

Income-Expenditure Dynamics across Districts in Khyber Pakhtunkhwa: A Multilevel Statistical Approach

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Abstract

Financial development in emerging economies, such as Pakistan, often leads to disparities in wealth, causing long-term financial and social instabilities. Dealing with these imbalances requires a holistic approach that incorporates financial expansion and equal distribution of wealth. This study assesses the relationship between earnings and expenses within multiple districts in Khyber Pakhtunkhwa, Pakistan, using a multilevel regression model to gain a localized understanding of wealth disparities and consumption patterns. The Tehsil Municipal Administration in Peshawar and the Bureau of Statistics in Khyber Pakhtunkhwa analyzed data from 24 districts throughout 2012/13, 2014/15, and 2018/19. The investigation seeks to assess the performance of multilevel modeling compared to classic regression techniques and analyze expenditure patterns among districts through multilevel models. Based on the outcomes, the multilevel model outperforms standard regression models and provides additional proof of districts' influence on expenditures and earnings interactions. The outcomes emphasize the crucial importance of incorporating hierarchical data frameworks when investigating economic interactions, as they demonstrate substantial variability within each person and district level. The multilevel analysis underscores the complexities of income-expenditure dynamics in Khyber Pakhtunkhwa and demonstrates the limitations of single-level models in adequately capturing this complexity.

Keywords: Income inequality, Traditional regression techniques, Multilevel regression model, Hierarchical data structures, District effects

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Introduction

After World War II, numerous economists began to emphasize the significance of Increase in GDP (Gross Domestic Product) in the advancement of developing nations. This concept has been widely seeking in the realm of economic sustainability, primarily concentrating on quantitative rather than qualitative aspects. Economic growth has primarily revolved around augmenting per capita income, national income, production, and investment (Baldwin, 2004).

Developed nations have extended financial support to underdeveloped countries to help them attain higher economic growth rates and alleviate poverty and unemployment levels. However, some developing nations have experienced adverse outcomes, including increased poverty, unemployment, and a widening wealth gap (Binns and Nel, 2002) (Qureshi & Ahmed, 2022). Additionally, certain nations achieved higher economic growth rates but with a skewed distribution of income, yielding unfavorable results for overall development. True development is achieved when a nation sustains a balanced income distribution (Murshed, 2023) (Yousfani et al., 2024).

In the present day, most economists advocate for an integrated approach that combines economic growth with income distribution, as well as other development paradigms (Hirai, 2022) (Iftikhar et al., 2024). Addressing the issue of unequal income distribution is a global imperative. Research has shown that unequal income distribution poses significant challenges to a country's development, often leading to resource disparities between the rich and poor, which in turn hinders sustainable growth. (Skoufias et al., 2021) examined the association between economic growth and income inequality in Sub-Saharan Africa, highlighting the necessity for policies that promote equitable growth. A cross-country investigation by (Mayshar et al., 2022) shown how income disparity might have a detrimental impact on economic growth in different geographical areas (Daniyal et al., 2024). To address these challenges, the concept of balanced development has been proposed. (Bhatt, 2022) highlights that equitable income distribution is essential for sustainable economic growth (Ramzan & Qureshi, 2022).

Furthermore, (Abdelghaffar et al., 2023) present an exhaustive development approach that links economic expansion to human development measures. (Langford et al., 2021) investigated the fundamental required strategy and its efficacy to lower income inequalities in emerging countries. (Jiang et al., 2024) explored the significance of financial accessibility and civic engagement on income inequality reduction, with a focus on emerging nations. Due to disparities in income distribution, there exist discrepancies in possession of resources throughout the development of a country (Qureshi et al., 2022) (Tawiah et al., 2023). Consequently, initiatives such as balanced development and increasingly civic engagement

convey more efficient remedies to tackle income disparities (Huang et al., 2023) (Qureshi et al., 2023) (Iftikhar et al., 2023).

Social welfare policies have played an important role in influencing income distribution equality. Comparative analysis (Collste, 2021) highlights their dual effect on income disparity, examining perspectives from both developed and developing countries. (Singh, 2024) suggests a paradigm shift towards equity and sustainability in regards to economic development by highlighting the flaws of traditional growth models. Moreover, (Sauer et al., 2022) emphasized the importance of education in lower and high incomes inequality levels especially in the OECD countries and (Tselios, 2021) showed that income redistribution through social capital can increase economic growth. Reducing income equality and the nurturing of social capital would be fundamental in increasing economic growth as well as enhancing the general welfare of people (Qureshi et al., 2022).

Over the years, the income and expenditure landscape of Pakistan has developed due to economic policies, global economy and domestic factors. The 1960s were viewed as a period of economic growth in Pakistan. However, the increase in defense spending during the late 1960s unfortunately interrupted the nation's economic progress. High defense expenditures adversely affected economic growth from 1958 to 1973, particularly during the India-Pakistan conflicts of 1965 and 1971 (Shahid et al., 2023) (Qureshi et al., 2023).

Pakistan's informal marketplace, like that of many emerging economies, is an intricate mixture of socioeconomic, political, and environmental considerations. Since acquiring freedom from British rule in 1947 and affected by deterioration in 1971, the country's economy has experienced booms as well as busts.

Those past circumstances have affected Pakistan's current economic condition, in which income disparity remains a prominent concern. Considering worldwide research on income distribution and economic expansion is particularly crucial to tackle the difficulties of Pakistan.

Although phases of economic expansion, the profits have not been delivered fairly, which led to stubborn socioeconomic inequalities.

As illustrated by international research, incorporating income distribution into economic expansion approaches is significant.

The economy has faced stumbles in recent years due to natural catastrophes, influential social and fiscal expenditures for the Afghan War, extreme electricity deficits, and price hikes (Hanif et al., 2022).

Adopting an economic paradigm that fosters fair expansion, equitable services, and engaged participation from all citizens might be the ultimate solution to tackle these discrepancies in Pakistan.

Throughout this challenging time, Pakistan's marketplace exerts a double-edged impact, distinguished by its extremely laborious dependency and linkages to the economy.

Local bodies, such as Municipal Corporations, hold a significant role in a functioning democracy, especially in a vast and diverse country like Pakistan with notable variations in population density, geographic characteristics, and natural resources from one region to another (Koven, 2021). By aligning its policies with these principles, Pakistan can address the deep-rooted issues of inequality and create a more inclusive and sustainable path for its future development.

The relationship between income and expenditure is a fundamental aspect of economic analysis, providing insights into consumer behavior, poverty levels, and economic development. Awareness of this interaction tends to be crucial in areas that encompass different demographic regions.

Insufficient investigate has been performed in Pakistan in order to examine persistent connections between unemployment, economic expansion, and distribution of revenue.

(Idrees, 2006) offered a relatively thorough investigation of this link by analyzing data from

1963/64 to 1993/94. This investigation utilized ordinary least squares (OLS) regression to analyze longer-term patterns and their impact on economic growth and poverty.

(Saboor et al., 2015) expanded the present investigation paying attention on remote regions between

1990/91 and 2001/02 This study applied OLS method to investigate the multidimensional dimensions of hunger and financial growth across rural region of Pakistan, gives evidence on how income gaps influence monetary behaviors and overall quality of life in primarily less developed areas.

More recent research by (Khushi et al., 2020) valuated the influence of fiscal adjustments on household revenues and spending habits in Pakistan from 2001 to 2015.

This study examined how policy modifications altered monetary policy across various revenue sectors employing panel data analysis ensuring a deeper analysis of income-expenditure trends.

(Rahman et al., 2021) explored the influence of local economic inequality on Pakistani household financial behaviors.

The research investigation, which employed cross-sectional and time-series data, identified that disparity in income between rural and urban regions alters expenditure decisions, emphasizing the relevance of regional economic initiatives.

Eventually, (Shuang et al., 2024) evolved around socioeconomic aspects which influence household income and expenditure in Pakistan from 2010 to 2020.

Their study, utilizing extensive econometric tools, examined how shifts in socioeconomic factors, such as education and employment, affect income distribution and expenditure preferences.

Although, availing OLS with pooled data has shortcomings just as it excludes geographic variations in poverty, inequality, and economic expansion throughout Pakistan.

Income levels, resource access, and cultural practices vary significantly between districts, making it essential to analyze these relationships at a more granular level. These variations arise because some regions have more natural resources and economic opportunities than others. To address and consider these differences, we employ panel data techniques, specifically fixed effects and random effects models. These methods help us understand the long-term connections between income and expenditures for the Tehsil Municipal Administration in Khyber Pakhtunkhwa, categorized by district. The data used for this analysis was collected from the Khyber Pakhtunkhwa Bureau of Statistics surveys conducted between 2012/13 and 2018/19.

Purpose of the Study

The main intention of the investigation is to inquire about economic disparity in various district of Khyber Pakhtunkhwa. To do this, we have specific objectives, which are:

- To analyze the total expenditure of various district by using multilevel models.
- To investigate the expenditure patterns within the study area.
- Evaluating the effectiveness of competitive models in comparison to multilevel modeling.

Significance of the Study

While this study may not capture a comprehensive overview of income and expenditure across the entire country, it provides valuable insights at a more localized level. By concentrating on data from twenty-four districts in Khyber Pakhtunkhwa for the years 2012/13, 2014/15, and 2018/19, the research offers a detailed view of economic conditions in these specific regions. Unlike broader national analyses, this study focuses on smaller geographic areas to deliver in-depth insights administrators and organizers can gain insight into the financial reality of individuals in specific areas, including earnings and spending behaviors that may not be readily visible in national records. This comprehensive framework highlights

regional imbalances and trends, allowing for precise measures and legislative choices to reduce economic inequality and improve regional financial management.

The study is arranged as follows: Section 2 describes the datasets and methods employed, Section 3 shows the outcomes, and Section 4 discusses the conclusion.

Data and Methodology

Datasets

Data for this study is taken from the Tehsil Municipal Administration in Peshawar, under the Bureau of Statistics in Khyber Pakhtunkhwa, Pakistan. The administration bears responsibility for gathering and analyzing statistics data in that area. The study revolves around income and expenditure data extracted from surveys conducted in 24 districts of the province.

These surveys cover three distinct periods: 2012/13, 2014/15, and 2018/19, providing a comprehensive view of economic conditions and household spending patterns over time. The chosen district for analysis, along with its precise geographical coordinates, is detailed in Table 2.1. Additionally, Fig 2.1 offers a visual representation of the geographical locations of the districts incorporated in the study, enhancing the spatial perception of the data.

Table 2.1: Name and Location of the Geographic Coordinates of Selected District

District	Latitude (Degrees)	Longitude (Degrees)	District	Latitude (Degrees)	Longitude (Degrees)
Abbottabad	34.169	73.221	Kohat	33.589	71.443
Bannu	32.991	70.646	Kohistan	35.261	73.277
Battagram	34.672	73.024	Lakki	32.614	70.901
Buner	34.394	72.615	Malakand	34.503	71.905
Charsadda	34.168	71.750	Mansehra	34.331	73.198
Chitral	35.770	71.774	Mardan	34.199	72.040
DIKhan	31.863	70.902	Nowshera	34.011	71.988

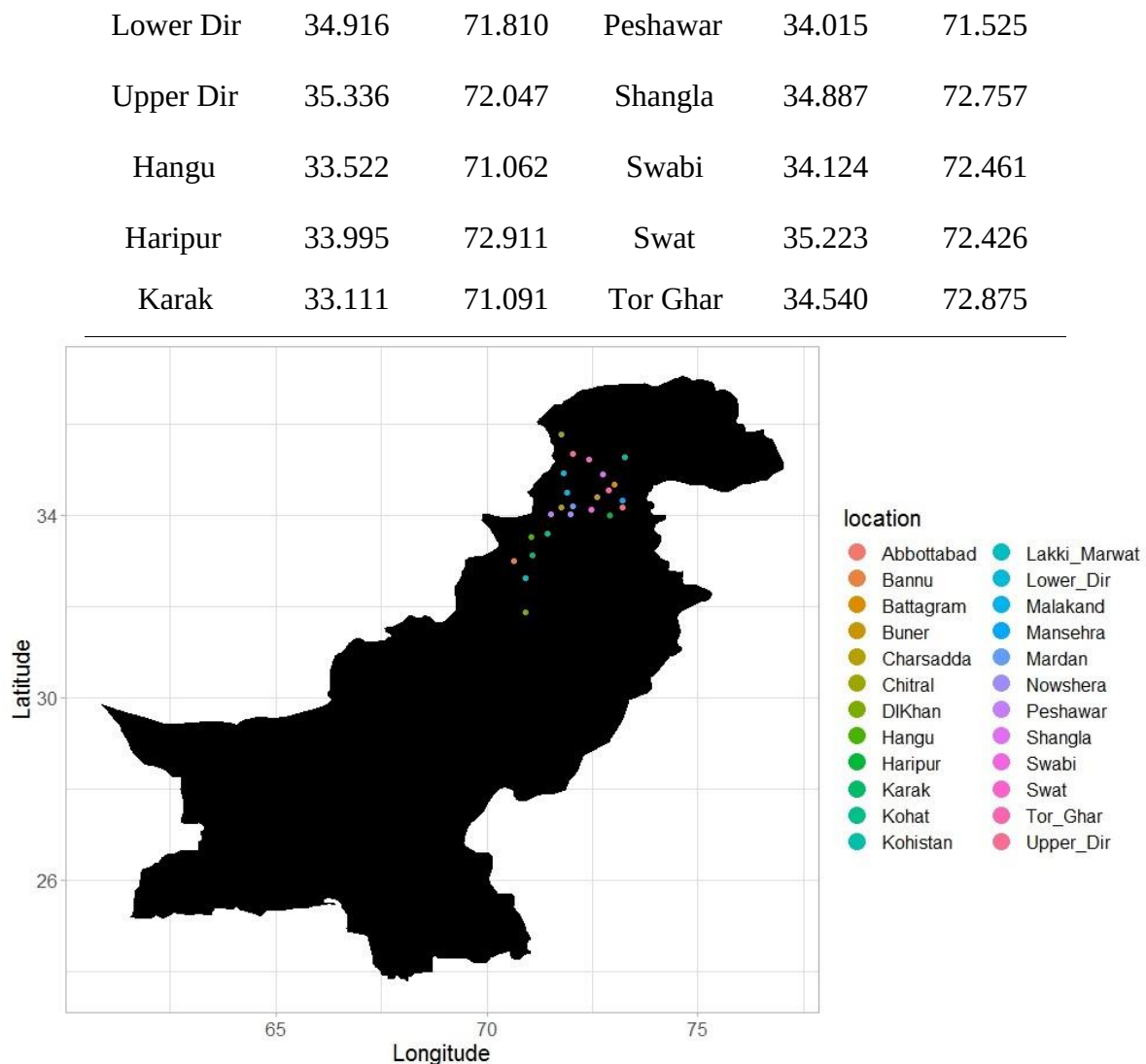


Figure 2.1: Geographical Location of Selected District of Khyber Pakhtunkhwa Pakistan

The study has examined the current income distribution and expenditure patterns in the study area. We have selected total expenditure as the dependent variable. The explanatory variable considered for this analysis include income variable. Both variable is measured in millions. A set of descriptive statistics is presented in Table 2.2.

Table 2.2: Descriptive Statistics of Study Variables

Variable	Observations	Mean	Std. dev.	Minimum	Maximum
Income	277	213.786	228.082	13	1124

Total Expenditure	277	139.536	166.225	2	780
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¹(Rs. in Million)

In order to meet the objective of the study we employed and multilevel regression model to estimate the long-lasting relationships between income and total expenditure. Comparison of multilevel and multiple regression methods is evaluated in relation to their utilization in the gathered data. Since the multilevel model builds on the single level model, it might be a good concept to start by explaining single level regression model first.

Single Level Modeling Structure

Let Y_i denote the observation of predictand, and X denotes the observation of predictor then the linear relationship between predictand and predictor is measured by simple linear regression model. The simple linear regression model is given by

$$Y_i = \beta_0 + \beta_1 X_i + \epsilon_i \quad i = 1, 2, 3, \dots, n \quad (1)$$

Where β_0 and β_1 are parameters and ϵ_i represent the residual term.

The goal is to estimate the values of β_0 and β_1 to make predictions or infer the strength and direction of the relationship between predictand and predictor.

Two Level Modeling Structure

If we represent the observation of the response variable at the the first level or the bottom level of the hierarchy with the symbol Y_{ij} then the two-level null or random intercept-only multilevel model is as follows:

$$Y_{ij} = \beta_{0j} + \epsilon_{ij} \quad (\text{Level} - 1) \quad i = 1, 2, 3, \dots, n \quad \text{and} \quad j = 1, 2, 3, \dots, k \quad (2)$$

$$\beta_{0j} = \gamma_{00} + u_j \quad (\text{Level} - 2)$$

This will calculate the number of parameters, which includes an estimated intercept for each group under consideration, as well as estimates for the disturbance terms at level one ϵ_{ij} and level two u_j both. The random intercept is considered to represent the mean value and reflects the variations in intercepts among different clusters. Here, γ_{00} represents the average intercept value and u_j illustrates the differences in intercepts among various clusters. If we use X_{ij} and X_j to

symbolize the predictor variables at both levels one and two at the same time, then the model 2 transforms into:

$$\begin{aligned} Y_{ij} &= \beta_{0j} + \beta_1 X_{ij} + \beta_2 X_j + \epsilon_{ij} & (Level - 1) & \quad i = 1, 2, 3, \dots, n \text{ and } j = 1, 2, 3, \dots, k \\ \beta_{0j} &= \gamma_{00} + u_j & (Level - 2) \end{aligned} \quad (3)$$

If we treat X_{ij} as a random variable, the model appears as follows:

$$\begin{aligned} Y_{ij} &= \beta_{0j} + \beta_1 X_{ij} + \beta_2 X_j + \epsilon_{ij} & (Level - 1) & \quad i = 1, 2, 3, \dots, n \text{ and } j = 1, 2, 3, \dots, k \\ \beta_{0j} &= \gamma_{00} + u_{0j} & (Level - 2) \end{aligned} \quad (4)$$

In the same way, the impact of β_{1j} varies across different groups, γ_{01} and u_{1j} representing the mean influence of X_{ij} and the average fluctuation in the predicted values β_{1j} for each group. Numerous widely-used statistical software packages, including HLM, MLwiN, R, SAS, Stata, and SPSS, have the capability to accommodate multilevel models. Specialized software for multilevel modeling, like MLwiN, offers the capability to treat intercepts or explanatory variables as either fixed or random.

Results and Discussions

We began the investigation with a basic model and a similar random intercept model in the multilevel scenario. We noticed some noticeable changes in standard error, degrees of freedom, and t-ratio. Although the actual estimates didn't change much, the standard error was significantly greater in the random intercept model in comparison with the basic model. This resulted in a significant drop in the t-value and degrees of freedom. The substantial decrease in the -2 log likelihood ratio points out that the multilevel model outperforms the traditional regression model.

Table 3.1: Null Regression Model

Parameter	Estimates	Std. Error	df	t-ratio	P-value	95% C.I.	
Intercept	139.536	9.987	275	13.95	0000	Lower	Upper
Residual	27530.763	2343.574				23537.183	2899.97

$$^{-2} \text{-2*loglikelihood} = 3604.818$$

Table 3.2: Multilevel Regression (Random Intercept Model)

Parameter	Estimates	Std. Error	df	t-ratio	P-value
Intercept	142.034	21.080	24	6.738	0000

Residual	$2\sigma_u$	8866.764	3082.672
	$2\sigma_e$	18630.894	1659.200

$$^3 -2 * \log \text{likelihood} = 3540.810$$

$$LRT = 3604.818 - 3540.810$$

$$LRT = 64.008$$

$$LRT = 64.008 \text{ } p\text{-value} = 0.000$$

There is strong evidence of a district effect and the null hypothesis that there is no district effect has been disapproved. This confirms the supremacy of the multilevel model over the traditional model. The outcomes of the multilevel analysis in Table 3.2 reveal variances at two levels: 18630.894 at level one and 8866.764 at level two, with corresponding standard errors of 1659.200 and 3082.672, respectively. However, when we look at the simple linear regression model presented in Table 3.3 it has been seen that the intercept term becomes insignificant while the explanatory is a significant variable with an estimate of 0.6864 with a standard error of 0.0148. There is a notable reduction in errors at both levels, with values of 2538.894 and 582.962 at levels one and two, along with standard errors of 226.057 and 237.728, respectively in the random intercept and fixed slope model. Additionally, It is crucial to point out that a major variable at level two, or the district level, can diminish variability at both levels. On the other hand, a substantial variable at level one will only minimize variation at level one.

These trends are also evident in Tables 3.4 and 3.5.

Table 3.3: Regression Model (by including One Variable)

Parameter	Estimates	Std. Error	t-ratio	P-value	95% C.I.	
Intercept	-7.1981	4.6235	-1.557	0.121	Lower	Upper
Income	0.6864	0.0148	46.362	0.000		
Residual	3112.671	264.968			2661.153	19.722

$$^4 -2 * \log \text{likelihood} = 3003.187$$

Table 3.4: Multilevel Regression (Random Intercept and Fixed Slope Model)

Parameter		Estimates	Std. Error	t-ratio	P-value
Intercept		-9.931	6.825	1.455	0.154
Income		0.699	0.016	43.405	0.000
Residual	σ_u^2	582.962	237.728		
	σ_e^2	2538.894	226.057		

$$^5 -2 \times \text{loglikelihood} = 2977.190$$

$$LRT = 3003.187 - 2977.190$$

$$LRT = 25.997$$

$$p\text{-value} = 0.000$$

Table 3.5: Multilevel Regression (Random Intercept and Random Slope Model)

Parameter		Estimate	Std. Error	t-ratio	P-value
Intercept		-11.890	5.649	-2.221	0.0404
Income		0.717	0.044	16.559	0.000
Residual	σ_{u0}^2	227.678	199.004		
	σ_{u1}^2	0.029	0.012		
	σ_e^2	1766.120	162.187		

$$^6 -2 \times \text{loglikelihood} = 2903.581$$

From the random intercept and random slope (regression coefficient) model, the variance component of the random intercept is 227.678, which remains significant compared to its standard deviation of 199.004. Therefore, some variability at the district level is still unaccounted for in the final model. Similarly, the variance component for the regression coefficient is also relatively large when compared to its standard deviation, indicating that it may

be appropriate to treat the effect as random. Figure 3.2 illustrates the differences among levels of your random effects in the null model that display how individual intercepts deviate from the overall model estimates. The values are the difference between the general estimate of the model and the specified level of random effect, be it intercept. Similarly, figure 3.3 provides a visual representation of the differences between various levels of your random effects in the random intercept and fixed slope model. Similarly, figure 3.4 visually illustrates the variations in random effects across different levels within the random intercept and random slope model. Also, a simple linear regression is run individually in each district.

Figure 3.2 shows the relationship between income and total expenditure of each district.

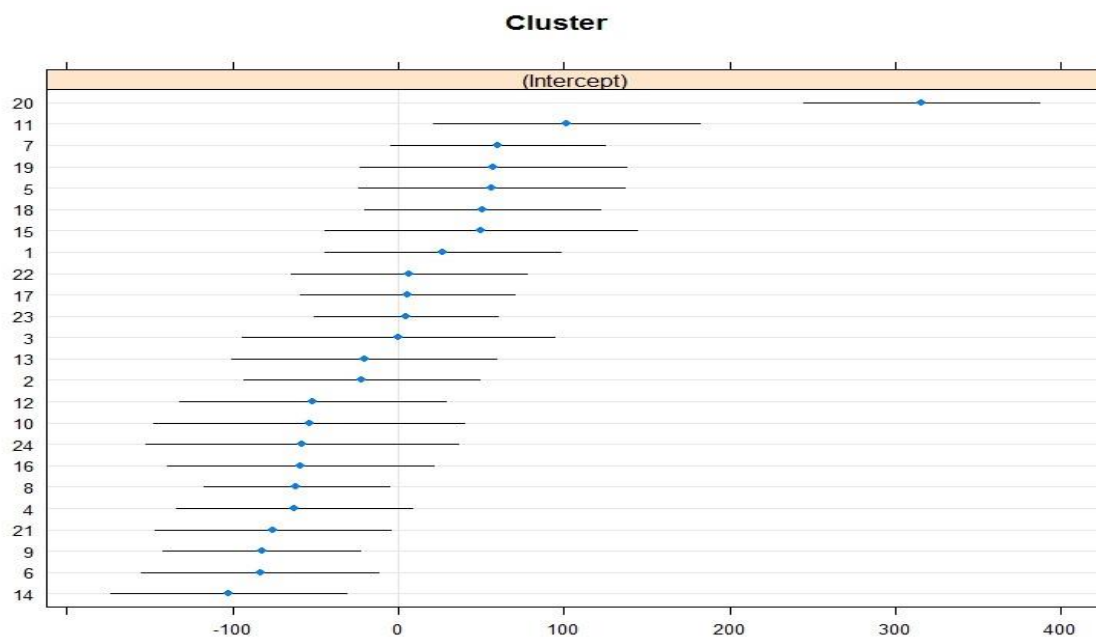


Figure 3.3: Differences between Various Levels of random effects in the Random Intercept Model

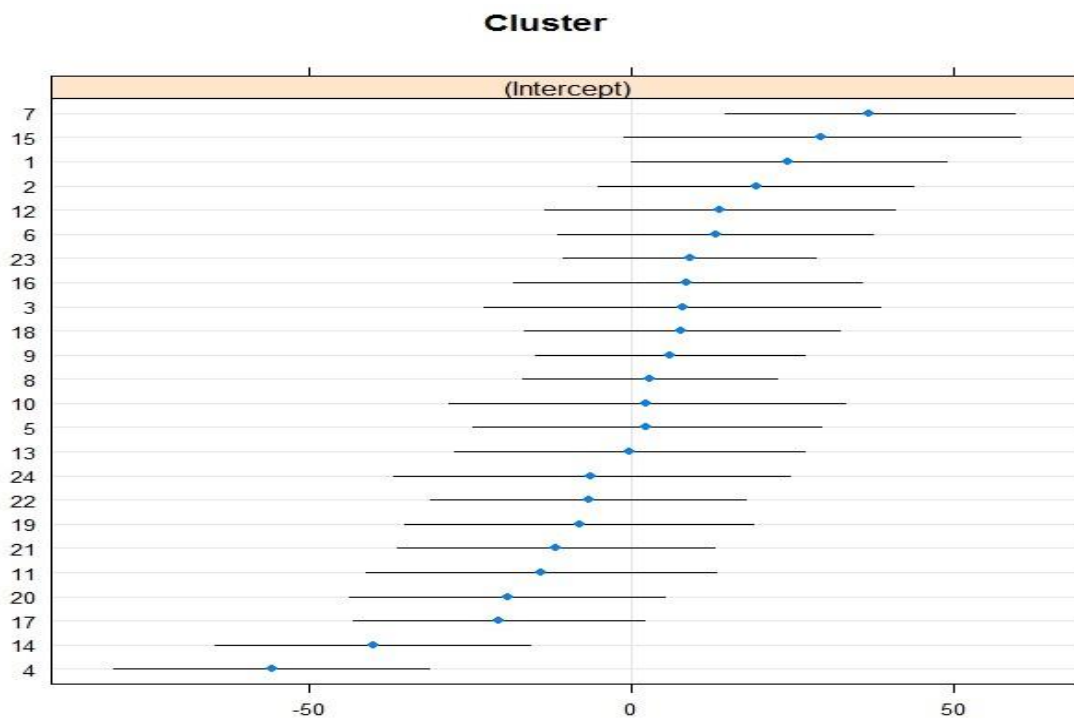


Figure 3.4: Differences between Various Levels of random effects in the Random Intercept and Fixed Slope Model

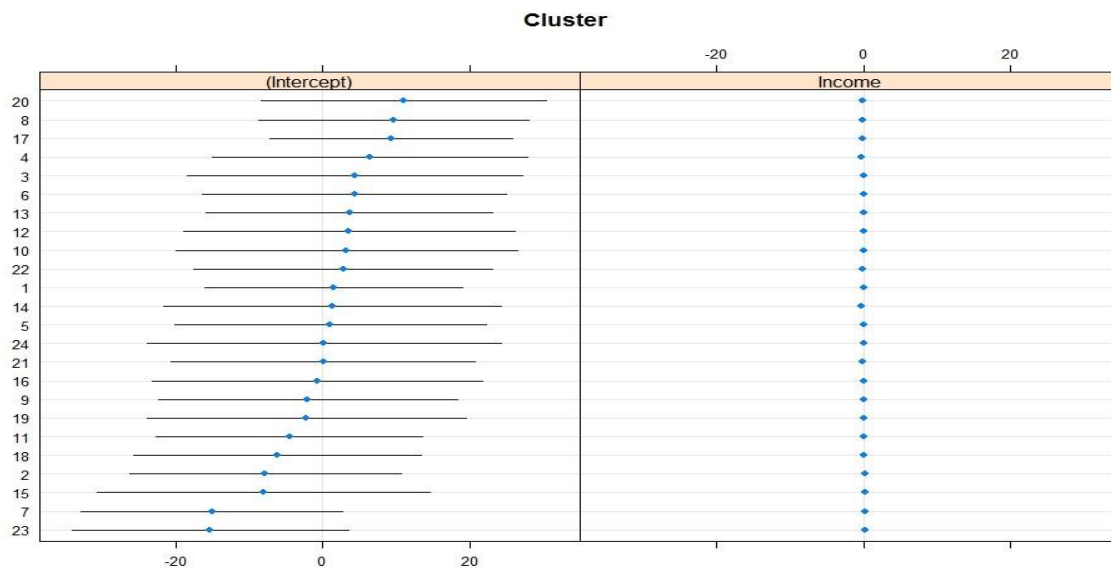


Figure 3.5: Differences between Various Levels of random effects in the Random Intercept and Random Slope Model

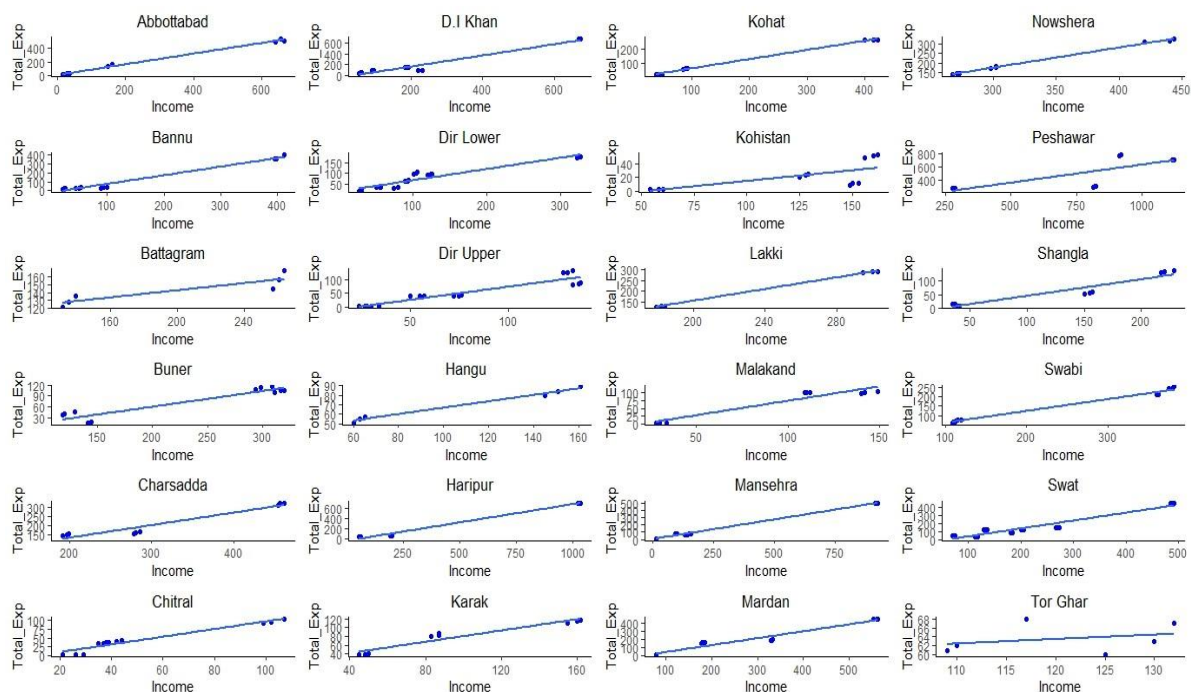


Table 3.6: Selection Criteria of Appropriate Model

Models	AIC	BIC	logLik	Deviance
Null Regression Model	3608.8			3604.818
Simple Linear Regression Model	3009.2			3003.2
Random Intercept Model	3546.8	3557.7	-1770.4	3540.8
Random Intercept and Fixed Slope Model	2985.2	2999.7	-1488.6	2977.2
Random Intercept and Fixed Slope Model	2915.7	2937.5	-1451.9	2903.7

Table 3.6 displays the deviance, logLik, AIC, and BIC. Comparing both the AIC and BIC statistics, it is clear that the random intercept and random slope model is preferable to existing models. Multilevel modeling is becoming increasingly popular for analyzing hierarchical data structures and often provides superior predictive accuracy compared to traditional regression methods.

Conclusion

In classical linear regression models, the model's parameters remain constant, and the explanatory variables are considered fixed. However, there are scenarios where the response variable is influenced by varying levels of the predictors variables or by the variable itself. In such cases, the regression coefficients, as well as intercepts, can also vary. In these situations, a multilevel model is better, suitable and effective choice.

Throughout this investigation, we examined the total expenditure from various district in Khyber Pakhtunkhwa and their influencing factors using a regression-type model. As previously mentioned, we employed a two-level multilevel model. The dependent variable, total expenditure is linked to the income variable. We observed that total expenditure varies among various district. Consequently, we opted for a multilevel model instead of a traditional linear regression model to analyze total expenditure, given its suitability for handling this variability. The results of the multilevel model in this study show large differences compared to a simple regression model. Nevertheless, we have noticed major variations in the estimates and their associated standard errors. So district-wise variation has been found between total expenditure and income variable. The results will differ from those of a simple regression model when the factors are considered random in a multilevel framework. Additionally, the random intercept and random slope model performs better than other models, as indicated by its lower AIC, BIC, and deviance values.

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