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Can Transport Infrastructure Reduce Inequality in Archipelagic Economies? Evidence from the Philippine Roll-on/Roll-off Network

Kris A. Francisco and Kimberly R. Librero

CONTACT US:
RESEARCH INFORMATION DEPARTMENT
Philippine Institute for Development Studies

18th Floor, Three Cyberpod Centris - North Tower
EDSA corner Quezon Avenue, Quezon City, Philippines

https://www.pids.gov.ph
publications@pids.gov.ph
(+632) 8877-4000

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Kimberly R. Librero

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Abstract

The Philippines demonstrates a puzzling disconnect between economic growth and distributional outcomes as decades of expansion have failed to deliver significant changes in poverty and income inequality. A frequently discussed strategy for inclusive growth is strategic investment in infrastructure, particularly in lagging regions. To augment limited literature on this topic, this study examines whether transport infrastructure investment can reduce income inequality by exploiting the staggered implementation of the nautical highways included in the Roll-on/Roll-off (RoRo) Terminal System that started in 2003. The staggered adoption design allows us to examine dynamic treatment effects and determine whether impacts vary with exposure duration and distance from infrastructure. Using a difference-in-differences approach, we assess how infrastructure affects the local income and inequalities, by comparing outcomes between port municipalities that joined the RoRo network and those that remained conventional ports over the period 2000 to 2020. We examine within-municipality inequality through Gini coefficients calculated from asset indices using Census data. Our analysis further extends to neighboring municipalities to capture possible externalities. Overall, our findings provide critical empirical evidence on infrastructure's distributional effects in developing, and archipelagic economies.

Keywords: income inequality, transport infrastructure, Roll-on/Roll-off, archipelagic economy, impact evaluation, Philippines

JEL Classification: O18, R11, R42, D63

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Can Transport Infrastructure Reduce Inequality in Archipelagic Economies? Evidence from the Philippine Roll-on/Roll-off Network

Kris Francisco and Kimberly Librero

1. Introduction

The Philippines presents a puzzling paradox as decades of economic growth did not result to corresponding reductions in poverty and income inequality. Between 2000 and 2018, the country's GDP per capita grew by an average of 3.5 percent annually, yet income inequality remained stubbornly high, with Gini coefficients persisting around 0.40 to 0.43 (Capuno 2022). This enduring inequality is not only a distributional concern but also a constraint to potential economic growth. Studies show that high level of income inequality is linked to poorer health and educational outcomes (Matthew and Brodersen 2018, Workman 2022), limiting long-run productivity and innovation capacity. Highly unequal societies are also prone to social tensions and political instability (Kakwani and Son 2016), creating unfavorable climate for sustained economic development.

The weak linkage between growth and poverty reduction in the Philippines has been well documented in the literature. Estudillo (1997) analyzed income inequality in the Philippines from 1960s to 1990s and found that estimated Gini coefficients based on household income was consistently close to .50, showing trends that appear to be on a stable path. Balisacan (2000) argues that compared with other East Asian countries like China, Thailand, and Indonesia, the Philippines experienced growth that was relatively short in duration and slow, constricting its capacity to reduce absolute poverty. This highlights a fundamental challenge wherein economic expansion bypasses large segments of the population.

On a positive note, Capuno (2022) demonstrates improvement in income inequality over recent years with computed Gini index based on consumption expenditures shrank from 43.1 percent in 2012 to 41.7 percent in 2015, and finally, 39.2 percent in 2018. According to this study, economic growth and income redistribution finally aligned after 2012, reflecting notable reductions in poverty levels. A similar finding was presented by Reyes et al. (2020) noticing the decrease in the magnitude and incidence of poverty, income gap as well as severity of poverty in 2018. Despite recent positive developments however, income inequality remains a pressing concern in the Philippines requiring targeted interventions.

A frequently proposed strategy for stimulating inclusive growth is strategic investment in infrastructure, particularly in lagging regions. This recommendation takes on special significance in the Philippine context due to the country's archipelagic geography. The fragmentation of the Philippines into more than 7,000 islands creates natural barriers to economic integration, with disparities in physical infrastructure across island economies constraining development (Llanto 2007; ADB 2010). Manasan and Chatterjee (2003) argue for well-distributed infrastructure investments to enable lagging regions to catch up with better-performing ones, reducing spatial inequalities that contribute to overall income disparities.

Despite the intuitive appeal of this argument and its prominence in policy discourse, empirical evidence on how infrastructure affects household income distribution remains surprisingly limited, especially in developing and archipelagic contexts. Most existing studies focus on infrastructure's aggregate growth effects or examine distributional impacts in continental settings, leaving a critical knowledge gap about whether or how connectivity improvements translate into more equitable development in island economies.

This study addresses this gap by conducting a rigorous empirical assessment of transport infrastructure's impact on local income and inequality in the Philippines. We exploit a unique quasi-experimental opportunity created by the Roll-on/Roll-off (RoRo) Terminal System, a transformative policy implemented starting in 2003 that established nautical highways connecting ports and major highways across the archipelago. The RoRo system represents a distinctive form of infrastructure intervention wherein instead of constructing entirely new facilities, it involved rehabilitating and redesigning existing ports and roads to accommodate roll-on/roll-off vessels, creating an integrated intermodal transport network. Crucially, different nautical highways became operational at different times (in 2003, 2008, 2009, and subsequently for lateral connections), providing temporal variation that enables the identification of causal effects.

Our empirical strategy leverages this staggered implementation through a difference-in-differences approach, comparing municipalities that gained access to the RoRo network at different times with municipalities that hosted ports but never became part of the network. This design allows us to track changes both within municipalities over time and between treated and control municipalities, capturing the potentially wide-ranging impacts of improved connectivity. We examine several outcomes including local taxes, business taxes and real property taxes to track changes in local income. We assess within-municipality inequality through Gini coefficients calculated from simulated income based on asset indices constructed from representative household surveys. By covering the period from 2000 to 2020, our analysis captures both short-term and long-term effects, as well as the cumulative impact of sustained network connectivity. Further, we extend our analysis to neighboring municipalities to capture possible spillover effects. We utilize the same staggered difference-in-differences approach, comparing municipalities in close proximity to RoRo ports, against those near ports that were never integrated into the RoRo network.

This study makes several significant contributions to the literature and policy discourse. First, it provides much-needed empirical evidence on infrastructure's inequality effects from a developing country perspective, addressing a gap in the existing literature that remains heavily concentrated on developed economies. Second, it offers insights specifically relevant to archipelagic economies, where connectivity challenges are particularly severe but empirical evidence is scarce. Third, methodologically, our exploitation of staggered policy implementation demonstrates how temporal variation in infrastructure development can be harnessed to establish causal relationships. This approach could inform evaluation strategies for other infrastructure programs. Finally, from a policy perspective, our findings offer concrete evidence on whether transport infrastructure investments deliver on their promise of inclusive growth, providing actionable insights for long-term infrastructure planning in the Philippines and similar contexts.

Our analysis centers on four specific research questions that hold direct policy relevance:

- *Do infrastructure projects have measurable effects on local income levels?*
  We assess whether gaining RoRo connectivity leads to increases in average municipal income, and if so, what magnitude of effects can be expected over different time horizons.

- *Does infrastructure affect income inequality within communities?*
  Beyond aggregate income effects, we examine whether RoRo connectivity reduces, increases, or leaves unchanged the distribution of income within municipalities, a critical question for inclusive growth.

- *Do effects vary by location relative to the infrastructure?*
  We explore whether impacts differ between municipalities directly hosting RoRo ports and neighboring municipalities, shedding light on the spatial extent of infrastructure benefits and potential spillover effects.

- *What policy adjustments might be necessary?*
  Based on our empirical findings, we identify implications for infrastructure planning, including whether network expansion should prioritize certain types of locations or whether complementary policies are needed to maximize distributional benefits.

The remainder of this paper proceeds as follows. Section 2 provides context on income inequality trends in the Philippines and details the establishment and evolution of the RoRo Terminal System. Section 3 reviews the relevant literature on infrastructure and inequality. Section 4 outlines our empirical strategy, identification approach, and sources of data. Section 5 presents our results and discusses the interpretation and implications of our findings. Finally, Section 6 concludes our paper.

2. Context and Background

2.1. Inequality in the Philippines

The Philippines has long struggled with persistent income inequality. Studies reveal that inequality has remained stubbornly high for many decades. Estudillo (1997) showed that Gini coefficients based on household income remained close to 0.50 from the 1960s through the 1990s, suggesting stable patterns of inequality. Throughout the 1990s and early 2000s, the Philippines maintained relatively high levels of income inequality, with the Gini coefficient ranging from 0.45 to 0.48, and reaching a peak of 0.52 during the 1997 Asian Financial Crisis (Abante et al. 2017, Reyes et al. 2012). Balisacan (2000) explained that economic development in the country was relatively short in duration and slow compared to other East Asian Economies, and this pattern limits our capacity to bring significant changes in the level of poverty and income inequality. Meanwhile, the Philippine economy was growing at an average of 5 percent annually between the 2000 and 2012 yet, it was only after 2012 that sustained improvements in inequality was finally evident. Capuno (2022) demonstrated a notable decline in Gini index based on household expenditures from 43.1 percent in 2012 to 41.7 percent in 2015, and further to 39.2 percent in 2018.

Beyond aggregate national trends, income inequality in the Philippines shows pronounced spatial dimensions rooted in the country's archipelagic structure. Regional disparities are substantial, with Metro Manila enjoying per capita income approximately 2.75 times the national average and more than twelve times that of the poorest regions, many of which are in Mindanao and the Visayas (Balisacan and Fuwa, 2004). The Asian Development Bank (2010) relates this uneven development patterns to disparities in physical infrastructure across Philippine regions, which was seen as a constraint to economic integration. Llanto (2007) likewise identifies critical infrastructure-related constraints to economic growth and equitable development, arguing that the archipelagic nature of the Philippines creates an additional layer of constraint beyond those faced by continental developing economies. The fragmentation across more than 7,000 islands creates natural barriers to trade, limits economies of scale, and constrains factor mobility.

Francisco and Lim (2022) document that despite the crucial role of infrastructure in facilitating interisland mobility and trade, public infrastructure investment in the Philippines was only about 3 percent of GDP from 2011 to 2016, well below the World Bank's recommendation of 4 percent of GDP for developing countries. More recently, Francisco (2024) reports that the Philippines continues to fall behind its Southeast Asian neighbors in transport infrastructure development, ranking lowest in infrastructure adequacy among eight ASEAN nations. This infrastructure deficit encompasses roads, railways, ports, and airports, raising serious concerns about the country's ability to sustain economic growth and enhance regional competitiveness.

2.2. The Roll-on/Roll-off Terminal System

Under the conditions of persistent inequality, archipelagic geography, and infrastructure deficits, the Philippine government implemented a transformative transport infrastructure policy, the Roll-on/Roll-off Terminal System (RRTS), also known as the Philippine Nautical Highway System or Strong Republic Nautical Highway (SRNH). The RoRo Terminal System emerged from recognition that the Philippines' maritime transport system was inefficient and costly, hindering economic integration across islands. An Asian Development Bank report (2010) presents a paradoxical situation that justifies the implementation of the RRTS, discussing that the cost of moving a twenty-foot container within the Philippines is three times more expensive than international shipping. This clearly illustrates the urgency of transport system reform.

The RRTS was established through Executive Order No. 170, issued on January 22, 2003. The inaugural 919-kilometer nautical highway was opened to the public on April 12, 2003, as the Strong Republic Nautical Highway. Executive Order No. 170-A, issued on June 9, 2003, expanded the coverage of the initial system. Subsequently, Executive Order No. 170-B signed on September 19, 2005, further encouraged expansion by mandating development of more RoRo-capable ports and conversion of private non-commercial ports into private commercial ports. The system comprises three primary nautical highways:

- *Western Nautical Highway* –this corridor was established in 2003 as the inaugural trunkline connecting Luzon and Mindanao. The route covers provinces and cities including Batangas City, Marinduque, Romblon, Oriental Mindoro, Aklan, Antique, Capiz, Iloilo, Guimaras, Negros Occidental, Negros Oriental, Siquijor, and portions of Zamboanga Peninsula. This flagship route serves as the tourism corridor, facilitating access to popular tourist destinations such as Boracay.
- *Central Nautical Highway* –this route was developed after the Western corridor, with initial links established between 2003 and 2005 and full operationalization achieved by 2008. The Central route provides crucial connectivity for the central Philippines, linking Luzon to Mindanao through the cities and provinces of Sorsogon, Masbate, Cebu, Bohol, Camiguin, and Cagayan de Oro.
- *Eastern Nautical Highway* –this route runs through southern Luzon, the Bicol region, provinces of Samar and Leyte, and connecting to eastern Mindanao in Surigao del Norte province. This corridor which integrates the Pan Philippine Highway, started operating around 2009.

- *Lateral routes* –lateral RoRo connections were subsequently developed to provide additional connectivity, extending the system by linking Visayas ports to key facilities in southwestern Mindanao, including connections to Zamboanga and General Santos with onward land routes to Davao. The lateral connections and expansion routes were added incrementally after 2009 through EO 170-B's provisions for private port conversion.

The RoRo system had expanded dramatically from the original 34 routes to over 113 routes throughout the country (MARINA 2020). The operation of the RRTS mainly involved the following:

Port rehabilitation and redesign: A main feature of the RRTS is the conversion and rehabilitation of existing ports and facilities to RoRo vessels. This involved construction of ramps, widening of berths, and improvements to approach channels, which avoided massive capital expenditures associated with building entirely new ports.

Road network improvements: Corresponding improvements were done by the Department of Public Works and Highways (DPWH) to road segments connected to RoRo ports. This ensured smooth vehicle transfer to and from ports.

Vessel deployment with private sector participation: Private shipping operators participated in RoRo operations by investing in RoRo-capable vessels designed to accommodate vehicles ranging from motorcycles and automobiles to ten-wheeler trucks and buses. These vessels feature bow and stern ramps enabling rapid loading and unloading.

Seamless intermodal integration: The RRTS facilitated door-to-door connectivity, allowing buses and trucks to board ferries directly and continue their journeys on the opposite shore without cargo transfer. In response, bus companies established routes utilizing the nautical highways, enabling passengers to travel from Manila to Iloilo, for example, with seamless transfers between road and sea segments.

Uniform pricing structure: Executive Order 170-B mandated all port authorities to implement uniform charges to RoRo cargoes in their respective ports. This promoted standardization and prevented discriminatory pricing, which is a perennial issue in maritime transport.

3. Literature Review

3.1. Transport infrastructure and economic growth

The relationship between transport infrastructure investment and economic growth represents one of the most extensively studied topics in development economics. Foundational theoretical work by Arrow and Kurz (1970) and Barro (1990) established how public capital accumulation affects economic growth, with Barro (1990) demonstrating that public services enhance private sector productivity through constant returns to scale when combined with private capital. Building on this foundation, subsequent empirical research established that transport infrastructure investment affects economic growth through multiple channels such as reducing transaction costs (De and Ghosh, 2006; Calderon et al., 2018), improving market access

(Donaldson and Hornbeck, 2016; Redding and Turner, 2015), enhancing productivity (Aschauer, 1989; Holtz-Eakin and Lovely, 1996), and enabling economies of scale (Holtz-Eakin and Lovely, 1996). This theoretical and empirical framework has generated broad consensus that transport infrastructure investment supports long-term economic expansion.

Recent empirical evidence supports transport infrastructure's growth-enhancing role while revealing critical nuances. Foster et al. (2023) conducted a comprehensive qualitative review of infrastructure and development linkages across digital, energy, and transport sectors, covering over 300 studies conducted between 1983 and 2022. This study confirms infrastructure's critical role in inducing development but underscores that impacts vary greatly based on context, project design, local conditions. Zhang and Cheng (2023) investigate the relationship between transport infrastructure development and economic growth in the UK from 1970-2017 and found that transport infrastructure has long-run positive impact on economic development. However, they also uncover that in the short-run, transport infrastructure construction harms the economy. This temporal pattern suggests that transport investments require extended periods to generate positive returns, with initial construction phases potentially disrupting economic activity before productivity benefits materialize.

Maritime transport infrastructure demonstrates significant economic impacts across diverse contexts. Munim and Schramm (2018) confirm that high-quality port infrastructure enhances logistics performance, leading to higher seaborne trade, and ultimately resulting to higher economic growth. This pathway is particularly important for developing nations that are heavily reliant on maritime trade. Recent quasi-experimental evidence demonstrates that port connectivity improvements generate significant regional economic growth. Zhao et al. (2023) exploit the 2016 Panama Canal expansion to show durable stimulating effects across multiple continents, identifying port infrastructure as a key transmission channel for development.

3.2. Transport infrastructure's distributional effects

While transport infrastructure's aggregate growth effects are well-established, empirical evidence on distributional impacts reveals considerable complexity. US evidence demonstrates that highway investments can serve as effective inequality-reduction mechanisms. Hooper et al. (2018) analyze US state-level panel data from 1950 to 2010 using fixed-effects regressions, revealing that growth in highway and higher education spending during a given decade correlates negatively with Gini indices at decade's end. Critically, this relationship proves more pronounced for inequality at the bottom 40 percent of the income distribution, indicating that infrastructure investments particularly benefit lower-income groups. Highway expenditures demonstrate greater effectiveness at reducing inequality compared to higher education spending. A counterfactual experiment reveals that US states with significantly higher bottom Gini coefficients in 2010 had systematically underinvested in highways during the previous decade. The authors suggest the mechanism operates through improved access to employment and education opportunities, with suggestive evidence from complementary analysis (Hooper et al., 2021) that construction sector wage growth serves as an important short-term transmission channel.

By contrast, evidence from China reveals complex distributional effects with substantial heterogeneity across regions and populations. Lu et al. (2023) investigate heterogeneous impacts of road infrastructure on rural residents' income using nationwide panel data from 2010 to 2018. They show that rural household incomes generally benefit from road infrastructure improvements, with effects varying significantly across population subgroups. Rural residents with lower initial farming and business income benefit more, suggesting progressive distributional impacts. However, those with low formal education experience smaller income improvements, underscoring the critical value of complementary human capital investments. This finding suggests that road infrastructure solely is insufficient for inclusive development because its distributional benefits depend on the populations' capacity to exploit improved connectivity.

Zhang et al. (2023) examine village road paving in China, and found that road projects increase rural household incomes, particularly for households with lower education levels and assets. Disaggregating income sources shows that road paving increases transfer payments and wages but decreases operating income significantly. Although village paved roads improve both migrant and local employment, the impact on local employment dominates, suggesting that the income gains primarily operate through enhanced local labor market opportunities rather than migration channels.

Lu et al. (2022) examine transport infrastructure's effects on urban-rural income disparities at the municipal level using Chinese data. They revealed that national, provincial, and municipal roads played positive roles in narrowing urban-rural income gaps by facilitating rural labor mobility. Provincial and municipal roads show particularly high coefficients due to their provision of access to local and regional job markets for migrant farmers. This finding suggests that different road hierarchies serve distinct functions such as national highways primarily facilitating long-distance trade, while lower-tier roads proving valuable for labor market integration and rural-urban connectivity.

Faber (2014) provides cautionary evidence on China's National Trunk Highway System, showing that while the highway network generated aggregate trade integration benefits, non-targeted peripheral counties connected to the network experienced reduced GDP growth due to significant reductions in industrial output. Improved connectivity allowed manufacturing activity to concentrate in core cities with better factor markets and agglomeration economies, draining peripheral counties of economic activity. The average pre-existing market size difference between peripheral counties and metropolitan centers was 1:25, and the evidence supports core-periphery effects predicted by increasing returns to scale trade theory. This finding reveals a critical distributional concern wherein transport infrastructure investments generate aggregate gains while simultaneously increasing spatial inequality, because improved connectivity enables economic activity to converge in already-advantaged locations.

Meanwhile, evidence from Indonesia reveals mixed distributional effects. Wahyuni et al. (2022) calculate the Rural Access Index (RAI) at district level in Indonesia from 2014-2020, evaluating the Nawacita programme's implementation. Results show RAI increased and inequality decreased during this period, with improvements particularly notable in priority regions (Papua and West Papua). The positive changes occurred predominantly in districts with initially low RAI in eastern Indonesia, suggesting that the programme's focus on underserved areas contributed to regional convergence and equity improvements. Comparably, Ghani et al. (2016) examine India's Golden Quadrilateral highway project. They note substantial positive effects on manufacturing activity and firm productivity in districts within 0-10 km of the highway corridor. The study finds heterogeneous effects, specifically, districts with higher population density and literacy rates show stronger responses to the highway upgrades. The upgrades facilitated better industrial sorting along the network, with land-intensive industries moving from congested nodal cities to non-nodal districts along the highway and improved the allocative efficiency of manufacturing activity. Conversely, Asher and Novosad (2020) analyze India's $40 billion rural road construction program using a fuzzy regression discontinuity design, four years after road construction. They note that the main effect of new feeder roads is to facilitate the movement of workers out of agriculture, however, they found no major changes in agricultural outcomes, income, or assets. Employment in village firms expands only slightly. They conclude that even with better market connections, remote areas may continue to experience limited economic opportunities, suggesting that transport infrastructure alone may be insufficient to transform rural economies without complementary inputs such as human capital and agglomeration economies.

4. Methodology

Conducting an empirical analysis of transport-related issues in the Philippines are usually difficult to undertake due to challenges in obtaining local data. In this study, we want to understand the effects of infrastructure on local economies, particularly on municipality level income and inequality. The establishment and operation of Ro-Ro ports all over the country provides a chance to perform micro-level analysis owing to the traceability of the whole transport network, timing of operation of Ro-Ro ports, and the ease of merging transport-related data to nationally representative household surveys using geographical information.

There are several identification challenges related to our topic of interest that necessitates a rigorous empirical approach to credibly separate the causal impact of RoRo connectivity from confounding factors and pre-existing trends. First, there exists selection bias in Ro-Ro port designation since port selection may not have been random due to factors such as pre-existing economic activity, strategic importance to inter-island trade, port capacity and infrastructure readiness, or political economy considerations. If chosen municipalities to host RoRo ports were already on different economic trajectories than control municipalities, then simple comparisons would conflate pre-existing differences with treatment effects. Second, simultaneous policies can confound the results. The time horizon of our study from 1990 to 2020 could capture numerous policies or investments that could influence local income and inequality like local government reforms, fiscal decentralization measures, etc. Without accounting for these confounders, we risk attributing effects to RoRo connectivity that are caused by other concurrent interventions. Third, there may be time-varying heterogeneity in the sense that treatment effects may vary across municipalities and over time since treatment. Municipalities treated earlier may experience different effects than those treated later, both because of genuine differences in treatment impact and differential exposure duration. Fourth, reverse causality. If RoRo nautical highway expansion was targeted toward municipalities experiencing economic gains, this would create spurious positive correlations between RoRo connectivity and outcomes even in the absence of any causal effect.

To address the identification challenges outlined above, we exploit variation in the timing of RoRo port implementation across municipalities within a difference-in-differences (DiD) framework specifically designed for staggered treatment adoption (Callaway and Sant'Anna, 2021). We consider a period between 1990 to 2020, within which the operation of each nautical highway of the Ro-Ro terminal system (RRTS) unfolded. The RRTS is composed of several Ro-Ro nautical highways that operated at different points in time, in 2003, 2008, 2009 and onwards for lateral connections. We focus on municipalities that are host to ports. In some of these municipalities, ports were rehabilitated and later became part of the Ro-Ro network – these will become our treated group. The municipalities hosting ports that did not become part of the RRTS at any point serve as our control group. This setup enables us to examine the changes in income and inequalities at the municipality level, after becoming part of the Ro-Ro network.

4.1. Setup and Notation

We observe municipalities $i = 1, \ldots, N$ over time periods $t = 1990, \ldots, 2020$. Let D_{it} be a binary indicator equal to 1 if municipality i hosts an operational RoRo port at time t, and 0 otherwise. We impose the **irreversibility of treatment assumption** (Assumption 1 in Callaway and Sant'Anna, 2021):

Assumption 1 (Irreversibility of Treatment):

Once a municipality's port becomes part of the RRTS network at time g, it remains in the network in all subsequent periods:

$$D_{t-1} = 1 \ implies \ D_t = 1 \ almost \ surely, for \ all \ t = 1991, \ldots, 2020$$

This assumption is plausible in our context, as ports were not removed from the network after integration, and the infrastructure investments (ramps, berthing facilities, road connections) represent irreversible changes.

4.2. Treatment Cohorts and Comparison Groups

We define treatment cohorts by the year a municipality first received RoRo connectivity. Let G_i denote the year municipality i was first treated. For municipalities that never receive RoRo connectivity during our study period, we set $G_i = \infty$.

Our sample is composed of **treated municipalities** –those municipalities that hosted ports integrated into the RRTS at different times ($G_i \in \{2003, 2008, 2009, \ldots, 2020\}$); and **control municipalities** –those municipalities hosting ports that were never incorporated into the RRTS ($G_i = \infty$), providing a natural comparison group of port municipalities that did not receive the specific treatment of RoRo integration.

4.3. Group-Time Average Treatment Effects

Following Callaway and Sant'Anna (2021), we focus on the **group-time average treatment effect** $ATT(g,t)$ as our fundamental causal parameter:

$$ATT(g,t) = \mathbb{E}[Y_t(g) - Y_t(0) \mid G = g]$$

where:

$Y_t(g)$ is the potential outcome at time t for a municipality first treated at time g

$Y_t(0)$ is the untreated potential outcome at time t

The expectation is taken over municipalities in treatment cohort g

$ATT(g,t)$ represents the average treatment effect at calendar time t for the group of municipalities first treated at time g. This parameter does not impose any restrictions on treatment effect heterogeneity across groups or time periods, allowing the effect of RoRo connectivity to vary both (1) **across cohorts** –earlier-treated municipalities (2003 cohort) may experience different effects than later-treated ones (2008, 2009, and onwards cohorts); (2) **over time within cohorts** –the effects may grow, diminish, or fluctuate as exposure duration increases. This flexibility is crucial for our research questions, particularly our interest in understanding whether effects vary with length of exposure to the RoRo network.

4.4. Identifying assumptions

We invoke three core identifying assumptions to establish causal identification of $ATT(g, t)$.

Assumption 2: No Anticipation

We assume that municipalities do not adjust their behavior in anticipation of future RoRo connectivity. Formally, with anticipation parameter $\delta = 0$:

$$\mathbb{E}[Y_{\mathrm{t}}(g) \mid X, G = g] = \mathbb{E}[Y_{\mathrm{t}}(0) \mid X, G = g] \; for\, all\, t < g$$

This assumption states that prior to actual RoRo integration ($t < g$), treated and untreated potential outcomes are identical. This is plausible in our context because (1) the specific timing of RoRo port operationalization was largely determined by national government; (2) municipalities were generally passive recipients of the RRTS program rather than active applicants; and (3) the infrastructure modifications required for RoRo operations were implemented rapidly, limiting the window for anticipatory responses.

Assumption 3: Conditional Parallel Trends Using Not-Yet-Treated Comparison Groups

Our primary parallel trend assumption conditions on **not-yet-treated municipalities** as comparison groups. Following Callaway and Sant'Anna (2021, Assumption 5), for each group $g \in \{2003, 2008, 2009, \dots, 2020\}$ and time periods s, t such that $t \geq g\; and\; s \geq t$:

$$\mathbb{E}[Y_{\mathrm{t}}(0) - Y_{\mathrm{t-1}}(0) \mid G = g] = \mathbb{E}[Y_{\mathrm{t}}(0) - Y_{\mathrm{t-1}}(0) \mid D_{\mathrm{s}} = 0, G \neq g]$$

This assumption states that municipalities in treatment cohort g and not-yet-treated control municipalities (those not treated by time s, excluding cohort g) would have experienced parallel trends in outcomes in the absence of treatment.

We employ not-yet-treated units rather than never-treated units as our primary comparison group for several reasons because of (1) **sample size considerations** –using not-yet-treated units increases the effective comparison group size, particularly for estimating effects in earlier time periods when later cohorts have not yet been treated; (2) **comparability** –municipalities that eventually receive RoRo ports may be more similar to currently treated municipalities than those that never receive ports, making the parallel trends assumption more plausible; and lastly, (3) **consistency with treatment timing** –this approach respects that "never-treated" municipalities may differ systematically from all treated municipalities in ways that violate parallel trends, even after conditioning on observables.

Assumption 4: Overlap

We require sufficient overlap in covariate distributions between treatment and comparison groups:

$$0 < P(G = g \mid X, G = g\; or\; D_{\mathrm{t}} = 0) < 1 \text{ almost surely for all } g \in \{2003, 2008, 2009, \dots, 2020\}\; and\; t \geq g.$$

This overlap assumption ensures that for any covariate profile observed in the treated group, there exist comparable control units, and vice versa.

4.5. Estimation: Outcome Regression Approach

Callaway and Sant'Anna (2021, Theorem 1) show that under Assumptions 1-4, $ATT(g,t)$ can be recovered using outcome regression, inverse probability weighting, or doubly robust methods. We employ their **outcome regression estimator**, which we implement using Stata's csdid command with method(reg) option.

For each group g and post-treatment time period $t \geq g$, the outcome regression estimator is:

$$\hat{A}TT\text{\^{}}OR(g,t) = \mathbb{E}[G^{g} / \mathbb{E}[G^{g}] \cdot (Y_{t} - Y^{g}{}_{-1} - \hat{m}^{g},{}_{t}{}^{ny})]$$

where:

$G^{g} = 1\{G_{i} = g\}$ is an indicator for being in treatment cohort g

$\mathbb{E}[G^{g}]$ is the sample proportion in group g

$m^{g},{}_{t}{}^{ny} = \mathbb{E}[Y_{t} - Y^{g}{}_{-1} \mid D_{t} = 0, G \neq g]$ is the estimated outcome evolution for not-yet-treated units

The fitted values from this regression, $\hat{m}^{g},{}_{t}{}^{ny}$, provide a predicted counterfactual outcome change for each treated municipality i in cohort g based on what happened to similar not-yet-treated municipalities.

The group-time ATT is then the average difference between actual and predicted counterfactual outcome changes for municipalities in cohort g:

$$\hat{A}TT\text{\^{}}OR(g,t) = (1/N^{g})\, \Sigma_{i}\!: G_{i} = {}^{g}\, [(Y_{it} - Y_{i},{}^{g}{}_{-1}) - \hat{m}^{g},{}_{t}{}^{ny}]$$

where N^{g} is the number of municipalities in cohort g.

4.6. Event-Study Parameters

To examine how treatment effects evolve with exposure to the RoRo network, we construct event-study parameters that aggregate across cohorts for each event time $e = t - g$ (the number of periods since treatment):

$$\theta_{es}(e) = \Sigma^{g} \in \mathcal{G}\; 1\{g + e \leq T\} \cdot P(G = g \mid G + e \leq T) \cdot ATT(g, g + e)$$

where $\mathcal{G} = \{2003, 2008, 2009, \ldots, 2020\}$ is the set of treatment cohorts and $T = 2020$ is the final period. This is the average effect of participating in the treatment e time periods after initially receiving RoRo connectivity, averaged across all cohorts that are observed at event time e. We compute $\theta_{es}(e)\; for\; e \in \{0, 1, 2, \ldots, 17\}$, allowing us to trace out the dynamic evolution of treatment effects.

4.7. Overall Average Treatment Effect on the Treated

We also construct a single summary measure of the average effect of RoRo connectivity across all treated municipalities and all post-treatment periods:

$$\theta^{O} = (1/\kappa)\, \Sigma^{g} \in \mathcal{G}\, \Sigma^{t}{}_{=}{}^{gT}\, ATT(g,t) \cdot P(G = g)$$

where $\kappa = \Sigma^{g} \in \mathcal{G}\, \Sigma^{t}{}_{=}{}^{gT}\, P(G = g)$ ensures weights sum to one. This parameter provides an interpretable overall summary analogous to the ATT in a canonical 2×2 DiD design, representing the average effect of ever being treated across all treated municipalities.

4.8. Extension: Spatial Spillovers to Neighboring Municipalities

Beyond examining direct effects on RoRo host municipalities, we also investigate potential spillover effects on neighboring municipalities to accommodate the reality that transport infrastructure may generate positive externalities (through improved market access) or negative externalities (through business relocation) for nearby municipalities. We define neighboring municipalities as those computationally near the coordinates of a RoRo host municipality.

For this analysis, we construct analogous treatment indicators based on proximity:

$D_{it}{}^{\text{neighbor}} = 1$ if municipality i is a neighbor (as defined above) of an operational RoRo port at time t

$G_{i}{}^{\text{neighbor}}$ = year when municipality i first becomes a neighbor of an operational RoRo port

We then apply the identical Callaway and Sant'Anna (2021) framework to estimate spillover effects $ATT^{\text{neighbor}}(g,t)$, using as control group municipalities that: (1) never host a RoRo port themselves; and (2) are never neighbors of a RoRo port during the study period. This parallel estimation strategy allows us to separately identify direct effects on host municipalities and indirect spillover effects on neighboring areas.

4.9. Data description and sources

We examine several outcome variables derived from the Statement of Receipts and Expenditures (SRE), which is the basic financial report prescribed by the Bureau of Local Government Finance (BLGF) to monitor LGU financial performance. The following are definitions derived from the SRE Manual (2007).

1) **Total Local Income** –this refers to Total Current Operating Income in the SRE framework, which equals Local Sources plus External Sources. Local Sources include: (a) Tax Revenue (Real Property Tax + Tax on Business + Other Taxes); and (b) Non-Tax Revenue (Regulatory Fees/Permits and Licenses + Service/User Charges + Income from Economic Enterprises + Other Receipts). External Sources include: (a) Internal Revenue Allotment (IRA); (b) Other Shares from National Tax Collections; (c) Inter-Local Transfer; and (d) Extraordinary Receipts/Grants/Donations/Aids.

   Total Local Income is measured on a cash basis as actual receipts collected during the period, recorded in the Record of Real Property Tax Collections and Record of General Collections maintained by the Treasury Office. It represents the total financial resources available to the municipality for current operations.

2) **Tax on Business (Business Tax Revenue)** –this includes taxes on: (a) manufacturers, assemblers, re-packers, processors, brewers, distillers, rectifiers, and compounders of liquors, distilled spirits, and wines or manufacturers of any article of commerce (LGC Section 131-o); (b) wholesalers, distributors, or dealers in any article of commerce (LGC Section 131-z); (c) exporters, manufacturers, millers, producers, wholesalers, distributors, dealers or retailers of essential commodities; (d) retailers (LGC Section 131-w); (e) contractors and other independent contractors (LGC Section 131-h); (f) banks and other financial institutions, including non-bank financial intermediaries, lending investors, finance and investment companies, pawnshops, money shops, insurance companies, stock markets, stock brokers and dealers in securities and foreign exchange (LGC Section 131-h); (g) peddlers who travel from place to place selling goods (LGC Section 131-t); and (h) printing and publication businesses.

   Business taxes are measured on a cash basis as actual collections received based on Official Receipts issued by the Treasury Office. The measure captures the taxable commercial activity including transaction volumes, number and size of businesses operating, and business profitability within the municipality.

3) **Real Property Tax Revenue** –this encompasses basic tax on real property, real property tax on idle lands, special assessment tax, and special education tax. Real property includes land, buildings, machinery, and other improvements affixed or attached to the real property. It is composed of: (a) Current Year tax - the share of the LGU on current year tax; (b) Discounts - discount granted for advance and prompt payments; (c) Prior Year tax - the share of LGU from total collections on real property tax delinquencies; (d) Penalties - the share of LGU on penalties for late payment of taxes; (e) Special Levy on Idle Lands - tax imposed on idle lands in addition to the basic real property tax (LGC Section 273); and (f) Special Levy on Land Benefited by Public Works Project - tax imposed on lands benefited by public works projects or improvements.

   Real property taxes are measured on a cash basis as collections received based on Official Receipts issued by the Treasury Office and Journal Entry Vouchers (JEVs) for un-receipted receipts directly deposited to the bank. The measure reflects the assessed value of taxable real properties in the municipality, which in turn reflects land and property values.

We likewise look at change in inequality and poverty levels by utilizing data from Census of Population and Housing (CPH), and Small Area Estimates (SAE) from the Philippine Statistics Authority:

4) **Income Inequality (Gini Coefficient)** –this measure is calculated from asset indices constructed from Census data. The asset index aggregates ownership of durable goods (TV, refrigerator, motorcycle, etc.) and housing quality indicators (materials, sanitation, water source) to proxy for household wealth[1]. The Gini coefficient measures the distribution of simulated income based on asset-based wealth index across households within a municipality, ranging from 0 (perfect equality) to 100 (perfect inequality).
5) **Poverty incidence** –these are generated poverty figures from the Philippine Statistics Authority, from combining information from large-scale surveys such as Family

[1] Details about Gini coefficient calculation based on asset indices are provided in the Annex.

Income and Expenditure Survey (FIES) with CPH data and other sources to produce reliable poverty estimates for cities and municipalities.

Our samples are drawn from an inventory of ports constructed based on the list of ports of several government agencies including Philippine Ports Authority, Maritime Industry Authority, Cebu Ports Authority, Philippine Statistics Authority. We also utilized the Philippine Standard Geographic Codes (PSGC) to refer to the exact location of the ports.

5. Results and Discussions

This study examines whether transport infrastructure investment can reduce income inequality by exploiting the staggered implementation of the Philippines' Roll-on/Roll-off Terminal System. Using difference-in-differences methodology specifically designed for staggered treatment adoption (Callaway and Sant'Anna, 2021), we analyze five outcomes namely total local income, business tax revenues, real property tax, income inequality (Gini coefficient), and poverty incidence across three spatial levels: port municipalities, neighboring municipalities, and second-degree neighbors.

Our findings reveal that maritime infrastructure creates clear spatial winners and losers at scale, generating concentrated economic benefits for a minority of municipalities while imposing welfare costs on the majority. This spatial distribution has important implications for how we understand infrastructure's role in inclusive growth, as well as for the design of complementary policies to manage distributional consequences.

5.1. Local Impacts of Ro-Ro Connection

Municipalities hosting operational RoRo ports integrated into the RRTS constitute approximately 20 percent of sample municipalities. These locations experienced multidimensional impacts across several outcome variables examined in our analysis.

In the following discussions, it is worthwhile to note that the validity of difference-in-differences estimates depends critically on the parallel trend assumption which assumes that treated and control groups would have followed similar trajectories in the absence of treatment. This assumption is assessed by examining pre-treatment average effects. Several spatial levels exhibit statistically significant pre-treatment differences ($p < 0.10$), indicating violations of parallel trends. For these cases, we flag results as not credible for causal interpretation, and either exclude detailed discussion or present findings with strong caveats as descriptive patterns only. Results meeting parallel trends assumptions ($p \geqslant 0.10$) are presented as credible causal estimates.

5.1.1. Total Income

Total local income denotes the aggregate revenue available to local government units from all sources. It serves as a comprehensive measure of municipal fiscal capacity. This outcome captures the full economic resource base that municipalities can deploy for public services and development initiatives. Our analysis examines whether integration to RORO network enhances local revenue generation through increased economic activity.

As shown in Table 1, the pre-treatment average effect is statistically significant at the 5% level, indicating a violation of the strict parallel trend assumption. However, the economic magnitude is very small (approximately 1.1% lower income growth), and the coefficient is modest relative to the observed treatment effect variation. While there exists a technical violation, the small economic magnitude and the pattern of individual pre-treatment period estimates (which show no consistent trend) suggest the concern may be limited. We proceed with interpretation but note this caveat.

Post-treatment effects, on the other hand, show considerable variation across time periods. The overall post-treatment average effect is 0.004 (p=0.893), suggesting no significant aggregate impact. The period-by-period analysis reveals immediate post-treatment periods (during treatment year and 1 year after) showing small positive but insignificant effects of 1.5% and 1.8% respectively, medium-term effects (2 years to 6 years after) fluctuating between negative and positive values without achieving statistical significance, and longer-term effects (7 to 8 years after) showing positive coefficients around 3%, though these remain statistically insignificant.

Table 1. ATT Estimates for Log Total Income at Host Municipalities

	Coefficient	Std. err.	z	P>|z|		[95% conf. interval]	
Pre-treatment average	-0.011	0.004	-2.59	0.010	***	-0.019	-0.003
Post-treatment average	0.004	0.033	0.13	0.893		-0.060	0.069
5 yrs before treatment	-0.018	0.014	-1.28	0.201		-0.045	0.009
4 yrs before treatment	0.005	0.016	0.34	0.733		-0.025	0.036
3 yrs before treatment	-0.003	0.012	-0.24	0.812		-0.026	0.021
2 yrs before treatment	-0.017	0.014	-1.23	0.217		-0.045	0.010
1 yrs before treatment	-0.022	0.013	-1.68	0.094	*	-0.047	0.004
0 (treatment year)	0.015	0.014	1.06	0.288		-0.013	0.043
1 yr after treatment	0.018	0.012	1.47	0.141		-0.006	0.043
2 yrs after treatment	-0.015	0.030	-0.50	0.620		-0.073	0.043
3 yrs after treatment	0.000	0.015	-0.02	0.986		-0.030	0.030
4 yrs after treatment	0.024	0.022	1.10	0.271		-0.019	0.067
5 yrs after treatment	0.011	0.025	0.45	0.654		-0.038	0.061
6 yrs after treatment	-0.012	0.050	-0.24	0.813		-0.109	0.085
7 yrs after treatment	0.031	0.031	1.00	0.316		-0.030	0.092
8 yrs after treatment	0.031	0.034	0.93	0.354		-0.035	0.097
9 yrs after treatment	-0.027	0.055	-0.50	0.619		-0.135	0.080
10 yrs after treatment	0.021	0.038	0.54	0.588		-0.055	0.096
11 yrs after treatment	0.012	0.045	0.27	0.790		-0.076	0.100
12 yrs after treatment	0.008	0.070	0.12	0.903		-0.128	0.145
13 yrs after treatment	-0.031	0.081	-0.39	0.697		-0.189	0.126
14 yrs after treatment	0.014	0.086	0.16	0.874		-0.155	0.183
15 yrs after treatment	-0.030	0.075	-0.40	0.691		-0.177	0.118

Source: Authors' calculation

Notes: Robust standard errors clustered at the municipality level. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

The standard errors range from 0.012 to 0.055, reflecting substantial heterogeneity in treatment effects across cohorts and calendar time. The lack of statistically significant positive effects suggests that while some ports may experience income growth, it is not a systematic pattern across all municipalities connected to the RoRo network (treated municipalities).

Estimates for neighbor municipalities paints a different picture (Table 2). The pre-treatment average effect for the immediate neighbor is -0.001 (p=0.781), strongly validating the parallel trends assumption. This provides the cleanest identification for spillover effects among all spatial levels for log Total Income analysis. The post-treatment average effect is -0.065 (p<0.000), indicating that nearest neighbors experience a highly significant 6.5% decline in total local income following the integration in RORO network.

Table 2. ATT Estimates for Log Total Income at Neighbor Municipalities

	Immediate neighbor		Second-degree neighbor	
	Coefficient	**P>|z|**	**Coefficient**	**P>|z|**
Pre-treatment average	-0.001	0.781	-0.013	0.008 ***
Post-treatment average	-0.065	0.000 ***	-0.052	0.002 ***
5 yrs before treatment	-0.005	0.705	-0.051	0.023 **
4 yrs before treatment	-0.003	0.851	-0.013	0.467
3 yrs before treatment	-0.009	0.487	0.009	0.592
2 yrs before treatment	0.000	0.987	-0.015	0.553
1 yrs before treatment	0.012	0.555	0.003	0.903
0 (treatment year)	-0.016	0.208	-0.013	0.425
1 yr after treatment	-0.036	0.017 **	0.006	0.728
2 yrs after treatment	-0.085	0.006 ***	-0.050	0.011 **
3 yrs after treatment	-0.036	0.074 *	-0.009	0.677
4 yrs after treatment	-0.036	0.048 **	-0.011	0.520
5 yrs after treatment	-0.025	0.223	-0.045	0.017 **
6 yrs after treatment	-0.014	0.573	-0.023	0.318
7 yrs after treatment	-0.072	0.002 ***	-0.089	0.000 ***
8 yrs after treatment	-0.086	0.000 ***	-0.084	0.000 ***
9 yrs after treatment	-0.033	0.156	-0.057	0.043 **
10 yrs after treatment	-0.099	0.000 ***	-0.077	0.001 ***
11 yrs after treatment	-0.060	0.006 ***	-0.040	0.053 *
12 yrs after treatment	-0.093	0.000 ***	-0.062	0.098 *
13 yrs after treatment	-0.126	0.000 ***	-0.120	0.000 ***
14 yrs after treatment	-0.059	0.070 *	-0.025	0.502
15 yrs after treatment	-0.169	0.000 ***	-0.131	0.000 ***

Source: Authors' calculation

Notes: Robust standard errors clustered at the municipality level. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Interestingly, period-specific analysis reveals persistent and growing negative impacts. A year after RoRo integration: -0.036 ($p=0.017$); 2 years after: -0.085 ($p=0.006$); 4 years after: -0.036 ($p=0.048$); 7 years after: -0.072 ($p=0.002$); 8 years after: -0.086 ($p<0.001$), and 10 years after: -0.099 ($p<0.001$). The increasing magnitude of negative effects over time, suggests cumulative economic disadvantages for municipalities adjacent to RORO ports. This pattern indicates substantial economic concentration at port locations occurring at the expense of neighboring municipalities.

Integrating findings from Table 1 and 2 imply that while RoRo host municipalities themselves do not show strong positive income effects, the highly significant negative effects in nearest neighbors (with validated parallel trends) provide compelling evidence of economic activity concentrating at port locations. The absence of positive effects in port municipalities combined with substantial negative effects in neighbors (-6.5% on average) indicates spatial redistribution rather than net creation of economic activity in the immediate region around ports. The pattern strongly suggests ports create competitive advantages that draw economic activity away from neighboring municipalities. This could occur through businesses relocating to port areas to minimize transport costs, consumers traveling to ports for shopping and services, or port municipalities capturing tax revenues from transactions that might otherwise occur in neighboring areas. The strengthening magnitude of negative effects over time in nearest neighbors (from -3.6% after 1 year to -9.9% at year 10) indicates mounting competitive disadvantages. This suggests economic concentration intensifies as ports develop and expand their sphere of economic influence.

5.1.2. Business Tax

Business tax revenues, derived from permits, licenses, and taxes on commercial activities, serve as a direct measure of local business sector vitality. Unlike total income which includes intergovernmental transfers, business taxes reflect endogenous economic activity driven by the commercial sector. This outcome is particularly relevant for understanding whether RORO infrastructure stimulates local entrepreneurship and business development.

Table 3 exhibits a near-zero, completely insignificant coefficient for pre-treatment average, providing the strongest possible validation of parallel trend assumption. The post-treatment average effect is 0.168 ($p=0.025$), indicating port municipalities experience approximately 17% higher business tax revenues following RORO integration. This represents substantial and statistically significant economic gains from enhanced business activity. The temporal pattern reveals delayed response wherein early effects (treatment year and 1 year after) are positive but marginally significant, with year 1 after RoRo integration showing 12.3% increase ($p=0.051$). The largest and most significant effects emerge 12+ years after integration; with 32.1% ($p=0.030$) at year 14 and 29.2% ($p=0.032$) at year 15. This delayed response likely reflects time required for businesses to recognize port-related opportunities, investment lags as entrepreneurs raise capital and establish operations, network effects as business clusters develop around ports, and gradual reputation building that attracts additional commercial activity.

The results for neighbor municipalities are revealing (Table 4). For immediate neighbors, pre-treatment average effect is -0.031 ($p=0.029$), indicating a statistically significant violation of parallel trends at the 5% level. Results for nearest neighbors, thus, cannot be interpreted as causal effects and are excluded from detailed discussion.

In contrast, parallel trend assumption is strongly validated for second-degree neighbors. The pre-treatment average effect is -0.004 (p=0.855). The post-treatment average effect is 0.047 (p=0.635), suggesting small positive but statistically insignificant spillovers at this spatial distance. Individual period estimates are noisy with large standard errors, providing no evidence of systematic effects.

Together, our results suggest that municipalities hosting RoRo ports experience substantial and highly credible business sector development, with tax revenues increasing approximately 17% on average (p=0.025). The ideal parallel trends validation (p=0.998) combined with economically and statistically significant treatment effects makes this one of our strongest findings. RORO infrastructure clearly stimulates commercial activity at port locations.

Contrariwise, the absence of significant effects at neighbor municipalities indicates business development benefits are highly concentrated at port locations. Economic impacts do not diffuse substantially beyond the immediate port municipality. This is highly consistent with transport cost economics where businesses locate as close as possible to infrastructure access points.

Table 3. ATT Estimates for Log Business Tax at Host Municipalities

	Coefficient	Std. err.	z	P>|z|	[95% conf. interval]	
Pre-treatment average	0.000	0.013	0.00	0.998	-0.026	0.026
Post-treatment average	0.168	0.075	2.24	0.025 **	0.021	0.314
5 yrs before treatment	0.005	0.029	0.18	0.856	-0.051	0.061
4 yrs before treatment	-0.008	0.060	-0.13	0.899	-0.124	0.109
3 yrs before treatment	0.021	0.038	0.57	0.568	-0.052	0.095
2 yrs before treatment	-0.025	0.031	-0.79	0.428	-0.086	0.036
1 yrs before treatment	0.005	0.035	0.15	0.878	-0.063	0.074
0 (treatment year)	0.046	0.050	0.92	0.358	-0.052	0.145
1 yr after treatment	0.123	0.063	1.95	0.051 *	-0.001	0.247
2 yrs after treatment	0.108	0.077	1.40	0.163	-0.044	0.259
3 yrs after treatment	0.135	0.080	1.69	0.092 *	-0.022	0.292
4 yrs after treatment	0.115	0.083	1.38	0.166	-0.048	0.277
5 yrs after treatment	0.119	0.087	1.37	0.171	-0.052	0.290
6 yrs after treatment	0.169	0.103	1.65	0.098 *	-0.031	0.370
7 yrs after treatment	0.160	0.105	1.53	0.127	-0.045	0.366
8 yrs after treatment	0.178	0.107	1.67	0.095 *	-0.031	0.388
9 yrs after treatment	0.196	0.108	1.81	0.070 *	-0.016	0.409
10 yrs after treatment	0.110	0.091	1.21	0.226	-0.068	0.288
11 yrs after treatment	0.113	0.096	1.17	0.242	-0.076	0.301
12 yrs after treatment	0.225	0.103	2.18	0.029 **	0.023	0.428
13 yrs after treatment	0.271	0.141	1.92	0.055 *	-0.005	0.547
14 yrs after treatment	0.321	0.148	2.17	0.030 **	0.030	0.611
15 yrs after treatment	0.292	0.136	2.14	0.032 **	0.025	0.559

Source: Authors' calculation

Notes: Robust standard errors clustered at the municipality level. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

5.1.3. Real Property Tax

Real property tax revenues reflect the value of land and built structures within a municipality's jurisdiction. This outcome serves as an indicator of property market development, construction activity, and wealth accumulation. Property values respond to infrastructure investments through improved accessibility enhancing location desirability, commercial development increasing demand for real estate, and overall economic growth raising willingness to pay for land and structures.

In Table 5, we show our main results for municipalities hosting RoRo ports. Estimate for pre-treatment average effect is 0.010 (p=0.319), validating parallel trend assumption. The post-treatment average effect is 0.110 (p=0.114), suggesting approximately 11% higher real property tax revenues in port municipalities after RORO integration. While economically substantial, this effect is marginally insignificant at conventional levels (falling just short of the 10% threshold).

Table 4. ATT Estimates for Log Business Tax at Neighbor Municipalities

	Immediate neighbor		Second-degree neighbor	
	Coefficient	**P>|z|**	**Coefficient**	**P>|z|**
Pre-treatment average	-0.031	0.029 **	-0.004	0.855
Post-treatment average	0.093	0.255	0.047	0.635
5 yrs before treatment	0.025	0.391	0.066	0.329
4 yrs before treatment	-0.079	0.046 *	-0.137	0.038 **
3 yrs before treatment	-0.028	0.321	0.022	0.695
2 yrs before treatment	-0.064	0.209	0.001	0.990
1 yrs before treatment	-0.007	0.861	0.029	0.748
0 (treatment year)	-0.005	0.876	0.060	0.376
1 yr after treatment	0.120	0.028 **	-0.013	0.817
2 yrs after treatment	0.079	0.239	0.061	0.580
3 yrs after treatment	0.117	0.109	-0.024	0.862
4 yrs after treatment	0.112	0.168	0.159	0.221
5 yrs after treatment	0.073	0.398	0.084	0.511
6 yrs after treatment	0.075	0.510	0.070	0.422
7 yrs after treatment	0.034	0.813	0.084	0.485
8 yrs after treatment	0.119	0.325	0.160	0.241
9 yrs after treatment	0.151	0.154	0.121	0.371
10 yrs after treatment	0.120	0.288	0.155	0.319
11 yrs after treatment	0.056	0.648	0.169	0.262
12 yrs after treatment	-0.036	0.818	0.067	0.690
13 yrs after treatment	0.139	0.361	-0.083	0.555
14 yrs after treatment	0.226	0.124	-0.195	0.172
15 yrs after treatment	0.114	0.433	-0.126	0.405

Source: Authors' calculation

Notes: Robust standard errors clustered at the municipality level. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 5. ATT Estimates for Log Real Property Tax at Host Municipalities

	Coefficient	Std. err.	z	P>|z|		[95% conf. interval]	
Pre-treatment average	0.010	0.010	1.00	0.319		-0.009	0.029
Post-treatment average	0.110	0.070	1.58	0.114		-0.026	0.247
5 yrs before treatment	0.007	0.040	0.17	0.865		-0.072	0.086
4 yrs before treatment	0.016	0.033	0.47	0.636		-0.049	0.080
3 yrs before treatment	0.030	0.037	0.81	0.418		-0.042	0.102
2 yrs before treatment	-0.011	0.043	-0.27	0.788		-0.095	0.072
1 yr before treatment	0.008	0.035	0.23	0.815		-0.061	0.078
0 (treatment year)	-0.042	0.035	-1.20	0.228		-0.110	0.026
1 yr after treatment	0.002	0.044	0.04	0.968		-0.084	0.088
2 yrs after treatment	0.045	0.054	0.84	0.402		-0.060	0.150
3 yrs after treatment	0.042	0.061	0.70	0.485		-0.077	0.161
4 yrs after treatment	0.064	0.075	0.86	0.392		-0.083	0.212
5 yrs after treatment	0.112	0.073	1.55	0.122		-0.030	0.254
6 yrs after treatment	0.067	0.086	0.79	0.432		-0.101	0.236
7 yrs after treatment	0.078	0.072	1.08	0.279		-0.064	0.220
8 yrs after treatment	0.100	0.088	1.13	0.257		-0.073	0.273
9 yrs after treatment	0.098	0.088	1.12	0.264		-0.074	0.269
10 yrs after treatment	0.124	0.090	1.37	0.171		-0.053	0.300
11 yrs after treatment	0.072	0.094	0.76	0.444		-0.113	0.257
12 yrs after treatment	0.183	0.102	1.78	0.074	*	-0.018	0.383
13 yrs after treatment	0.292	0.168	1.74	0.082	*	-0.037	0.621
14 yrs after treatment	0.348	0.165	2.10	0.035	**	0.024	0.672
15 yrs after treatment	0.177	0.175	1.01	0.310		-0.165	0.519

Source: Authors' calculation

Notes: Robust standard errors clustered at the municipality level. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

The temporal pattern reveals property market effects take substantial time to develop. The delayed response pattern is striking. Estimates exhibit mixed or negative effects for initial periods (-0.042 for treatment year), while positive effects emerge gradually in medium-term periods (2 to 6 years after integration, ranging from 0.045 to 0.112), and the largest impacts appear 12-14 years after RoRo integration (14 years after: 0.348, p=0.035).

Results from neighbor municipalities show minimal spillovers (Table 6). Estimates for nearest neighbor in Table 6 shows credible results for causal effects (pre-treatment average effect is 0.002 (p=0.820)). Quite notably, increase in real property tax is only evident 5 years after RoRo integration (15.4%, p=0.14). No significant spillovers are observed for second-degree neighbors.

Taken as a whole, municipalities hosting RoRo ports show evidence of property tax revenue growth with point estimates suggesting approximately 11% gains. However, the marginal statistical significance (p=0.114) indicates considerable heterogeneity where some ports experience substantial property value appreciation while others see more modest gains. The validated parallel trends provide confidence in the identification strategy even as the treatment effect heterogeneity reduces precision.

Relative to business tax results, property market effects take even longer to materialize, as evident in the observed delayed effects. The initial post-treatment periods showing no positive impacts or even slight negatives, possibly reflects construction-related disruptions or uncertainty during port development. The largest effects emerge only after 12-14 years, with the 14th year after RoRo integration showing almost 35 percent gains (p=0.035). This extended timeline reflects time for property market participants to recognize and capitalize on improved accessibility, construction lags as developers plan and build, gradual commercial development driving demand for real estate, and network effects as property values influence neighboring properties.

Table 6. ATT Estimates for Log Real Property Tax at Neighbor Municipalities

	Immediate neighbor		Second-degree neighbor	
	Coefficient	P>|z|	Coefficient	P>|z|
Pre-treatment average	0.002	0.820	0.034	0.072 *
Post-treatment average	0.030	0.596	-0.071	0.379
5 yrs before treatment	0.094	0.010 ***	0.186	0.001 ***
4 yrs before treatment	-0.096	0.007 ***	-0.185	0.037 **
3 yrs before treatment	0.044	0.193	0.128	0.185
2 yrs before treatment	-0.070	0.074 *	0.020	0.783
1 yr before treatment	0.040	0.288	0.024	0.712
0 (treatment year)	-0.052	0.146	-0.034	0.580
1 yr after treatment	-0.018	0.668	0.008	0.906
2 yrs after treatment	0.009	0.855	-0.164	0.074 *
3 yrs after treatment	-0.024	0.597	-0.076	0.275
4 yrs after treatment	0.022	0.685	-0.013	0.885
5 yrs after treatment	0.154	0.014 **	0.042	0.660
6 yrs after treatment	0.070	0.276	-0.174	0.193
7 yrs after treatment	0.119	0.125	-0.108	0.318
8 yrs after treatment	0.091	0.229	-0.078	0.450
9 yrs after treatment	0.000	0.997	-0.133	0.207
10 yrs after treatment	0.073	0.341	-0.072	0.533
11 yrs after treatment	0.042	0.560	-0.061	0.609
12 yrs after treatment	0.073	0.391	-0.099	0.347
13 yrs after treatment	-0.014	0.898	-0.075	0.524
14 yrs after treatment	-0.023	0.871	-0.137	0.285
15 yrs after treatment	-0.044	0.713	0.036	0.816

Source: Authors' calculation

Notes: Robust standard errors clustered at the municipality level. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

5.1.4. Income inequality

The Gini coefficient measures income inequality within a municipality, ranging from 0 (perfect equality) to 1 (maximum inequality). This outcome captures how RORO infrastructure affects the distribution of economic gains across different income groups within communities. Infrastructure projects can either exacerbate inequality by disproportionately benefiting those with existing resources or reduce inequality by creating opportunities for lower-income groups and promoting inclusive growth.

Table 7 shows an encouraging story on inequality. First, the pre-treatment average effect is 0.003 (p=0.760), providing strong validation of parallel trends. The post-treatment average effect is -0.027 (p=0.001), indicating port municipalities experience approximately 2.7 percentage point reductions in Gini coefficients following RORO integration. This is highly statistically significant (p=0.001) and meaningful inequality reduction. Given mean Gini coefficients around 0.38-0.42 in Philippine municipalities, this represents approximately 6-7% reduction relative to baseline levels.

Table 7. ATT Estimates for Gini Coefficients at Host Municipalities

	Coefficient	Std. err.	z	P>|z|		[95% conf. interval]	
Pre-treatment average	0.003	0.008	0.31	0.760		-0.014	0.019
Post-treatment average	-0.027	0.008	-3.44	0.001	***	-0.042	-0.011
10 yrs before treatment	0.003	0.016	0.18	0.861		-0.028	0.034
5 yrs before treatment	0.002	0.005	0.42	0.672		-0.008	0.013
0 (treatment year)	-0.013	0.009	-1.41	0.158		-0.031	0.005
5 yrs after treatment	-0.009	0.005	-1.86	0.062	*	-0.019	0.000
10 yrs after treatment	-0.025	0.013	-2.03	0.043	**	-0.050	-0.001
15 yrs after treatment	-0.024	0.009	-2.68	0.007	***	-0.041	-0.006
20 yrs after treatment	-0.062	0.019	-3.28	0.001	***	-0.099	-0.025

Source: Authors' calculation

Notes: Robust standard errors clustered at the municipality level. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 8. ATT Estimates for Gini Coefficients at Neighbor Municipalities

	Immediate neighbor			Second-degree neighbor		
	Coefficient	P>|z|		Coefficient	P>|z|	
Pre-treatment average	-0.014	0.090	*	0.012	0.109	
Post-treatment average	-0.001	0.891		0.005	0.540	
10 yrs before treatment	-0.028	0.072	*	0.027	0.000	***
5 yrs before treatment	0.000	0.970		-0.003	0.856	
0 (treatment year)	0.014	0.095	*	-0.002	0.840	
5 yrs after treatment	-0.001	0.907		0.006	0.646	
10 yrs after treatment	-0.014	0.148		-0.019	0.050	**
15 yrs after treatment	-0.002	0.862		0.029	0.193	
20 yrs after treatment	-0.002	0.867		0.010	0.395	

Source: Authors' calculation

Notes: Robust standard errors clustered at the municipality level. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Period-specific estimates reveal progressive inequality reduction that strengthens over time; treatment year: -0.013 (p=0.158), 5 years after: -0.009 (p=0.062), 10 years after: -0.025 (p=0.043), 15 years after: -0.024 (p=0.007), and 20 years after: -0.062 (p=0.001). The doubling of effects between 10 years after RoRo integration (2.5 percentage points) and 20 years after (6.2 percentage points) indicates cumulative equalizing dynamics where initial connectivity improvements create conditions for subsequent inclusive growth.

Unfortunately, we find no systematic inequality effects for neighbor municipalities. As shown in Table 8, pre-treatment average is marginally significant for immediate neighbors, violating parallel trend assumption. Post-treatment average is also not significant, suggesting no spillover effect. All post-treatment effects are likewise insignificant except the treatment year (0.014; p=0.095). Estimates for second-degree neighbors show minimal and inconsistent results. A small reduction is observed at 10 years after RoRo integration; all other periods are insignificant.

Overall, our results demonstrate that municipalities hosting RoRo ports experience significant and sustained inequality reductions averaging 2.7 percentage points (p=0.001), with effects strengthening to 6.2 percentage points by 20 years post-integration to the RoRo network (p=0.001). This represents a 15-16% decline from typical baseline levels of about Gini 0.40. Combined with validated parallel trends, this provides compelling evidence that RORO ports promote inclusive economic growth. The infrastructure creates economic opportunities that are relatively accessible to certain income groups. Several channels may explain these equalizing effects:

- *Labor Market Access* –RoRo ports create employment related to port operation or complementary services, compressing the income distribution.
- *Cost of Living Effects* –Improved maritime connectivity may reduce prices for consumer goods. If lower-income households spend larger shares of income on tradable goods, price reductions disproportionately benefit them, increasing real income equality.
- *Entrepreneurship Opportunities* –Enhanced connectivity may reduce barriers to small business creation by lowering transport costs and expanding market access.
- *Agricultural Market Access* –for agricultural communities, improved port access provides farmers better market access and higher prices for produce. If small farmers capture these benefits, this raises incomes at the lower end of the distribution.

To verify the above-mentioned mechanisms, complementary data and analysis is required.

Meanwhile, the absence of inequality effects in neighbor municipalities indicates inclusive growth benefits are geographically concentrated at port locations and do not spill over to surrounding municipalities. This contrasts with business tax results where neighbors experienced pre-trend violations. The inequality results demonstrate that while ports reduce inequality within host municipalities, they do not promote regional equality as neighboring municipalities experience no distributional changes. From a policy perspective, spatial concentration of benefits implies careful site selection to target inclusive growth to specific communities. Complementary policies are also necessary to avoid infrastructure projects from creating new forms of inequalities at the regional level.

5.1.5. Poverty incidence

Poverty incidence measures the percentage of families falling below the official poverty line, representing the most direct indicator of welfare for the most vulnerable populations. While the Gini coefficient captures overall distributional changes, poverty incidence specifically focuses on whether infrastructure affects those at the bottom of the income distribution, which is the most policy-relevant population from a welfare perspective.

As shown in Table 9, the pre-treatment average effect is 0.098 (p=0.860), strongly validating parallel trends. The post-treatment average effect is 0.921 (p=0.496), suggesting approximately 0.9 percentage point higher poverty incidence on average, though this effect is not statistically significant (essentially no effect on poverty). The large standard error (1.353) and high p-value indicate substantial heterogeneity and imprecision in poverty effects. All period-specific estimates are statistically insignificant with p-values far above conventional significance thresholds, ranging from p=0.371 to p=0.780.

Table 9. ATT Estimates for Poverty Incidence at Host Municipalities

	Coefficient	Std. err.	z	P>|z|	[95% conf. interval]	
Pre-treatment average	0.098	0.556	0.18	0.860	-0.991	1.188
Post-treatment average	0.921	1.353	0.68	0.496	-1.731	3.573
4 yrs before treatment	-0.373	1.043	-0.36	0.720	-2.416	1.670
1 yr before treatment	0.570	0.985	0.58	0.563	-1.361	2.500
2 yrs after treatment	-0.256	0.917	-0.28	0.780	-2.053	1.540
5 yrs after treatment	0.832	1.360	0.61	0.541	-1.834	3.498
8 yrs after treatment	0.727	1.338	0.54	0.587	-1.896	3.349
11 yrs after treatment	0.586	1.858	0.32	0.753	-3.056	4.228
14 yrs after treatment	2.716	3.036	0.89	0.371	-3.235	8.668

Source: Authors' calculation

Notes: Robust standard errors clustered at the municipality level. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 10. ATT Estimates for Poverty Incidence at Neighbor Municipalities

	Immediate neighbor		Second-degree neighbor	
	Coefficient	P>|z|	Coefficient	P>|z|
Pre-treatment average	0.329	0.605	-1.615	0.217
Post-treatment average	-1.416	0.246	3.058	0.116
4 yrs before treatment	-0.051	0.967	0.332	0.848
1 yr before treatment	0.710	0.516	-3.562	0.029 **
2 yrs after treatment	0.035	0.972	1.997	0.157
5 yrs after treatment	-2.542	0.019 **	2.127	0.315
8 yrs after treatment	-1.978	0.122	4.146	0.081 *
11 yrs after treatment	-3.355	0.035 **	4.859	0.113
14 yrs after treatment	0.758	0.757	2.160	0.459

Source: Authors' calculation

Notes: Robust standard errors clustered at the municipality level. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

The estimate for neighbor municipalities shows a paradoxical pattern (Table 10). Immediate neighbors show poverty reduction; 5 years post-RoRo integration: -2.5 percentage points, 11 years post-RoRo integration: -3.4 percentage points, and post-treatment average: -1.416 (p=0.246) is directionally negative. Estimates for second-degree neighbors, on the other hand, show concerning results. We observe a marginally significant poverty increase in more distant municipalities, 8 years after RoRo integration (4.146, p=0.081). However, pre-treatment volatility is evident (1 year before RoRo integration: -3.562, p=0.029), raising parallel trend concerns. Post-treatment results are generally positive, suggesting worsening poverty but estimates are insignificant.

Our findings for local poverty effects contrasts sharply with the strong inequality reduction. Standard development economics predicts that (1) reduced inequality typically accompanies poverty reduction; (2) infrastructure that benefits the poor should result to reduced inequality and poverty; and (3) equally distributed economic growth should lift bottom earners. Our results violate all three expectations as we have shown that access to the RoRo network resulted to lower inequality and unchanged poverty.

We offer potential explanations for our results:

- *Spatial redistribution and geographic concentration* –Our empirical evidence shows three distinct spatial zones. Port municipalities exhibit significant inequality reduction but no poverty change. Immediate neighbors show significant poverty reduction but no inequality effects. Second-degree neighbors experience marginal poverty increases. This hub-and-spoke pattern indicates RORO ports function as concentration nodes.

  The mechanism operates through agglomeration economies. RORO integration attracts formal businesses to port municipalities, compressing the income distribution among formal sector participants and reducing inequality. However, aggregate poverty rates remain stable due to compositional population changes.

  Three demographic dynamics may occur simultaneously: some poor households transition out of poverty through formal sector access; others migrate to neighboring municipalities where lower living costs enable commuting to port employment; middle-class households migrate into ports for business opportunities or out to larger urban centers. The net result is stable municipal poverty rates despite underlying individual mobility and welfare changes.

- *Threshold effects and the rigidity of absolute poverty measures* –Philippine poverty measurement faces unique challenges in capturing real welfare changes. Poverty lines are consumption-based and updated for national inflation but may not adequately reflect local cost-of-living changes in rapidly transforming port municipalities. If RORO integration triggers localized inflation in housing, land, or food prices, nominal income gains may translate into minimal real welfare improvements for those near the poverty line, keeping them trapped below the threshold even as measured inequality falls.

- *Cost-of-living effects and real income stagnation* –RoRo integration may trigger cost-of-living increases that disproportionately affect the poor. While nominal incomes may rise across the distribution, real welfare improvements for the poor are minimal when accounting for price changes.

RORO infrastructure fundamentally alters local price structures through two channels. First, improved market access exposes previously isolated areas to national price levels. Remote municipalities maintained lower prices for housing and land due to isolation but suffered higher prices for imported goods. RORO integration equalizes prices upward as local markets integrate nationally. Second, RORO-driven economic expansion creates demand pressures inflating prices for non-tradable goods and services. Commercial development increases demand for land and housing, raising rents and property values. Increased formal employment raises demand for local services such as food vendors, transportation, and retail, potentially increasing prices. Construction activity during port development may temporarily inflate wages but also increase the costs for building materials and housing.

These price increases affect income groups unevenly. Middle-income households, with diversified income sources and lower expenditure shares on basic needs, benefit from rising nominal incomes while absorbing price increases. Improved market access to diverse goods and employment opportunities offsets higher housing costs. Poor households in contrast, spend a huge chunk of their income on food and housing, making them acutely vulnerable to price inflation. If nominal income rises 15 percent but food prices rise 10 percent and rent rises 20 percent, real welfare improvement is minimal, keeping households below the poverty line despite nominal income compression that reduces measured inequality.

5.2. Summary of Results and Policy Implications

Our findings reveal a complex geographic pattern of winners and losers, generating concentrated economic benefits for port municipalities while imposing welfare costs on neighboring and more distant areas. Our key empirical findings are as follows:

5.2.1. Economic and Fiscal Impacts

Business tax revenues. Port municipalities experience substantial business sector development, with tax revenues increasing approximately 17 percent on average (p=0.025). The strongest validation of parallel trends (p=0.998) combined with economically significant treatment effects makes this our most robust finding. Effects emerge gradually, with the largest gains appearing 12-15 years after RORO integration (29 to 32 percent increase). This delayed response reflects time required for businesses to recognize opportunities, raise capital, establish operations, and build reputations. Notably, business development benefits remain highly concentrated at port locations with no significant spillovers to neighboring municipalities, consistent with transport cost economics where firms locate as close as possible to infrastructure access points.

Real property tax revenues. Port municipalities show evidence of property value appreciation with point estimates suggesting approximately 11 percent gains (p=0.114). While the marginal statistical significance indicates heterogeneity across ports, the validated parallel trends (p=0.319) provide confidence in identification. Property market effects develop even more slowly than business effects, with the largest impacts emerging 12-14 years after integration (35 percent gains at year 14, p=0.035). This extended timeline reflects lags in property market recognition, construction planning and execution, gradual commercial development, and network effects in property values. Immediate neighbors show minimal spillovers, with only marginal effects appearing five years post-integration.

Total local income. Direct effects at port municipalities show no significant aggregate impact (post-treatment average: 0.004, p=0.893), despite individual periods showing modest variation. Standard errors range from 0.012 to 0.055, reflecting substantial heterogeneity across cohorts and calendar time. In stark contrast, immediate neighboring municipalities experience highly significant income declines averaging 6.5 percent (p<0.001), with validated parallel trends (p=0.781) providing clean identification. The negative spillover strengthens over time, from -3.6 percent one year after integration to -9.9 percent at year ten, indicating mounting competitive disadvantages. This pattern strongly suggests economic activity concentrates at port locations at the expense of neighbors through business relocation, consumer travel to port areas, and tax revenue capture.

5.2.2. Distributional Outcomes

Income inequality. Port municipalities experience substantial and sustained inequality reductions averaging 2.7 percentage points (p=0.001), with strong validation of parallel trends (p=0.760). Given mean Gini coefficients around 0.38-0.42 in Philippine municipalities, this represents approximately 6-7 percent reduction relative to baseline. Effects strengthen progressively over time, doubling from 2.5 percentage points at ten years to 6.2 percentage points at twenty years post-integration. This cumulative pattern suggests initial connectivity improvements create conditions for subsequent inclusive growth. No systematic inequality effects appear in neighboring municipalities, indicating inclusive growth benefits remain geographically concentrated at port locations.

Poverty incidence. Port municipalities show no significant poverty effects (post-treatment average: 0.921 percentage points, p=0.496), with validated parallel trends (p=0.860) but large standard errors indicating substantial heterogeneity. This null result contrasts sharply with the strong inequality reduction, creating an apparent paradox where infrastructure reduces income inequality without reducing poverty. Neighboring municipalities reveal a more complex spatial pattern: immediate neighbors show directional poverty reduction (post-treatment average: -1.4 percentage points, p=0.246) with significant effects appearing at specific horizons (5 years: -2.5 percentage points, p=0.019; 11 years: -3.4 percentage points, p=0.035). Second-degree neighbors show concerning poverty increases (8 years: +4.1 percentage points, p=0.081), though pre-treatment volatility raises parallel trend concerns.

With the empirical evidence presented, we conclude that RORO infrastructure creates economic transformation but not universal prosperity. We argue that infrastructure investment is a necessary but insufficient condition for inclusive development. With this study, we demonstrate the importance of disaggregating development outcomes and reveal the limits of infrastructure-led growth without complementary social policies.

5.2.3. Policy Implications

Our findings generate several critical policy implications for infrastructure investment and inclusive development:

Infrastructure Site Selection and Regional Planning

The substantial negative spillovers to neighbor municipalities (6.5 percent income decline) and marginal poverty increases in distant areas demonstrate that infrastructure creates regional winners and losers. Policymakers must adopt regional planning frameworks that account for these spatial effects. Site selection should consider not only direct benefits to port municipalities but also impacts on surrounding areas. Complementary investments in affected neighboring municipalities become critical for managing distributional consequences. This might include secondary transport links connecting peripheral municipalities to the port network, targeted economic development programs for areas experiencing negative spillovers, or fiscal transfer mechanisms to compensate municipalities losing economic activity to port concentration.

Managing Cost-of-Living Pressures

The delayed emergence of property tax increases (peaking at 35 percent after 14 years) signals substantial property value appreciation that likely translates into housing cost pressures for low-income residents. Municipalities experiencing RoRo integration should implement proactive housing policies including affordable housing requirements for new commercial development, rent stabilization programs during infrastructure-driven transitions, and property tax relief for long-term residents facing assessment increases. Without such interventions, infrastructure improvements risk displacing poor households through cost-of-living increases even as aggregate inequality measures improve.

Complementary Labor Market Interventions

The strong business sector development (17 percent tax revenue increase) combined with inequality reduction but absent poverty effects suggests formal sector expansion benefits those already participating in formal markets while excluding the poorest households. Bridging this gap requires active labor market policies including skills training programs aligned with port-related industries, job placement services connecting informal sector workers to formal employment opportunities, microenterprise development support for those unable to access formal wage employment, and business formalization assistance reducing regulatory barriers for small operators. The 12 to 15-year lag before peak business effects provides a window for building human capital among vulnerable populations.

Temporal Sequencing of Interventions

The progressive strengthening of effects over time (business taxes peaking at 12-15 years, property values at 12-14 years), and inequality reduction (doubling from 10 to 20 years), reveals that infrastructure impacts unfold gradually. This temporal pattern allows for sequenced policy responses. Immediate post-integration priorities should focus on mitigating negative spillovers to neighbors and managing initial displacement pressures. Medium-term interventions (years 5 to 10) can target human capital development and business formalization as formal sector opportunities expand. Long-term strategies (years 10+) should address cumulative effects including property market pressures and regional inequality. Early intervention during the 5 to 10-year window before effects peak may prove more cost-effective than reactive policies implemented after economic patterns solidify.

Measurement and Monitoring

The inequality-poverty paradox highlights limitations in standard welfare measurement. Policymakers should supplement official poverty rates with complementary indicators including poverty gap and severity measures capturing welfare improvements among the poor even when they remain below thresholds, income percentile analysis tracking changes across the full distribution, and real income measures accounting for local cost-of-living changes.

Regular monitoring of these indicators in infrastructure-affected areas would provide early warning of adverse distributional outcomes and enable mid-course policy corrections.

6. Conclusion

The Roll-on/Roll-off network infrastructure demonstrably promotes business development, property value appreciation, and inequality reduction in host municipalities. However, these benefits come with substantial costs of neighboring municipalities experiencing significant income declines, poverty effects remain absent or negative despite inequality reduction, and impacts take 10 to 15 years to fully materialize. Our results contradict simplistic assumptions that building infrastructure inevitably promotes inclusive growth, showing that connectivity must be paired with complementary policies to achieve equitable development outcomes. Translating infrastructure investment into broad-based welfare improvements requires complementary policies addressing spatial spillovers, cost-of-living pressures, labor market segmentation, and measurement limitations. The 12 to 15-year lag before peak effects requires sustained commitment across multiple administrations, but also allows policymakers to redirect economic patterns before they become entrenched. Future infrastructure investments should integrate these lessons, embedding distributional considerations and complementary policies into project design rather than treating them as afterthoughts.

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Annex 1. Asset Index Construction and Municipal-Level Inequality Estimation

This appendix describes our methodology for constructing asset indices and estimating municipal-level inequality using household asset data. Following Harttgen and Vollmer (2013), we leverage the complementary strengths of the Census of Population and Housing (CPH) and the Family Income and Expenditure Survey (FIES) to overcome data limitations in Philippine inequality measurement. While the CPH provides representative samples at the municipal level with detailed asset ownership data, it lacks income and expenditure information. Conversely, recent FIES datasets contain income data but are only representative at the provincial level, particularly in the 2010s, limiting municipal-level analysis.

Asset-based inequality measures offer distinct advantages beyond addressing data gaps. Harttgen and Vollmer (2013) argue that asset ownership may better proxy long-term income than current income, as assets are less susceptible to measurement error from underreporting and less sensitive to year-to-year income fluctuations (McKenzie, 2005). Our approach relies on two key assumptions: (1) national income distribution follows a log-normal distribution, and (2) household ranks in the asset index distribution match their ranks in the income distribution.

We organize this appendix into three sections. First, we construct household asset indices using principal component analysis. Second, we simulate the national income distribution using FIES Gini coefficients and mean household income, then map asset index percentiles to income percentiles. Third, we estimate municipal-level Gini coefficients using the simulated income distribution.

Asset Index Construction

Following Filmer and Pritchett (2001), we employ principal component analysis (PCA) to construct a composite asset index from multiple household characteristics. The asset index aggregates information from dichotomous variables capturing housing quality, infrastructure access, and durable goods ownership into a single wealth measure:

Equation 1: $A_i = \Sigma w_j \times a_{ij}$

where A_i represents the asset index for household i, a_{ij} indicates possession of asset j, and w_j denotes the weight assigned to each asset.

PCA identifies linear combinations of variables that capture the maximum common variance, with the first principal component serving as our asset index due to its maximum explained variance. We harmonize asset variables across CPH survey years (1990-2020) to ensure temporal comparability. The harmonized variables include: roof materials (3 categories), wall quality (3 categories), lighting fuel (1 category), cooking fuel (3 categories), water source (4 categories), toilet facilities (5 categories), land ownership (1 category), and ownership of radio, television, refrigerator, telephone, and vehicle.

As expected, high-quality housing characteristics and infrastructure access receive positive weights, while poor-quality materials and lack of access receive negative weights. Asset ownership patterns vary systematically across income levels, validating the wealth-ranking capability of our index.

National Income Distribution Simulation

We simulate the national income distribution assuming log-normality, following standard practice for approximating income distributions. For a log-normal distribution where $Y = \exp(X)$ and $X \sim N(\mu, \sigma^2)$, the Gini coefficient G relates to the standard deviation as: $G = 2\Phi(\sigma/\sqrt{2}) - 1$, where Φ represents the cumulative distribution function of the standard normal distribution.

Given observed mean income E(Y) and Gini coefficient G from FIES data, we estimate the parameters μ and σ using the relationships between mean, variance, and the Gini coefficient for log-normal distributions (Equation 2).

Table 2 shows the macroeconomic data—FIES mean household income and Gini coefficients—used to parameterize the log-normal distributions for each survey year.

Table 2. Computed Gini coefficients from FIES, various years

Survey year	Avg. household income	Gini
1991	72,457	0.477
2000	144,506	0.4507
2009	206,000	0.4484
2018	313,000	0.4267

Source: FIES, Gini estimates of World Bank

Mapping Asset Index to Income Distribution

We assign each household to a percentile (p-quantile) based on its rank in the asset index distribution, then map it to the corresponding percentile in the simulated income distribution. This critical step assumes rank invariance: a household at the p_{th} percentile of the asset distribution also occupies the p_{th} percentile of the income distribution. Figure a illustrates this mapping process. Households with lower asset indices receive lower simulated incomes, while those with higher asset indices receive higher simulated incomes.

Municipal Gini Coefficient Estimation

We compute municipal-level Gini coefficients using the simulated income distribution. The Gini coefficient measures wealth concentration within a community, ranging from 0 (perfect equality) to 1 (complete inequality) (Gini, 1912). It is calculated as the ratio of areas on the Lorenz curve. We apply household sampling weights to account for clustered survey design and employ jackknife resampling to estimate both the Gini coefficient and its standard error (Berger, 2008). McKenzie (2005) demonstrates that predicted state-level Gini coefficients using asset indices closely approximate actual Gini coefficients based on consumption data in Mexico, supporting the validity of this approach.

Validation Against Actual Income Data

We cannot directly compare our results to CPH income data, as the CPH does not collect income information. Instead, we validate our estimates using the 1991 FIES, the most recent FIES dataset with municipal-level representativeness (over 25,000 households across 900+ municipalities). We compare estimated municipal income and Gini coefficients from our asset-based approach with actual FIES income-based measures.

Our validation reveals that estimated municipal household income and Gini coefficients satisfactorily reflect both levels and rankings of actual income and inequality across municipalities. This concordance supports the reliability of our asset-based inequality measures for municipal-level analysis.

Principal Component Analysis Results

Table 3 presents PCA weights for each survey year separately and harmonized weights pooled across all years. The close similarity between year-specific and harmonized weights validates our harmonization approach. We adopt harmonized weights to ensure bounded score ranges across all surveys and temporal comparability.

Table 3. PCA weights per year and harmonized weights

Variable	1990	2000	2010	2020	All years
High quality roof materials	0.2866	0.2643	0.2645	0.242	0.2737
Low quality roof materials	-0.2808	-0.2576	-0.2603	-0.2359	-0.2684
Other roof materials	-0.0273	-0.0305	-0.038	-0.0404	-0.0408
High quality outer walls	0.303	0.2998	0.3037	0.3341	0.3047
Low quality outer walls	-0.29	-0.2848	-0.2973	-0.3246	-0.2957
other outer walls	-0.0237	-0.0318	-0.036	-0.0554	-0.0411
Use of electricity for light	0.2814	0.2813	0.2598	0.2251	0.2695
Electricity/Kerosene/LPG cooking	0.2795	0.3009	0.2758	0.3208	0.2718
Wood/charcoal cooking	-0.2777	-0.2926	-0.2745	-0.3187	-0.2683
Other materials for cooking	-0.0027	-0.0082	-0.0025	-0.0025	-0.0042
Pipe water for drinking	0.225	0.2049	0.2379	0.2691	0.2498
Well water for drinking	-0.0828	-0.0527	-0.1352	-0.1285	-0.1152
Surface water for drinking	-0.1246	-0.1424	-0.1379	-0.1504	-0.1337
Other water for drinking	0.0003	0.0196	-0.004	-0.027	-0.008
Flush toilet	0.2494	0.2453	0.2656	0.2329	0.2671
Closed pit	-0.0753	-0.1113	-0.1373	-0.0886	-0.1178
Open pit	-0.1313	-0.1321	-0.1296	-0.0631	-0.1385
Other toilet	-0.0258	-0.0428	-0.043	-0.0858	-0.0465
No toilet	-0.1507	-0.146	-0.1573	-0.1879	-0.1656
Radio	0.1553	0.1541	0.1273	0.0356	0.0453
Television	0.3024	0.2974	0.284	0.2569	0.2792
Refrigerator	0.2802	0.2748	0.2487	0.2595	0.2461
Phone	0.1466	0.2007	0.2357	0.1777	0.2309
Vehicle	0.1667	0.1598	0.1292	0.1354	0.1613
Own land (residence/agricultural/other)	0.051	0.0576	0.0494	0.0592	0.0586

Source: Authors' calculations, CPH 1990-2020

A harmonized asset index maintains uniformity: households with identical assets score identically regardless of survey year (Staveteig & Mallick, 2014). Table 4 presents descriptive statistics of the harmonized asset index across survey years, with values ranging from -1.13 to 2.66. In recent surveys (2010 and 2020), we observe limited variation at the upper end of the distribution among wealthy households. However, Staveteig and Mallick (2014) note that this compression among affluent households does not generally pose problems when using percentile categories rather than raw continuous scores.

Table 4. Descriptive statistics of harmonized index, 1990-2000

	No. of observations	Mean	Std. dev.	Min	Max
1990	1,155,917	0.3092	1.1312	-1.1317	2.6580
2000	1,511,718	0.8624	1.1395	-1.1317	2.6580
2010	4,133,649	1.3081	1.0782	-1.1317	2.6580
2020	5,223,870	1.7271	0.8544	-1.1317	2.6580

Source: Authors' calculations, CPH 1990-2020

Tables 5 and 6 provide detailed breakdowns of asset indicators for 1990 and 2020, including mean ownership rates, standard deviations, and distribution across asset index quintiles. The scoring factors confirm intuitive patterns: positive weights for high-quality housing (improved roofs and walls), infrastructure access (piped water and flush toilets), and durable goods, with negative weights for poor-quality materials and infrastructure deficits.

Table 5. PCA and summary statistics, 1990

Variable	**Scoring factor for 1st principal component**			**Means by wealth quintile of asset index indicators**				
	Score	Mean	Std. dev.	Poorest	Lower Income	Lower Middle	Middle	Upper Income
High quality roof materials	0.274	0.557	0.497	0	0.50	0.93	1	1
Low quality roof materials	-0.268	0.426	0.494	0.99	0.47	0.06	0	0
Other roof materials	-0.041	0.017	0.129	0.01	0.03	0.01	0	0
High quality outer walls	0.305	0.342	0.474	0	0.09	0.65	0.97	1
Low quality outer walls	-0.296	0.631	0.483	0.98	0.86	0.33	0.03	0
other outer walls	-0.041	0.027	0.161	0.02	0.05	0.02	0	0
Use of electricity for light	0.270	0.547	0.498	0.05	0.45	0.91	0.98	0.99

Electricity/Kerosene/LPG cooking	0.272	0.333	0.471	0	0.16	0.52	0.97	1
Wood/charcoal cooking	-0.268	0.661	0.474	1	0.83	0.47	0.03	0
Other materials for cooking	-0.004	0.006	0.076	0	0.01	0.01	0	0
Pipe water for drinking	0.250	0.225	0.417	0.01	0.10	0.31	0.64	0.95
Well water for drinking	-0.115	0.302	0.459	0.43	0.33	0.24	0.17	0.03
Surface water for drinking	-0.134	0.117	0.322	0.26	0.13	0.02	0.01	0
Other water for drinking	-0.008	0.017	0.130	0.01	0.02	0.02	0.01	0
Flush toilet	0.267	0.451	0.498	0	0.39	0.68	0.95	0.99
Closed pit	-0.118	0.095	0.294	0.16	0.13	0.04	0	0
Open pit	-0.139	0.145	0.353	0.32	0.17	0.03	0	0
Other toilet	-0.047	0.020	0.140	0.03	0.02	0.01	0	0
No toilet	-0.166	0.160	0.367	0.41	0.14	0.03	0	0
Radio	0.045	0.686	0.464	0.49	0.62	0.80	0.96	0.99
Television	0.279	0.328	0.469	0	0.10	0.58	0.97	1
Refrigerator	0.246	0.209	0.406	0	0.03	0.28	0.82	1
Phone	0.231	0.035	0.184	0	0	0.01	0.06	0.64
Vehicle	0.161	0.082	0.274	0	0.02	0.08	0.18	0.80
Own land	0.059	0.550	0.497	0.47	0.54	0.56	0.65	0.79

Source: Authors' calculations

Table 6. PCA and summary statistics, 2000

Variable	**Scoring factor for 1st principal component**			**Means by wealth quintile of asset index indicators**				
	Score	Mean	Std. dev.	Poorest	Lower Income	Lower Middle	Middle	Upper Income
High quality roof materials	0.274	0.933	0.250	0.76	0.98	1	1	1

Low quality roof materials	-0.268	0.062	0.240	0.23	0.01	0	0	0
Other roof materials	-0.041	0.003	0.054	0.01	0	0	0	0
High quality outer walls	0.305	0.724	0.447	0.17	0.81	1	1	1
Low quality outer walls	-0.296	0.263	0.440	0.79	0.18	0	0	0
other outer walls	-0.041	0.010	0.101	0.03	0.01	0	0	0
Use of electricity for light	0.270	0.923	0.266	0.74	0.97	0.99	1	1
Electricity/Kerosene/LPG cooking	0.272	0.599	0.490	0.07	0.53	1	1	1
Wood/charcoal cooking	-0.268	0.395	0.489	0.92	0.46	0	0	0
Other materials for cooking	-0.004	0.003	0.055	0	0.01	0	0	0
Pipe water for drinking	0.250	0.685	0.465	0.28	0.69	0.91	1	1
Well water for drinking	-0.115	0.095	0.293	0.21	0.10	0.03	0	0
Surface water for drinking	-0.134	0.053	0.225	0.15	0.04	0.01	0	0
Other water for drinking	-0.008	0.015	0.123	0.02	0.02	0.01	0	0
Flush toilet	0.267	0.912	0.283	0.73	0.95	0.99	1	1
Closed pit	-0.118	0.024	0.152	0.06	0.02	0.01	0	0
Open pit	-0.139	0.005	0.068	0.02	0	0	0	0
Other toilet	-0.047	0.018	0.133	0.05	0.01	0	0	0
No toilet	-0.166	0.033	0.179	0.12	0.01	0	0	0
Radio	0.045	0.430	0.495	0.38	0.43	0.43	0	1
Television	0.279	0.760	0.427	0.38	0.79	0.97	1	1
Refrigerator	0.246	0.465	0.499	0.06	0.35	0.74	1	1
Phone	0.231	0.835	0.371	0.61	0.85	0.95	1	1
Vehicle	0.161	0.477	0.499	0.25	0.43	0.46	1	1
Own land	0.059	0.642	0.479	0.56	0.57	0.62	1	1

Source: Authors' calculations

Asset ownership clearly differentiates across wealth quintiles. In 1990, only 1% of the poorest quintile had access to piped drinking water and flush toilets, compared to 95% and 99% respectively in the richest quintile. No households in the poorest quintile owned televisions or refrigerators, while 100% of the richest quintile possessed these items. Similarly in 2020, only 17% of the poorest households had high-quality walls, 28% had piped drinking water, and 6% owned refrigerators, compared to universal ownership (100%) among the richest quintile. All durable goods show monotonically increasing ownership with higher wealth quintiles, confirming that the first principal component effectively measures household wealth.

Robustness of Household Rankings

We assess the robustness of household rankings using Spearman rank correlation coefficients (Table 7). Rankings based on different asset subsets show high consistency. Excluding drinking water and toilet facilities yields a rank correlation exceeding 0.97, while excluding electricity, drinking water, and toilet facilities maintains a correlation above 0.89. Even using durable goods alone produces a rank correlation exceeding 0.72, demonstrating substantial robustness to variable selection.

Table 7. Classification differences of poorest 25% and rank correlation with alternative asset indices

	Base: All variables	**Excluding drinking & toilet facilities**	**Durables, housing & land ownership**	**Durables only**	**Excluding drinking and toilet facilities**	**Durables, housing & land ownership**	**Durables only**
		1990			2020		
Poorest (25%)	100	90.2	71.4	50.6	91.5	85.3	68.8
Lower income (35%)		9.8	28.6	48.7	8.5	14.5	28.9
Lower middle (25%)				0.7		0.2	1.5
Middle middle (10%)						0.0	0.8
Upper middle-rich (5%)							
Rank Correlation of Households	1.0	0.97	0.91	0.72	0.98	0.89	0.77

Source: Authors' calculations

The asset index also produces consistent wealth quintile classifications across alternative specifications. The table reports cross-classification of the poorest 25% under different asset combinations. Over 90% of households classified as poorest using all variables remain in the poorest quintile when excluding drinking water and toilet facilities. When excluding electricity, drinking water, and toilet facilities, 71% (1990) and 85% (2020) of poorest households remain correctly classified. Using only durable goods, approximately 50-70% remain in the poorest quintile, with most misclassified households shifting to adjacent lower-income quintiles rather than dramatically different categories. Classification consistency extends to middle-income and wealthy groups as well.

Regional Validation

Table 8 compares regional asset indices with GDP per capita and poverty rates. The patterns align with economic expectations: regions with higher per capita GDP (NCR, CAR, Regions 3 and 4) exhibit the highest average asset indices, while regions with lower GDP (Regions 5, 8, and 9) show negative asset indices and rank at the bottom. Negative asset indices also correspond to high poverty levels in regions such as Regions 5, 9, and 10, providing construct validity for our wealth measure.

Table 8. Region asset index, domestic product and poverty rate

	Asset index	GDP per capita, 1988	Poverty rate, 1988	Asset index	GDP per capita, 2020	Poverty rate, 2018
	1990			2020		
Ilocos Region	0.47	6,222	44.9	1.97	113,452	7
Cagayan Valley	0.05	6,292	40.4	1.79	100,361	12.5
Central Luzon	0.83	11,112	29.3	2.15	151,287	5.2
Calabarzon/MIMAROPA	0.52	13,511	41.1	2.14	159,748	5.1
Bicol Region	-0.24	4,942	54.5	1.31	84,090	20
Western Visayas	-0.21	8,947	49.4	1.39	107,623	11.9
Central Visayas	-0.08	10,224	46.8	1.6	146,376	13.4
Eastern Visayas	-0.34	5,155	48.9	1.35	87,149	23.9
Zamboanga Peninsula	-0.34	6,614	38.7	1.11	104,307	25.4
Northern Mindanao	-0.03	10,262	46.1	1.37	171,716	17.3
Davao Region	0.03	11,554	43.1	1.5	168,112	13.9
SOCCSKSARGEN	-0.22	8,484	36.1	1.34	106,855	22.4
CARAGA	-0.22			1.27	105,940	24.1
NCR	1.6	27,810	21.6	2.22	419,935	1.4
CAR	0.25	11,772	41.9	1.74	164,030	8.6
ARMM/BARMM	-0.42			1.27	55,087	54.2

Source: Authors' calculations

National and Municipal Income and Gini Estimates

Table 9 demonstrates that simulated national income and Gini coefficients closely approximate actual FIES estimates across all survey years. Differences average approximately 10,000 pesos for mean income and 0.03 or less for Gini coefficients, indicating strong aggregate accuracy.

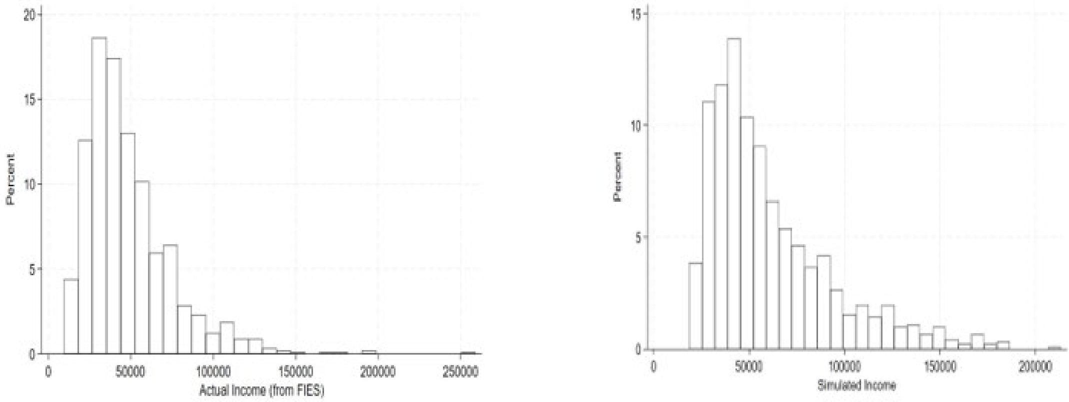
Table 9. National estimates comparison of simulated income and Gini

CPH survey year	FIES average household income	Average simulated income	Simulated income-based Gini	Actual Gini estimates
1990	40,408	81,151 (median 54,956)	.469	.48 (Estudillo, 1997) .456 (Balisacan, 2000) .438 (World Bank)
2000	144,039	155,023	.454	.487 (Capuno, 2022) .477 (World Bank)
2010	206,000	195,862	.414	.429 (Capuno, 2022) .463 (World Bank)
2020	305,000	302,25	.413	.392 (Capuno, 2022) .423 (World Bank)

Source: Authors' calculations

At the municipal level, Figure 1 compares the distribution of actual (FIES 1991) and estimated municipal mean household income. We observe a moderate rank correlation of 0.62 between actual and estimated income. Approximately 90% of municipalities occupy the same percentile in both distributions, meaning these municipalities receive identical wealth quintile classifications. High-income municipalities under the asset-based approach also rank high in actual income, and similarly for low-income municipalities. The remaining 10% of municipalities—primarily those ranked in the middle of the actual income distribution—receive higher ranks in the estimated income distribution.

Figure 1. FIES actual income and Simulated income

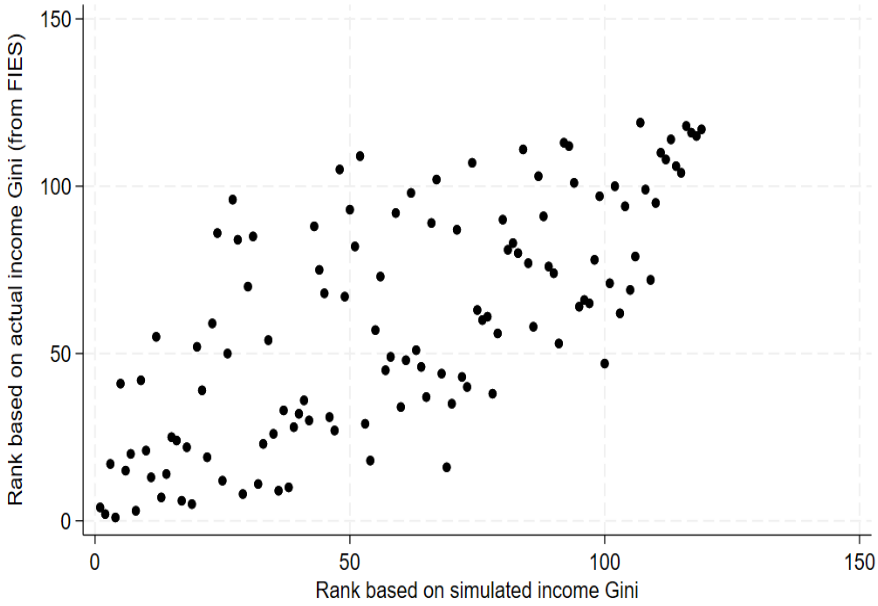


Source: FIES; Authors' calculations

The asset index approach may overestimate income for middle-class households, potentially due to urban-rural differences where asset ownership converges at higher wealth levels. Mean estimated income (60,000 pesos) exceeds mean actual income (48,000 pesos). However, for the bottom 25%, both measures yield approximately 30,000 pesos, while for the top 25%, actual income reaches 60,000 pesos compared to 75,000 pesos for estimated income. Despite this upward bias at higher income levels, the strong concordance in rankings and levels for most municipalities supports using asset-based estimated income as a reliable proxy for municipal-level income measurement.

Figure 2 compares municipal rankings for actual (FIES-based) and estimated Gini coefficients. Actual Gini estimates exhibit larger confidence intervals due to smaller FIES sample sizes (median standard error = 0.06) compared to estimated Gini coefficients (median standard error = 0.01). For validation, we restrict the comparison to municipalities with confidence intervals of approximately ±0.05 for actual Gini and sample sizes of at least 10 households, representing diverse income and population levels.

Figure 2. Ranking of municipalities for FIES income Gini and Simulated income Gini



Source: Authors' calculations

Within this validation sample, differences between actual and estimated Gini range from 0.01 to 0.02. Mean actual Gini is 0.34 compared to mean estimated Gini of 0.35. The top 25% of municipalities have actual and estimated Gini of 0.37 and 0.39, respectively, while the bottom 25% have 0.30 and 0.32. Municipal rankings in actual and estimated Gini show strong correlation (rank correlation = 0.72).

Consistent with existing literature (Gavilanes, 2025), higher-population and higher-income municipalities exhibit higher estimated Gini coefficients. For the Gini-population relationship, the top and bottom 25% of municipalities by population have mean actual Gini of 0.40 and 0.32, and estimated Gini of 0.41 and 0.33. For the Gini-income relationship, the top and bottom 25% by simulated income have actual Gini of 0.36 and 0.31, with a narrower gap in estimated Gini of 0.35 and 0.34. These results confirm that our estimated Gini coefficients based on simulated household income effectively proxy the level and ranking of actual municipal-level Gini coefficients for municipalities with adequate sample sizes.

As an alternative validation using recent data, Table 10 presents rank correlations between asset-based poverty classifications and actual poverty incidence for 2020. We find strong correlations (0.74-0.83) between the proportion of poor households based on asset index percentiles and official poverty estimates at the municipal level, further validating our approach.

Table 10. Rank correlation of municipalities based on poverty level using asset index and actual poverty incidence

	Percentage in nationwide poorest 25%, 2020 asset index	Actual Poverty incidence, 2018	Actual Poverty incidence, 2021
Percentage in nationwide poorest 25%, 2020 asset index	1.00		
Actual Poverty incidence, 2018	0.83	1.00	
Actual Poverty incidence, 2021	0.74	0.80	1.00

Source: Authors' calculations

Finally, we examine consistency at the regional level (Table 11). Estimated income levels and rankings at the regional scale show strong concordance with actual measures, with regional rankings generally more accurate than absolute income levels. Differences between actual and estimated Gini coefficients remain within 0.03 for most regions. Estimated income levels tend to be higher than actual income in urban regions, but regional rankings remain largely consistent across both measures.

Table 11. Region actual income and Gini estimate comparison with simulated income and Gini

	1991 FIES mean income	1990 CPH simulated income	1991 FIES income-based Gini	1990 CPH simulated income-based Gini
Ilocos Region	57,737	84,852	.419	.395
Cagayan Valley	56,294	61,966	.439	.405
Central Luzon	78,122	113,324	.412	.405
Calabarzon/MIMAROPA	74,449	98,014	.442	.475
Bicol Region	42,145	50,885	.416	.484
Western Visayas	50,948	54,343	.426	.509
Central Visayas	47,311	61,520	.474	.501
Eastern Visayas	40,218	45,878	.441	.470
Zamboanga Peninsula	45,189	47,308	.423	.500
Northern Mindanao	46,292	62,544	.451	.475
Davao Region	54,512	65,730	.453	.473
SOCCSKSARGEN	48,074	51,653	.421	.471

National Capital Region	153,409	208,210	.490	.400
CAR	65,817	77,750	.464	.451
ARMM	43,987	41,194	.332	.430

Source: Authors' calculations

Conclusion

Our asset-based approach to estimating municipal-level income and inequality demonstrates strong validity across multiple validation exercises. The harmonized asset index produces consistent household rankings, closely approximates national and municipal income distributions, and reliably captures inequality patterns. While the method exhibits some upward bias in estimated income levels, particularly for middle and upper-income households, the strong concordance in rankings and inequality measures supports its use for longitudinal municipal-level analysis where direct income data are unavailable or lack geographic representativeness.

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