KaryaRiset NUSANTARA
IJDE
Indonesian Journal of Development and Economics
https://journal.karyarisetnusantara.com
IJDE
Internasional Journal of Development and Economics

THE INFLUENCE OF THE PKH AND BPNT PROGRAMS ON POVERTY RATE PERCENTAGE IN CENTRAL JAVA PROVINCE: A QUANTITATIVE ANALYSIS

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Artikel Info

Keywords:
Poverty, PKH, BPNT, Panel Data, Fixed Effect Model, Social Assistance

JEL Classification: C54; H2; H3; H53

DOI:

Artikel History
Received: June 2025
Accepted: December 2025
Published: April 2026

Abstract

This study aims to analyze the influence of the Family Hope Program (PKH) and the Non-Cash Food Assistance (BPNT) on poverty levels in Central Java Province. Employing a quantitative approach and panel data from 35 regencies/municipalities over the period 2021–2023, the study applies panel regression methods using the Fixed Effect Model (FEM), selected based on the results of the Chow, Hausman, and Lagrange Multiplier tests. The findings indicate that PKH has a negative and significant effect on poverty, suggesting that the program is effective in reducing poverty levels by improving access to education and healthcare for poor households. Conversely, BPNT shows a positive and significant effect on poverty, suggesting that food aid is not sustainable in nature and has not yet succeeded in fostering economic independence among beneficiaries. These findings underscore the importance of reformulating social assistance program designs to not only be charitable but also oriented toward empowerment and sustainability. This study supports the theory of dynamic poverty as well as the concept of social safety nets in the context of evidence-based poverty alleviation.

INTRODUCTION

Poverty remains a critical issue in Indonesia, not only due to its increasing trend but also because of its broad scope and profound economic implications. Poverty is a condition of material deprivation experienced by individuals relative to the prevailing standard of living within a society. This lower standard of living has a significant impact on the quality of social life (Andrean *et al*., 2023). As a complex and multidimensional issue, poverty demands special attention as a development priority. One of the key indicators used to evaluate the success and effectiveness of government-led development services is the poverty line (Melayanti & Indrajaya, 2021).

A major underlying cause of poverty in Indonesia is the high level of inequality between regions and among societal groups. This inequality stems from the uneven distribution of income and the rising number of people living at or below the poverty line (Buheji *et al*., 2022). Poverty reflects an extremely low standard of living a level of material deficiency experienced by a group of individuals compared to the general societal norm. This condition adversely affects public health, education, and social well-being.

Although the government has implemented various strategies to reduce poverty over the years, data from the Central Statistics Agency (Badan Pusat Statistik, 2022) indicate that poverty levels have not shown significant improvement (Wang *et al*., 2023). While there has been qualitative progress, the actual impact has yet to be clearly evidenced. In some areas, the poverty situation has even worsened (Yokoyama *et al*., 2023). Poverty can also be examined through other dimensions, such as health, nutrition, education, and literacy indicators commonly used to measure the poverty line (Zakar & Iqbal, 2024). From an economic perspective, overall well-being is assessed not only through a single metric but as a composite of consumption expenditure, education, and healthcare (Wibowo & Setyowati, 2024). Contributing factors to poverty include inadequate minimum wages, low living standards, and rising unemployment rates that are not matched by sufficient job creation (Diana *et al*., 2022).

This complex poverty problem is clearly evident in Central Java Province. Many areas in the province continue to face major challenges in efforts to lift communities out of poverty (Yu *et al*., 2024). Rural dominance, limited infrastructure, and disparities in access to education and healthcare further reinforce the entrenched poverty cycle (Chen *et al*., 2023). Although the government has introduced several social protection programs, such as the Family Hope Program (PKH) and the Non-Cash Food Assistance Program (BPNT), their implementation at the local level often falls short. This is due to various technical constraints, administrative challenges, and a lack of coordination and integration among the institutions involved (Kaiser & Barstow, 2022).

These conditions suggest that poverty alleviation efforts in Central Java cannot rely solely on material aid. A more comprehensive development strategy is needed one that can adapt to the socio-economic dynamics of local communities and is grounded in measurable and sustainable impact evaluations (Bonan *et al*., 2022). Based on data released by the Central Statistics Agency, poverty levels in Central Java for the period 2021 to 2023 by regency/municipality are presented as follows.

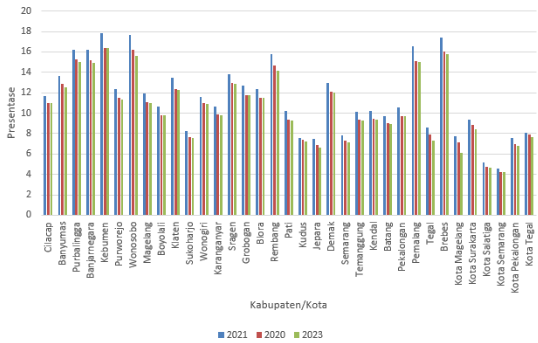

Figure 1 Percentage of Poverty Rate in Central Java by Regency/Municipality Source: Central Statistics Agency (BPS), 2021–2023

The data in Figure 1 indicate that poverty levels across regencies and municipalities in Central Java Province varied significantly during the 2020–2023 period. In 2020, several regions recorded high poverty rates, such as Kebumen Regency (17.66%), Banyumas (16.73%), and Wonosobo (16.60%). However, by 2023, there was a general decline in poverty rates across most regions. For instance, the poverty rate in Kebumen fell to 15.73%, Banyumas to 14.96%, and Wonosobo to 14.71%. This downward trend reflects the economic recovery following the COVID-19 pandemic, which had previously triggered a sharp rise in poverty rates in 2020 (Boza-kiss *et al*., 2021).

On the other hand, major urban centers such as Semarang, Surakarta, and Salatiga consistently recorded relatively low poverty levels. In 2020, the poverty rate in Semarang City was 4.05%, in Surakarta 8.79%, and in Salatiga 6.89%. By 2023, these figures had either declined or remained stable at 3.89%, 8.00%, and 6.61%, respectively. These findings suggest that urban areas tend to exhibit stronger economic resilience than rural regions (Calzada, 2023).

Nevertheless, several regencies such as Brebes and Pemalang continued to report persistently high poverty rates. Brebes Regency had a poverty rate of 16.88% in 2020, which only slightly decreased to 15.67% by 2023. Similarly, Pemalang experienced a modest decline from 16.49% to 15.42% over the same period. These results suggest that, although aggregate poverty has decreased, some regions still face structural constraints that hinder poverty alleviation efforts (Huang *et al*., 2024). This phenomenon highlights the importance of designing poverty reduction strategies that consider the unique characteristics of each region ((Li *et al*., 2024); (Cabanillas-carbonell *et al*., 2023)). Thus, policy interventions must be region-specific, data-driven, and responsive to interregional disparities to ensure that poverty reduction benefits reach the most vulnerable populations (Rodríguez-Pose & Hardy, 2015).

This dynamic illustration of poverty underscores the fact that individuals and households can fall into or escape poverty within relatively short timeframes. Poverty, therefore, is a fluid and dynamic condition ((Dercon & Shapiro, 2007); (Dartanto & Otsubo, 2016)). Households previously considered non-poor may fall below the poverty line due to negative shocks such as economic crises, illness, or crop failure. Conversely, poor households may escape poverty through improved employment opportunities, job promotions, or access to adequate infrastructure ((Dartanto & Nurkholis, 2013); (Kawinata *et al*., 2022)).

In response to this reality, Sen (1981) proposed two distinct forms of poverty dynamics: chronic poverty and transient poverty. Chronic poverty refers to long-term deprivation in which households remain below the poverty line over an extended period. In contrast, transient poverty describes temporary changes in welfare status, where households move in and out of poverty over time ((Hulme & Shepherd, 2003); (Sugiharti *et al*., 2022)).

The contrasting characteristics between chronic and transient poverty necessitate differentiated policy approaches. Addressing chronic poverty requires long-term investments in human and physical capital development. In contrast, tackling transient poverty involves providing responsive social safety nets that can buffer against short-term economic shocks ((Jalan & Ravallion, 1998); (Hulme & Shepherd, 2003)). In this context, measuring poverty dynamics plays a critical role. Where chronic poverty dominates, policies should focus on expanding access to education and health services as part of human capital strengthening strategies (Moeis *et al*., 2020). Conversely, where transient poverty is more prevalent, the priority should be expanding access to financial services, such as small business credit or health insurance (Sugiharti *et al*., 2022).

Although numerous studies have examined poverty dynamics and mitigation strategies, research that explicitly links these dynamics to the local context at the regency or municipal level remains limited particularly in Central Java, a region marked by considerable socioeconomic diversity (Purwono *et al*., 2021). Most existing literature still approaches poverty from an aggregated perspective, without distinguishing between chronic and transient poverty (Pratama *et al*., 2025). Therefore, this study adopts a more specific and localized approach by identifying types of poverty based on regional characteristics and analyzing their relationships with the effectiveness of social programs and structural indicators (Amin *et al*., 2025). Therefore, this study adopts a more specific and localized approach by identifying types of poverty based on regional characteristics and analyzing their relationships with the effectiveness of social programs and structural indicators.

LITERATURE REVIEW

Definition of Poverty

Subsistence, basic needs, and relative deprivation are the three main approaches in defining poverty (Sharift, 1986; Sen, 1979; Nandy & Pomati, 2015; Decerf, 2021; Lazár dkk., 2020; Bharati, 2004; Badland dkk., 2012). When the income of individuals or households is insufficient to meet their minimum physical needs, such a condition is referred to as subsistence poverty (Sharift, 1986; Sen, 1979).

Meanwhile, the basic needs concept refers to the ability to sustain a decent standard of living by fulfilling needs for clothing, food, shelter, and adequate household equipment (Fedele et al., 2021; Lázár et al., 2020; Decerf, 2021). Furthermore, according to Chattopadhyay dkk. (2020), Poudyal dkk. (2024), dan Dumitru dan Stanescu (2014), basic needs also include access to clean water, sanitation, public transportation, healthcare services, as well as educational and cultural facilities.

More social factors are involved in relative poverty (Alkire et al., 2021). n this approach, the poverty threshold is determined based on income limits analyzed from various household needs and characteristics at different levels individual, family, and community (Spada et al., 2024). Factors such as age, gender, and race also influence the distribution of resources and needs within a family or society (Balasubramanian et al., 2024).

In this regard, Kotze states that poor communities possess relatively strong capabilities to access resources through available opportunities (Pham & Mukhopadhaya, 2022). Although external aid is often used, it cannot be assumed that communities will rely on such support (Stark *et al*., 2025). This empowerment approach is considered ineffective because no society can live and develop in isolation from others (Brando & Fragoso, 2020). Isolation breeds passivity and may even worsen poverty (Adetoro *et al.*, 2023). Additionally, according to Todaro and Smith (2020), poverty can be categorized into two types: absolute and relative poverty. Absolute poverty occurs when an individual's income is below the established poverty line, while relative poverty compares an individual's condition with the standard of living of the majority in their surrounding society.

Furthermore, according to Alkire et al. (2023), poverty is a condition of limitation that does not arise voluntarily. According to Spada et al. (2024), a population is considered poor if it exhibits cycles of powerlessness and suffers from low levels of education, labor productivity, income, health, nutrition, and overall well-being. The lack of human resources, both through formal and informal education, may cause poverty that results in low informal educational attainment (Liu et al., 2022).

Emil Salim also outlined five characteristics of poor individuals (Mtocha et al., 2024), which are: 1) lacking ownership of production factors; 2) unable to acquire productive assets by their own means; 3) generally having low educational attainment; 4) lacking access to facilities; and 5) relatively young and without the necessary education or skills (Amir-ud-Din et al., 2018).

In the report titled *"Poverty and Human Development"*, the World Bank (1990) stated that the main issue in human development is not only or even primarily economic in nature. Nearly everyone agrees that reducing child mortality, eliminating hunger, and increasing enrollment in primary education are significant goals (Cluver et al., 2016; Lyatuu et al., 2021). Human development does not solely focus on economic aspects, but also emphasizes the importance of universal education principles for the benefit of all people in order to enhance their socio-economic quality of life (X. Zhang, 2024; Singh & Chudasama, 2020).

Booth and McCawley stated that “in many countries, there has indeed been an increase in societal welfare levels as measured by per capita income, but this improvement is only enjoyed by a small portion of the population, while the majority of the poor do not benefit much and are even severely disadvantaged” (Amponsah et al., 2023; Acheampong et al., 2021; Dorband et al., 2019).

Social Assistance Theory

According to Robson *et al*., (2024), social assistance refers to government budget-based transfers aimed at addressing poverty by targeting highly vulnerable groups. These programs are designed to provide a social safety net, either in the form of cash or in-kind transfers (Aleksandrova & Costella, 2021). Social assistance encompasses various program types, including unconditional cash transfers, conditional cash transfers, public employment guarantees, and multidimensional social programs that integrate economic support with social services (Rukiko et al., 2023). The objectives extend beyond poverty alleviation, aiming also to empower communities by enhancing access to essential services such as healthcare, education, and social inclusion.

Furthermore, Ozcurumez & Hoxha (2020) argue that social assistance is not contingent on prior individual contributions to the state economy. Instead, it is distributed solely based on current need, reflecting the human rights principle that every individual has the right to basic support, without discrimination (Pinilla-Roncancio et al., 2023).

Various types of social assistance have been developed to address the specific needs of vulnerable populations (Komarawati et al., 2025). The primary categories commonly discussed in the international literature include:

1. Conditional Cash Transfers (CCTs): These programs provide cash to low-income households under specific conditions, such as ensuring children’s school attendance or regular health check-ups. The primary goal is to incentivize human capital investment. Notable examples include Mexico’s "Prospera" and Brazil’s "Bolsa Família" ((Breckin, 2023); (Rubio-Sanchez *et al*., 2021))
2. Unconditional Cash Transfers (UCTs): Unlike CCTs, UCTs are provided without specific requirements. They are commonly used in emergency contexts or in areas with limited administrative capacity. Evidence shows that UCTs can improve beneficiaries' welfare without reducing their participation in the labor market ((Crosta *et al*., 2025); (Baird *et al*., 2018))
3. Public Works Programs: These initiatives offer temporary employment to unemployed or underemployed individuals, typically through public infrastructure projects. In return, participants receive wages that help meet basic living needs, while simultaneously contributing to the development of community assets (Bagga *et al*., 2024).
4. Food and In-Kind Transfers: This form of assistance is delivered in goods rather than cash, such as food, clothing, or other basic necessities. It is often used in humanitarian settings or regions with malfunctioning markets ((Chorniy *et al*., 2025); (McIntosh & Zeitlin, 2021)).
5. Social Pensions: Social pensions are regular cash payments to elderly individuals without access to formal pension systems. The purpose is to reduce poverty among older populations and provide economic security (Gutie *et al*., 2018).
6. Fee Waivers and Subsidies for Health and Education: These programs reduce or eliminate costs associated with critical services such as education and healthcare, thereby improving access for impoverished groups (Zozoungbo, 2023).
7. School Feeding Programs: These programs offer free or subsidized meals in schools to boost student enrollment and focus, while also easing the financial burden on poor families (Barnabas *et al*., 2024).

8. Universal Basic Income (UBI): UBI involves unconditional, regular cash payments to all citizens, regardless of income or employment status. Although still in pilot stages in many countries, UBI is increasingly viewed as a structural solution to poverty and inequality (Luduvice, 2021).

Dynamic Poverty Theory

The Dynamic Poverty Theory posits that poverty is not a static condition but rather a dynamic state that fluctuates over time, influenced by both internal and external factors experienced by individuals or households. Poverty may be transient or chronic, depending on the household's ability to adapt to economic, environmental, and social shocks. As noted by Osinubi *et al*. (2024) in the context of Nigeria, social instability and low literacy rates are key drivers of recurring poverty, reinforcing a vicious socio-economic cycle. Similarly, (Orukpe, 2025) argues that imbalanced population growth vis-à-vis public resources and services can lead to structural poverty crises. This dynamic becomes even more complex when gender dimensions are considered. Airaoje *et al*. (2025) highlight that structural poverty disproportionately affects women due to limited access to technology and social capital.

Buheji (2024) underscores the importance of path dependence theory in explaining why vulnerable groups remain impoverished across generation. Meanwhile, Y. Zhang (2025) mphasizes the role of AI-based educational technologies in creating dynamic learning ecosystems that help address education-based poverty. In line with this, Kamal & Islam (2025) propose that mathematical modeling of social dynamics can be used to identify structural weaknesses that exacerbate poverty. In terms of mobility and accessibility, Fredericks (2025) demonstrates that the lack of transportation access among people with disabilities intensifies inequality and worsens poverty dynamics. Furthermore, Vidal (2025) illustrates how low literacy levels and social exclusion within the deaf community in Mexico represent a form of dynamic socio-cultural poverty that continues to evolve.

Social Safety Net Theory

The Social Safety Net Theory explains the structure of policies and social interventions designed to protect individuals or households from extreme poverty and vulnerability caused by economic shocks, social crises, or disability. This safety net includes cash transfers, food subsidies, free healthcare services, social insurance, and minimum guarantee programs. Kriger (2025) illustrates this through community-based disaster preparedness training in British Columbia, which serves as an ecological and social safety net to strengthen local resilience. (Shah & A, 2023) developed a feminist approach to community social work as a non-state safety net strategy grounded in social relationships and empathy. The study by Heslin *et al*. (2025) investigates family experiences in accessing advanced-stage cancer healthcare services and finds that public hospital social security systems play a crucial role in alleviating household burdens. Benatar *et al*. (2025) emonstrate that basic income guarantee programs in California complement traditional safety nets, which are often administratively complex and bureaucratic. Ornelas *et al*. (2025) propose a model for community-based, anti-racist, and equity-focused maternity care as a reformulation of social protection for vulnerable populations. Balestrery (2023) emphasizes the importance of Ubuntu values in constructing a locally rooted social safety net within child and family social work frameworks. Berkowitz (2025) critically examines the structure of social insurance systems and recommends an economic-political theoretical approach to improve their efficiency and fairness. Lastly, Jain *et al*. (2021) caution that the digitalization of social protection systems is highly vulnerable to cybercrime and requires robust governance mechanisms as part of systemic safeguards.

RESEARCH METHODS

1. Type and Source of Data

   This research adopts a quantitative methodology utilizing panel data, which integrates both time-series and cross-sectional dimensions. The use of panel data is justified by its capacity to observe the dynamic behavior of variables over time and across entities concurrently, thereby yielding more robust and efficient parameter estimations. The empirical analysis encompasses 35 regencies and cities in Indonesia over a three-year period (2021 to 2023), resulting in a total of 104 panel observations.

The data used in this study are secondary data obtained from various official and reliable sources, such as Statistics Indonesia (Badan Pusat Statistik/BPS), the Ministry of Social Affairs of the Republic of Indonesia, and relevant local government publications. The variables employed in the analysis include the poverty rate as the dependent variable, and the number of recipients of the Family Hope Program (Program Keluarga Harapan/PKH) and the Non-Cash Food Assistance (Bantuan Pangan Non-Tunai/BPNT) as independent variables.

2. Data Analysis Method

The data analysis was conducted using panel data regression with the assistance of Stata software version 16. Prior to selecting the appropriate estimation model, model specification tests were carried out to determine whether the data are best analyzed using the Common Effect Model, Fixed Effect Model, or Random Effect Model. The model specification tests were conducted through the following stages:

   a. Chow Test (F-Test)

   The Chow Test is used to compare whether the Common Effect Model (CEM) or the Fixed Effect Model (FEM) is more appropriate for the analysis. This test is conducted using the command testparm i.id in Stata to assess the significance of individual effects across cross-sectional units. The hypotheses for the Chow Test are as follows:

      1) Null hypothesis (H_0): The Common Effect Model is appropriate (no significant individual effects).
      2) Alternative hypothesis (H_1): The Fixed Effect Model is appropriate (significant individual effects are present).

   If the probability value (Prob > F) is less than 0.05, the null hypothesis (H_0) is rejected and the alternative hypothesis (H_1) is accepted, indicating that the Fixed Effect Model is more appropriate. Based on the test results, the value of Prob > F is 0.0000, thus it can be concluded that the Fixed Effect Model is the most suitable model for this analysis.

   b. Hausman Test

   Next, the Hausman Test is conducted to determine whether the Fixed Effect Model or the Random Effect Model is more appropriate. This test examines whether there are systematic differences between the coefficient estimates of the two models. The hypotheses for the Hausman Test are as follows:

      1) Null hypothesis (H_0): The Random Effect Model is the appropriate model (the differences in coefficients are not statistically significant).
      2) Alternative hypothesis (H_1): The Fixed Effect Model is the appropriate model (the differences in coefficients are statistically significant).

   The decision is based on the probability value (Prob > chi^2). If the probability value is less than 0.05, the null hypothesis (H_0) is rejected and the alternative hypothesis (H_1) is accepted. The test results show that Prob > chi^2 = 0.0000, indicating a significant and systematic difference between the coefficients of the Fixed Effect and Random Effect models. Therefore, the Fixed Effect Model is considered the most appropriate model for this study.

c. Lagrange Multiplier Test (LM Test)

To compare the Common Effect Model and the Random Effect Model, the Lagrange Multiplier Test (Breusch and Pagan LM Test) is employed. The hypotheses for the test are as follows:

1) Null hypothesis (H_0): The Common Effect Model is the appropriate model.
2) Alternative hypothesis (H_1): The Random Effect Model is the appropriate model.

The decision is based on the probability value (Prob > chibar²). If the value is less than 0.05, the null hypothesis (H_0) is rejected, indicating that the Random Effect Model is more appropriate than the Common Effect Model. Overall, the results of the LM Test provide strong evidence that the Random Effect Model is worth considering, as there is significant variability across cross-sectional units. However, the final model selection refers to the results of the Hausman Test, which more specifically compares the Fixed Effect and Random Effect models. Therefore, if the Hausman Test indicates that the Fixed Effect Model is more appropriate, it is the model used as the basis for the panel regression analysis in this study.

3. Panel Regression Estimation Model

After determining that the most appropriate model is the Fixed Effect Model, panel regression estimation was conducted using the FEM approach. The estimation was performed by enabling the cluster-robust standard error option on the variable *id*, which represents each regency/city, in order to address potential heteroskedasticity and autocorrelation in the panel data. The regression model employed in this study can be formulated as follows:

$$Poverty_{it} = a + \beta_1 PKH_{it} + \beta_2 BPNT_{it} + u_i + \epsilon_{it}$$

Where:

a. $Poverty_{it}$ = Poverty rate in regency/city i in year t
b. PKH_{it} = Number of recipients of the Family Hope Program (PKH) in regency/city i in year t
c. $BPNT_{it}$ = Total beneficiaries of the Non-Cash Food Assistance (BPNT) program
d. u_i = Time-invariant individual effect that reflects the distinct characteristics of each regency/city
e. ϵ_{it} = Error term

This model is employed to measure the extent to which government social assistance programs contribute to changes in poverty levels across different regions during the observation period. The estimation is conducted by incorporating both fixed time effects and fixed cross-section (individual) effects, in accordance with the results of the previously conducted model specification tests.

RESULT AND DISCUSSION

RESULT

1. Chow Test

The Chow Test is conducted to determine the most appropriate model between the Common Effect Model (CEM) and the Fixed Effect Model (FEM). This test is performed using the F-test (F-restricted) through the command testparm i.id, which examines whether the individual (cross-sectional) effects are statistically significant in the panel model. The hypotheses for this test are as follows:

a. H_0 : Common Effect Model (There are no significant differences across individuals)

b. H_1 : Fixed Effect Model (There are significant differences across individuals)

The test is conducted based on the following criteria:

a. If the p-value is greater than 0.05, the null hypothesis (H_0) is not rejected and the alternative hypothesis (H_1) is rejected, indicating that the Common Effect Model should be used.
b. If the p-value is less than 0.05, the alternative hypothesis (H_1) is not rejected and the null hypothesis (H_0) is rejected, indicating that the Fixed Effect Model should be used.

The test is conducted based on the following criteria:

Tabel 1 Result Chow test

F(34, 67) =	*68.04*
Prob > F =	*0.0000*

Source:Data processed using Stata

Based on the results of the Chow Test in Table 1 above, the probability value (Prob > F) is 0.0000, which is less than 0.05. Therefore, the alternative hypothesis (H_1) is not rejected and the null hypothesis (H_0) is rejected. This indicates that there are significant differences across cross-sectional units, and thus, the most appropriate model to be used is the Fixed Effect Model (FEM).

2. Hausman Test

The Hausman Test is a statistical test used as a basis for determining whether the Random Effect Model or the Fixed Effect Model is more appropriate. The test is conducted using the cross-section random effects specification. The hypotheses for the test are as follows:

a. H_0 : Random Effect Model is the appropriate model.
b. H_1 : Fixed Effect Model is the appropriate model.

The test is conducted based on the following criteria:

a. If the probability value of the Hauman test is greater than 0.05, the null hypothesis (H_0) is not rejected and the alternative hypothesis (H_1) is rejected.
b. If the probability value of the Hausman test is less than 0.05, the alternative hypothesis (H_1) is not rejected and the null hypothesis (H_0) is rejected.

Tabel 2 Result Hausman Test

chi2(2) =	(b-B) ' [(V_b-V_B)^(-1)](b-B)
=	34.91
Prob>chi2 =	0.0000

Source:Data processed using Stata

Based on the results of the Hausman Test in Table 2 above, the chi² value is 34.91 with a probability value (Prob > chi²) of 0.0000. Since the probability value is less than 0.05, the null hypothesis (H_0) is rejected. This indicates that there are significant and systematic differences between the coefficients of the Fixed Effect Model and the Random Effect Model. Therefore, the Fixed Effect Model (FEM) is the most appropriate model to be used in this study.

3. LM Test

LM Test (Lagrange Multiplier Test) The Breusch and Pagan Lagrange Multiplier (LM) Test is a statistical test used as a basis for deciding between the Pooled Least Squares (PLS) method and the Random Effect Model (REM). This test is conducted under the following hypotheses:

a. H_0 : Common Effect Model
b. H_1 : Random Effect Model

The test is conducted based on the following criteria:

a. If the probability value (Prob > chibar²) is greater than 0.05, the null hypothesis (H_0) is not rejected, and the Common Effect Model should be used.
b. If the probability value (Prob > chibar²) is less than 0.05, the null hypothesis (H_0) is rejected, and the Random Effect Model should be used.

Tabel 3 Result Lagrange Multiplier Test

chibar2(01) =	63.31
Prob > chibar2 =	0.0000

Source:Data processed using Stata

Based on the results of the Breusch and Pagan Lagrange Multiplier (LM) Test presented in Table 3, the chibar² value is 63.31 with a probability of 0.0000. Since the probability value is lower than the 5% significance level, the null hypothesis (H_0) is rejected, indicating significant variance in the individual effects (uuu). Therefore, the Random Effect Model is more appropriate than the Common Effect Model. However, the final model selection refers to the results of the Hausman Test. As the Hausman Test indicates that the Fixed Effect Model is the most appropriate, the Fixed Effect Model is ultimately used in this study.

4. Fixed Effect Model (FEM) Panel Regression Model

   In the panel data regression estimation, the best-fitting model is the Fixed Effect Model (FEM). The results of the data estimation using FEM in this study are presented in the following table:

Tabel 4 Result Panel data regression

Kemiskinan	Coef	Robust Std. Eror.	t	P > |t|
PKH	-0.11515	0.013494	-8.53	0.000
BPTN	0.083236	0.01717	2.23	0.033
_cons	11.9231	0.51561	23.12	0.000

Source:Data processed using Stata

Based on the estimation results of the panel data regression model using the Fixed Effect Model (FEM), adjusted with cluster robust standard errors for 35 regencies/cities, the within R-squared value is 0.3542. This indicates that 35.42% of the variation in poverty levels within each regency/city during the observation period can be explained by the Family Hope Program (PKH) and the Non-Cash Food Assistance (BPNT) variables. The F-test result shows an F-statistic value of 40.15 with a probability of 0.0000, indicating that the model is jointly significant at the 5% significance level. Therefore, the PKH and BPNT variables collectively have a significant influence on poverty levels.

Partially, the PKH variable has a negative and statistically significant effect on poverty, with a coefficient of -0.1152 and a probability value of 0.000. This indicates that an increase in PKH assistance tends to significantly reduce poverty levels, demonstrating that the PKH program is effective in helping poor households escape poverty. On the other hand, the BPNT variable has a positive and significant effect on poverty, with a coefficient of 0.0382 and a probability value of 0.033, suggesting that an increase in BPNT is associated with higher poverty levels. This finding may reflect that the distribution or effectiveness of the BPNT program is not yet optimal in reducing poverty, or that the assistance provided is insufficient to generate a long-term impact on the well-being of poor households. The correlation coefficient between the individual effects and the independent variables is -0.4777, indicating a negative correlation, which supports the selection of the Fixed Effect Model as the most appropriate model, in line with the results of the previous Hausman Test.

DISCUSSION

The Impact of PKH on Poverty

This study employed estimation using the Stata software program. The findings indicate that the Family Hope Program (PKH) has a positive effect on poverty reduction in Central Java Province. The statistical test results show that the significance value is lower than the alpha level specified in this study, thus supporting the basic hypothesis that there is a significant relationship between the variables tested. As expenditures for the PKH program increase, poverty in Central Java tends to decline. This suggests that PKH has successfully played a strategic role as an effective socio-economic intervention tool in reducing the number of poor people.

PKH, as a conditional cash transfer (CCT) scheme, provides financial support to low-income household heads who have vulnerable family members such as pregnant women, infants, school-aged children, persons with disabilities, and the elderly. The conditional nature of the program requires beneficiaries to meet certain obligations, such as enrolling children in school and attending routine health check-ups. Through this mechanism, PKH not only offers short-term financial relief, but also contributes to building a long-term foundation for well-being by improving the quality of human capital. This aligns with the social safety net theory, which posits that conditional social assistance programs can help break the intergenerational cycle of poverty.

In addition, the success of PKH can be observed in its ability to promote social inclusion, expand access to basic services, and reduce household vulnerability to economic shocks. As compliance with education and health service requirements increases, PKH recipient households are more likely to improve their productive capacity and social mobility. This has significant implications for reducing structural poverty, particularly in high-poverty districts such as Brebes, Wonosobo, and Kebumen, which have consistently reported poverty rates above the provincial average in recent years.

Empirically, the results of this study support the dynamic poverty theory, which asserts that poverty is fluctuating and influenced by both external shocks and the effectiveness of social programs. When aid is well-targeted and utilized to enhance human capital, poor households can gradually escape poverty traps. Therefore, optimizing budget allocations, improving the accuracy of beneficiary targeting, and conducting continuous monitoring and evaluation of PKH implementation are critical to ensuring the sustainability of its impact on poverty reduction at both local and national levels.

This study is supported by the findings of Baird *et al*. (2018) in the *Policy Research Working Paper*, which show that both conditional and unconditional cash transfer programs generally do not reduce adult labor participation. In fact, in some cases, these programs encourage self-employment and income generation, particularly when the aid is used to start a business or seek employment. These findings refute the notion that social assistance discourages work. On the contrary, cash assistance can serve as a solution to liquidity and risk constraints that often prevent the poor from enhancing their labor capacity and productivity. Hence, the results reinforce the view that well-targeted cash interventions not only provide economic relief but also contribute positively to recipient autonomy.

The Impact of BPNT on Poverty

This study also examines the impact of the Non-Cash Food Assistance Program (BPNT) on poverty levels in Central Java Province. The regression results show that the BPNT variable has a positive coefficient. Statistically, BPNT demonstrates a significant effect on poverty, but the positive direction of the relationship indicates that increased spending on BPNT is correlated with rising poverty levels. This finding signals that the implementation of the BPNT program in Central Java has not been optimal in reducing poverty.

As a food assistance initiative, BPNT is designed to support poor households by providing access to basic food items such as rice and eggs through an electronic distribution system. However, the in-kind and consumptive nature of this assistance tends to address only short-term needs (e.g., daily food consumption), with little to no contribution to enhancing the economic capacity or productivity of beneficiary households. Several factors may explain this outcome:

1. Targeting inaccuracies, where non-poor individuals are included as beneficiaries, while those in extreme poverty remain unserved.
2. The relatively low and inconsistent value of the assistance, which fails to establish sustainable food security for poor families.
3. Limited oversight and control in distribution, including potential local-level mismanagement or corruption.
4. The absence of empowerment components in BPNT, in contrast to

PKH which requires beneficiaries to engage with education and health services.

From a theoretical perspective, these findings are consistent with critiques of in-kind transfer programs such as those presented by Cuesta *et al*. (2024) in the context of multidimensional poverty. They argue that aid programs not linked to capacity building tend to be ineffective in the long term and may even foster beneficiary dependency. This result also highlights the urgent need for policy reformulation regarding social assistance programs particularly BPNT. One recommended approach is to integrate BPNT's consumptive support with complementary interventions, such as vocational training, access to microenterprise capital, or financial literacy education. This integration could transform the assistance into a pathway for enhancing productivity and economic self-reliance, rather than merely maintaining a static consumption pattern.

By way of comparison, Rubio-Sanchez *et al*. (2021) found similar results in Mexico, where food assistance programs had minimal impact on poverty when not accompanied by other social interventions. Therefore, programs like BPNT should be re-evaluated within a framework of empowerment-based social assistance transformation so they can meaningfully contribute to structural and sustainable poverty reduction.

CONCLUSION

This study reveals the significant impact of social assistance programs on poverty levels in Central Java Province. Specifically, the Family Hope Program (PKH) demonstrates a negative and statistically significant effect on poverty, indicating that higher allocations of PKH are associated with reductions in poverty levels. The effectiveness of PKH lies not only in its cash transfer mechanism but also in the conditional requirements that promote access to education and healthcare. As such, PKH serves as a social safety net instrument that enhances human capital and breaks the intergenerational cycle of poverty.

In contrast, the Non-Cash Food Assistance (BPNT) program exhibits a positive and significant effect on poverty levels, suggesting that its implementation has not been optimal in supporting poverty reduction. Its consumptive nature and limited integration with economic empowerment initiatives result in a short-term impact that fails to improve the long-term productivity of beneficiaries. These findings reinforce the theory of dynamic poverty, emphasizing that sustainable poverty alleviation requires well-targeted, locally adaptive interventions that can foster economic self-reliance among low-income populations.

Therefore, it is essential for the government to re-evaluate the effectiveness and design of social assistance programs, particularly BPNT, to ensure they are not merely charitable but also empowering. Greater emphasis should be placed on integrating consumptive assistance with economic capacity-building programs such as vocational training, access to microfinance, and financial literacy education, to prevent long-term dependency. Additionally, accurate beneficiary data updates and robust field-level monitoring are critical to ensuring that aid reaches the intended recipients. These efforts are expected to foster more adaptive, inclusive, and sustainable interventions for poverty alleviation, particularly in high-vulnerability areas such as rural regions of Central Java.

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