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Does Wealth Decrease Victimization in Property Crime?: Evidence from Thailand

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Abstract

The relationship between wealth and property crime victimization remains debated in criminological research. This study examines this relationship using data from Thailand's Multiple Indicator Cluster Surveys (MICS) conducted in 2019 and 2022. While the MICS wealth index serves as the primary measure, potential endogeneity issues arise from unobserved factors, such as security investments in wealthier areas. To address this, the study employs an instrumental variable Probit (IV-Probit) model. The results reveal a negative association between wealth and property crime victimization in Thailand, contradicting conventional economic theory, which assumes wealthier individuals are more attractive crime targets. This unexpected finding suggests that enhanced security measures among affluent households may effectively deter criminal activity. The study contributes to the literature by overcoming methodological limitations of past research and providing evidence-based insights for targeted crime prevention policies. Policymakers may consider strengthening security infrastructure in lower-income areas to mitigate disparities in victimization risk.

Keywords: crime victimization; property crime; wealth; Thailand; instrumental variable Probit

JEL classification: C36; K40; K42

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1. Introduction

Wealth has been widely recognized as a critical determinant of victimization, yet its effect on property crime victimization remains ambiguous. According to Becker's (1968) theoretical framework, criminals are more likely to target wealthy individuals due to higher potential returns. Conversely, individuals with greater financial resources can implement preventive measures, such as investing in security systems, potentially making them less attractive targets for criminals (Levitt, 1999).

Economic research has disproportionately focused on crime studies rather than victimization studies (Entorf, 2015). To date, only one empirical study has examined the wealth-victimization relationship: Justus and Kassouf (2013) identified an inverted-U-shaped relationship between household spending and victimization risk in São Paulo, Brazil. Their findings indicated that for most Brazilians, the relationship between wealth and victimization is positive, with only a small portion of the sample exhibiting a negative relationship. However, their study relied on household spending as a proxy for wealth—a potentially problematic indicator—and established correlation rather than causation. The present study addresses these limitations by employing a more robust wealth variable to estimate the causal relationship between wealth and victimization using data from Thailand.

In Thailand, crime is categorized into four types: crimes against persons, property crimes, special offenses, and offenses against the state. Property crime ranks second among these categories, following offenses against the state (Tongsamsi & Tongsamsi, 2019). Thailand's transition from an agricultural to an industrial economy has elevated living costs, potentially contributing to increased property crime rates (Phlicharoenphon & Rober, 2023). Despite this concerning trend, property crime remains understudied.

Thailand faces significant income inequality challenges. The World Bank Group (2023) reported that Thailand maintained the highest income-based Gini coefficient (43.3%) in East Asia and the Pacific in 2021. Although this coefficient decreased from 52.4% to 43.3% between 2000 and 2021, it experienced a slight increase of approximately 0.03% from 2019 to 2021 during the COVID-19 pandemic. Government assistance programs helped mitigate further inequality increases during this period. However, urban areas, particularly Bangkok, experienced a more substantial increase in income inequality of about 4% in 2021.

Empirical evidence suggests a strong correlation between income inequality and property crime (Choe, 2008; Metz & Burdina, 2018; Sugiharti et al., 2022). Cross-country analysis, including data from Thailand, has demonstrated a positive relationship between income inequality and robbery rates (Fajnzylber et al., 2002). Although income inequality in Thailand has declined significantly over time, it remains high and appears to be rising, especially in urban areas. Therefore, it is reasonable to expect that property crime will increase in the future due to high income inequality.

This study addresses the following research question: What is the relationship between wealth and victimization, and which demographic groups are most vulnerable to property crime? Understanding victimization patterns is crucial for policymakers developing effective crime prevention strategies (Barslund et al., 2007; Gomes & Paz, 2008). Moreover, investigating property crime victimization determinants is essential as fear of victimization can significantly impact individual well-being (Sant'Anna et al., 2016). Therefore, enhancing understanding of victimization patterns offers potentially substantial social and economic returns

(Barslund et al., 2007).

The study employs an instrumental variable probit (IV-Probit) model to address endogeneity in the wealth index variable. To solve the endogeneity problem and ensure it is not only a correlational relationship, this study utilizes a variable indicating whether a household received assistance through an old age allowance as an instrumental variable for the wealth index variable. Because this variable is correlated with the wealth index but uncorrelated with the error term, it satisfies the conditions for a valid instrument.

The IV-Probit models reveal a negative relationship between the wealth index and property crime victimization experience. This finding suggests that wealthy individuals' greater investment in protective measures may reduce their victimization probability. Notably, this result contradicts traditional economic theory, which posits that criminals typically target individuals offering higher returns.

The remainder of this paper is organized as follows: Section 2 reviews relevant literature, Section 3 describes the dataset, Section 4 presents the empirical methodology, and the final three sections detail the model results, discussion, and conclusions, respectively.

2. Literature Review

2.1 Theoretical Framework

There are several theoretical frameworks that pertain to criminal victimization. One of the most renowned theories is the routine activity approach proposed by Cohen and Felson (1979). According to this approach, most crimes require the convergence of three essential elements: a motivated offender, an attractive target, and the absence of capable guardianship. Therefore, criminals target individuals who lack capable guardianship because their chances of success are greater in these cases. Similarly, the dispersal of activities away from households and families increases the opportunity for crime, leading to higher crime rates.

Another notable theory is the opportunity theory of criminal victimization proposed by Cohen et al. (1981). It identifies exposure, guardianship, proximity to motivated offenders, target attractiveness, and properties of crimes as factors influencing victim risk. In particular, exposure, proximity to motivated offenders, and target attractiveness are assumed to increase the risk of victimization, while guardianship decreases it. Furthermore, the difficulty of the crime affects the victim's risk. For example, larcenies are easier to commit and require less knowledge of the victim's routine activities (Barslund et al., 2007).

Relevant theoretical frameworks can be found not only in the field of criminology but also in economics. The most famous economics theory about crime was proposed by Becker (1968). According to this theory, criminals consider the potential benefits and costs of committing a crime. For example, one benefit may be the money that can be obtained from the crime, while costs include the likelihood of being caught and the severity of the punishment. Criminals decide to commit a crime if the benefit is higher than the cost. On the other hand, this theory assumes that crime does not occur if the cost is higher. Accordingly, based on this theoretical framework, the difference between a criminal and a non-criminal lies in their differing assessments of benefits and costs, and the characteristics of being a victim can be understood similarly.

2.2 Review of Empirical Literature

In this section, this study first reviews relevant studies about crime victimization. Many factors affect the probability of being a victim of property crime. These determinants can be separated into two groups: individual attributes and area attributes. One crucial individual attribute is education. According to at least one study, education may reduce the probability of becoming a victim by increasing awareness and preventing risky behaviors (Cuesta & Alda, 2012). By contrast, Barslund et al. (2007) found a significant positive relationship between the risk of victimization and education in Mozambique. This may be because educational attainment and family income have a close relationship, i.e., more highly educated people have a higher income (Martinez & Cortez-Yactayo, 2015). Therefore, from a criminal's view, higher education levels of potential victims may signal higher economic returns. However, most studies have found significant positive results, even when controlling for the income variable; for this reason, Martinez and Cortez-Yactayo's (2015) explanation for the mechanism between education and victimization is unclear and inconsistent with previous findings.

Another significant individual attribute that is a determinant of victimization is age. For example, younger people may experience more victimization because they lack self-protective responsibilities—such as avoiding going out at night—which increases their exposure to criminals (Bunch et al., 2015; Justus & Kassouf, 2013). However, some studies have presented an opposite view, finding that older people are more likely to be victimized because they may be wealthier than younger individuals and cannot defend against physical attacks as easily (Barslund et al., 2007; Gomes & Paz, 2008). Additionally, Sant'Anna et al. (2016) reported that the relationship between age and victimization has an inverted U-shape and emphasized that the risk for children and older people is lower than for people at intermediate ages.

Regarding area attributes, the conditions of the resident place are related to property crime victimization. For example, Gaviria and Pagés (2002) observed a positive relationship between larger cities and victimization in Latin America. This may be because crime returns can be higher in larger cities, as larger cities usually have wealthier victims and more developed markets for secondhand goods. Similarly, using micro-data from the United States, Glaeser and Sacerdote (1999) found that victimization rates are much higher in big cities. One reason for this positive relationship may be the lower probability of arrest and recognition in cities. As criminals usually compare the benefits and costs of crime and make rational choices, it is logical that there would be more victimization in high-return, low-cost areas (Becker, 1968).

Regarding crime in Thailand specifically, this study highlights four empirical studies: Grote et al. (2024), Phlicharoenphon and Rober (2023), Punyasavatsut (2016), and Tongsamsi and Tongsamsi (2019). Grote et al. (2024) used rural household data from Thailand and Vietnam to evaluate the determinants of crime victimization and their impact on food consumption and child health outcomes. They found that victimization negatively affects these two outcomes, and that inequality plays a critical role in the determinants of crime victimization. However, Grote et al. (2024) specifically examined the rural areas of three provinces (Buriram, Nakhon Phanom, and Ubon Ratchathani) and did not include urban areas in Thailand. Therefore, to more precisely estimate the causal relationship between the determinants of crime victimization and fill this research gap, this study utilizes data that encompasses all areas of Thailand.

Next, using macro-level panel data with a fixed effect model, Punyasavatsut (2016) analyzed the determinants of the weighted crime rate (weighted by their legal punishment, i.e., years in prison) and found significant relationships between all crime type rates and the police clear-up crime rate (negative), number of illegal immigrant workers (positive), number of monks (negative), number of tourists (positive), and national educational test scores (negative). However, as Punyasavatsut (2016) did not separate the results by crime type, the determinants of each crime type remain unclear.

Meanwhile, Tongsamsi and Tongsamsi (2019) provided evidence that economic conditions (unemployment, average monthly expenditure) in Thailand impact property crime rates. Nevertheless, their estimation model lacks consideration of omitted variables bias, as only four variables (unemployment, average monthly expenditure, urbanization, and population density) were included in their empirical analysis. Lastly, Phlicharoenphon and Rober (2023) utilized spatial analysis to examine property crime in Nakhon Pathom Province and reported that property crime clustered around crowded residential areas and villages, dark alleys, and deserted streets. Nonetheless, three of them used macro-level data or analyzed only a specific province, which is not enough to inform policymakers on how to reduce property crime. As emphasized by Martinez and Cortez-Yactayo (2015), researchers must consider the perspective of victimization and analyze individual-level data to more adequately inform the design and implementation of appropriate measures to reduce property crime.

3. Data

This study examines data from the Thailand Multiple Indicator Cluster Survey (MICS), which was conducted in 2019 and 2022 by the National Statistical Office of Thailand (NSO, 2020; 2023) with technical support from the United Nations Children's Fund (UNICEF). The MICS is a vital source of information utilized to help monitor the progress toward achieving the Sustainable Development Goals (SDGs). The data are from a nationally representative sample survey of households and include children aged 0–5 years, women aged 15–49 years, and men aged 15–59 years.

The MICS's fieldwork was conducted from May to November 2019 and from June to October 2022. Urban and rural areas by province were identified as the main sampling strata, and the sample was selected in two stages. In the first stage, survey enumeration areas (EAs) were selected systematically with probability proportional to size (PPS). After household listing was carried out within the selected enumeration areas, households with and without children under 5 years were identified. In the second stage, a systematic sample of households was selected separately from each group within the sample EA using random systematic selection procedures.

For the purposes, this study utilized a sample of women aged 15–49 years and men aged 15–59 years. Women were surveyed in each sampled household, but men were surveyed in every second sampled household (i.e., in half of the sample of households). Therefore, this study adjusted the weight variable to ensure that the sex ratio in MICS 2019 and 2022 is the same as the actual ratio. The details of the survey sample are shown in Table 1.

Table 1: Details of survey samples

Year	Sex	Eligible for interview	Interviewed	Response rate
2019	Women	21,663	21,089	97.4%
	Men	9,844	9,452	96%
2022	Women	26,002	25,087	96.5%
	Men	11,700	11,023	94.2%

Source: Author's calculation

For this study, the dependent variable is the experience of property crime victimization from the MICS data. The question for individual men and women about the experience of victimization was as follows: "In the last 12 months, has anyone taken or tried taking something from you by using force or threatening to use force?"

According to the Royal Thai Police, the property crime category in Thailand includes 11 types of crimes: gang robbery, robbery, snatching, theft, extortion, fraudulent, misappropriation, mischief, receiving stolen property, kidnapping, arson, and others including car theft and motorcycle theft. However, it was difficult to cover all types of property crime in this study due to data limitations in the MICS dataset. As this study focuses on property crime where property is taken unwillingly or without permission, property crime in this study refers to most types of property crime except fraudulent, receiving stolen property, kidnapping, and arson.

The MICS datasets do not collect data about income but rather calculate the wealth index based on household characteristics related to wealth. Thus, this study uses the wealth index to control for individual financial status. In the MICS dataset, the wealth index was calculated based on household characteristics such as ownership of durable assets, materials used for housing construction, and water and sanitation facilities (Anton et al., 2021)[1].

Next, the variables that were potential determinants of property crime victimization were controlled as independent variables. Most have been considered in previous studies, such as education level, gender, age, and residence place. Additionally, the survey year dummy and region dummy were controlled. As Grote et al. (2024) found that inequality increases victimization, the Gini coefficient at the region level was added as a control variable. Table 2 provides the definitions of all variables, and Table 3 presents descriptive statistics.

[1] The calculation of the wealth index is detailed in the National Statistical Office of Thailand (2023, p.30).

Table 2. Definition of variables

Variable	Definition
Victimization	1 if the individual was a victim in the last 12 months and 0 otherwise
Wealth index	Wealth index score
Marriage	1 if the individual is currently married and 0 otherwise
Widowed	1 if the individual is currently widowed and 0 otherwise
Urban area	1 if the individual lives in municipality (urban area) and 0 if lives in non-municipality (rural area)
Age	Age in years
Primary school	1 if the highest level of education is primary school and 0 otherwise
Lower secondary school	1 if the highest level of education is lower secondary school and 0 otherwise
Upper secondary school	1 if the highest level of education is upper secondary school and 0 otherwise
University or above	1 if the highest level of education is university or above and 0 otherwise
Male	1 if the individual is male and 0 if female
Male adult	The number of men aged 15–49 in the household
Inequality	Gini coefficient of Consumption Income at the region level (using 2021 data, as 2022 data is unavailable)
Old age allowance (IV)	1 if household received assistance through an old age allowance and 0 otherwise

Source: Author's compilation

Table 3. Descriptive statistics (N = 63,574)

Variable	*M*	*SD*	Min.	Max.
Victimization	0.002	0.042	0	1
Wealth index	0.323	0.955	−5.755	2.848
Marriage	0.258	0.437	0	1
Widowed	0.009	0.092	0	1
Urban area	0.512	0.500	0	1
Age	33.521	10.101	15	49
Primary school	0.193	0.394	0	1
Lower secondary school	0.211	0.408	0	1
Upper secondary school	0.272	0.445	0	1
University or above	0.312	0.463	0	1
Male	0.493	0.500	0	1
Male adult	1.077	0.751	0	7
Inequality	0.402	0.029	0.339	0.444
Old age allowance (IV)	0.300	0.458	0	1
Year 2022	0.457	0.498	0	1
Central	0.314	0.464	0	1
North	0.146	0.353	0	1
Northeast	0.238	0.426	0	1
South	0.138	0.344	0	1

Source: Author's calculation

Note: These descriptive statistics are shown after weighting by the weight variable.

4. Empirical Methodology

The most utilized basic models when the dependent variable is a binary variable are the probit and logit models. Although the linear probability model, which can be estimated with ordinary least squares (OLS), is appropriate for estimations when the dependent variable is binary and increases the ease of explanation, it has some problems, such as fitted probabilities being less than zero or greater than one and the partial effect of any independent variable (appearing in level form) being constant (Wooldridge, 2006). The probit and logit models can address these issues: fitted probabilities are between zero and one, and the partial effects are diminished (Wooldridge, 2006). For this reason, almost all previous studies about crime victimization have utilized the probit model or logit model if their victimization variable is a binary variable (Barslund et al., 2007; Gaviria & Pagés, 2002; Gomes & Paz, 2008; Milani et al., 2022; Sant'Anna et al., 2016; Scorzafave et al., 2015; Truzzi et al., 2022). Following the example of previous studies, this study employs the probit model to estimate the determinants of property crime victimization.[2]

However, this study's estimations also face the endogeneity problem. More specifically, if any independent variable is correlated with the error term ($E[U|X] \neq 0$), omitted variable bias, which is one form of bias in endogeneity problems, will occur (Greene, 2003; Wooldridge, 2009). In this study, the wealth index variable may be related to other determinants that are not included in the questionnaire and for which it is difficult to obtain data for controlling, e.g., investment in private protection and the security measures of the resident place (as, for example, rich areas mostly have good security measures). These unobserved factors are captured in the error term, potentially causing the wealth index to be correlated with them.

Another endogeneity problem this study faces is reverse causation. First, high wealth-index individuals may be more likely to be targets of property crime because they offer high benefits. However, property crime victimization also affects individuals' wealth index; that is, experiences of victimization may reduce individuals' wealth index because of criminals taking their assets. Therefore, it is unclear which is the cause, as both are possible.

Additionally, according to previous studies, the mechanisms between income and victimization indicate a preference for wealth index over income. For instance, it is challenging for a criminal to know an individual's income before committing a crime, but a criminal can determine whether an individual is wealthy through asset ownership or the area of residence. Accordingly, the wealth index is more likely to be a determinant of victimization compared to income.

To address these endogeneity issues, a suitable instrumental variable (IV) is necessary. The MICS dataset included a yes/no question on whether a household received assistance through an old age allowance. Accordingly, this study proposes that old age allowance can serve as an instrumental variable for the wealth index, as it is likely closely related to the wealth index (with households receiving the allowance potentially being

[2] In this dataset, reported crime victimization within the last 12 months constitutes only about 0.2% (108 cases). Although this low rate might suggest an underestimation of crime victimization, there is no significant difference in the results between the rare event logit model developed by King and Zeng (2001), which corrects for rare event bias, and the standard logit model. This finding supports the idea that bias is not present and that the IV-Probit model is unaffected by the low victimization rate.

wealthier) but unlikely to have a relationship with the error term.

Ultimately, this study employed the instrumental variable probit model (IV-Probit) because it is suitable for models with binary dependent variables.

$$victim_i = \beta_0 + B_1 wealth_i + B_2 control_i + \varepsilon_i \quad (1)$$

$$wealth_i = b_0 + b_1 IV_i + b_2 control_i + u_i \quad (2)$$

This study estimated the IV-Probit model in two stages. The first stage involved calculating Equation (2), i.e., regressing the endogenous variable (wealth index) on the instrumental variable and other control variables. The fitted value was obtained as follows in Equation (3):

$$\widehat{wealth_i} = \widehat{b_0} + \widehat{b_1 IV_i} + b_2 \widehat{control_i} + \widehat{u_i} \quad (3)$$

The IV should be significant at a small significance level; indeed, it is meaningless if not significant (Wooldridge, 2006). The $\widehat{wealth_i}$ replaces $wealth_i$ in Equation (1) to be estimated for the second stage, and this estimated version of $wealth_i$ is uncorrelated with ε_i. Therefore, endogenous problems can be solved using these estimations.

To confirm the suitability of the IV, this study utilized the Wald test of exogeneity, Anderson–Rubin (AR) statistics, and Wald statistics. All were statistically significant, meaning the null hypothesis of no endogeneity and the null hypothesis that the IV's coefficient on the wealth index variable is zero are rejected. Therefore, this study considered the IV to be a suitable instrumental variable for the wealth index.

5. Results

Table 4 presents the results of the Probit and IV-Probit models (the results of the first stage are in Table A1). First, there are significant differences in the wealth index between the standard Probit model and the IV-Probit model. The coefficient of the wealth index changed significantly in the IV-Probit model, from -0.172 to -1.173, indicating that the effect of the wealth index on victimization is underestimated due to the endogeneity problem. Although this relationship is also negative in the probit model, the significance of wealth index decreases from the 1% to the 5% level.

Table 4. Results of the probit and IV-probit models

	Probit model			IV-Probit model		
	Coefficient	Robust Std. error	P-values	Coefficient	Std. error	P-values
Wealth index	-0.172	0.079	0.028	-1.173	0.097	0.000
Marriage	0.000	0.154	0.998	0.255	0.051	0.000
Widowed	0.460	0.373	0.217	0.294	0.125	0.019
Urban area	-0.332	0.137	0.016	0.062	0.092	0.500
Age	0.006	0.008	0.486	0.008	0.002	0.000

	Probit model			IV-Probit model		
	Coefficient	Robust Std. error	P-values	Coefficient	Std. error	P-values
Primary school	0.026	0.378	0.946	0.391	0.127	0.002
Lower secondary school	0.146	0.380	0.701	0.786	0.135	0.000
Upper secondary school	0.182	0.408	0.655	1.152	0.152	0.000
University or above	0.033	0.418	0.937	1.635	0.218	0.000
Male	0.021	0.134	0.873	-0.097	0.038	0.011
Male adult	0.048	0.071	0.504	0.128	0.023	0.000
Inequality	7.692	6.491	0.236	3.222	2.533	0.203
Cons	-5.675	2.402	0.018	-3.556	1.164	0.002
Survey year dummy & region dummy	Yes			Yes		
Number of observations	63,574			63,574		
Pseudo R2	0.064					
Log pseudolikelihood	-777.058			-75699.944		
Wald test of exogeneity (Prob > chi2)				0.001		
AR (Prob > chi2)				0.010		
Wald (Prob > chi2)				0.000		

Source: Author's calculation

Note: Robust std. error is clustered by primary sampling units (using cluster in Stata). Std. error is not clustered in the IV-Probit model because the weak-instrument test from the code rivtest does not allow for robust or clustered std. error.

Next, this study observed that several variables are significant in the IV-Probit model but not in the Probit model. In particular, the marriage, widowed dummy, age, and male adult variables are positively related to property crime victimization. Additionally, the education dummy variables are particularly interesting: Four of the education dummy variables are statistically significant and have a positive relationship with victimization. Notably, the university or above dummy variable has the highest coefficient among them. Conversely, being female is also positively associated with property crime victimization.

Because the coefficients in the IV-Probit model cannot be easily explained like those in the linear probability model, this study calculated the average marginal effects to evaluate the strength of the independent variables' effect on victimization. These average marginal effects in the IV-Probit model are reported in Table 5.

Table 5. Average marginal effects of the IV-probit model

	dy/dx	Delta-method std. err.
Wealth index	-0.012	0.005
Marriage	0.003	0.001
Widowed	0.003	0.001
Urban area	0.001	0.001
Age	0.000	0.000
Primary school	0.004	0.002
Lower secondary school	0.008	0.004
Upper secondary school	0.012	0.005
University or above	0.017	0.008
Male	-0.001	0.001
Male adult	0.001	0.001
Inequality	0.034	0.023
Number of obs	63,574	

Source: Author's calculation

First, the probability of being a victim of property crime over the past year decreases by about 1.2% when the wealth index score increases by 1 point. Next, inequality has the strongest effect on crime victimization, with an average marginal effect of 0.034, although this effect is not statistically significant. On the other hand, the average marginal effects of the education level dummy variables range between 0.004 and 0.017. If the individual's highest level of education is university or above, the probability of having victimization experiences increases the most, by nearly 1.7%.

6. Discussion

Overall, the results suggest that a higher wealth index is associated with lower victimization rates in Thailand, which differs significantly from Becker's (1968) economic theoretical framework. However, this finding aligns with Levitt's (1999) view that wealthy individuals are more likely to protect their assets by investing in security measures, such as alarm systems in their homes. This study suggests that increased wealth leads to greater investment in security, thereby lowering the probability of criminal success and increasing the risk of arrest.

This relationship can also be explained by criminology theory. According to Cohen and Felson's (1979) routine activity approach, an attractive target and the absence of capable guardianship are crucial determinants of crime. While high wealth may increase a target's attractiveness to criminals, it also enhances capable guardianship. Although the routine activity approach emphasizes human guardianship, investments in security measures also serve as guardianship, reducing the likelihood of victimization.

Next, the results indicate a positive relationship between age and victimization. Previous studies (Barslund et al., 2007; Gomes & Paz, 2008; Sant'Anna et al., 2016) have found that victimization is lower for children and older individuals compared to those of intermediate ages, who are generally wealthier. Given that

the MICS dataset includes individuals aged 15–49, it is unsurprising that the age variable is positively correlated with victimization. Additionally, according to our results, males experience less victimization, which aligns with the findings of Kuo et al. (2012). This may be due to women having a generally smaller stature and less guardianship or a lesser ability to defend against the force of robbers (Kuo et al., 2012).

This study also found that education has a positive relationship with victimization, with the strength of the relationship increasing with higher education levels. This result is similar to the findings of Martinez and Cortez-Yactayo (2015), who suggest that individuals with lower education levels may not constitute economically viable targets, reducing the probability of victimization. This explanation fits with the theory of Cohen et al. (1981), which posits that higher education levels increase target attractiveness for criminals, thereby increasing the risk of victimization.

7. Conclusions

This study makes two significant contributions. First, it addresses the limitations of previous research by establishing a negative causal relationship between wealth and property crime victimization, thereby advancing theoretical understanding in this field. Second, it provides crucial insights for Thai society, offering evidence-based guidance for law enforcement to target interventions toward groups at elevated risk of victimization. Additionally, the study extends the work of Grote et al. (2024) by examining property crime victimization determinants across all regions of Thailand.

The research establishes the wealth index as a causal factor through rigorous instrumental variable methodology. The negative relationship between wealth and victimization represents a novel finding that challenges traditional economic theoretical frameworks. While conventional wisdom suggests criminals primarily target wealthy individuals, this study indicates that enhanced protective measures among the wealthy may effectively deter criminal activity.

Although this study focuses on specific empirical questions rather than explicit policy recommendations, it highlights the potential effectiveness of security investments in reducing crime victimization. A key insight emerges: Criminal behavior in Thailand may be deterred by the higher likelihood of unsuccessful attempts against wealthy targets, rather than by the assumed lack of valuable possessions among poorer individuals. This finding emphasizes the importance of vigilance against property crime across all socioeconomic groups.

The study acknowledges certain limitations. The MICS 2019 and 2022 datasets, while offering excellent response rates and sample sizes, are restricted to individuals aged 15–49 years. Given the challenges of finding comprehensive datasets that include criminal victimization data, future research should prioritize data collection across all age ranges in Thailand to provide a more complete understanding of victimization patterns.

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Appendix

Table A1. Results of the First Stage of the IV-Probit Model

	IV-Probit model		
	Coefficient	Std. err.	P>z
Marriage	0.248	0.008	0.000
Widowed	0.061	0.034	0.078
Urban area	0.219	0.007	0.000
Age	0.005	0.000	0.000
Primary school	0.339	0.029	0.000
Lower secondary school	0.644	0.029	0.000
Upper secondary school	0.961	0.029	0.000
University or above	1.476	0.029	0.000
Male	-0.098	0.007	0.000
Male adult	0.093	0.005	0.000
Inequality	-0.611	0.402	0.129
IV	0.084	0.007	0.000
Cons	-0.609	0.147	0.000
Survey year dummy & region dummy	Yes		
Number of observations	63,574		

Source: Author's calculation