Minding the Gap: Modeling Gentrification Dynamics in the Philippines Using Socioeconomic and Development Indicators

A research paper in partial fulfillment of the requirements in

Stat 136: Introduction to Regression Analysis

by

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ABSTRACT

Gentrification has become a growing concern in rapidly urbanizing parts of the world over the past few decades, being linked to issues of displacement and widening socioeconomic gaps. The present study gained insights into this complex phenomenon in the Philippine context, where urban growth patterns are vastly different compared to Western nations, using Palma Ratio — a measure of income inequality. Data from local provinces were gathered from different government agencies in which a multiple linear regression model involving 21 literature-backed regressors (including two geographic dummy variables) was developed.

After transformations and iterative variable selection processes, eight predictors in the final model were considered significant at $\alpha = 0.05$ including centered poverty incidence, centered underemployment rate, GDP growth rate in manufacturing, GDP growth rate in construction, log of GDP growth rate in transportation and storage, log of unemployment rate, and centered domestic travelers. Correspondingly, the entire framework was observed to be significant as well with $R^2 = 0.5923$. Its relatively moderate explanatory power implies that the model captures meaningful relationships between variables; however, it cannot entirely address variability in the outcome. This could be attributed to a lack of available data covering other factors possibly at play in gentrification dynamics.

While the research is limited by data unavailability in cultural and spatial dimensions, its findings offer a foundational structure for future investigations and evidence-based interventions addressing gentrification-related concerns in the country at a provincial level.

INTRODUCTION

This chapter discusses the study's background, significance, problem statement, and objectives. This chapter provides the reader with sufficient information as to why we conducted the study.

Background of the Study

Persistent social inequality manifests through significant disparities in income, quality of education, healthcare, and opportunities. Across the world, a substantial portion believes that gentrification is among its primary drivers. An analysis by Hoover (2023) defines it as a diagnosis of injustice and a distinctive demonstration of unequal and damaging relationships resulting in exploitation, dispossession, displacement, marginalization, and violence. The worsening divide among Filipinos in these and many more aspects, as reported by the World Bank in 2022, amplifies the need for further understanding on the matter. The situation calls for an investigation regarding urban developments that trigger disproportionate effects on low-income communities.

According to Capuno (2022), local poverty reductions from 2012 to 2018 are modest compared to those in Vietnam, China, and Indonesia. In fact, using the official national household survey, it was concluded that inequality has somehow improved. Observations revealed that the proportions of residences with heads and spouses employed or receiving domestic assistance have risen faster among the poor than non-poor. Nevertheless, McDoom et al. (2018) add that overall decline in inequality within a country, assessed through national-level measures, cannot completely capture important variations in the subnational categories. He details that while the archipelago has made noteworthy improvements in mending disparities across education sectors and access to public services, results in the sublevels do not reflect the same conclusion. Using spatial and social boundaries specified for their socio-political significance in the Philippine context, the change appears to be less positive when taken at grass roots.

Furthermore, multiple studies have investigated the concept of urbanization, as well as its role in widening social gaps and gentrification. Marked by demographic shifts due to remarkable transferring of people from rural to urban areas in search of better opportunities, urbanization is strongly associated with racial-gender wage and salary inequality (Buchholz, 2023). His findings illustrate that the wage gap increases as population density increases. Flores et al. (2018) state further that housing infrastructures cannot keep up with rapid population growth causing families to push each other out. They detail that the fixation on business investments over the provision of affordable housing plans contributes to displacement and exacerbates inequalities. These accounts solidify the necessity to comprehend the complex interplay of factors, such as economic growth, real estate development, and government policies, in driving significant societal transformations.

As of their latest poverty survey in 2023, the Philippine Statistics Authority (PSA) discloses that income inequality remains to be a crucial issue, with the top 1% earning a disproportionately large share of the national income. This exists alongside enduring poverty among sectors like indigenous peoples, fisherfolks, and farmers. With that, the present investigation aims to identify possible contributors that explain current statistics behind illustrated polarities.

Significance of the Study

Given the recognition that gentrification and income inequality are pressing social issues, the present investigation poses significance in deepening public understanding about their causes and effects to ordinary Filipinos. By employing multiple linear regression analysis, the proponents hope to provide evidence-based reports essential in policymaking, urban development planning, and community development efforts. The findings will benefit local government officials in crafting policies to assure pro-poor housing, the academia in widening the body of knowledge on socioeconomic inequalities, and the residents in forwarding inclusive development strategies that preserve culture, livelihood, and sustainable-practical opportunities.

Statement of the Problem

Gentrification occurs when more affluent individuals and businesses occupy urban neighborhoods causing increased property values and other various forms of economic inequality. While considered a driver of infrastructure development, the process also fuels displacement and cultural erosion, significantly impacting the impoverished communities and marginalized populations. Despite growing foreign literature, the issue remains to lack assessment in the local context. Empirical research on the socioeconomic factors that contribute to gentrification appears to be stagnant. Consequently, the study seeks to address this existing gap by conducting a multiple linear regression analysis examining possible key predictors and eventually furthering investigations on its consequences to the disenfranchised Filipino sectors that continuously seek government attention.

General and Specific Objectives

The proponents aim to evaluate existing relationships between income inequality, as a representative for the measure of gentrification, and socioeconomic independent variables using multiple linear regression analysis. In addressing the general objective, the paper focuses on the following specific intents:

- Assess the strength and direction of associations between predictors and the Palma ratio
- Identify which regressor significantly predicts income inequality
- Evaluate the model for needed regression assumptions
- Compare models (full and reduced) based on legitimate statistical criteria
- Interpret and relate results to previously conducted research and literature

Scope and Limitations

The study centers on analyzing literature-supported socioeconomic variables associated with gentrification and income inequality in 71 Philippine provinces — highly urbanized cities not included. The selection is based on the completeness of information provided by government websites, particularly of Philippine Statistics Authority, Bureau of Local Government Finance, and Department of Trade and Industry in the year 2023. The analysis is heavily reliant to available secondary data sources such as online census records with the research procedure constrained with time and resource. As such, the paper cannot capture other related dimensions including expanded demographic factors, displacement rates, and amount of cultural erosion present.

RELATED LITERATURE

This section is dedicated to the review of relevant studies and articles about gentrification and its proxy variable, income inequality. This also includes studies that explored the relationship of various variables with income inequality. These studies will be useful in determining the regressors that would be included in the final model.

Gentrification

Gentrification is characterized by shifts in locality in response to migration of residents, particularly those from wealthier backgrounds (Glass, 1964). It can be understood as the process through which geographical areas become increasingly inclusive, disproportionately affecting people in poverty and of color along the way (Thurber & Krings, 2021). In the Philippines, Choi (2016) discusses that Metro Manila demonstrates socio-spatial exclusion of the working class from their homes and communities to cater the more affluent — a core feature of gentrification. In her paper, she illustrates the demarcation line between the weak metropolitan state and the power of landed elites by questioning the authority of urban space usage. This scenario highlights that informal settlement is a forgotten planning concern in the country and as an output of gentrification, informal settlers are physically excluded from the city. Such occurrence can be traced from the rampant displacement instigated by several urban development projects.

The University of Texas (n.d.) supports this explanation by introducing the three dimensions of gentrification: the displacement of lower income residents, the physical transformation of the neighborhood, and the change in its cultural character. These sections, still, point to the changing living conditions among localities where concentrated poverty and for more heterogenous localities, racial segregation exists.

Income Inequality as Proxy

Wang (2023) defines gentrification as a process in which communities undergo economic and social changes aimed at attracting wealthier residents and businesses, leading to increased property value and rents. These changes often result in the displacement of lower-income residents and contribute to issues like widening economic inequality. According to Chapple (2017), a hallmark of contemporary gentrification is that the households most protected from displacement are the wealthiest—those at the top of society. In the past, economic gains were more evenly distributed across income levels, but today, profits are primarily accruing to a small group supplying luxury housing for high-income residents. This concentration of wealth contributes to rising income inequality, which can be viewed as one of the core symptoms of gentrification. As areas change and develop, the widening income gap reflects issues, such as displacement, which are central to the gentrification process.

The Palma Ratio

In a study by Palma (2011) on the global income disparities within nations, he found that there is a tendency that half of the national incomes are attributed to the middle and upper-middle classes – those belonging in the fifth to ninth income deciles. Meanwhile, the other half is shared by the richest 10% and the poorest 40%, wherein their respective contributions vary across countries. This varying share of the rich and the poor on the national income inspired Cobham and Sumner (2013) to propose an alternative measure of income inequality other than the Gini coefficient, that is, the Palma Ratio. In comparison to the Gini coefficient, an advantage of the Palma Ratio is that it is much more intuitive in interpretation (i.e. the rich getting richer and the poor getting poorer is a key factor of income inequality). Moreover, considering that the Gini coefficient accounts the entire wealth distribution across a population, it is not sensitive to changes in the extremes but only to the middle that is inert. Unlike the Gini, the Palma Ratio is sensitive to changes in the extremes (poorest 40% and richest 10%) to which there are most likely changes as indicated by Palma (Cobham & Sumner, 2013; Floyd, 2025).

Soto et al. (2023) utilized the Palma Ratio as a dependent variable, wherein significant regressors were found namely Gross Domestic Product (GDP) growth rate, Tax Revenue, Internal Conflict, and the interaction between Foreign Direct Investment and Tax Revenue. Also, 94.1% of variation in the Palma Ratio can be explained by the regressors in the said study.

On Philippine settings, the Palma Ratio is calculated by the PSA (2022) as the ratio of the "total family income of the upper 10 percent income decile group to the lower 40 percent income decile group". With this, the Palma Ratio will be used as the dependent variable for this study.

Poverty Incidence and Income Inequality

According to Dabla-Norris et al. (2015), income inequality is an impediment to poverty reduction. Their investigation suggests an existing relationship between the two concepts emphasizing that growth is less efficient in lowering poverty in countries with high levels of inequality or in situations where the distributional pattern of growth favors the non-poor. Further, in contexts where economies are periodically subjected to shocks that may undermine growth, higher inequality makes a bigger fraction of the population susceptible to poverty.

Unemployment Rate and Income Inequality

In an article entitled "An Empirical Analysis of the Impact of Unemployment Rate and Economic Development Level on Income Inequality," it was found that high unemployment rate along with high inflation aggravates income inequality in Germany (Gu, 2023). Moreover, in a study by Mooi-Reci and Liao (2024) on the dynamics of unemployment with wage inequality, results showed that previously unemployed individuals had lower and more varied wages than those of continuously employed individuals. It was also found that previously unemployed men had more wage variation than women. Both studies indicate a positive association between unemployment rate and income inequality.

Underemployment Rate and Income Inequality

Underemployed workers are those who would like to work more than they currently do, because they want to earn more since they have low paying jobs. In the Philippines, there is a high incidence of low paying employment which contributes to income inequality (World Bank, 2016). This suggests a positive association between the underemployment rate and income inequality.

Tourism and Income Inequality

In a study of Zhang (2021), it was found that tourism is positively associated with income inequality. Although tourism provides employment and income to individuals, the income distribution is not balanced.

Public Transit and Income Inequality

Transportation investments, including expanded routes, new transit lines, and other relevant railway projects, trigger declines in housing affordability. According to Nilsson and Delmelle (2018), typically impoverished areas transition to physically advantaged neighborhood types given improved transit connections. These changes attract wealthier individuals and businesses, whose relation to displacement is continuously researched. Leung and Choy (2025) add that new metro developments increase rent and entice post-secondary educated and higher-income residents. They detail that the introduction of new mass transit systems is associated with a significant gentrification impact in lower-income localities. Bardaka et al. (2018) state that the construction of new urban rail lines near the city centers is associated with private fundings that turn said sites into high-density developments. Further, a surge of renovations often leads to a rise in rent prices.

While heightened public transit is considered generally beneficial to Filipinos, its other impacts on different population groups are widely debated. Chen et al. (2023) argue that transit-oriented development causes property renewal and potentially prices out residents. Despite the mobility increase, the most vulnerable sectors are often left out of its benefits. Fang (2023) reveals that newly established or rehabilitated housing causes upward social filtering. Chapple and Zak (2020) detail that TODs outside of major cities have a higher likelihood of losing low-income households.

Gross Domestic Product (GDP) and Income Inequality

In a literature review by Mdingi and Ho (2021), it was found that there is a varying association between GDP and Income inequality. For instance, they noted that most studies showed a positive association between GDP and income inequality for high-income countries, while negative for low-income countries. It was also noted that some studies found no relationship between GDP and income inequality.

Government Investment and Income Inequality

Government investments are crucial in reducing various inequalities in an area. For instance, infrastructure developments in the education, health, and utility sectors could help diminish inequalities, because marginalized individuals can directly benefit from these developments (Bajar, 2018). In addition, a study investigating the relationship between poverty, income inequality, and inclusive growth in Sub-Saharan Africa showed that domestic investment has the potential to reduce poverty and inequality. It also has the capacity to enhance inclusive growth, which entices governments to make domestic investment a necessity (Amponsah et al., 2023). These articles suggest a negative association between government investment and income inequality.

Taxation and Income Inequality

In a study by Eydam and Qualo (2023), it was found that there is a statistically significant negative association between income inequality and taxation – in particular personal income taxation. Moreover, Miguel et al. (2022) found that there is a negative association between income inequality and tax revenue in the Philippines.

Disparities in Luzon, Visayas, and Mindanao

A study entitled "Inequality Between Whom? Patterns, Trends, and Implications of Horizontal Inequality in the Philippines" tackled the question of between whom does inequality exist in the Philippines. It was found that there are differences within and between the three major Philippine Island groups — Luzon, Visayas, and Mindanao — with regards to horizontal inequality, an inequality defined as existing "among culturally defined (or constructed) groups" (Langer, 2006, as cited in McDoom et al., 2018).

With regards to income inequality, solely looking at certain regions already implies income inequality between the three major island groups. According to the Philippine Statistics Authority (2023), the National Capital Region (NCR) in Luzon, had the highest average annual family income at PHP 513.52 thousand. Meanwhile, Bangsamoro Autonomous Region in Muslim Mindanao had the lowest average annual family income at PHP 206.88 thousand.

METHODOLOGY

Data Collection

The 2023 provincial-level data used in the analysis was obtained from the websites of the Philippine Statistics Authority (PSA), the Bureau of Local Government Finance (BLGF), and the Department of Trade and Industry (DTI). The data was manually compiled into a single Microsoft Excel worksheet. After the deletion of rows with missing values, the resulting dataset contains a total of 71 observations (provinces).

Definition of Variables

This section defines some of the key variables used in the study, with the corresponding codes used in the model and applied transformations listed in Table 1.

Dependent Variable

Palma ratio (PALMA)

The Palma ratio is a measure of income inequality which is computed by dividing the total family income of the richest 10% by the total family income of the poorest 40% (Philippine Statistics Authority, 2022). A higher Palma ratio indicates higher income inequality.

Independent Variables

Underemployment Rate (UNDEREMP)

Underemployment rate is a measure of the percentage of employed individuals who have expressed a desire to work more hours. (Philippine Statistics Authority, 2018).

GDP Growth Rate

This refers to the annual percentage change in the Gross Domestic Product (GDP) generated by different economic sectors listed in Table 1.

Table 1
List of All Variables and Corresponding Transformations

Variable	Code	Unit	Transformation
Palma ratio	PALMA		Box-Cox
Poverty incidence rate	POV	%	polynomial term
Unemployment rate	UNEMP	%	log
Underemployment rate	UNDEREMP	%	
Number of foreign travelers	TRV_FOR	persons	log
Number of domestic travelers	TRV_DOM	persons	polynomial term
Competitiveness score	COMPET		
GDP growth rate by sector		%	
Manufacturing	GDP_MFG		
Construction	GDP_CONSTR		
Wholesale & Retail Trade	GDP_WRT		
Transportation & Storage	GDP_TRANSP		log
Accommodation & Food Services	GDP_AFS		
Information & Communication	GDP_ICT		
Financial & Insurance Activities	GDP_FIN		log
Real Estate and Ownership of Dwellings	GDP_REOD		
Professional & Business Services	GDP_BUS		polynomial term
Per Capita Local Development Fund	LDF	millions (Php)	sqrt
Per Capital Local Development Fund Total Expenditure	LDF_EXP	millions (Php)	sqrt
Per Capita Revenue from Real Property Tax	REV_TAX_RP	millions (Php)	log
Per Capita Revenue from Business Tax	REV_TAX_BUS	millions (Php)	sqrt
Visayas dummy variable	VIS_GRP		
Mindanao dummy variable	MIN_GRP		

Competitiveness Score (COMPET)

The competitiveness score used in this study is the Cities and Municipalities Competitiveness Index (CMCI). The CMCI measures the overall competitiveness of local government units on a scale from 0 to 100, where 100 represents a fully competitive locality. The index is composed of five equally weighted core components, each contributing 20% to the total score: Economic Dynamism, Governance Efficiency, Infrastructure, Resiliency, and Innovation (Department of Trade and Industry, n.d.).

Per Capita Local Development Fund (LDF)

This refers to the per capita Local Development Fund provided to Local Government Units, which is 20% of the National Tax Allotment.

Per Capita Revenue from Real Property Tax (REV_TAX_RP)

This refers to the total revenue collected from real property tax by each province/HUC divided by the population in each province/HUC. Real property tax is defined as a tax levied on land, buildings, machinery, and other improvements attached to the property (Bureau of Local Government Finance, 2016).

Per Capita Revenue from Business Tax (REV_TAX_BUS)

This refers to the total revenue collected from business tax by each province/HUC divided by the population in each province/HUC. Business tax is defined as the yearly tax charged on engaging in trade or commercial activities within the local government unit (Bureau of Local Government Finance, 2016).

Visayas (VIS_GRP) and Mindanao (MIN_GRP)

The Visayas dummy variable takes on the value of 1 if the observation is from the Visayas island group and 0 if it is not. The Mindanao dummy variable takes on the value of 1 if the observation is from the Mindanao Island group and 0 if it is not. Thus, a province from Luzon will have a value of 0 for both variables.

Model Specification

The proposed model is a multiple linear regression with Palma Ratio as the dependent variable and 21 socio-economic indicators as independent variables.

$$PALMA_i = \beta_0 + \beta_1 POV_i + \beta_2 UNEMP_i + \beta_3 UNDEREMP_i + \beta_4 TRV\_FOR_i + \beta_5 TRV\_DOM_i + \beta_6 COMPET_i + \beta_7 GDP\_MFG_i + \beta_8 GDP\_CONSTR_i + \beta_9 GDP\_WRT_i + \beta_{10} GDP\_TRANSP_i + \beta_{11} GDP\_AFS_i + \beta_{12} GDP\_ICT_i + \beta_{13} GDP\_FIN_i + \beta_{14} GDP\_REOD_i + \beta_{15} GDP\_BUS_i + \beta_{16} LDF_i + \beta_{17} LDF\_EXP_i + \beta_{18} REV\_TAX\_RP_i + \beta_{19} REV\_TAX\_BUS_i + \beta_{20} VIS\_GRP_i + \beta_{21} MIN\_GRP_i + \varepsilon_i$$

Model Assumptions

To ensure the reliability of the results, the analysis relies on the following assumptions:

- Relationship between Palma Ratio and the independent variables are linear and subject to random error
- Error terms are normal, homoscedastic, and uncorrelated
- There is no linear dependence of the predictor variables (no multicollinearity)
- There is no autocorrelation between observations,

Data Analysis

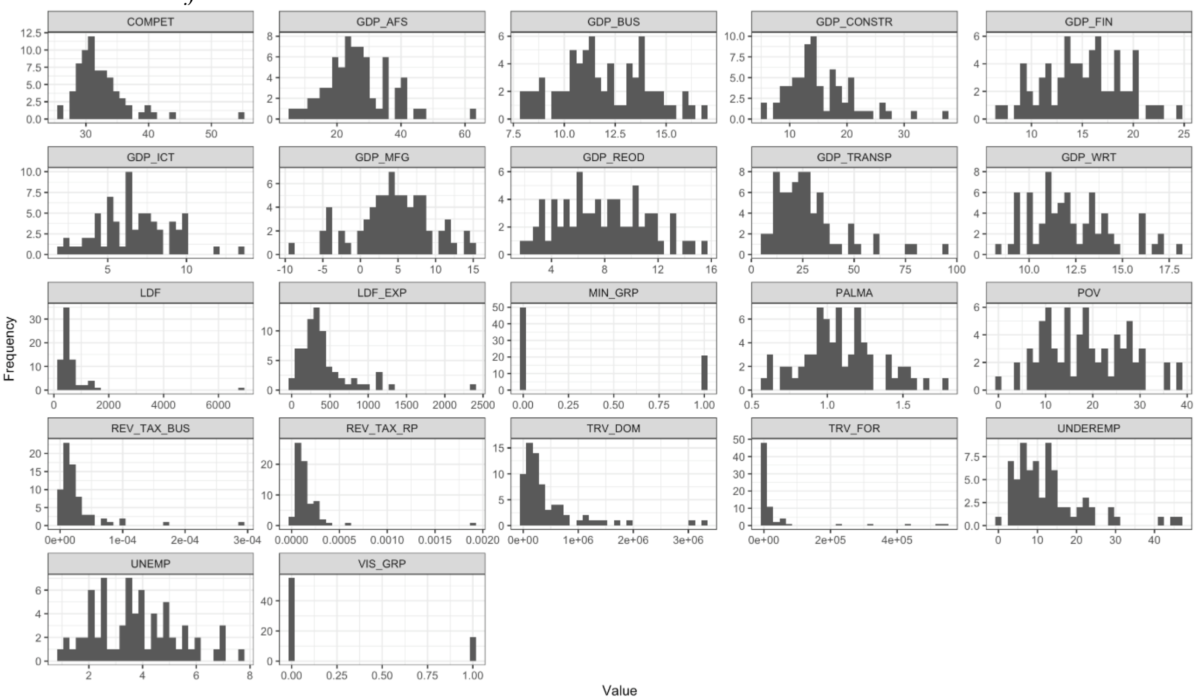
A multiple linear regression model was fitted to examine the relationship between the independent variables listed above and income inequality (measured by the Palma Ratio). The level of significance for all tests was set to $\alpha = 0.05$. Transformations—such as logarithmic, square root, Box-Cox, and the addition of polynomial terms—were applied to improve model fit. The model was refined using stepwise selection based on the Akaike Information Criterion (AIC) to retain significant predictors. After model fitting, diagnostic checking was done to ensure the validity of the model's assumptions. In addition to methods discussed in class, the Ramsay Regression Equation Specification Error Test (RESET) was used to check for potential nonlinearity and specification errors. This test examines whether nonlinear combinations of predictors improve the model’s fit (Oxford Reference, n.d.).

RESULTS AND DISCUSSION

From a preliminary assessment of individual plots and distributions (Figure 1), we see that some variables seem to be only mildly skewed. In particular, the response variable PALMA appears to be roughly symmetrical and bell-shaped, as well as the regressors GDP_FIN, POV, and UNEMP among others. On the other hand, a considerable number of variables are rather heavily skewed. For example, variables LDF, REV_TAX_BUS, REV_TAX_RP, and TRV_FOR have distributions with extreme right skew. These distributions, alongside their corresponding scatter plots, were used as graphical bases for the transformations on each variable, as stated in Table 1.

Figure 1

Distributions of All Variables in Full Model



The full model, treated as the baseline prior to variable transformation or selection, is found to be significant at $\alpha = 0.05$, with $R^2 = 0.456$ and $R_a^2 = 0.2228$ (Table A1). However, REV_TAX_BUS is the lone significant predictor in the model. Upon checking for assumptions, we observed issues with linearity and normality and a presence of multicollinearity, hence the need for transformations.

Throughout the entire process of diagnostic checking, a total of three iterated models were produced. The first was obtained upon applying transformations, including Box-Cox on the response and logarithmic, square root, and added polynomial terms on the different regressors, as a remedy to nonnormality and nonlinearity in the initial model. Next, in response to multicollinearity, the variables with added polynomial terms were centered, and we further performed a backward elimination procedure to limit the number of predictors, resulting in the two subsequent iterations of the model, the latter of which was deemed final. The summary ANOVA statistics of each model in the study can be found in Table A1.

The final and best fit regression model is linear but with polynomial features to account for seemingly nonlinear trends in the data. It is also significant at $\alpha = 0.05$, with $R^2 = 0.5923$ and $R_a^2 = 0.4823$ (Table 2). Note that this obtains a higher R^2 than the full model and a higher R_a^2 than the other two intermediate models as well (Table A1).

Furthermore, due to the variable selection procedure used, not all of the remaining predictors are significant (Table 2). Only eight to nine significant regressors remain: POV_CEN, POV_CEN^2, *log*(UNEMP), UNDEREMP, TRV_DOM_CEN, TRV_DOM_CEN^2, GDP_MFG, GDP_CONSTR, and *log*(GDP_TRANSP). Albeit obtaining a p-value slightly greater than the set α value, we still consider TRV_DOM_CEN in the model to ensure a meaningful joint interpretation with its corresponding squared term.

To verify model assumptions once again, we find that the final model obtains an insignificant Ramsay RESET test statistic, suggesting nonviolation of the linearity assumption (Table 3). Moreover, the model's residual plot and the corresponding component-plus-residual plots each show approximately linear trends closely resembling a horizontal band (Figure 2 and 3).

Next, both the normal probability plot and the distribution of model residuals do not suggest violation of the normality assumption, that is, the residuals lie roughly along a line,

Table 2
ANOVA Statistics of Final Model

	Estimate	Std. Error	*t* value	p-value
(Intercept)	-7.021×10^{-1}	1.779×10^{-1}	-3.946	0.000228
POV_CEN	9.712×10^{-3}	3.142×10^{-3}	3.092	0.003124
POV_CEN^2	-7.706×10^{-4}	2.526×10^{-4}	-3.051	0.003508
log(UNEMP)	1.150×10^{-1}	5.501×10^{-2}	2.091	0.041146
UNDEREMP	4.938×10^{-3}	2.432×10^{-3}	2.030	0.047212
TRV_DOM_CEN	-1.635×10^{-7}	8.187×10^{-8}	-1.997	0.050818
$TRV\_DOM\_CEN^2$	9.163×10^{-14}	3.828×10^{-14}	2.394	0.020127
GDP_MFG	-1.155×10^{-2}	5.232×10^{-3}	-2.208	0.031447
GDP_CONSTR	1.239×10^{-2}	4.062×10^{-3}	3.051	0.003511
log(GDP_TRANSP)	1.217×10^{-1}	4.338×10^{-2}	2.806	0.006929
GDP_BUS_CEN	-1.806×10^{-2}	1.131×10^{-2}	-1.597	0.115960
$GDP\_BUS\_CEN^2$	-7.889×10^{-3}	4.760×10^{-3}	-1.657	0.103146
sqrt(LDF)	4.840×10^{-3}	2.868×10^{-3}	1.688	0.097106
sqrt(REV_TAX_BUS)	-1.741×10^{-1}	9.269	-1.878	0.065629
VIS_GRP	9.749×10^{-2}	6.216×10^{-2}	1.568	0.122520
MIN_GRP	7.930×10^{-2}	5.645×10^{-2}	1.405	0.165683

Multiple R^2	0.5932	*F*-statistic	5.347
Adjusted R^2	0.4823	p-value	1.968×10^{-6}

Note: Variables with added polynomial terms are centered, hence the variable code “CEN.”

Table 3
Test for Linearity

	Test Statistic	p-value
Ramsay RESET test	$R = 1.301$	0.2808

Figure 2
Residual Plot of Final Model

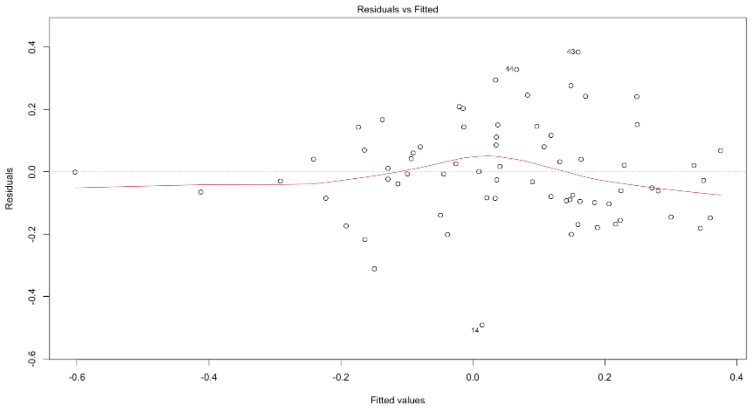
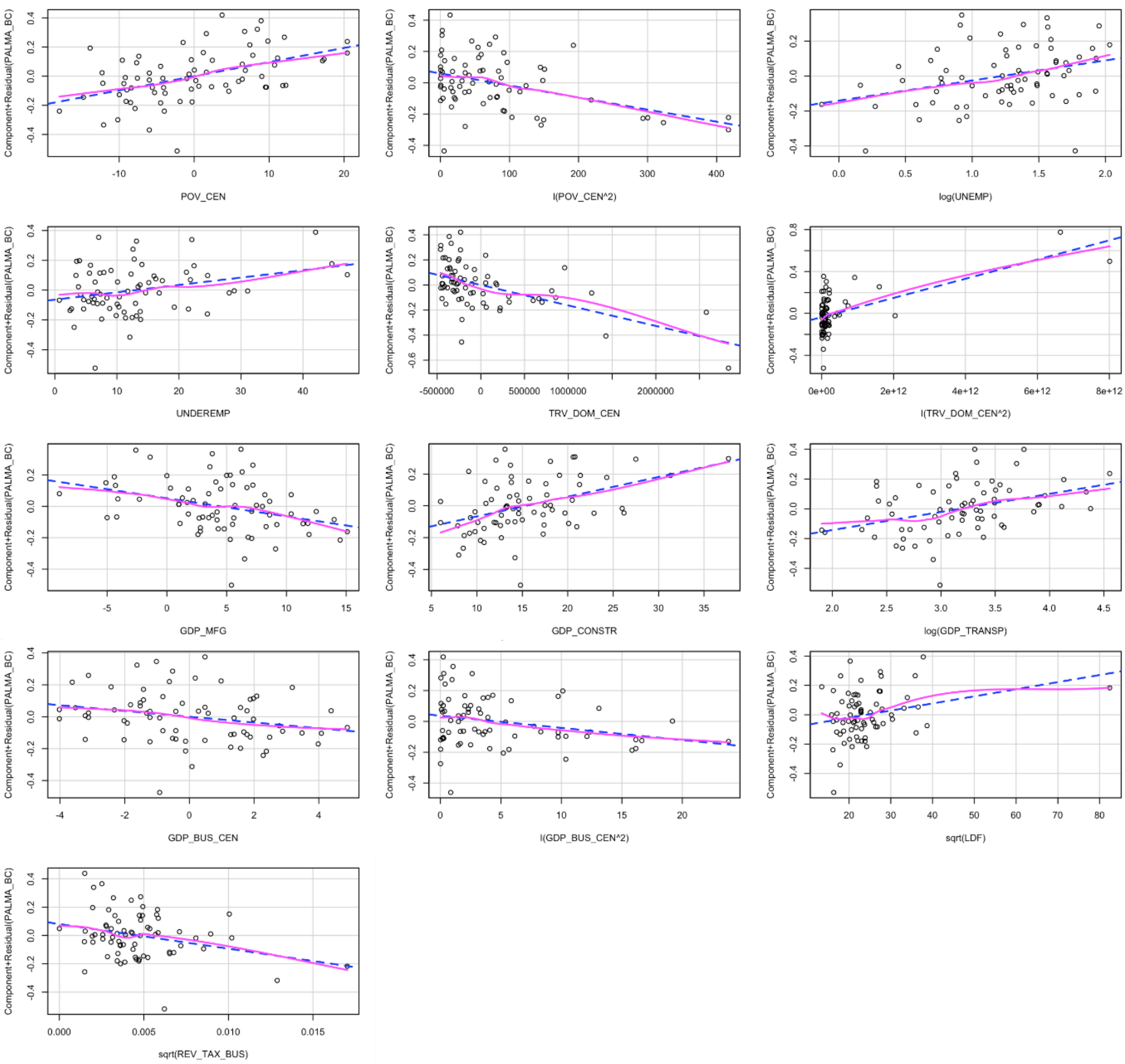


Figure 3
Partial Residual Plots Corresponding to Each Regressor in Final Model



whereas the histogram forms an approximately symmetrical curve (Figure 4). All tests for normality also obtain p-values exceeding $\alpha = 0.05$, as shown in Table 4. Therefore, we have no sufficient evidence to doubt the normality of error terms in the model.

Figure 4

Residuals and Normal Probability Plot of Final Model

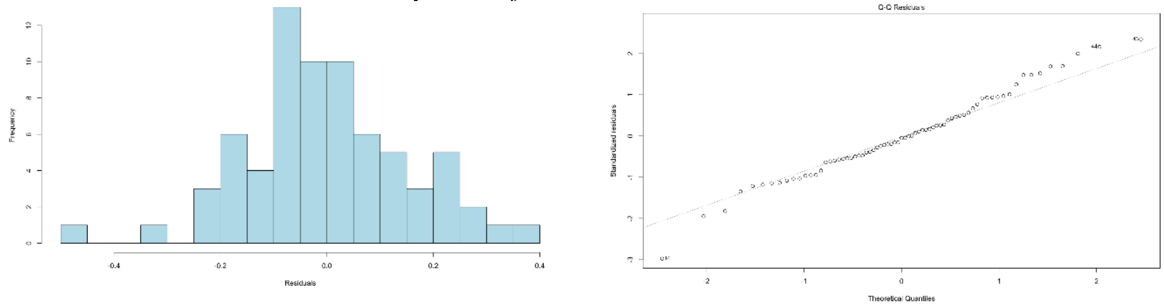


Table 4

Tests for Normality

	Test Statistic	p-value
Kolmogorov-Smirnov test	$D = 0.06971$	0.8566
Shapiro-Wilk test	$W = 0.98223$	0.4127
Anderson-Darling test	$A = 0.39644$	0.3609
Cramer-von Mises test	$W = 0.058216$	0.3944
Jarque-Bera test	$X^2 = 1.0885$	0.5803

Likewise, all tests for heteroskedasticity obtain p-values greater than the set α value (Table 5). Hence, we also have insufficient reason to question whether the variances of error terms in the model are constant. The final model thus far contains no observed violations of classical assumptions.

Table 5

Tests for Heteroskedasticity

	Test Statistic	p-value
Goldfeld-Quandt test	$GQ = 0.59656$	0.8699
White's test	$BP = 2.06$	0.356968
Breusch-Pagan test	$BP = 9.3998$	0.8557

The final model obtains an insignificant test statistic in the Durbin-Watson test, with a p-value exceeding the α value, as shown in Table 6. This also clears out a potential issue of autocorrelation among the data.

Table 6
Test for Autocorrelation

	Test Statistic	**p-value**
Durbin-Watson test	$DW = 1.8938$	0.1617

Examining the correlation matrix of all variables under consideration, we observe that the regressors in their original form are not highly correlated with one another, with values on the upper end sitting at around 0.3481 between GDP_MFG and GDP_BUS, –0.3812 between POV and GDP_MFG, and 0.3931 between POV and MIN_GRP (Figure A1).

Additionally, all variables (or their transformations) in the final model correspond to variance inflation factors (VIF) that are within the threshold, that is, $\text{VIF}_i < 10$ (Table A2), indicating that any forms of linear dependence among the regressors do not significantly inflate variances. The eigensystem analysis, on the other hand, obtains a maximum condition index of 28.8292 < 30 (Figure A2), refuting the possibility of a multicollinearity issue among the data.

Lastly, influence measures including standardized residuals, leverages, hat values, Cook's distances, DFFITS, and DFBETAS identify a total of 13 influential outlying observations: Mountain Province, Ilocos Norte, Batanes, Bulacan, Pampanga, Batangas, Laguna, Catanduanes, Antique, Guimaras, Zamboanga del Norte, Misamis Occidental, and Davao Oriental (Figure 5 and 6). However, further transformations did not help in reducing outlier count, and we could not reasonably pinpoint any errors in the data sources. Therefore, we are left to assume that the mentioned provinces are "natural" outliers, especially given the volume of variables under study.

Figure 5

Standardized Residuals, Leverages, and Cook's Distance Threshold of Final Model

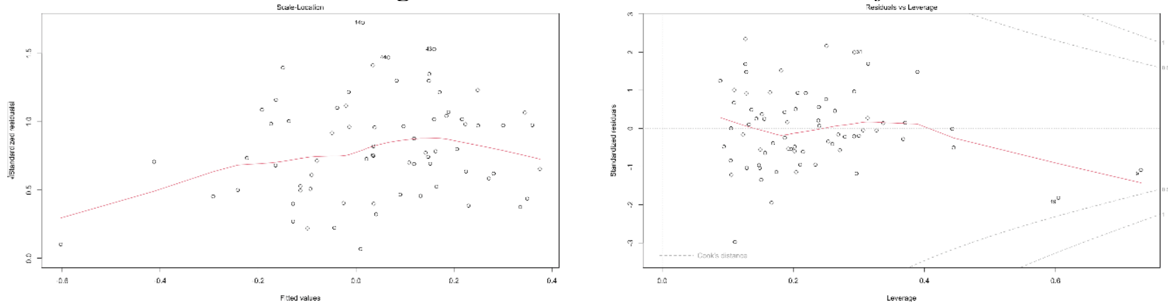
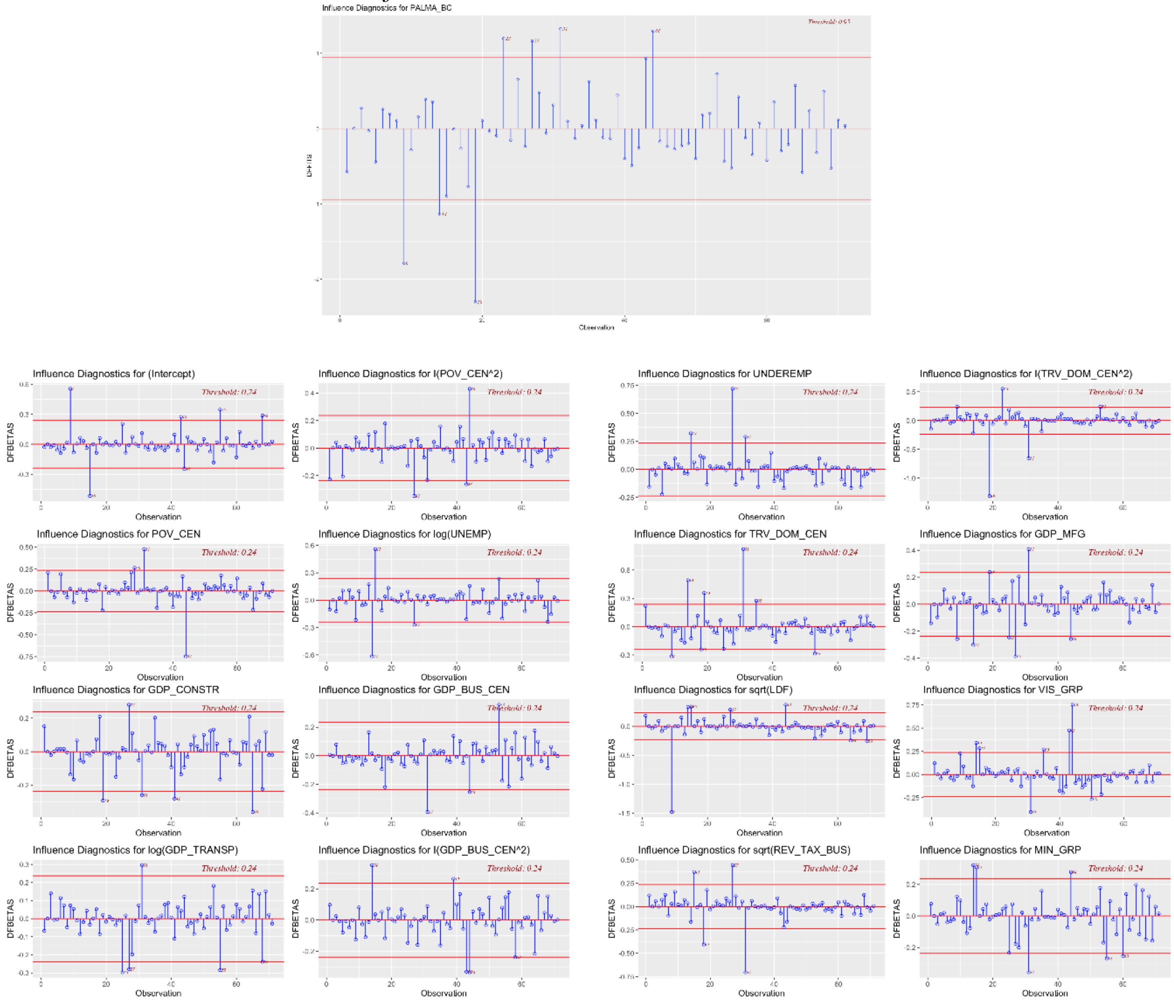


Figure 6

DFFITS and DFBETAS Plots of Final Model



Finally, we establish the final model, which explains 59.32% of the variability in the Box-Cox transformed response, denoted by PALMA_BC (Table 2). Moreover, holding all other variables fixed, we expect:

- A 1.150×10^{-1} unit increase in estimated mean PALMA_BC for every unit change in *log*(UNEMP);
- A 4.938×10^{-3} unit increase in estimated mean PALMA_BC for every percent change in UNDEREMP or underemployment rate;
- A 1.155×10^{-2} unit decrease in estimated mean PALMA_BC for every unit change in GDP_MFG or GDP growth rate in manufacturing;
- A 1.239×10^{-2} unit increase in estimated mean PALMA_BC for every unit change in GDP_CONSTR or GDP growth rate in construction; and
- A 1.217×10^{-1} unit increase in estimated mean PALMA_BC for every unit change in *log*(GDP_TRANSP) or GDP growth rate in transportation and storage.

Note further that the interacting polynomial terms POV_CEN-POV_CEN^2 and TRV_DOM_CEN-TRV_DOM_CEN^2 are significant components as well, indicate a curvature in the relationship and changes in the slope. Lastly, there is no significant difference in estimated mean PALMA_BC among provinces in Luzon versus those in Visayas or Mindanao.

CONCLUSION

In the final multiple linear regression model, there were fifteen remaining regressors, namely: POV_CEN, POV_CEN^2, *log*(UNEMP), UNDEREMP, TRV_DOM_CEN, TRV_DOM_CEN^2, GDP_MFG, GDP_CONSTR, *log*(GDP_TRANSP), GDP_BUS_CEN, GDP_BUS_CEN^2, *sqrt*(LDF), *sqrt*(REV_TAX_BUS), VIS_GRP, and MIN_GRP. Among these, statistical significance at the $\alpha=0.05$ level was observed only for POV_CEN up to log(GDP_TRANSP). The final model has an R^2 of 0.5932, indicating that 59.32% of the variation in the Box-Cox-transformed Palma Ratio can be explained by the fifteen remaining regressors through the model.

Six of the nine significant regressors showed a positive association with the transformed Palma Ratio: POV_CEN, log(UNEMP), UNDEREMP, TRV_DOM_CEN^2, GDP_CONSTR, and log(GDP_TRANSP). In contrast, POV_CEN^2, TRV_DOM_CEN, and GDP_MFG were negatively associated with the transformed Palma Ratio,

The literature supports that higher poverty incidence (POV_CEN) tends to increase income inequality because when more people are poor, wealth is concentrated among fewer individuals. Interestingly, however, the negative association with POV_CEN^2 suggests that beyond a certain point, the effect on inequality changes its behavior, possibly because extreme poverty is associated with more uniformly low income, and consequently less income disparity.

Consistent with the literature linking tourism to rising inequality, the contrasting signs between domestic travelers and its squared term suggest that at lower levels, tourism may help in distributing income more evenly, but that higher levels of tourism are associated with greater inequality.

Unemployment and underemployment both showing a positive association aligns with the literature that the two contribute to aggravating the problem of income disparities. With regards to positive correlation of GDP growth rate for construction, one possible explanation is that most of the workers in construction are minimum-wage earners, which could give rise to income inequality among areas. Similarly, the positive association between GDP growth rate in transportation and income inequality aligns with existing studies, suggesting that growth in this sector may disproportionately benefit higher-income groups, thereby widening the income gap.

On the other hand, the GDP growth rate in manufacturing shows a negative association with income inequality. This suggests that expansion in this sector may be contributing to economic growth that is inclusive of all socioeconomic classes, by providing more stable employment opportunities (as compared to construction), especially for middle- and lower-income workers, and thus helping to reduce income disparities.

To further improve the model, especially considering the relatively low R^2, future researchers are encouraged to incorporate additional variables that are closely related to the Palma Ratio. As indicated by the findings of Soto et al. (2023), factors such as the mean number of years of education, urbanization, internal conflict, and political stability may significantly contribute to explaining income inequality. In addition, other gentrification-specific factors — such as the displacement of low-income groups, the influx of affluent individuals and businesses, changes in rental or property values, and any other indicators of neighborhood redevelopment—should be considered. Including interaction terms between existing regressors may also help in better understanding the dynamics influencing the Palma Ratio. Finally, if not restricted to a linear regression model, and data across multiple years or regions is available, a time-series analysis may be explored instead, as gentrification is a temporal phenomenon that might be better understood through changes over time.

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APPENDIX

Dataset and Codes

The dataset and R codes used in this study can be accessed through the link: tinyurl.com/STAT136-GRP5.

Some Notable Statistics and Outputs

This section goes through notable parts of data analysis including the comparison of model statistics and the process of diagnostic and assumption checking.

Table A1
Summary of ANOVA Statistics of All Models

	Full Model	**Intermediate Model (1)** *after transformations*	**Intermediate Model (2)** *after centering*	**Final Model** *after variable selection*
Multiple R^2	0.456	0.6177	0.6177	0.5932
Adjusted R^2	0.2228	0.4182	0.4182	0.4823
F-statistic	1.956	3.097	3.097	5.347
p-value	0.02733	0.0004872	0.0004872	1.968×10^{-6}

Table A2
VIFs Corresponding to Each Regressor in Final Model

Regressor	**VIF**
POV_CEN	1.761495
POV_CEN^2	1.242120
log(UNEMP)	1.527834
UNDEREMP	1.228107
TRV_DOM_CEN	5.932554
TRV_DOM_CEN^2	5.143329
GDP_MFG	1.524094
GDP_CONSTR	1.273415
log(GDP_TRANSP)	1.298605
GDP_BUS_CEN	1.378257
GDP_BUS_CEN^2	1.502209
sqrt(LDF)	1.506990
sqrt(REV_TAX_BUS)	1.422445
VIS_GRP	1.560640
MIN_GRP	1.535783

Figure A1

Correlation Matrix of All Variables in Full Model

	PALMA	POV	UNEMP	UNDEREMP	TRV_FOR	TRV_DOM
PALMA	1.00000000	0.42239760	0.118374735	-0.059789066	-0.053949576	-0.191764181
POV	0.42239760	1.00000000	0.101440785	-0.097056643	-0.190646267	-0.187227804
UNEMP	0.11837473	0.10144079	1.000000000	-0.070356888	-0.018472001	0.465352232
UNDEREMP	-0.05978907	-0.09705664	-0.070356888	1.000000000	0.226856567	-0.028275025
TRV_FOR	-0.05394958	-0.19064627	-0.018472001	0.226856567	1.000000000	0.256340750
TRV_DOM	-0.19176418	-0.18722780	0.465352232	-0.028275025	0.256340750	1.000000000
COMPET	-0.21706653	-0.20375765	0.094187048	-0.073530533	-0.028638689	0.348753093
GDP_MFG	-0.27002030	-0.38117244	-0.177802081	0.092952336	-0.047072975	-0.007633098
GDP_CONSTR	0.16291056	-0.03836685	0.082254833	-0.126312058	0.202659633	0.074287675
GDP_WRT	-0.13190463	-0.14650869	-0.045914681	0.032980794	-0.076445300	0.054842770
GDP_TRANSP	0.17451747	-0.03668189	-0.166720757	-0.073562015	-0.154069062	-0.218288411
GDP_AFS	0.2	-0.22287582	0.070129613	-0.035819009	0.434247347	0.101333107
GDP_ICT	-0.09408010	-0.02275032	-0.289914508	0.158542214	-0.133895538	-0.284911039
GDP_FIN	-0.14672463	-0.03886223	0.372427498	-0.190601030	0.031691048	0.423729272
GDP_REOD	-0.19397438	-0.09040541	0.143324856	-0.077826886	0.111316724	0.316478004
GDP_BUS	-0.09873890	-0.07217614	-0.046490962	0.195620629	0.010834275	-0.150467366
LDF	0.05316764	-0.14476386	-0.191845977	-0.009197516	-0.073051383	-0.221813761
LDF_EXP	-0.03338458	-0.17682381	-0.283693333	0.039114485	-0.146978638	-0.267967684
REV_TAX_RP	-0.14416537	-0.24806110	0.160009358	0.060649851	-0.003919999	0.136877436
REV_TAX_BUS	-0.29144871	-0.21285991	0.149883630	0.126355456	0.538598517	0.282179071
VIS_GRP	0.14709534	0.09107595	0.006103022	-0.049021711	0.161067436	-0.083746133
MIN_GRP	0.22126843	0.39306887	-0.165685654	-0.065149398	-0.194969016	-0.191926732
PALMA_BC	0.98269837	0.44699307	0.127108569	-0.071005670	-0.093088249	-0.182455638

	COMPET	GDP_MFG	GDP_CONSTR	GDP_WRT	GDP_TRANSP	GDP_AFS
PALMA	-0.21706653	-0.270020298	0.162910562	-0.1319046281	0.174517467	-0.09744340
POV	-0.20375765	-0.381172442	-0.038366845	-0.1465086858	-0.036681886	-0.22287582
UNEMP	0.09418705	-0.177802081	0.082254833	-0.0459146813	-0.166720757	0.07012961
UNDEREMP	-0.07353053	0.092952336	-0.126312058	0.0329807944	-0.073562015	-0.03581901
TRV_FOR	-0.02863869	-0.047072975	0.202659633	-0.0764453004	-0.154069062	0.43424735
TRV_DOM	0.34875309	-0.007633098	0.074287675	0.0548427698	-0.218288411	0.10133311
COMPET	1.00000000	0.024968482	0.231093051	0.2868502681	-0.201446182	-0.22655143
GDP_MFG	0.02496848	1.000000000	0.180205216	0.3473035324	0.143076686	0.17261045
GDP_CONSTR	0.23109305	0.180205216	1.000000000	0.1894110762	-0.059478429	0.34195845
GDP_WRT	0.28685027	0.347303532	0.189411076	1.0000000000	0.002436048	0.05615997
GDP_TRANSP	-0.20144618	0.143076686	-0.059478429	0.0024360480	1.000000000	-0.04289891
GDP_AFS	-0.22655143	0.172610453	0.341958452	0.0561599748	-0.042898911	1.00000000
GDP_ICT	-0.09990670	0.319326273	0.100225522	0.1918033968	-0.075459857	-0.04536333
GDP_FIN	0.34048010	0.097771072	0.258150904	0.0931781007	-0.244706211	0.03637680
GDP_REOD	0.24599997	0.004792093	-0.022543295	-0.1354100095	-0.205860792	-0.10629739
GDP_BUS	-0.19432400	0.348103542	0.160035904	0.0732759577	0.065621934	0.17273637
LDF	-0.20384454	0.209797400	0.006903135	-0.1223381912	0.360138486	0.03527643
LDF_EXP	-0.23294315	0.217051148	-0.113746885	-0.0602720901	0.394277803	-0.02251341
REV_TAX_RP	0.13480325	0.168819283	-0.040353551	-0.0003083431	-0.097285605	0.05943629
REV_TAX_BUS	0.06563763	0.020252367	-0.069760363	-0.1384996143	0.058965363	0.18120793
VIS_GRP	-0.24897369	0.199923599	0.218000674	0.2060261425	0.082123954	0.39780267
MIN_GRP	0.16504650	-0.227108900	-0.071828668	0.0048539072	0.026798145	-0.57125416
PALMA_BC	-0.20839907	-0.288944823	0.160980295	-0.1245815829	0.183663241	-0.13809491

	GDP_ICT	GDP_FIN	GDP_REOD	GDP_BUS	LDF	LDF_EXP
PALMA	-0.09408010	-0.14672463	-0.193974383	-0.09873890	0.053167641	-0.033384582
POV	-0.02275032	-0.03886223	-0.090405415	-0.07217614	-0.144763857	-0.176823808
UNEMP	-0.28991451	0.37242750	0.143324856	-0.04649096	-0.191845977	-0.283693333
UNDEREMP	0.15854221	-0.19060103	-0.077826886	0.19562063	-0.009197516	0.039114485
TRV_FOR	-0.13389554	0.03169105	0.111316724	0.01083428	-0.073051383	-0.146978638
TRV_DOM	-0.28491104	0.42372927	0.316478004	-0.15046737	-0.221813761	-0.267967684
COMPET	-0.09990670	0.34048010	0.245999973	-0.19432400	-0.203844543	-0.232943154
GDP_MFG	0.31932627	0.09777107	0.004792093	0.34810354	0.209797400	0.217051148
GDP_CONSTR	0.10022552	0.25815090	-0.022543295	0.16003590	0.006903135	-0.113746885
GDP_WRT	0.19180340	0.09317810	-0.135410010	0.07327596	-0.122338191	-0.060272090
GDP_TRANSP	-0.07545986	-0.24470621	-0.205860792	0.06562193	0.360138486	0.394277803
GDP_AFS	-0.04536333	0.03637680	-0.106297395	0.17273637	0.035276434	-0.022513410
GDP_ICT	1.00000000	0.02737374	-0.393739679	0.22902577	0.088408349	0.097103082
GDP_FIN	0.02737374	1.00000000	0.197506477	0.08809691	-0.214044892	-0.238101895
GDP_REOD	-0.39373968	0.19750648	1.000000000	-0.22590940	-0.186052984	-0.299000477
GDP_BUS	0.22902577	0.08809691	-0.225909398	1.00000000	0.219407172	0.258073820
LDF	0.08840835	-0.21404489	-0.186052984	0.21940717	1.000000000	0.825809966
LDF_EXP	0.09710308	-0.23810190	-0.299000477	0.25807382	0.825809966	1.000000000
REV_TAX_RP	-0.06527326	0.22514244	0.144371144	0.13339740	-0.009051372	-0.026571414
REV_TAX_BUS	-0.02939899	0.18055798	0.222441815	-0.07040679	-0.115257710	-0.135053258
VIS_GRP	-0.08094646	-0.31517543	-0.210812423	0.21535045	-0.061115528	-0.137953676
MIN_GRP	0.09538315	0.01467930	0.033115976	-0.07028196	-0.046051604	-0.008307331
PALMA_BC	-0.09774725	-0.16507356	-0.231683098	-0.11656145	0.076936252	0.008780083

	REV_TAX_RP	REV_TAX_BUS	VIS_GRP	MIN_GRP	PALMA_BC
PALMA	-0.1441653734	-0.29144871	0.147095344	0.221268430	0.982698365
POV	-0.2480610957	-0.21285991	0.091075953	0.393068874	0.446993070
UNEMP	0.1600093581	0.14988363	0.006103022	-0.165685654	0.127108569
UNDEREMP	0.0606498506	0.12635546	-0.049021711	-0.065149398	-0.071005670
TRV_FOR	-0.0039199991	0.53859852	0.161067436	-0.194969016	-0.093088249
TRV_DOM	0.1368774362	0.28217907	-0.083746133	-0.191926732	-0.182455638
COMPET	0.1348032517	0.06563763	-0.248973687	0.165046498	-0.208399067
GDP_MFG	0.1688192830	0.02025237	0.199923599	-0.227108900	-0.288944823
GDP_CONSTR	-0.0403535509	-0.06976036	0.218000674	-0.071828668	0.160980295
GDP_WRT	-0.0003083431	-0.13849961	0.206026142	0.004853907	-0.124581583
GDP_TRANSP	-0.0972856049	0.05896536	0.082123954	0.026798145	0.183663241
GDP_AFS	0.0594362915	0.18120793	0.397802668	-0.571254162	-0.138094913
GDP_ICT	-0.0652732638	-0.02939899	-0.080946456	0.095383147	-0.097747245
GDP_FIN	0.2251424363	0.18055798	-0.315175429	0.014679297	-0.165073556
GDP_REOD	0.1443711444	0.22244181	-0.210812423	0.033115976	-0.231683098
GDP_BUS	0.1333973961	-0.07040679	0.215350451	-0.070281958	-0.116561446
LDF	-0.0090513716	-0.11525771	-0.061115528	-0.046051604	0.076936252
LDF_EXP	-0.0265714136	-0.13505326	-0.137953676	-0.008307331	0.008780083
REV_TAX_RP	1.0000000000	0.10115707	-0.134325184	-0.111670312	-0.142557297
REV_TAX_BUS	0.1011570683	1.00000000	-0.188262154	-0.131756417	-0.346613174
VIS_GRP	-0.1343251835	-0.18826215	1.000000000	-0.349545159	0.155038521
MIN_GRP	-0.1116703119	-0.13175642	-0.349545159	1.000000000	0.231207663
PALMA_BC	-0.1425572969	-0.34661317	0.155038521	0.231207663	1.000000000

Note: The variable PALMA_BC (last row) represents the response variable after Box-Cox transformation.

Figure A2
Condition Numbers, Condition Indices, and Variance Proportions of Final Model

	Eigenvalue	Condition Index	intercept	POV_CEN	I(POV_CEN^2)	log(UNEMP)
1	8.180098321	1.000000	1.967793e-04	2.199697e-07	0.0032993837	1.083306e-03
2	2.017428967	2.013632	2.238164e-06	2.743159e-02	0.0003333242	1.656233e-04
3	1.529702632	2.312468	1.194219e-05	9.629310e-02	0.0171252237	2.803310e-04
4	1.009278620	2.846910	7.697333e-05	1.510831e-01	0.0105034741	7.115603e-05
5	0.772668781	3.253738	3.490839e-05	2.552992e-02	0.0012484048	6.002679e-05
6	0.620241406	3.631607	4.132967e-06	8.975125e-03	0.1494376336	5.441678e-07
7	0.476746510	4.142242	2.879495e-04	7.605452e-02	0.5927713054	1.391716e-02
8	0.341773366	4.892267	1.729201e-05	9.392694e-04	0.0003210336	8.198916e-03
9	0.290111119	5.310031	1.355407e-04	4.354076e-01	0.0067724728	2.052971e-04
10	0.236856515	5.876742	6.088921e-04	2.292800e-02	0.0411840664	4.506556e-03
11	0.205458078	6.309830	1.567035e-03	4.217049e-02	0.0494152051	5.825075e-06
12	0.119471064	8.274617	5.612944e-04	3.310115e-02	0.0199591278	8.792597e-02
13	0.090257303	9.520025	1.605464e-04	5.668484e-02	0.0113613194	3.476228e-01
14	0.067003102	11.049225	1.009402e-04	1.619914e-02	0.0678613725	1.818129e-01
15	0.033061993	15.729494	5.889280e-02	2.600944e-03	0.0281012895	2.429650e-01
16	0.009842223	28.829205	9.373407e-01	4.601044e-03	0.0003053635	1.111785e-01

	UNDEREMP	TRV_DOM_CEN	I(TRV_DOM_CEN^2)	GDP_MFG	GDP_CONSTR	log(GDP_TRANSP)
1	2.853751e-03	4.518886e-06	0.0002933939	2.825197e-03	1.297192e-03	3.158965e-04
2	4.091103e-04	3.447151e-02	0.0323530868	6.223437e-05	1.561137e-06	1.763626e-05
3	4.631997e-04	7.779676e-04	0.0010915417	3.298373e-02	2.942753e-05	5.991299e-06
4	1.119547e-02	5.476190e-03	0.0052425693	1.612841e-03	3.880763e-05	8.035567e-05
5	8.322854e-04	1.410611e-02	0.0061452416	7.397196e-04	7.012685e-05	6.981365e-05
6	7.779296e-02	9.588277e-03	0.0039608405	2.050045e-02	1.434251e-03	2.469624e-06
7	4.323666e-03	5.412304e-03	0.0017007047	1.634110e-02	1.870740e-03	1.661039e-04
8	3.383675e-03	2.219519e-03	0.0053952963	3.049558e-01	1.254292e-03	3.962377e-07
9	4.177957e-02	6.019710e-04	0.0020430411	5.081236e-01	2.164237e-03	1.709584e-04
10	7.448016e-01	9.719745e-04	0.0006050707	2.461856e-02	7.395699e-03	2.412688e-03
11	1.715989e-02	6.094157e-02	0.1646033598	1.302074e-02	4.274913e-04	3.477530e-03
12	6.387569e-05	4.400160e-02	0.1064011839	3.302664e-03	2.959792e-01	1.524194e-03
13	1.888089e-02	5.725320e-02	0.1161220894	2.364107e-02	4.682087e-01	2.104377e-03
14	3.063781e-03	6.942374e-01	0.4986778450	5.425328e-03	7.881775e-03	3.833888e-04
15	5.840381e-03	6.562239e-02	0.0486149822	4.082596e-02	5.065081e-02	3.376779e-01
16	6.715589e-02	4.313549e-03	0.0067497529	1.020964e-03	1.612957e-01	6.515903e-01

	GDP_BUS_CEN	I(GDP_BUS_CEN^2)	sqrt(LDF)	sqrt(REV_TAX_BUS)	VIS_GRP	MIN_GRP
1	2.907340e-05	3.006022e-03	1.039007e-03	1.969548e-03	0.002028071	1.956245e-03
2	1.620189e-02	4.132517e-06	2.219894e-04	5.881084e-04	0.002440184	9.960123e-03
3	1.287475e-01	9.538358e-04	3.348300e-05	1.634076e-04	0.023618386	5.055703e-02
4	2.623126e-02	3.582571e-02	1.051955e-03	9.407996e-03	0.174641362	1.672918e-02
5	4.963321e-01	2.340451e-04	7.237491e-05	1.425494e-04	0.095152178	1.091356e-01
6	4.733172e-02	2.152215e-01	3.083957e-04	9.622465e-03	0.010139453	6.479613e-02
7	8.902467e-07	5.554583e-02	9.351777e-04	2.615955e-02	0.040913635	1.664718e-05
8	5.157763e-02	2.387199e-01	2.132993e-03	1.475089e-02	0.205327705	3.140490e-01
9	6.533049e-02	9.299032e-03	1.841546e-03	1.229204e-03	0.222815818	2.102450e-01
10	5.333809e-02	1.526005e-01	8.116298e-03	5.073449e-02	0.042992294	6.807025e-02
11	5.030702e-03	1.287348e-01	8.571196e-02	2.430645e-01	0.024034689	7.683666e-02
12	5.861767e-03	4.453903e-02	4.380204e-02	4.056024e-01	0.091336038	4.350839e-03
13	2.867746e-04	1.047710e-02	1.048702e-02	9.314407e-02	0.000188470	1.520622e-02
14	7.208158e-02	1.800424e-02	4.110338e-01	3.170462e-02	0.005435706	1.826582e-04
15	1.019872e-02	6.058189e-02	4.272353e-01	1.116447e-01	0.057505111	4.273575e-02
16	2.141977e-02	2.625236e-02	5.976677e-03	7.149752e-05	0.001430899	1.517267e-02