labor demanded is a factor of considerable interest in determining current demand for educated services. The nature of panel data used could not allow the use of lagged variables. However, the fixed effects partly eliminate their impacts.

6.4. Conclusion of study

Based on the estimation results and their implications, any household that chooses to breakthrough poverty should ideally educate its labor and make its acquired skills available for production. Optimal education of labor enables families to secure a job. When they are in employment, it maximizes their wages through the optimality of marginal products of their appropriately improved labor. This guide and the associated empirical backing and real-life usefulness could apply to every poor household, no matter the continent of the world, especially those in Latin America and some countries in Asia.

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CHAPTER FIVE

EVALUATING THE IMPLICATIONS OF ECONOMIC DEVELOPMENT FOR INCREASING DIETARY DIVERSITY

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1. INTRODUCTION

At this juncture of my doctoral dissertation, I ask: Does increasing economic development imply increasing dietary diversity? In one of its simplest definitions, economic growth involves increase in the per capita income. Conversely, economic development incorporates the income growth and overall improvements in the living standards of the people. Increasing dietary diversity is one of the indicators of economic development. Additionally, quality healthcare and institutions, and transformative infrastructure and technology as well as good education are important indicators, too. It implies that improvements in households' diets resulting from income increases is one of the ways to evaluate development's implications for dietary diversity.

2. WHAT ECONOMIC DEVELOPMENT IMPLIES FOR DIETARY DIVERSITY

2.1. Clarifying interpretation issues in this study

Before evaluating economic development implications for increasing dietary diversity, I wish to comment on economic interpretations of some of the statistical relationships contained in this work. For example, ignoring heterogeneity in education of labor produced a coefficient estimate on EDL of 0.014 (Chapter 4, table 3, row (a_3), column (1)). A statistical interpretation of this point estimate is that: One additional year of education of labor leads to about 1.4 percent average increase in per capita income, ceteris paribus. While this statistical interpretation prevails where it reasonably reflects practical past experiences, it should be modified where it does not. (The conformity of economic meaning of estimates with practical experiences should supersede their statistical interpretations.) A brief illustrative example may be important for a clearer understanding of this point. To provide it, recall that most households had education of labor that averaged about 11 years over the 7-year periods (Chapter 4, table 2, row (a_4), column 'All').

This suggests that most of the employed individuals earned income of (0.014×11) or roughly 15.4 percent for increasing education of their labor from one year to about 11 years. Using the previous sum of the EXP variable, this amounted to a labor-income of ($0.154 \times 18{,}100.56$) or about 2,787.5 naira per day.

Given that approximately four individuals were in employment in most households (Chapter 4, table 2, row (b_1), column 'All'), income of most families averaged (4 × 2,787.5) or roughly 11,150 naira a day. Using the roughly seven individuals that lived in most of the households (row (b_6), column 'All'), income per capita averaged (11,150 / 7) or about 1,592.9 naira every day. This estimate is far greater than the per capita income of ($e^{5.003}$) or about 148.9 naira of most households at that time (Table 2, row (a_1), column 'All').

If this statistical interpretation does not meaningfully agree with past experiences of most households, it may not make economic sense to draw statistical inference from it into the future. A standard interpretation of the estimate on EDL is as follows. If other factors are held constant, most employed individuals had an average income growth rate of about 1.4 percent per day from skills gained by investing roughly 11 years in education of their labor. This growth rate amounted to a (0.014 × 18,100.56) or about 253.4 naira a day for every employed labor. This earning is calculated at (4 × 253.4) or roughly 1,013.6-naira households' income per day. It, in turns, corresponds to (1,013.6 / 7) or about 144.8-naira per capita income, which is close to the expenditure per capita previously reported for most individuals.

In elaborating this interpretation, heterogenous coefficient estimates on educated labor is considered. For example, the point estimate on the LOW.EDL variable is 0.015 (Chapter 4, table 3, row (a_4), column (3)). Similarly, coefficient estimate on MEDIUM.EDL is 0.021 (row (a_5), column (3)). There is additional four years of education of labor from low to medium schooling. These years of schooling amounted to an extra labor-income of [(0.015 / 11) × 4] or about 0.545 percent. It mplies that a mediumly educated labor received an income growth of (0.015 + 0.00545) or roughly 2.05 percent. This roughly corresponds to the regression estimate on MEDIUM.EDL that was previously reported. To further justify interpretations in this dissertation, consider the estimate of 0.018 on HIGH.EDL (row (a_6), column (3)). This shows a decreasing economic growth rate between medium education of labor and high schooling of labor. The point estimate on MEDIUM.EDL suggests a growth rate of 2.1 percent as previously explained.

The gap between medium education of labor and high schooling of labor is (20 – 15) or about 5 years. This can be calculated to an income growth reduction rate of [(0.021 / 15) × 5] or approximately 0.7 percent.

It shows that income of a highly educated labor can be computed at (-0.007 + 0.021) or about 1.4 percent, which is again close to its regression estimate of 1.8 percent that was earlier presented.

In sum, interpretations provided to the EDL variable does not only reflect real-life experiences of households but consistent with results estimated from data, too. Having known that the coefficient estimates in this dissertation are reasonable approximations of past practical experiences of households, it is acceptable to draw statistical future predictions based on the results. In doing so, a discussion of an extent the economic growth increases had improved the dietary diversity of households is undertaken.

2.2. Responses of dietary diversity to income growth increases

To assess the response of dietary diversity to increasing economic growth, individuals in households are believed to be in employment having acquired productive skills through the guide in chapter four. Additionally, the estimated effect of educated labor on economic growth that ignores differences in schooling is evaluated with the pooled regression on dietary diversity. In doing so, most individuals witnessed an income growth of about 1.4 percent of national income per day through the productive contributions of their educated labor (Chapter 4, table 3, row (a_3), column (1)). This amounted to an economic growth increase of (0.014×7 days) or about 9.8 percent per week. (Recall that dietary diversity is measured in weeks.) The coefficient estimates on expenditure is 2.556 for the FVS (Chapter 1, table 4, panel B, column (i)) and 1.008 for the DDS (Table 5, panel E, column (i)).

The economic growth increase of 9.8 percent allowed for a consumption of $[(2.556\ln(100+9.8)/100) \times 60]$ or roughly 14.3 increased food variety over the sample periods. The income growth also enabled a consumption of $[(1.008\ln(100+9.8)/100) \times 12]$ or about 1.13 more food groups. (The figures: 60 and 12 are numbers of food items and food groups available for households' consumption, depending on their income level.) These imply that income increases of most Nigeria's households allowed them to consume over 14 more food items in about one food group between 2010 and 2016.

To recognize the credit status of households as discussed in chapter one, families with low education of labor which was considered poor in chapter four could likely be credit constrained. Since those households lived below the lowest poverty line, it is sensible to think that they were credit constrained because of associating savings. In this sense, the point estimate on the LOW.EDL variable in chapter four is evaluated with that on EXP for the credit-constrained households in chapter one. The coefficient estimates on LOW.EDL is 0.015 (Chapter 4, table 3, row (a_3), column (3)). This amounted to (0.015 × 7 days) or about 10.5 percent increase in income growth per week. Similarly, the point estimate on expenditure for the credit-constrained households is (2.291+0.967) or about 3.258 for the FVS (Chapter 1, table 6, column (ii)) and (0.910+0.337) or roughly 1.247 for the DDS (Chapter 1, table 7, column (ii)).

Repeating previous calculations show that increase in income growth of 10.5 percent allowed credit-constrained households to eat (3.258ln(1.105) × 60) or approximately 19.5 more food items and (1.247ln(1.105) × 12) or about 1.49 increased food groups over the 7-year periods. Importantly, increase in economic growth could change status of credit-constrained households into credit-unconstrained one. As income increases, economic rationality requires that credit-constrained households increase their saving even though they consume much of their increased income because they exhibit hand-to-mouth behavior. Several credit-constrained households might have experienced the economic growth importance of the credit-unconstrained households. To evaluate how far economic growth had affected dietary diversity of the credit-unconstrained households, individuals with medium education of labor are considered credit-unconstrained. The rational is that they earned the highest possible income and might have had substantially increased savings relative to other households over the sample periods considered.

The estimated coefficient on MEDIUM.EDL (likely credit-unconstrained) is 0.021 (Chapter 4, table 3, row (a_5), column (3)). This again amounted to a weekly income growth of (0.021 × 7 days) or around 14.7 percent of total income at that time. In chapter two, the effect of expenditure on dietary diversity for the credit-unconstrained households was estimated at 2.291 for the FVS indicator (Table 6, column (ii)), and 0.910 for the DDS indicator (Table 7, column (ii)). Using these estimates, the income growth increase resulted to a consumption of (2.291ln(1.147) × 60) or roughly 18.9 increased food items. It also amounted to (0.910ln(1.147) × 12) or approximately 1.50 additional food groups consumed over the periods.

Moreover, highly educated individuals had high potentials for securing employment because they were better match to job vacancies. As it was emphasized in chapter four, households that had such highly educated labor in wage job were not poor during the sample coverage. Such households were likely credit-unconstrained just like families with medium education of labor. Table 3 in chapter four shows that the point estimate on the HIGH.EDL variable is 0.018 (row (a_6), column (3)). This corresponded with a (0.018 × 7 days) or about 12.6 percent increase in income per capita per week. Following previous calculations, this increase in economic growth led to (2.291ln(1.126) × 60) or around 16.3 more food items consumed. It generated (0.910ln(1.126) × 12) or about 1.30 more consumption of food groups, too.

Clearly, increasing economic growth is substantially significant in improving dietary diversity. Notice that increase in food items (food groups) consumed out of the income growth is far lower than those available but not yet feasible to households. This suggests that food support programs of various forms may complement the economic growth efforts for increasing dietary diversity of households. However, analysis of the economic growth's importance for the dietary diversity's increases considered is the growth generated by educated labor. Incorporating income growth from infrastructure and capital stock and of increased economic diversity could expand the growth significance for increasing dietary diversity. Before a concluding judgement on this assessment, economic growth increases from the literacy-measure of educated labor are compared with those of years of schooling. This comparison summarises this assessment.

3. SUMMARY OF EVALUATION

This chapter evaluates responses of dietary diversity to increasing economic growth generated by the education of labor. Between 2010 and 2016, education of labor generated 9.8 percent increase in income of Nigeria's households per week. This allowed households to consume about 14.3 increased food items and roughly 1.13 more food groups. Comparatively, literacy increased economic growth by 11.2 percent, which is greater than the growth increase from the years of schooling-measure of educated labor. This literacy-generated economic growth amounted to an additional consumption of about 16.3 food items and roughly 1.28 food groups. These are greater than dietary diversification that was previously achieved.

Individuals that had low education of labor were possibly credit constrained because they were poor at that time. Their income increased by 10.5 percent which enabled them a consumption of about 19.5 more food items and approximately 1.49 increased food groups. This dietary diversification is consistent with that achieved from the literacy-generated economic growth. However, individuals that mediumly educated their labor (possibly credit unconstrained) consumed roughly 18.9 greater food items and 1.50 more food groups. This dietary diversity was attained by the 14.7 percent income growth of the households.

Moreover, households that had high education of their labor were likely credit unconstrained, too. They consumed about 16.3 increased food items and approximately 1.30 extra food groups out of their 12.6 percent growth in income. The same household-sets earned about 22.4 percent of aggregate income when they are examined by their literacy level. This income growth led to the households' consumption of approximately 27.8 more food items and about 2.21 extra food groups, on average.

It is important to note that dietary diversity's response to economic growth gained from infrastructural development is not considered in this doctoral dissertation. Reason is because data on Nigeria were excluded in the infrastructure and economic growth relationship investigated in chapter two. Moreover, infrastructural provision in most African countries is a sole responsibility of government. Private individuals play minimal roles. Considering the severity of income inequality highlighted in the concluding section of chapter four, labor was the top source of income for the households considered. However, incorporating other sources would substantiate economic growth's importance for the improvement of dietary diversity. This forms a basis for this doctoral dissertation's general conclusion provided underneath.

0.2. GENERAL CONCLUSION

As it was explained in chapter one, food production diversity is not enough to account for dietary losses from shocks to income of Nigeria's households. Moreover, neither personal saving nor transfers reasonably insure households' consumption against macroeconomic instabilities. (This is, however, results of an ongoing study that is not fully advanced in this doctoral dissertation.) These indicate that increase in income growth is most important for increasing the dietary diversity of households. However, chapter two suggests that most African countries do not gain substantial economic growth advantages of infrastructure. Similarly, chapter three shows that most workers in African countries (especially West African countries) have low education of their labor. These imply that African countries have not achieved substantial increase in economic growth over the past decade. Results in chapter four buttresses those in chapter three.

Reason is that most households (as shown in chapter four) were poor during the study's periods because they lived below the lowest international poverty line. This was partly led by low education of their labor. The overall indication is that Nigeria has had little national income growth in the recent years. This low economic growth transmitted to an infinitesimal economic development measured as small increases in the dietary diversity generated by the income growth's increases. The demonstrated low economic development corresponds the malnutrition in chapter one and extreme unemployment and poverty in chapter four. It also reflects inadequate infrastructure in chapter two and poor education in chapter three.

To improve the dietary diversity of households, Nigeria as well as some other developing countries should prioritise economic development. Quality education and adequate infrastructure are central to achieving this economic development's goal. These empirical findings led to the title of my doctoral dissertation, "Prioritising economic development for increasing dietary diversity of households" While this conclusion is reached using panel data on Nigeria, it may be valid for other African countries, too.

THIS IS THE END OF MY DOCTORAL DISSERTATION