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The Impact Of The Village Fund Policy On Reducing Rural Criminal Incidents In Indonesia

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ABSTRACT

This study aims to evaluate the impact of the Village Fund policy on reducing criminal incidents in Indonesian villages through improvements in environmental security systems. Utilizing a Difference-in-Differences (DiD) approach within a Poisson regression model, the study examines the effects of the Village Fund policy implementation across 36,889 villages during the 2011–2021 period. The analysis reveals that, following the implementation of the Village Fund policy, villages in the treatment group—characterized by relatively low environmental security systems—experienced a 0.937 times lower variation in criminal incidents compared to villages with high environmental security levels, with a statistical significance of 1%. These findings indicate that infrastructure development, community empowerment, and the enhancement of environmental security systems in more vulnerable areas contribute significantly to the reduction of criminal incidents in Indonesian villages.

INTRODUCTION

Crime has become a global issue with significant implications for social, economic, and political stability in many countries. It not only poses a threat to individual security but also hampers sustainable development. Within the framework of Human Security, crime is regarded as a serious threat that harms society as a whole, particularly in terms of inequality, injustice, and violations of human rights (Takasu, 2020). The Human Security approach calls for cross-sectoral collaboration, the strengthening of legal institutions, and the empowerment of local communities to create a safe and equitable environment. This aligns with Sustainable Development Goals (SDGs) 16, which emphasizes reducing violence, enhancing access to justice, and building inclusive institutions as strategic measures to support long-term peace and stability. The high incidence of crime has become a major concern at the global level. The Global Organized Crime Index (2023) reports that more than 80% of the world's population is affected by organized crime, with nearly half of all criminal activities concentrated in developing regions such as Southeast Asia and the Western Pacific. Indonesia, as one of the countries in this region, is not immune to crime-related challenges. Indonesia ranks 20th worldwide with a score of 6.85, encompassing various types of crime such as theft, fraud, and illicit trade (Rasyid, 2024). These data indicate that crime is not only a security challenge but also has the potential to hinder economic development and community welfare.

Crime is also a critical issue influencing the success of national development in Indonesia. Criminal statistics from the Central Bureau of Statistics (BPS) reveal an increasing trend of crime at the village level. In 2011, theft was recorded in 36.78% of villages in Indonesia, rising to 41.05% in 2014, and peaking at 45.01% in 2018 (BPS, 2023). Western regions of Indonesia, such as West Java (73.76%), Banten (71.13%), and Lampung (70.65%), report significantly higher theft rates compared to eastern regions, such as West Papua (11.42%) and Maluku (21.45%) (BPS, 2018). The higher crime rates in western Indonesia are associated with factors such as population density, rapid urbanization, and socioeconomic pressures, while the eastern regions with their more communal lifestyles, exhibit lower crime rates. These regional differences underscore the importance of adopting policies tailored to local characteristics in the pursuit of national development.Community security systems are a crucial element in crime prevention. One indicator used to measure the effectiveness of such systems is the ratio of civil defense officers (Hansip) to neighborhood units (RT), which reflects the number of security personnel per smallest administrative unit at the village level. Based on Routine Activity Theory (Cohen & Felson, 1979), the presence of active surveillance, such as Hansip, can deter opportunities for crime by enhancing the sense of security within communities. However, the effectiveness of a security system depends not only on active surveillance but also on adequate infrastructure, such as street lighting, accessibility, and public facilities (Glover, 2011; Wilson & Kelling, 1982). Moreover, community participation through strengthened social bonds is also a key factor in creating safer environments (Sampson & Laub, 1994; Shaw & McKay, 1942).

A growing body of research supports the importance of community-based security approaches. In the Philippines, the KALAHI-CIDSS program has demonstrated success in reducing crime through community empowerment and the strengthening of social cohesion (World Bank, 2020). This program involves communities in planning and implementing security projects, thereby fostering a strong sense of ownership. In Scotland, the Violence Reduction Unit (VRU) succeeded in reducing violence by up to 50% through a combination of skills training, education, and community participation (World Economic Forum, 2018). In Tanzania, the decentralization of budgets for security patrols and training has been proven to significantly reduce crime, with a focus on strengthening the capacity of local communities (Seleo, 2023). However, while these studies provide important insights, their contexts are more relevant to urban settings or specific regions.Trends in Indonesia show a decline in the number of civil defense officers from 794,053 in 2011 to 706,698 in 2021, while the number of neighborhood units (RT) has continued to rise from 770,191 to 816,771 during the same period (BPS, 2023). This imbalance poses challenges to strengthening community security systems, particularly in rural areas. The Village Fund policy, implemented since 2015, offers an opportunity to analyze the relationship between enhancing community security systems and reducing crime. The Village Fund is designed to support infrastructure development and community empowerment, with an average allocation of 80% for physical development and 20% for empowerment programs (Kementerian Keuangan, 2019). However, the effectiveness of Village Fund utilization in the context of security has not been comprehensively evaluated.

Previous studies have shown that budget allocations supporting security patrols and training can significantly reduce crime. Research in Tanzania found that the decentralization of security budgets increased the capacity of local patrols and reduced crime incidents (Seleo, 2023). Another study in India found that improved security infrastructure, such as street lighting and better accessibility, contributed substantially to reducing crime in rural areas (Ceccato, 2015). Meanwhile, in developed countries such as the United States and the United Kingdom, evaluations of security programs have focused more on expenditure levels, program duration, and the presence of formal patrols (Bennett et al., 2008; Lurigio & Skogan, 1998; Maguire, 2004).

However, these approaches are less relevant in the Indonesian context, which is characterized by distinct social and institutional dynamics.This study fills a gap in the literature by exploring the influence of the Hansip-to-RT ratio on crime rates in rural Indonesia before and after the implementation of the Village Fund policy. Using a Difference-in-Differences (DiD) method, this study aims to evaluate the impact of the Village Fund policy on crime while considering variations in the Hansip-to-RT ratio as an indicator of strengthened community security systems. This approach contributes empirically to the security literature and offers new insights for policymakers in designing locally responsive security strategies.

The study draws on Routine Activity Theory, which emphasizes the importance of active surveillance, as well as Broken Windows Theory, which underscores the role of infrastructure in creating safe and orderly environments (Wilson & Kelling, 1982). Empirically, this research seeks to integrate findings from various international studies with the Indonesian context, which has unique social, economic, and institutional characteristics. With the rising trend of crime in Indonesia and the substantial Village Fund allocations since 2015, this research is timely and relevant in addressing the challenge of crime reduction at the village level while contributing to the global literature on security and development.

LITERATURE REVIEW

Crime in Indonesia represents a serious issue that reflects the lack of a sense of safety within society. According to the World Justice Project (2011), Indonesia ranks as the fourth lowest country in Southeast Asia in terms of order and security, standing at 54th out of 66 countries with a score of 0.50. Although this ranking is better than that of Thailand, the Philippines, and Cambodia, it nevertheless indicates that crime, conflict, and violence remain significant challenges. From the perspective of Lacassagne and Karl Marx (as cited in Atmasasmita & Wibowo, 2016), deteriorating socioeconomic conditions and the dominance of capitalism are often the main drivers of crime. The lack of adequate security patrols in rural areas, as noted by Painter and Farrington (1999), further exacerbates the situation. In addition, improved infrastructure, such as well-built roads, may unintentionally facilitate the mobility of offenders from urban to rural areas, thereby increasing crime risk (Gibbons & Machin, 2008).

The government is committed to enhancing public safety, as mandated in Article 28G paragraph 1 of the 1945 Constitution and Law No. 17 of 2007. One of the measures implemented is the strengthening of community-based security through Hansip (civil defense units), which have a long history dating back to the struggle for independence. Hansip plays an important role in maintaining political stability and local security, although its effectiveness is often constrained by limited resources and training (Ministry of Home Affairs of the Republic of Indonesia, 2012). In these regulations, the ratio of Hansip officers to neighborhood units (RT) serves as an important indicator for assessing the adequacy of village-level security systems.

Routine Activity Theory (RAT), developed by Cohen and Felson (1979), provides a framework for understanding the dynamics of crime. This theory states that crime occurs when there is a motivated offender, a suitable target, and the absence of a capable guardian. In this context, Hansip serves as a "capable guardian," whose presence can reduce opportunities for crime through active patrolling and community surveillance. The visible presence of guardians has a significant deterrent effect (Sherman, 1995; Weisburd & Eck, 2004). Meanwhile, the Broken Windows Theory (Wilson & Kelling, 1982) emphasizes that poorly maintained environments, such as streets without adequate lighting, tend to increase crime risks. On the other hand, Social Disorganization Theory (Shaw & McKay, 1942) highlights that strong social cohesion and collective efficacy can reduce crime even when physical infrastructure is weak.

The utilization of the Village Fund (*Dana Desa*) as a strategic policy represents an important step in efforts to reduce crime. Since its implementation under Law No. 6 of 2014, the Village Fund has been allocated primarily for infrastructure development (80%) and community empowerment (20%). Improvements in infrastructure, such as street lighting and the construction of security posts, have proven effective in creating safer environments (Vidyaras, 2022). In addition, economic empowerment programs supported by the Village Fund help to reduce unemployment and poverty, thereby indirectly lowering the economic motivation to commit crime (Ilham & Mafruhat, 2024). Transparent public participation in Village Fund management also increases community trust and reduces criminal incidents associated with fund misappropriation (Zakariya, 2020).

The allocation of central government budgets to villages, such as through the Village Fund, has produced varying impacts. Positive effects are evident when infrastructure improvements and community empowerment successfully lower crime rates. Security posts funded by the Village Fund can enhance community surveillance and foster a sense of safety among residents (Rangkuti et al., 2024). Conversely, negative effects may arise when inefficient fund management exacerbates social inequality or worsens local conflicts (Tapscott, 2023). In some cases, similar fiscal policies have had no significant impact on crime, often due to poor coordination and ineffective program implementation (Smith, 2004).

The effectiveness of the Village Fund in reducing crime strongly depends on synergy between infrastructure development, community-based surveillance, and social empowerment. This study offers both theoretical and empirical contributions by analyzing the impact of Hansip-based local security systems on crime, while simultaneously evaluating the success of the Village Fund policy in creating safer and more sustainable communities. The following graph illustrates the expected lifetime income between agricultural use (X_1) and other uses (X_2), which heavily depend on the relative return of the two sectors (productivity and land prices in alternative uses).

METHODS

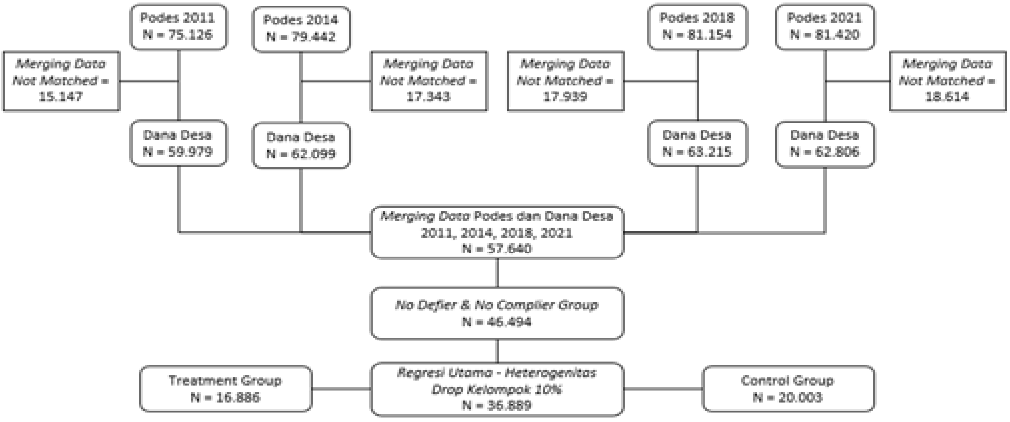
Data Sources and Unit of Analysis

This study employs a panel data analysis (pooled data), which combines time-series and cross-sectional data. The primary data source is the Potensi Desa (PODES) survey published by the Central Bureau of Statistics (BPS), covering four periods: 2011, 2014, 2018, and 2021. In addition, the study utilizes Village Fund data obtained from the Ministry of Finance for the period 2015–2021. The main focus of the research is to analyze the impact of the Village Fund policy on the likelihood of crime at the village level by leveraging variations across time and regions. A Difference-in-Differences (DiD) approach is applied to evaluate changes in crime before and after the implementation of the Village Fund policy, namely during the pre-policy period (2011 and 2014) and the post-policy period (2018 and 2021).

The panel dataset includes information on the number of hansip (village security personnel) and the number of neighborhood units (RT) in each village for the period 2011–2021. The main independent variable in this study is high-risk density, measured by the ratio of hansip to RT. This ratio is used to classify villages into two groups: high-risk density with a Hansip/RT ratio greater than 100 (treatment group) and low-risk density with a Hansip/RT ratio less than 100 (control group). This variable aims to explore how improvements in community security systems influence crime levels.

Crime incidence is measured based on the probability of four types of crime: theft, violent theft, drug abuse, and gambling. Crime data are categorized in the form of a dummy variable, with a value of 1 if a crime incident occurred and 0 if not. The data selection process yielded 36,889 observations, consisting of 16,886 observations in the treatment group and 20,003 observations in the control group. The dataset was filtered to ensure analytical quality.

Figure 1 Data Sources and Unit of Analysis



Source: BPS PODES data, author's processed

Operational Definition of Variables

The dependent variable in this study is the incidence of crime, which encompasses four main categories. Theft is defined as the unlawful taking of property, while violent theft involves threats or the use of physical force against victims. Drug abuse refers to the illegal use of narcotic substances that negatively affects health, causes dependency, and undermines social stability. Gambling involves placing wagers whose outcomes depend on chance, which often has detrimental impacts on the economic and social conditions of individuals and their families. All of these crime types carry serious implications for the social stability of communities.

In addition to the main independent variable, this study also incorporates a policy intervention variable, represented by the implementation of the Village Fund. This variable is measured using a dummy indicator that reflects the periods before (2011–2014) and after (2018–2021) the policy implementation. Other control variables include the establishment of community-based security teams, the quality of road infrastructure, and the presence of neighborhood security posts. The establishment of community security teams is particularly relevant, as demonstrated by Etcuban et al. (2018), who found that community-based security teams in the Philippines effectively reduced crime and addressed drug abuse. Furthermore, Gibbons and Machin (2008) highlighted that improvements in road accessibility may increase the mobility of potential offenders, thereby raising crime risks. The presence of security posts, as described by Bennett et al. (2006), plays a crucial role in enhancing local security through preventive effects and rapid response to incidents.

Model Analysis

This study employs the Difference-in-Differences (DiD) method, which is considered effective in controlling for unobserved fixed effects across periods (Fredriksson & Oliveira, 2019; Lucas & Mbiti, 2012). The Village Fund policy, implemented uniformly throughout Indonesia, is analyzed through variations in intensity (Lucas & Mbiti, 2012), using the ratio of hansip (civil defense officers) to neighborhood units (RT) as the primary indicator. An interaction variable between the Village Fund policy years and high-risk density in villages within the 10th to 50th highest percentiles is utilized to evaluate the variation in the intensity of the policy's impact on strengthening community security systems and reducing crime.

Hypothesis testing is conducted using Poisson regression, which is appropriate for count data (0–4), such as the number of crime incidents. This method allows for the conversion of coefficients into incidence rates or probabilities, thereby facilitating the evaluation of policy impacts (Bennett et al., 2006; Gibbons & Machin, 2008). By combining the DiD approach, policy intensity variations, and control variables, this study provides an in-depth analysis of the effectiveness of the Village Fund in creating enhanced security, even amid the challenges of a policy implemented universally across Indonesia. Based on the explanation above, the basic equation of the DiD model is as follows:

$$
\begin{aligned}
Crime\ Incidence_{it} &= \beta_0 + \beta_1\, HighRiskDensity_{it} \\
&+ \beta_2 VillageFundPolicy_{it} + \beta_3 HighRiskDensity_{it}\ x\ VillageFundPolicy_{it} \\
&+ \beta_4 Control_{it} + \delta_i \\
&+ \varepsilon_{it} \qquad (1)
\end{aligned}
$$

Where Crime Incidenceit is a count variable representing the number of crime incidents in village i during year t (with values ranging from 0 to 4). Village Fund Policyit is a dummy variable indicating the implementation of the Village Fund policy (taking the value 1 for the years 2018 and 2021, and 0 for the years prior to the implementation, namely 2011 and 2014). High-Risk Densityit is a dummy variable indicating the number of hansip in village$i$ during year t (taking the value 1 if the village has a Hansip/RT ratio of less than 100, and 0 otherwise). Controlit is a set of control variables consisting of dummies for villages with security teams, security posts, and road access in village$i$ during year t a value of 1 indicates the presence of a security team or security post, while 0 indicates their absence. For road access, a value of 1 denotes asphalt/concrete roads, 2 denotes gravel roads, and 3, 4, and 5 represent other road types. δi is the fixed effect, and εit is the error term for each crime incident in village$i$ during year t. The inclusion of fixed effects is intended to ensure that the main coefficient $\beta 3$ accurately captures the variation in the impact of the Village Fund policy over time on the treatment and control groups.

From Equation (1), the coefficient of the interaction between High-Risk Density and Village Fund Policy ($\beta 3$) represents the treatment effect. This coefficient reflects the difference between the pre-policy and post-policy conditions in the treatment group, which is then compared with the control group. Since the dependent variable is a count variable, such as the number of crime incidents (1, 2, 3, or 4), Equation (1) is transformed into a Poisson regression model. The basic form of this model then becomes:

$$
\begin{aligned}
Poisson\ Regression\ (\mathrm{P(X = k)}) &= \alpha_0 + \alpha_1\, HighRiskDensity_{it} \\
&+ \alpha_2 VillageFundPolicy_{it} + \alpha_3\, HighRiskDensity_{it}\ x\ VillageFundPolicy_{it} \\
&+ \beta_4 Control_{it} \\
&+ \varepsilon_{it} \qquad (2)
\end{aligned}
$$

Where X represents the number of incidents, and k denotes a specific count of incidents (an integer value of 0, 1, 2, 3, or 4). The estimation results are interpreted as odds ratios or probabilities of the number of incidents. In the context of this study, the dependent variable is defined as the probability of the occurrence of theft, violent theft, drug abuse, and gambling. To interpret the coefficients in the Poisson regression, the Incident Rate Ratio (IRR) is used. In Poisson regression, the exponential value of the coefficient $\alpha 3$ yields the IRR, which is then used to interpret the effect of an independent variable on the dependent variable expressed as a count of events. If the IRR is less than 1, it indicates a reduction in the number of incidents. For example, an IRR of 0.75 indicates a 25% decrease in incidents (1−0.75). Conversely, if the IRR is greater than 1, it indicates an increase in the number of incidents.

Poisson regression does not require classical assumption tests such as normality and homoscedasticity (Ekananda, 2016) because the model is based on panel data. Poisson regression is more effective than Ordinary Least Squares (OLS) regression for modeling crime data with low frequencies. This model is able to handle common issues such as count data distribution and overdispersion. Previous studies show that this approach provides more accurate results in crime rate analysis (Osgood, 2000).

We conducted a series of robustness checks and heterogeneity analyses to ensure more valid and reliable results. The parallel trend assumption was tested to confirm that the trends in crime incidents between the treatment and control groups were similar before the implementation of the Village Fund policy. This assumption is crucial to ensure that any change in trends after the policy implementation can be attributed directly to the policy's impact. The test was conducted using regression methods that identify similar trends prior to the policy implementation, as adapted from the approach of Gultom (2019). The equation is as follows:

$$Crime\ Incidence_{it} = \beta_0 + \beta_1\ Time\ Rescale + \beta_2\ Time\ Rescale\ x\ High\ Risk\ Density_{it} + \delta_i + \varepsilon_{it} \quad (3)$$

The sample used to test this assumption only covers the pre-treatment period, namely the years 2011–2014. The variable timescale represents a range of time measured relative to the implementation of the policy. A value of 0 (timescale < 0) indicates years prior to the implementation of the Village Fund policy (in this study, the baseline year is 2015). A value of –1 corresponds to the year 2014, and –4 corresponds to 2011. For years after the implementation of the Village Fund policy (timescale > 0), a value of 3 refers to 2018, and 6 refers to 2021. High-Risk Density is a dummy variable measured by the number of hansip per neighborhood unit (RT) in villages with weak community security systems based on village i in period t. δi represents village fixed effects, and εit is the error term for each crime incident in village i during year t. The coefficient $\beta 2$ is used to measure the trend of crime incidents (prior to the Village Fund policy) in both the treatment and control groups. The null hypothesis $H0\ \beta 2{=}0$ indicates that there is a common trend in crime incidents between treatment and control villages during the pre-treatment period.

A placebo test was then conducted to confirm the validity of the parallel trend assumption, which states that the trend in crime incidents between the treatment and control groups is similar prior to the implementation of the Village Fund policy. This method tests whether significant differences in trends emerge only after the policy intervention, not beforehand. In this test, data from the pre-policy period are manipulated to simulate a fictitious intervention, using 2013 as the "placebo policy" year. The year 2011 is assigned a value of –2, representing two time units before the fictitious intervention, while 2014 is assigned a value of +1, as if it were one time unit after the intervention. If the analysis shows no significant change in the dependent variable during this placebo period, the parallel trend assumption is considered valid. This provides confidence that the identified policy impact is truly attributable to the policy itself, rather than natural trends or data bias.

We also ensured the robustness of our estimation results against potential bias from unobserved variables by applying the Oster Test. This method evaluates the stability of regression coefficients by comparing estimation results from a model without controls to those from a fully controlled model. In this approach, the $R2$ values from both models and the assumed maximum value Rmax are calculated to estimate the adjusted coefficient ($\beta*$). The value of Rmax, typically set at 1.3 times the $R2$ of the fully controlled model, is used to assess the extent to which unobserved variables might influence the estimation results. This approach provides additional validation for the causal interpretation of the regression results and ensures the consistency of the estimates against selection bias, thereby strengthening the study's findings.

In addition, we performed a heterogeneity test to identify variations in the effects of the Village Fund policy across different subgroups. This test evaluates whether the policy's impact differs between western regions (including Sumatra, Java, and Kalimantan) and eastern regions (including Bali, Nusa Tenggara, Sulawesi, Maluku, and Papua). The analysis also covers different types of crime to ensure that the policy's impact is consistent across categories such as theft, violent theft, drug abuse, and gambling. The heterogeneity test provides deeper insight into the effectiveness of the policy across diverse local contexts, ensuring that the main findings remain relevant to various regional characteristics. Through this step, the study not only guarantees the validity of its results but also provides a foundation for more context-specific and well-targeted policy recommendations.

RESULTS AND DISCUSSION

This analysis examines the impact of the LP2B protection policy on LBS changes across Java and Non-Java regions, as well as differences between rice production center and non-center regions. Production centers are defined as districts/cities within the 10 provinces with the highest rice production from 2010 to 2022. Figure 1.4 illustrates the dominance of major rice-producing provinces, while contributions from other provinces remain relatively smaller.

Table 1 Descriptive Statistics of the Study

	High Risk Density (*Treatment Group*)			
	Mean	SD	Min	Max
Crime Incidence	0,63	0,89	0	4
Neighborhood Units (RT)	17,07	17,19	1	196
Number of Village Security Personnel (Hansip)	7,78	10,52	0	98
Security Team	0,43	0,49	0	1
Neighborhood Security Post (Poskamling)	0,53	0,49	0	1
Road Access	2,34	1,08	1	5

Source: Author's Analysis, 2024

The parallel trend test ensures that crime trends between the treatment and control groups were similar prior to the implementation of the Village Fund policy. The test was conducted through a regression by dividing the treatment groups based on the ratio of hansip per RT. The results indicate an initial similarity in trends between the two groups within the top 20% to 50% range, thereby validating the subsequent policy impact analysis.

Table 2 Parallel Trend Test Results

Dependent Variable Variation of Crime Incidence	Group 10% IRR	Group 20% IRR	Group 30% IRR	Group 40% IRR	Group 50% IRR
timerescale x high risk density	0,930***	0,998	1,027	1,044	1,004
	(0,021)	(0,033)	(0,030)	(0,027)	(0,025)
Observations	38.420	4.804	6.616	9.908	11.988
Number of village	9.605	1.201	1.654	2.477	2.997
Pseudo R-squared	0,005	0,005	0,005	0,005	0,005
Note: significance levels are indicated as *10 percent; **5 percent; and ***1 percent. Figures in parentheses represent clustered standard errors by village. *Source: Processed data, 2024.*					

The regression results of the parallel trend test in Table 2 show that for villages with high-risk density in the top 20%–50% range, the interaction coefficients for timescale × high-risk density are not statistically significant (coefficients of 0.998, 1.027, 1.044, and 1.004), thus the null hypothesis cannot be rejected. This indicates similar crime trends between the treatment and control groups prior to the implementation of the Village Fund policy, supporting the validity of the policy effect claim. However, for villages with high-risk density in the top 10%, the coefficient is statistically significant (0.930; significant at the 1% level), indicating a difference in pre-policy trends. Therefore, the policy effect for this subgroup cannot be claimed without further analysis. To ensure the parallel trend assumption is met, we conducted a placebo test by analyzing data from the period prior to the implementation of the Village Fund policy. This test used years that were not directly associated with the actual intervention (2011 and 2014), with the year 2013 treated as a fictitious intervention point. The details are as follows:

Table 3 Placebo Test Results

Dependent Variable Variation of Crime Incidence	Group 10% IRR	Group 20% IRR	Group 30% IRR	Group 40% IRR	Group 50% IRR
timerescale x densitas rawan tinggi	0,952***	0,998	1,018	1,029	1,002
	(0,014)	(0,022)	(0,020)	(0,018)	(0,017)
Observations	38.420	4.804	6.616	9.908	11.988
Number of village	9.605	1.201	1.654	2.477	2.997
Pseudo R-squared	0,005	0,005	0,005	0,005	0,005
Note: significance levels are indicated as *10 percent; **5 percent; and ***1 percent. Figures in parentheses represent clustered standard errors by village. Source: Processed data, 2024.					

The analysis results show that in villages with high-risk density within the top 10%, the Incident Rate Ratio (IRR) value of 0.952 is significant at the 1% level, indicating a small but significant difference in trends between the treatment and control groups. Therefore, the policy impact for this subgroup cannot be claimed as the effect of the Village Fund. In contrast, for the group with high-risk density in the 20%–50% range, the IRR values range from 0.998 to 1.029 and are not statistically significant, indicating no significant differences in crime trends between the treatment and control groups before the policy was implemented. This consistency supports the parallel trend assumption, suggesting that the impact of the Village Fund policy can be evaluated without bias from differing initial trends.

The main analysis was conducted using the Difference-in-Differences Poisson (DiD-Poisson) model, with the primary dependent variable being variations in crime incidence. The estimation results from the DiD-Poisson Regression model show the relationship between high-risk density—referring to villages with weak community security systems—and crime incidence in the context of the Village Fund policy (2015–2021). Four regression models were run, differing in terms of control variables and the application of fixed effects.

In this model, the top 10% group that did not meet the parallel trend assumption was excluded, and it was ensured that no observation unit switched between the treatment and control groups (No Defier and No Complier assumptions were maintained). No Defier refers to the assumption that no unit acted contrary to the assigned treatment—that is, no unit consistently moved from the control group to the treatment group solely because of the intervention. Meanwhile, No Complier refers to the assumption that all units in the treatment group actually received the intended treatment, with no units failing to implement or consistently receive the intervention. By eliminating units that did not meet these assumptions, the analysis aims to enhance the validity and accuracy of the results, ensuring that the regression findings can be more reliably interpreted as representing the causal impact of the Village Fund policy on crime.

Table 4 Main Regression Results

Dependent Variable Variation of Crime Incidence	Village Fund Policy (2015 - 2021)			
	(1)	(2)	(3)	(4)
High risk density	0,952***	0,945***	0,944***	0,937***
	(0,011)	(0,011)	(0,011)	(0,012)
Observations	147.556	147.556	147.556	147.556
Number of village	36.889	36.889	36.889	36.889
Pseudo R-squared	0,011	0,011	0,002	0,003
Controls:				
Security Team	YES	YES	YES	YES
Neighborhood Security Post (Poskamling)	NO	YES	YES	YES
Road Access	NO	NO	YES	YES
Fixed Effects	NO	NO	NO	YES
Note: significance levels are indicated as *10 percent; **5 percent; and ***1 percent. Figures in parentheses represent clustered standard errors by village. Source: Processed data, 2024.				

The estimation results of the regression models reveal significant variations in the effect of the Village Fund policy on reducing crime incidence in villages with low levels of community security systems (high-risk density). In Model (1), the interaction coefficient $\beta 3$ indicates that the probability of crime incidence in villages with high-risk density is 0.952 times lower than in villages with low-risk density after the Village Fund policy was implemented, with a significance level of 1%. This model includes only the security team as a control variable.

In Model (2), after adding the control variable for the presence of neighborhood security posts (poskamling), the probability of crime incidence in high-risk density villages decreases to 0.945 compared to low-risk density villages, with the significance level remaining at 1%. This demonstrates the additional contribution of poskamling in supporting crime reduction.

Model (3) incorporates security teams, poskamling, and road access as control variables, resulting in an IRR of 0.944. The inclusion of road access does not change the significance of the results, suggesting that road infrastructure plays a smaller role compared to other security elements.

Model (4) is the most comprehensive, incorporating all control variables (security teams, poskamling, and road access) along with village-level fixed effects. The estimation results show that the Village Fund policy significantly reduces the probability of crime incidence in villages with weak community security systems (high-risk density). The interaction coefficient $\beta 3$ yields the lowest Incident Rate Ratio (IRR) of 0.937, indicating that after the implementation of the Village Fund policy, the probability of crime occurrence in high-risk density villages is 0.937 times lower than in low-risk density villages, with a significance level of 1%.

The inclusion of fixed effects in this model provides analytical advantages by controlling for unobserved village-specific characteristics that remain constant over time, such as social norms, local culture, or unique geographic conditions. This strengthens the causal validity of the relationship between the Village Fund policy and the reduction in crime levels. The larger reduction in IRR compared to previous models suggests that the combination of the Village Fund policy with strengthened community security elements—such as security teams and poskamling is effective in reducing crime. Model (4) demonstrates the robustness of the relationship between the Village Fund policy and improved community security, while also highlighting the importance of controlling for fixed village-level variables.

The analysis proceeds by focusing on the group with high-risk density in the 20% to 50% range. The DiD regression tests based on Equation (1) were conducted only on this group to ensure consistency of the study's results with respect to the main variables. The complete estimation results are presented in Table 5.

Table 5 The Impact of the Village Fund Policy on Reducing Crime Incidence Variations in Treatment Villages with High-Risk Density (Top 20%–50% Group)

Dependent Variable Variation of Crime Incidence	Group 20%	Group 30%	Group 40%	Group 50%
high risk density x village fund policy	0,891**	0,927	0,917**	0,950
	(0,045)	(0,041)	(0,038)	(0,036)
Observations	147.556	147.556	147.556	147.556
Number of village	1.201	1.654	2.477	2.997
Pseudo R-squared	0,002	0,002	0,002	0,002
Controls	YES	YES	YES	YES

Note: significance levels are indicated as *10 percent; **5 percent; and ***1 percent. Figures in parentheses represent clustered standard errors by village.
Source: Processed data, 2024.

Table 5 presents the estimated IRRs of the effect of the Village Fund policy on variations in crime incidence based on the level of community security systems. The regression results are divided into four groups: 20%, 30%, 40%, and 50%, with the benchmark model yielding an IRR of 0.937. The 20% group shows an IRR of 0.891 (significant at the 5% level), which is lower than the benchmark, indicating that the Village Fund policy is most effective in reducing crime in villages with the lowest security levels. The 30% group has an IRR of 0.927 but is not statistically significant, suggesting that the policy impact begins to decline. The 40% group, with an IRR of 0.917 (significant at the 5% level), still benefits from the policy, although the effect is weaker compared to the 20% group. Meanwhile, the 50% group has an IRR of 0.950 and is not significant, indicating that the policy is less effective in villages with stronger security systems.

The Village Fund policy has a greater impact on villages with weaker security systems, as observed in the 20% and 40% groups. However, as the security system improves, the policy's effectiveness diminishes, consistent with the benchmark regression results (IRR 0.937), which account for control variables such as security teams, neighborhood security posts (poskamling), and road access.

Oster Test

The Oster Test takes into account the R2 values from both models as well as the assumed maximum value Rmax, which is defined as 1.3×R2 from the fully controlled model. The details are as follows:

Table 6 Oster Test Result

Dependent Variable Variation of Crime Incidence	No Control	(+ Security Team)	(+Security Team + Poskamling)	(+Security Team + Poskamling + Road Access)	(+Security Team + Poskamling + Road Access + FE)
High risk density x village fund policy	0,948***	0,952***	0,945***	0,944***	**0,937*** **
	(0,012)	(0,011)	(0,011)	(0,011)	(0,012)
$\dot{R}, \bar{R}$	0,043	0,011	0,011	0,002	0,003
$\beta*$		0,944	0,951	0,953	**0,961**

Source: Processed data, 2024.

The values of $\beta*$ in each column represent the adjusted coefficient estimates that account for potential bias from unobserved variables. This calculation applies the assumed maximum $R2$ value (Rmax) to assess the extent to which the regression results remain consistent and robust. The increase in $\beta*$ from 0.937 to 0.961 indicates that the regression results are fairly robust to potential bias from unobserved variables. The difference between the fully controlled β and $\beta*$ is relatively small (0.961 – 0.937 ≈ 0.024), suggesting that the control variables used in the model (Security Team, Poskamling, Road Access, and Fixed Effects) already explain a substantial portion of the variation in the data.

The results of the test, after incorporating control variables and fixed effects, show that the regression model in Column 5 yields the most stable and consistent estimates. The value of $\beta*$ remains positive and statistically significant, reinforcing the conclusion that villages with high-risk density have a significant effect on crime incidence, even in the presence of potential unobserved variables.

Heterogeneity Analysis

The heterogeneity analysis was conducted to examine how the effect of the Village Fund policy on crime varies between western and eastern regions. The results reveal differences in community security systems and their influence on crime across these regional groups.

Table 7 Results of Heterogeneity Analysis by Region

Dependent Variable Variation of Crime Incidence	West (Jawa, Sumatera, Kalimantan)	East (Bali, Nusa Tenggara, Sulawesi, Maluku, Papua)
High risk density x village fund policy	0,912***	0,999
	(0,013)	(0,028)
Observations	112.116	35.440
Number of village	28.029	8.860
Pseudo R-squared	0,017	0,004
Controls	YES	YES

Note: significance levels are indicated as *10 percent; **5 percent; and ***1 percent. Figures in parentheses represent clustered standard errors by village.
Source: Processed data, 2024.

In the western region, an IRR value of 0.912 (significant at the 1% level) indicates that the Village Fund policy reduces variations in crime incidence in villages with low security systems to 0.912 times compared to villages with higher security systems. This model includes control variables such as security teams, poskamling (neighborhood security posts), and road access, without fixed effects.

Table 8 Heterogeneity Analysis by Crime Type

Dependent Variable Variation of Crime Incidence	Theft	Robbery	Drug Abuse	Gambling
High risk density x village fund policy	0,934***	0,825***	1,134***	0,885***
	(0,015)	(0,062)	(0,038)	(0,028)
Observations	141.176	18.192	46.088	66.604
Number of village	35.294	4.548	11.522	16.651
Pseudo R-squared	0,003	0,013	0,078	0,004
Controls	YES	YES	YES	YES

Note: significance levels are indicated as *10 percent; **5 percent; and ***1 percent. Figures in parentheses represent clustered standard errors by village.
Source: Processed data, 2024.

The heterogeneity analysis indicates that the effectiveness of the Village Fund policy varies across regions. The western region experienced a significant reduction in crime, whereas in the eastern region the policy was less effective. This finding is consistent with Firdaus (2013), who highlighted that infrastructure development in areas with high economic activity can exacerbate social inequality and crime due to increased accessibility for potential offenders. More advanced infrastructure in the western region accelerates economic activity but also raises crime risks.

Based on crime types, the Village Fund policy reduced variations in theft (IRR 0.934) and violent theft (IRR 0.825), both significant at the 1% level. However, drug abuse increased (IRR 1.134, significant at the 1% level), suggesting that improved infrastructure facilitates drug distribution. This finding aligns with Nugent (1997), who observed that villages with weaker economies are vulnerable to black markets for narcotics. Gambling also decreased (IRR 0.885, significant at the 1% level), indicating that the policy is effective for several types of crime but requires a more targeted approach for addressing drug-related issues.

CONCLUSION

This study demonstrates that the Village Fund policy is effective in reducing variations in crime incidence, particularly in villages with weak community security systems. However, there is one subgroup (the top 10%) that does not meet the requirements of the parallel trend test and placebo test; therefore, its impact cannot be measured accurately. The policy is most effective in the top 20% and 40% groups, where factors such as security teams, poskamling, and road infrastructure also contribute to reducing crime.

The policy's effectiveness is more pronounced in the western regions than in the eastern regions, likely because rapid infrastructure development not only increases economic mobility but also creates opportunities for criminal activity. By crime type, the policy successfully reduced theft, violent theft, and gambling. However, drug abuse increased due to weak supervision and improved infrastructure access, which facilitates the distribution of narcotics to remote areas.

SUGGESTION

The government should prioritize crime prevention as a key focus in the allocation of Village Funds, particularly by strengthening security systems in the western regions. Oversight of drug distribution must be intensified through the use of technology and the active involvement of local communities in detecting illegal activities. In addition, education and public outreach on the dangers of narcotics should be expanded to raise awareness and encourage community participation in prevention efforts.

The Village Fund should not only serve as a vehicle for physical development but also function as a primary instrument for establishing resilient and sustainable security systems. With more targeted policies and strengthened oversight, villages can become safer, more stable, and more conducive to the social and economic growth of their communities.

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