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Nexuses between Food, Energy, and Water Consumption on Urban-Rural Income Gap in South-Eastern Asian Countries Using Difference in Difference in Modelling Technique

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ABSTRACT

South Asian countries are still battling hunger and poverty, especially in rural areas. Empirical evidence attributes the urban-rural income gap to inadequate infrastructure, such as electricity and water supply. This article uses a difference-in-difference model to examine how emerging trends in Food, Energy, and Water (FEW) resources influence the urban-rural income gap. Using data from 2000 to 2019 from China, Indonesia, and India, the results showed that high food insecurity increases income inequality, whereas electricity supply significantly reduces the income gap. Thus, Asians should ensure a sustainable and equitable distribution of FEW resources to improve agricultural productivity and create jobs.

Keywords: Food, Energy, Income Gap, Poverty, Water
JEL Classification: D31, Q11, Q41, Q25

1. INTRODUCTION

Although South Asian countries have made remarkable progress in socio-economic development in recent years, challenges persist in ending hunger and poverty and ensuring food and nutritional security, an adequate standard of living, access to modern energy, and healthy lives for the vast population. Despite the impressive economic growth in fighting global hunger over the last decade, some South Asian countries are still battling serious food deficits. The GHI in East and Southeast Asia fell from 11.0 in 2012 to 8.5 in 2021, ranking second after Europe and Central Asia (7.5 in 2012 vs. 6.5 in 2021). Yet, some Southeast Asian Countries had moderate (GHI: 10.0-19.9) to serious food deficit (GHI: 20.0-34.9) in 2021, including Timor-Leste (32.4) leads in terms of GHI, followed by Laos (19.5), Cambodia (17.0), Indonesia (18.0), the Philippines (16.8), Vietnam (13.6). Malaysia (12.8), and lastly Thailand (11.7) (Grebmer et al., 2021 (Our World in Data, n.d.). Such shocks could be attributed to the COVID-19 pandemic that wreaked havoc on supply chains from 2020 through 2021, restricting life and livelihoods in Asia and the Pacific. Thus, the MDGs remain an unfinished agenda among Southeast Asian Countries. More efforts are required to eradicate hunger and poverty and mitigate against such shocks.

Despite recent rapid economic development in Asian countries over the past decades, large disparities in infrastructure and incomes between rural and urban areas remain. Given their large populations, China and India explain the major contributors to the rural-urban gap of the trends in regional inequality. While there is rising economic growth, infrastructure between urban and rural areas in China has grown significantly rather than diminishing, contrary to Lewis's (1954) prediction. The World Bank's statistics indicate that China's GDP rose exponentially from 1.211 trillion USD in 2000 to 17.73 trillion USD in 2021. However, it is not welfare-oriented since it does not consider income distribution. Although China has eradicated extreme poverty, many people remain vulnerable, with incomes below the poverty threshold in upper-middle income countries (World Bank, 2022a; 2022b).

China's disposable income ratio of urban and rural residents was at 3.20:1 in 2019, indicating that China's–rural income gap is still high.

`Existing empirical evidence attributes the urban-rural income gap in SEA countries to poor resource access in rural areas. About 50% of the population in Asia and the Pacific live in rural areas (United Nations Centre for Regional Development [UNCRD], 2021). These people face many challenges due to the lack of adequate and reliable infrastructure, such as roads, railways, electricity, water supply, and communication networks (Yoshino et al., 2019). These challenges limit their income-generating activities through access to markets, services, and employment opportunities (Engel et al., 2017). Adequate supply of infrastructure formation in rural areas, such as roads, irrigation systems, clean sources of water, and electricity, is essential in reducing poverty (International Labour Organization [ILO], n.d.). Investing in these productive assets creates income opportunities and generates jobs, increasing incomes and reducing hunger and malnutrition. For instance, electricity enables the operation of small businesses and industries since it supports the use of modern machinery and cold storage facilities, hence creating more jobs and diversifying incomes.

Water supply enhances agricultural productivity and food security through irrigation. Yet, the lack of proper irrigation facilities is one of the major constraints to agricultural productivity in rural areas of Asia. Common problems inhibiting the spread of irrigation in Asia and Africa are lack of access to water, lack of access to energy, and lack of access to finance (Mashnik et al., 2017). The same problem is still evident in rural areas due to causality with poverty and the cost of irrigation and access to water supply. For instance, Quddus and Kropp (2020) labor accounted for the highest proportion of agriculture expenditures (51.3%), followed by equipment rental (11.8%), pesticides (9.3%), and irrigation (8.2%) in five lagging districts of Bangladesh based on the percentage of the population below the lower poverty line. This sad reality gives greater reason to focus on the inclusivity in the distribution of enablers of poverty reduction. Specifically, improving access to FEW resources is critical in improving the livelihoods of millions of people in rural areas in Asia, where most low-income earners reside (UNCRD, 2021). Yet, researchers have largely overlooked the emerging trend on FEW resources' supplies concerning the urban-rural income gap. While existing empirical evidence literature indicates that FEW resources are essential in eradicating hunger, they are often at the national level and might bias the rural sector. For instance, the agricultural sector has been established to reduce poverty rates in ASEAN countries, including Indonesia, Malaysia, Philippines, Thailand, Cambodia, and Myanmar (Mukhlis et al., 2021). This study explores the Economic analysis of the Food, Energy, and Water (FEW) Nexus in Urban and Rural Income Gap in Southeast Asian Countries. It draws empirical evidence from three Asian countries: China, Indonesia, and India.

2. LITERATURE REVIEW

2.1. Dual-Sector Model of Economic Growth and Agglomeration Economies

Every economy has two major social classes: Rural and urban population. Arthur O. Lewis postulated the dual-sector model of economic growth and structural transformation (1954). He predicted that transferring surplus labor from a traditional agricultural sector to the modern industrial and services sector would stimulate sustainable development and increase the population's average income. Lewis (1954) anticipates that such a labor switch shifts an economy from a high to a low urban-rural income gap in the long run. The rural sector is predominantly agricultural, with low productivity, low wages, and abundant labor. Contrarily, the urban areas are industrial-based, characterized by high productivity, high wages, and a demand for more workers. The high wages in urban areas incentivize the surplus labor from the rural areas to migrate to the urban areas, where they can earn higher incomes and improve their living standards. Since the marginal product of labor in the agricultural sector is zero or negative, surplus labor can be moved to another sector without affecting agricultural output. According to Lewis, such wage-differential induced urban-rural migration is critical in reducing urban-rural. The development process continues until the surplus labor in the agricultural sector is exhausted, and the wage differential between the two sectors disappears. The reduced rural population reduces the pressure on the land, increasing the agricultural sector's productivity. Besides, the industrial sector grows faster than the agricultural sector, leading to structural change in the economy. The share of industry in GDP and employment increases, while the share of agriculture decreases. In the long run, the economy from agriculturally based growth, associated with low incomes, to industrial growth, associated with higher wages. Here, the economy reaches a stage of maturity, and growth depends on technological progress and human capital accumulation. Asian countries have not yet attained this equilibrium. However, there has been an impressive growth in the reduction of rural income gaps in recent years, indicating that Lewis's equilibrium might still be feasible in the long run.

Using China as an example, it has undergone rapid urbanization, yet the rural-urban income gap is still evident. Over the period 1978-2019, China's urbanization rate increased from 17.9% to 60.6% (National Bureau of Statistics of China, 2020). Rural living standards have risen significantly in China during the last two decades, but urban households still earn much more than them. In 2010, the average annual per capita disposable income of rural households in China was 18779, about 2.99 times higher than the income of urban households (6272 yuan. In 2022, the average annual per capita disposable income of urban households in China was 49 283 yuan, 2.45 times higher than that of rural households (20,133 yuan) (Statista, 2023). The trends indicate that China's rural income gap has not substantially fallen in expectation of Lewis's theory but could be feasible in the long run. Empirical evidence in Asia has demonstrated substantial evidence of Lewis's theory. Using spatial data from Chinese cities from 2006 to 2014, Zhong et al. (2022) established an inverted U-shaped relationship between urban expansion and the urban-rural income gap. The authors observed that a 1% urban expansion decreases the urban-rural income gap by 0.005% to 0.011%. Thus, while urbanization seems to reduce the urban-rural income gap, the urban-rural income gap is still a persistent problem in Asia.

The inconsistency of the Lewis theory can be explained by the agglomeration economies, which adds a geographic dimension to the Lewis dual sector model (World Bank, 2009). Agglomeration economies benefit the urban setting since it affects industrial and services sectors but not agriculture. Increasing urbanization tend to concentrate the transport, service, and industrial sector in urban areas due to high demand from the high population (Krehl et al., 2016). While wage differential explains why a high concentration of industries in urban areas accelerates rural-urban migration, agglomeration economies predict such migration tends to benefit the urban setting. The rising urban population and rapid urbanization increase the demand for food, energy, and water (FEW). Existing industries profit from the rising urban population demand, further supporting employment opportunities and growth in urban areas. Thus, such a migration further stimulates the expansion of industry and services in urban agglomerations and the growth of incomes in urban areas. Increasing concentration of economic activities in urban areas deepens the urban-rural income gap.

The difference is that the two approaches are the agricultural views of Lewis, which is more supply-sided, and the agglomeration economies, which are demand-based. According to Lewis (1954), wage differential and labor mobility narrow the urban-rural wage differential. Lewis (1954) postulates that the government plays a critical role in counterbalancing the development in both sectors by ensuring equity in distributing public goods and infrastructure such as education, health, and infrastructure. The transport, service, and industrial sectors are often more concentrated in urban areas due to accessible water supply (Leigh and Lee, 2019) and energy (Fouquet, 2016; Wang and Chen, 2016).

2.2. Empirical Literature

FEW resources are the most critical in improving the incomes of rural households since the rural setting is predominantly agriculture. Nations have made huge investments in agricultural productivity through the supply of capital, including water and energy, to mitigate the impacts of climate change, such as severe drought. Therefore, there seems to be FEW resources synergy in enhancing household incomes. Empirical evidence indicates substantial evidence that agricultural production, especially from rice growing in Asia, has been established to reduce income inequality and poverty rates. In Bangladesh, Alamgir et al. (2021) established that higher income from agriculture contributed to lower income inequality in the districts. The authors also observed that the loss of rice yields due to climate change leads to increasing poverty rates in districts where rice is the main cash crop. As a result, food supplies help households from rural areas, where agriculture is the main economic activity, improve their incomes. Koswana (2019) found provinces in serious poverty and food security problems in South Africa. This could be due to their low income, which does not support their daily and basic household needs such as transport costs, medical care, and clothes. They tend to their social income grants or incomes and household needs, leaving less for food purchases and agricultural development, further deepening their food insecurity. Generally, the empirical evidence indicates that poverty and food security are positively correlated predominantly in rural areas. This study also shows sufficient evidence that reducing food insecurity could alleviate poverty, especially in rural areas.

Electricity supply is also crucial in enhancing socio-economic development. Raghutla and Chittedi (2022) analyzed the impact of access to electricity on economic development across five emerging countries (Brazil, Russia, India, China, and South Africa), spanning 1990-2018, and using the panel modeling methodology. They found that access to electricity played a considerable role in promoting economic development across these countries. In China, Xie and Xie (2023) established that improving electricity accessibility and promoting clean cooking energy are important policy measures for alleviating energy poverty and improving rural development. Electricity supply reduces the energy poverty index based on five dimensions: Household cooking fuel, lighting, household electrical appliance services, entertainment/education, and communication. These welfare measures are essential in enhancing incomes in rural households by improving employment outcomes.

3. MATERIALS AND METHODS

3.1. Data and Variables

The study targeted Asian countries. However, due to data constraints on the rural and urban setting measures, the study used a convenient sample of panel data over 20 years from 2000 to 2019 from three Asian countries: China from Eastern Asia, India from Southern Asia, and Indonesia from Southeast Asia.

3.1.1. Dependent variables

The study operationalized the income gap using two metrics: Poverty rates and income gap as defined by the World Bank. (n.d.-a). Poverty rates refer to the percentage of the population that lives below the poverty line. The study operationalized the poverty rate as the percentage of the population living below $2.15. The poverty gap, a ratio by which the mean income of the poor falls below the poverty line, shows how much income would be needed to lift all the poor out of poverty. The study operationalized the poverty rate as the ratio by which the mean income of the poor falls below the poverty line, $2.15, expressed as a percentage. Both poverty rates and gaps data were downloaded from the World Bank. (n.d.-a).

3.1.2. Independent variables

The FEW resource metrics are outlined as follows:

Food insecurity: This study operationalized food insecurity using two metrics due to data access constraints. First, the prevalence of undernourishment (% of the population) indicates the proportion of people who do not have enough food to meet their minimum dietary energy requirements over 1 year. For Indonesia, the prevalence of undernourishment (% of the population) was downloaded from FAO (2019). Second, the Food Insecurity Experience Scale (FIES) is a tool that measures the severity of food insecurity at the household or individual level based on people's own experiences and perceptions of not having enough food (Ballard, Kepple, and Cafiero, 2013). Prevalence of severe food insecurity in China and India: Food Insecurity Experience Scale (FIES). This indicator measures the proportion of people uncertain of having or unable to acquire enough food because they have insufficient money or other resources. Due to significant data gaps by urban and rural areas were incomplete were imputed using MA (3) and empirical studies.

Access to electricity: Access to electricity is a widely used and important metric to understand what share of the population has access to modern, clean energy seeking to decarbonize power systems rapidly. This study is an operationalized dissertation using the World Bank's definition. According to the World Bank, access to electricity is the percentage of the population with access to electricity. In this study, access to electricity was operationalized as the percentage of the cohort population with access to clean fuels and technologies for cooking (World Bank, n.d.-b).

Access to clean fuels and technologies for cooking: Access to clean fuels and technologies for cooking is a measure of how many people in a population have access to cooking methods that are not harmful to their health or the environment. According to the World Health Organization [WHO] (2020), clean fuels and technologies are those that attain the fine particulate matter (PM 2.5) and carbon monoxide (CO) levels recommended in the WHO global air quality guidelines. Clean fuels and technologies include solar, electric, biogas, natural gas, liquefied petroleum gas (LPG), and alcohol fuels, including ethanol. In this study, the proportion of the urban and rural population with access to clean fuels and technologies for cooking was extracted from the World Bank (n.d.-b).

Improved water access: In this study, improved water access was operationalized as the people using at least a basic improved drinking water source, including piped water on premises (piped household water connection located inside the user's dwelling or plot) and other improved drinking water sources (public taps or standpipes, tube wells or boreholes, protected dug wells, protected springs, and rainwater collection). The data for this series was extracted from OWID (Our World in Data, n.d).

Urban: Binary urban identifier coded 1 if urban otherwise, 0.

3.1.3. Control variable

To avoid omitted variable bias, the study controls for population growth since it may affect the urban-rural income gap. According to the Malthusian theory of population (Malthus, 1986), high population growth can exceed the ability of agriculture to produce enough food, which could limit the impact of food on reducing poverty and income gaps. The annual population size of urban and rural areas was extracted from Our World in Data [OWDI] (n.d.-c).

3.2. Design

The data is stacked panel data across rural-urban settings with each country over 2000 and 2019, given the two cross-section IDs (setting and country). This study adopted a Difference-in-Differences DID model framework to control for group differences (rural-urban settings) and time differences. Unlike other novel time series regression models, the DID does not assume continuity in time, assumes a major disruption shock, and performs a contrast of two periods. It eliminates the autoregressive short-term trends and considers the long-run change in urban-rural dynamics over time. Besides, the analysis adopts the DID model to circumvent the typical endogenous problems, such as an unobserved confounder whose effects do not change over time (Meyer, 1995). The DID model also allows for control of the systematic differences between the treatment and control groups and isolates the changes in outcomes over time. Thus, the DID approach covariates can remove the biases resulting from trends caused by other factors.

The motivation to adopt the DID model is to examine how the global financial crisis of 2008 and 2009 shaped income inequality and poverty index in rural and urban Southeast Asian Countries.

The setup for the DID model in this study has four components: Two groups, two periods, outcomes, and covariates (Sun and Shapiro, 2022; Wooldridge, 2023), which are described as follows. Under this framework, rural and urban settings denote the groups, and the global financial crisis of 2008-2009 is the treatment. The urban setting is assumed to be treated, whereas the rural setting is controlled. The pre-treatment period will be the period before 2010, and the post-treatment period between 2010 and 2020. The coding of the periods was done as follows. First, we have *two groups*: D = 1 if treated or D = 0 for control groups. In this case, we consider the residents in urban settings as the treated group due to their strategic location to take advantage of urbanization, which comes along with increased water supply and energy access to support industrialization, then those in rural settings. Secondly, two *periods are* defined as T = 0 for the pre-treatment period and T = 1 for the post-treatment period. Unlike panel regression analysis, which uses a dummy for years to capture the time effects, the DID model assumes pre- and post-treatment periods.

The global financial crisis of 2008-2009 (financial crisis) is a major economic disruption that shaped the major economic sectors, such as the financial and service sectors. The epicenter of the financial crisis was the housing market bubbles, which started in the United States and spread to countries like the UK, Spain, and Ireland. The crisis profoundly impacted the global economy and reshaped market dynamics across private funds, bankruptcy, and real estate sectors since households borrowed more than they could afford (Bartmann, 2017). As a result, the shock might have shaped the growth of other sectors twofold. First, there could be a possible investment switching to other more resilient sectors, such as the energy and food supplies sector, which are essentials of life. Secondly is lending institutions' moral hazard. The novel financial crises amplified the financial systems' vulnerabilities, challenging lending institutions to be more prudent and proactive when lending. Plausibly, banks fund investments with a higher probability of returns. As in the current, we would expect bank investment to have shifted to more resilient sectors dealing with FEW resources since they are the basic life-supporting resources. Thus, we consider it a major disruption that shaped pivotal growth in sectors dealing with FEW supplies. But to what extent rural and urban settings are preferential is to be uncovered in this study. The study anticipates that urban settings would make preferential funding to FEW supply investors in urban settings due to higher expected returns than funding rural areas investments. Consequently, a dummy for the pre-crisis and crisis period will be the pre-treatment period and the post-crisis period as the post-treatment period.

Third are *outcomes*: Income inequality and poverty index. $Y_{0i}(t)$ denote the outcome i in period t if not treated before t, and $Y_{1i}(t)$: Outcome i in period t if treated before t. The treatment effect is estimated as the difference between the two entities $Y_{1i}(t) - Y_{0i}(t)$; hence, DID. Further, let D_i be a Bernoulli distribution (outcomes 0 and 1), then the outcomes at time t are represented in Equation 1 (Callaway & Sant'Anna, 2021; Wooldridge, 2023).

$$Y_{i(t)} = Y_{0i(t)}\left(1 - D_{i(t)}\right) + Y_{1i(t)Di(t)} \tag{1}$$

Define Average Treatment Effect (ATET) in Equation 2.

$$ATET = E\left[Y_{1(1)} - Y_{0(1)}|D = 1\right] \tag{2}$$

However, if it assumed that both urban (treated) and rural (non-treated) had the same trend in the absence of the treatment,

$$E[Y_{0(1)} - Y_{0(0)} \mid D = 1] = E[Y_{0(1)} - Y_{0(0)} \mid D = 0];$$
$$\rightarrow ATET = \left[E\left[Y_1|D = 1\right] - E\left[Y_1|D = 0\right]\right]$$
$$-\left[E[Y_0|D = 1] - E\left[Y_0|D = 0\right]\right] \tag{3}$$

Considering the model covariates, the DID model in Equation 4 will be fitted.

$$\Delta Y_i = \mu + \gamma D_i + \delta T_i + \alpha D_i T_i + \beta \Delta X_i + \tau \Delta X_i \Delta X_j$$
$$+ \vartheta Cov + \pi_i \Delta lnpop + \varepsilon_i \tag{4}$$

Where Y_i are the two outcome variables (income inequality and poverty index), $\propto$ is the constant, X is a matrix of time-varying FEW resources; Δ is the differential operator whose order is dependent on the stationarity of the data; γ is the treatment effect, δ is the time effect; α is the interaction effect between treatment and time, β_s are the regression coefficients of each of the FEW metrics, namely the prevalence of severe food insecurity, access to electricity, clean fuels and technologies for cooking, and water; τ denotes the interaction effect of the FEW resources that help identify the nexus between FEW in influencing in urban and rural income gap; ϑ is the variant controlling for the Covid-19 dummy (*Cov*) coded 1 for the years 2020 and 2021 otherwise zero, and ε_i is the error term capturing the variation in outcome measures not accounted for by the model.

The data analysis was done using R Version 4.3.1 (R Core Team, 2023).

4. RESULTS AND DISCUSSION

4.1. Trends

Poverty gaps and rates have substantially declined over the past two decades for the three countries, China, India, and Indonesia. On average, China has significantly progressed, followed by Indonesia and China. In all three countries, poverty gaps and rates in the pre-crisis period were higher than in the post-crisis period. Besides, there is evident urban-rural disparity in poverty gaps and rates. See Figure 1.

Income inequality is generally significantly higher in rural areas pre-crisis than in urban areas. However, the disparity is in the post-crisis period: Poverty gaps and rates. Generally, urban areas have historically been higher in urban areas than rural areas. However, there is evidence that the margin is declining over time. This study's narrowing margins are linked with FEW resources using a DID model. The goal is to control group differences between urban and rural settings and time differences. The 2008/09 financial crisis was a structural breaking point that delimits the sample period to pre- and post-crisis periods.

4.2. Regression Results

4.2.1. Poverty rates

Table 1 shows the two-way fixed effects regression results on poverty rates with and without adjustments for covariates while controlling for population size. Model 1 shows the two-way fixed effects regression results while controlling for population size. The treatment effect is not statistically significant ($\beta = 0.1916$, $P > 0.05$), implying that the financial crisis did not significantly influence poverty rates in urban areas than rural areas, assuming all other confounders were kept constant. Different sub-models were fitted to establish potential FEW influencers on urban and rural poverty-rated differential. In model 2, food insecurity is added to model 1. The results show that food insecurity significantly increased poverty rates over the study period by 0.56% ($\beta = 0.0056$, $P < 0.01$). However, the treatment effect on poverty rates is still not statistically significant ($\beta = 0.1934$, $P > 0.05$). The results imply that if food insecurity in rural and urban areas were kept constant, poverty rates in urban areas in the post-crisis period would not be significantly different from rural areas.

In model 3, improved water access is added to model 1. The results show that improved water access did not significantly affect poverty rates over the study period ($\beta = -0.0023$, $P > 0.1$). However, the treatment effect becomes statistically significant ($\beta = 0.1683$, $P < 0.05$). The results imply that if the water supply in rural and urban areas were kept constant, poverty rates in the post-crisis period would be 16.83% higher in urban areas than in the rural areas.

Model 4 adds improved clean fuel and cooking technology to Model 1. The results show that clean fuel and cooking technology did not significantly affect poverty rates over the study period ($\beta = -0.009$, $P > 0.1$). However, the treatment effect becomes statistically significant ($\beta = 0.1919$, $P < 0.05$). The results imply that if clean fuel and cooking technology in rural and urban areas were kept constant, poverty rates in the post-crisis period would be 19.19% higher in urban areas than in the rural areas.

In model 5, an electricity supply is added to model 1. The results show that electricity supply significantly reduced poverty rates over the study period by 16.70% ($\beta = -0.1670$, $P < 0.001$). However, the treatment effect on poverty rates is still not statistically significant ($\beta = 0.1934$, $P > 0.1$). The results imply that if electricity supply in rural and urban areas were kept constant, poverty rates in urban areas in the post-crisis period would not be significantly different from rural areas.

Figure 1: The Graph Shows the Poverty Rates Trend in Rural and Urban Areas in China, India, And Indonesia Over 20 years between 2000 and 2021

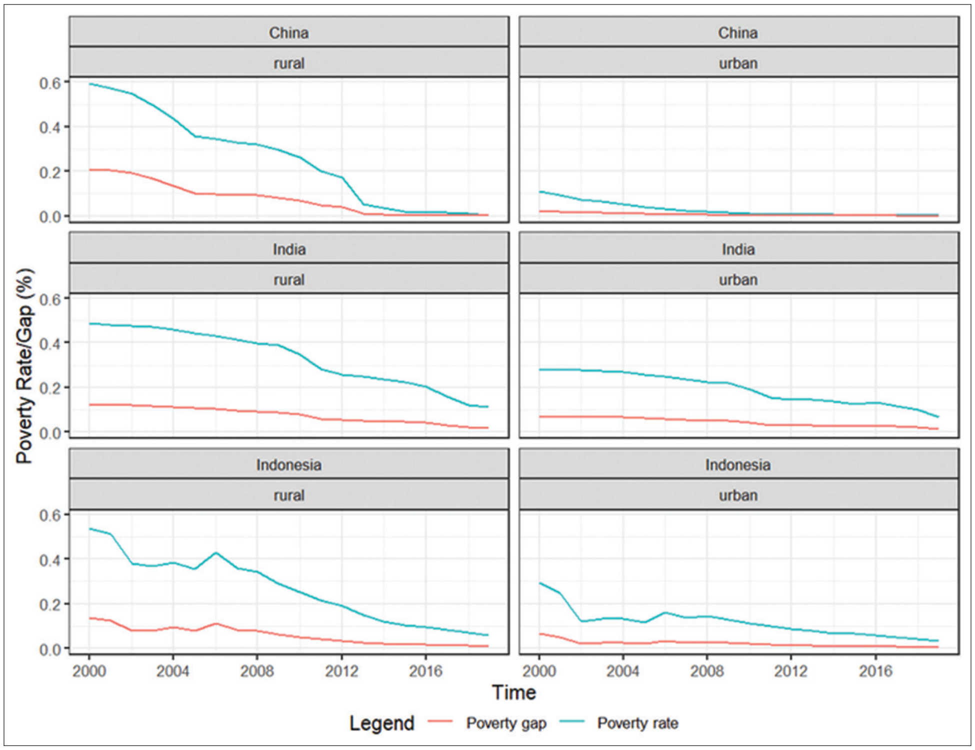


Table 1: Difference-in-differences estimate of the effect of financial crisis and few resources on poverty rates

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Treated	0.190	0.193	0.1683**	0.1919*	0.169	0.082	0.052	0.089	0.027
	(0.076)	(0.069)	(0.034)	(0.063)	(0.088)	(0.029)	(0.035)	(0.048)	(0.02)
Population	0.000	0.000**	0.000	0.000	0.000	0.000	0.000***	0.000	0.000**
	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)
Food insecurity		0.006***				0.006**	0.001	−0.006*	0.012**
		(0.001)				(0.001)	(0.001)	(0.002)	(0.002)
Water			−0.002			−0.011	−0.013**	−0.013*	−0.012**
			(0.004)			(0.005)	(0.003)	(0.005)	(0.003)
Clean fuel				−0.002		0.001	0.002**	−0.002**	0.005***
				(0.002)		(0.001)	(0.0002)	(0.0003)	(0.001)
Electricity					−0.167***	−0.081	0.086	0.032	0.044
					(0.003)	(0.039)	(0.08)	(0.059)	(0.079)
China							−0.186**		
							(0.024)		
India								0.249**	
								(0.056)	
Indonesia									0.283**
									(0.038)
N	120	120	120	120	120	120	120	120	120
R^2	0.815	0.915	0.817	0.834	0.835	0.935	0.966	0.950	0.965
R^2 Adj.	0.773	0.894	0.773	0.795	0.796	0.917	0.956	0.936	0.955
R^2 Within	0.333	0.692	0.338	0.403	0.406	0.766	0.878	0.821	0.874
R^2 Within Adj.	0.319	0.682	0.317	0.384	0.387	0.750	0.868	0.807	0.864
AIC	−258.8	−349.6	−257.8	−270.1	−270.8	−376.4	−452.4	−406.5	−448.6
BIC	−194.7	−282.7	−190.9	−203.2	−203.9	−301.1	−374.3	−328.5	−370.5
RMSE	0.070	0.050	0.070	0.060	0.060	0.040	0.030	0.040	0.030
FE: Setting	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
FE: Time	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Country and time-fixed effects were excluded from the table but included in the regression model. The treatment coefficient is an interaction between treated-group" and "after-treatment/post-crisis periods (after 2011). Statistics robust to heteroskedasticity are based on clustering by country.; ***Significant at the 1% level.; **Significant at the 5% level; *Significant at the 10% level

Model 6 pools are the FEW resources in model 1. Food insecurity is the only predictor with a statistically significant effect on poverty rates. On average, food insecurity increased poverty rates over the study period by 0.62% ($\beta = 0.0062$, $P < 0.01$). However, the treatment effect on poverty rates is still not statistically significant (β = 0.0823, P > 0.1). The results imply that if FEW resources in rural and urban areas were kept constant, poverty rates urban areas in the post-crisis period would not be significantly different from rural areas. See Figure 2.

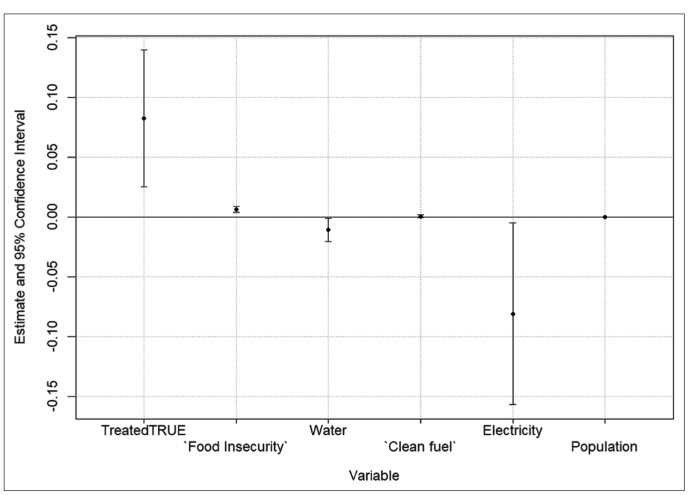
Models 7, 8, and 9 show within-country analysis. China has significantly lower poverty rates (β = −0.1858, P < 0.05), whereas India (β = 0.2486, P < 0.05) and Indonesia (β = 0.2833, P < 0.05) have significantly higher poverty rates. The FEW resources seem to have different effects on poverty rates. Food insecurity has no significant effect on poverty rates in China (β = 0.0013, P > 0.05) but has a negative significant effect in India (β = − 0.0056, P < 0.1) and a positive significant effect in Indonesia (β = 0.0122, P < 0.05). Water has a negative significant effect on poverty rates in China (β = −0.0134, P < 0.05), India (β = −0.0133¸ P < 0.1) and Indonesia (β = −0.0118, P < 0.05). Clean fuels and energy technologies have a positive significant effect on poverty rates in China (β = 0.0017, P < 0.05) and Indonesia (β = 0. 0049, P < 0.01 but a negative significant effect on poverty rates in India (β = −0. 0016¸ P < 0.05) However, electricity seems to have no partial effect (all P < 0.055). The established heterogeneity in the effect of FEW resources is controlled for by clustered standard errors by country in models 1 and 6.

Generally, the results indicate that food insecurity increases poverty rates, whereas electricity supply reduces poverty. Besides, water and clean fuels and technologies are essential in reducing poverty rates in rural areas of SEA than in urban areas. See Figure 2.

4.3. Poverty Gaps

The two-way fixed effects regression results on poverty gaps with and without adjustments for covariates while controlling for population size are presented in Table 2. Model 1 shows the two-way fixed effects regression results while controlling for population size only. The treatment effect is not statistically significant (β = 0.060, P > 0.05), implying that the financial crisis did not significantly influence poverty gaps in urban areas than rural areas, assuming all other confounders were kept constant. In model 2, food insecurity significantly increased poverty gaps over the study period by 0.09% (β = 0.0009, P < 0.05). However, the treatment effect on poverty gaps is still not statistically significant (β = 0.0609, P > 0.05). The results imply that if food insecurity in rural and urban areas were kept constant, poverty gap in urban areas in the post-crisis period would not be significantly different from rural areas.

Figure 2: Covariates effects on poverty rates. Notes: The regression coefficients of each variable and 95% confidence interval are estimated using a Difference-in-differences Estimate of the Effect of financial crisis and FEW resources on poverty rates while controlling for population growth. Time and country fixed effects are included in the model



Improved water access did not significantly affect poverty gaps over the study period (β = − 0.0026, P < 0.001) (Model 3). However, the treatment effect becomes statistically significant (β = 0.0357, P < 0.05). The results imply that if the water supply in rural and urban areas were kept constant, poverty gaps in the post-crisis period would be 3.57% higher in urban areas than in the rural areas. In Model 4, no significant improvement in clean fuel and cooking technology on poverty gaps (β = − 0.0001, P < 0.01) and the treatment effect (β = 0.0605, P > 0.1). The results imply that if clean fuel and cooking technology in rural and urban areas were kept constant, poverty gaps in urban areas in the post-crisis period would not be significantly different from rural areas. In model 5, no significant electricity supply on poverty gaps (β = 0. 0041, P < 0.01) and the treatment effect (β = 0. 0609, P > 0.1). The results imply that if electricity supply in rural and urban areas were kept constant, poverty gaps in urban areas in the post-crisis period would not be significantly different from rural areas.

In Model 6, clean fuel is the only predictor with a statistically significant effect on poverty gaps. On average, clean fuel and energy technologies increased poverty gaps over the study period by 0.04% (β = 0.0004, P < 0.01). However, the treatment effect on poverty gaps is statistically insignificant (β = 0.0230, P > 0.1). See Figure 3. The results imply that if FEW resources were kept constant in rural and urban areas, poverty gaps in urban areas in the post-crisis period would not be significantly different from rural areas.

The cross-country analysis results indicate that China has significantly lower poverty gaps (β = −0.0576, P < 0.05), whereas India (β = 0.0678, P < 0.1) and Indonesia (β = 0. 0940, P < 0.1) have significantly higher poverty gaps (Models 7, 8, and 9, respectively). The FEW resources have different effects on poverty gaps. Food insecurity has no significant effect on poverty gaps in China ($\beta \leq$ 0.0001, P > 0.1) but has a negative significant effect in India (β = − 0.0017, P < 0.1) and a positive significant effect in Indonesia (β = 0.0035, P < 0.05). Water has a negative significant effect on poverty gaps in China (β = −0.0049, P < 0.1) and Indonesia (β = −0.0044, P < 0.1) only.

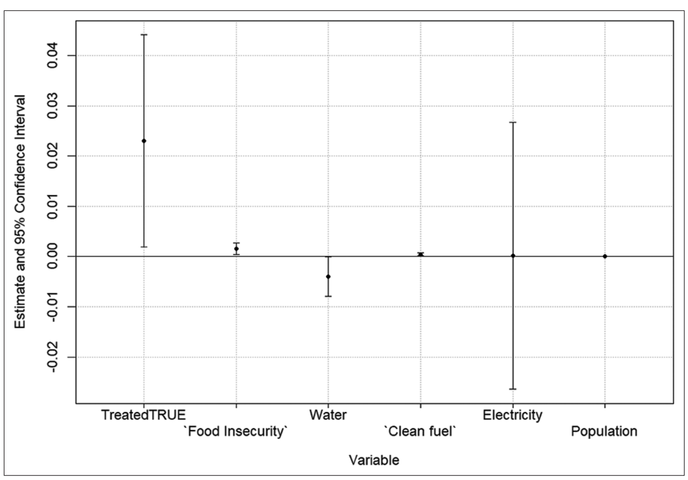
Clean fuels and energy technologies have a positive significant effect on poverty gaps in China (β = 0.0008, P < 0.05) and Indonesia (β = 0.0018, P < 0.01 only. Lastly, electricity seems to have no partial effect (all P < 0.055). The established heterogeneity in the effect of FEW resources is controlled for by clustered standard errors by country in models 1 and 6. Generally, the results indicate that food insecurity increases poverty gap gaps. Besides, clean fuels and technologies are essential in reducing poverty gaps in rural areas of SEA than in urban areas.

Table 2: Difference-in-differences estimate of the effect of financial crisis and few resources on poverty gaps

Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Treated	0.0604	0.0609	0.0357*	0.0605	0.0609	0.023	0.0135	0.0249	0.0048
	(0.026)	(0.025)	(0.008)	(0.025)	(0.027)	(0.01)	(0.012)	(0.016)	(0.006)
Population	<0.001	<0.001	<0.001**	<0.001	<0.001	<0.001	<0.001***	<0.001	<0.001**
	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)
Food insecurity		0.001**				0.002	<0.0001	−0.002*	0.004**
		(0.0002)				(0.001)	(0.001)	(0.0004)	(0.001)
Water			−0.0026			−0.004	−0.005*	−0.0047	−0.004*
			(0.0015)			(0.002)	(0.0013)	(0.002)	(0.001)
Clean fuel				−0.0001		0.0004*	0.0008**	−0.0002	0.0028**
				(0.0003)		(0.0001)	(0.0001)	(0.0001)	(0.0003)
Electricity					0.0041	0.0001	0.0518	0.0309	0.0417
					(0.014)	(0.014)	(0.043)	(0.03)	(0.044)
China							−0.058**		
							(0.012)		
India								0.068*	
								(0.018)	
Indonesia									0.094*
									(0.022)
N.	120	120	120	120	120	120	120	120	120
R^2	0.811	0.844	0.834	0.812	0.811	0.897	0.932	0.91	0.936
R^2 Adj.	0.768	0.807	0.794	0.767	0.766	0.868	0.912	0.884	0.917
R^2 Within	0.402	0.507	0.473	0.404	0.402	0.674	0.785	0.716	0.797
R^2 Within Adj.	0.39	0.491	0.456	0.385	0.384	0.653	0.769	0.694	0.782
AIC	−552.7	−573.8	−565.8	−551.1	−550.8	−617.3	−665.6	−632.1	−672.4
BIC	−488.6	−506.9	−498.9	−484.2	−483.9	−542.1	−587.6	−554.0	−594.3
RMSE	0.02	0.02	0.02	0.02	0.02	0.01	0.01	0.01	0.01
FE: Setting	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
FE: Time	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Country and time-fixed effects were excluded from the table but included in the regression model. The treatment coefficient is an interaction between treated-group" and "after-treatment/post-crisis periods (after 2011). Statistics robust to heteroskedasticity are based on clustering by country.; ***Significant at the 1% level.; **Significant at the 5% level.; *Significant at the 10% level

Figure 3: Covariates effects on poverty gap. Notes: The regression coefficients of each variable and 95% confidence interval are estimated using a Difference-in-differences Estimate of the Effect of financial crisis and FEW resources on poverty gaps while controlling for population growth. Time and country fixed effects are included in the model



5. DISCUSSION

This study examined how FEW influences the urban-rural income gap using a DID model. Using annual data from China, India, and Indonesia from 2000 to 2019, the results indicate that food insecurity increases the poverty gap or rates. Generally, food insecurity was higher in rural areas than in urban areas due to confounders such as household size, income, education, gender, occupation, and region were significant factors influencing food insecurity. Food insecurity can widen income gaps between urban and rural households' gap since it can have a negative causality effect on other socio-economic well-being measures such as wealth, health, education, income, and social relations (Hameed et al., 2023; Mota et al., 2019). Koswana (2019) established that poverty and food security are positively corelated predominantly in rural areas in South Africa. Mota et al. (2019) established that households with large family sizes who cannot read and write are more likely to be food insecure than their counterparts. Thus, food insecurity can lead to poverty by reducing human capital, productivity, and income (Bartelmeß et al., 2022). Therefore, addressing food insecurity is not only a matter of ensuring adequate food supply but also a matter of enhancing opportunities and empowerment. Improved electricity and water supply could be potential avenues for enhancing agricultural productivity to mitigate food insecurity.

The study also established that electricity supply significantly reduces poverty rates. Electricity supply is essential for economic and social development, especially in developing countries (Raghutla and Chittedi, 2022; Xie and Xie, 2023). Electricity can improve the quality of life of low-income people by providing access to education, health, communication, entertainment, and other services. Electricity can also enhance the productivity and income of people experiencing poverty by enabling them to use modern technologies, machinery, and equipment in various sectors such as agriculture, industry, and commerce. Besides, improved electricity supply provides adequate energy resources to support income-generating activities such as irrigation and farm machinery in agriculture. Electricity can be used to power pumps for groundwater or surface water, modern irrigation systems such as sprinkler or drip, processing centers for coffee, cereals, grain and rice mills, crop drying, animal husbandry, and centers for processing and storing dairy products and meat, heated shelters, feed mixing and processing (Cook, 2012; Singh et al., 2021; Uddin et al., 2021). Electricity can also support small businesses such as bakery, hairdressing, carpentry, and welding. All these economic activities support the employment of rural households and increase their income levels. Besides, electricity can also enable the use of computers, the internet, mobile phones, and other communication devices that can improve access to information, markets, and customers. Besides, electricity or clean fuel technologies can provide lighting, heating, cooling, refrigeration, sterilization, and other services in social amenities such as health facilities and schools. Moreover, the quality of education improves since schools can be equipped with computers, the Internet, and other learning resources for schools and training centers. As a result, rural residents are equipped with soft and technical skills that enhance their employability.

6. CONCLUSION

This study examined how FEW influences the urban-rural income gap using a DID model. Using annual data from China, India, and Indonesia from 2000 to 2019, the results provide substantial evidence that high food insecurity increases income inequality. Besides, urban areas benefit significantly from improved electricity, water access, clean fuel, and cooking technology and have lower poverty rates than rural areas. Generally, water and energy can enhance income and welfare by creating employment opportunities and improving learning outcomes in rural populations. Improving water and electricity supply enhances agriculture, service, and industry employment opportunities, increasing rural households' income levels. The results indicate that if the water supply, clean fuel, and cooking technology in rural and urban areas were kept constant, income inequality would be higher in urban areas in the post-financial crisis than in rural areas. Free or subsidized water and energy sources such as clean fuels or electricity can enhance investment in water and energy-saving technologies in agriculture and industry.

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