ICDSOS
The 3rd International Conference on Data Science and Official Statistics
November 27 - 28, 2025

"From Data to Impact: Leveraging Innovation in Data Science and Official Statistics for Data-Driven Policy Making and Global Competitiveness"

Shadow Economy Estimation Across ASEAN Member States: MIMIC Model Approach

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Abstract. As a measure of official output, GDP remains incomplete, omitting the substantial economic transactions that occur within the shadow economy. The shadow economy reduces government tax revenues and weakens fiscal capacity. It also contributes to the underestimation of macroeconomic indicators. This study estimates the size of the shadow economy in ASEAN member states (AMS) using the Multiple Indicators and Multiple Causes (MIMIC) model. The model employs three causal variables and two indicator variables to capture the latent construct. Inflation, unemployment rate, and GDP per capita growth are identified as the main causal determinants. Economic growth and M2 growth are validated as significant indicators constructed for the shadow economy. The estimation covers the period from 2000 to 2023 and reveals an upward trend in the shadow economy across ten AMS, with an average size of 37.75 percent of GDP. These findings emphasize the need for policy actions that focus on maintaining price stability, promoting inclusive economic growth, and expanding formal employment opportunities to mitigate the expansion of the shadow economy.
Keyword: ASEAN, MIMIC Model, Shadow Economy

1. Introduction

Gross domestic product (GDP) often provides an incomplete account of economic activity as they exclude the shadow economy. The shadow economy comprises transactions that remain outside official registration, taxation, and regulation, yet continue to produce goods and services that contribute to the functioning of the formal market [1]. These activities are commonly classified into four categories: the informal economy, the unreported economy, the illegal economy, and the unrecorded economy [2]. The expansion of shadow economy activities introduces distortions in the assessment of several macroeconomic indicators, including GDP, national accounts, and inflation [3]. A substantial shadow economy often leading to inefficiencies in policymaking derived from inaccurate macroeconomic indicators [4]. Additionally, the shadow economy generates fiscal losses through foregone tax revenues, which in turn diminishes public financial resources and constrains the effectiveness of government functions [5]. Therefore, fighting shadow economy should be an important agenda for any government [6]

As a regional economic integrator, the Association of Southeast Asian Nations (ASEAN) has played a pivotal role in accelerating members economic growth, while simultaneously creating conditions that could foster the expansion of the shadow economy. In 2022, ASEAN recorded a GDP of USD 3.6 trillion with a growth rate of 5.7%, positioning the region as the third-largest economy in Asia and the fifth-largest in the world. Nevertheless, rapid economic growth does not necessarily ensure equitable improvements in the socio-economic conditions of all AMS [7]. An estimated 244 million individuals, representing 78.6 percent of the labour force aged above 15 years are employed in the informal sector

[8]. Owing to its relatively low barriers to entry, this sector constitutes a major source of income for a significant proportion of the population. Nevertheless, the widespread incidence of informal employment poses considerable challenges for ASEAN. Mitigating labour risks and socio-economic vulnerabilities associated with informality might be a big obstacle, even though the sector is frequently regarded as the backbone of ASEAN's economies.

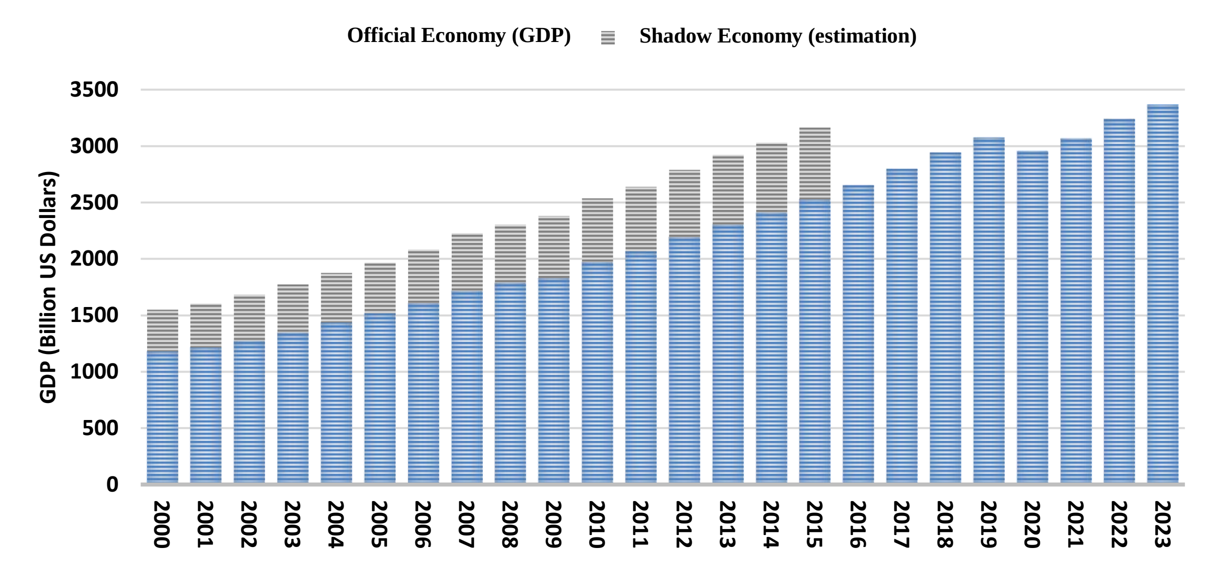

Figure 1. ASEAN's shadow economy estimation and its GDP 2000-2023
Sources: Medina & Schneider (2018) and The World Bank (processed)

Recent estimates indicate that the size of the shadow economy in ASEAN member states (AMS) has expanded alongside the growth of their formal economies between 2000 and 2023 (figure 1). This pattern implies that the scale of official economic activities is systematically underestimated due to unrecorded transactions that remain outside formal oversight. z020 and found that the average shadow economy size in AMS was 32.88 percent of GDP [25]. Medina and Schneider (2018) refined the estimation for 158 countries between 1991 and 2015, reporting an average of 33.36 percent of official GDP for AMS [15]. Although governments continuously attempt to reduce the shadow economy, producing reliable estimates at both national and regional levels remains essential for effective policy formulation. The persistence of unobserved economic activities underscores the importance of updated estimation. However, the availability of recent shadow economy estimates among AMS is still limited. This study aims to estimate the shadow economy in ASEAN member states using the MIMIC model and provides more recent and comprehensive findings compared to previous research.

2. Research Method

2.1. Shadow Economy

The shadow economy encompasses the production of goods and services, both legal and illegal, that are excluded from official GDP calculations [13]. The shadow economy has several other names, such as the underground economy, cash economy or informal economy, hidden economy, grey economy, unofficial economy, and black economy [14]. Variations in terminology reflect the conceptual complexity of the shadow economy, which in general refers to all economic activities excluded from national accounts but theoretically included in GDP measurement. These activities are undertaken by diverse economic agents, including firms, wage earners, and the self-employed, and may occur through both monetary and non-monetary transactions that ought to be captured in official statistics. Within the framework of national accounts, the notion of the shadow economy closely corresponds to the concept of the Non-Observed Economy (NOE).

According to the System of National Accounts (SNA), non-observed economy (NOE) refers to forms of economic activity that, for various reasons, are not captured in conventional statistical records [15]. The OECD (2002) defines the NOE as encompassing informal, illegal, and other activities that are omitted due to data limitations, even though they should be included in GDP. These activities are not reflected in statistical surveys or administrative records, which serve as the foundation for compiling national accounts [21]. The measurement of NOE activities follows an analytical framework consisting of seven classifications, as recommended by the Italian National Institute of Statistics (ISTAT). However, no aggregate measure currently exists that fully aligns with the broader economic concept of the shadow economy. Within the ISTAT framework, the shadow economy corresponds to the aggregation of unobserved NOE classifications driven by economic factors (T4 and T5) and informal production (T6) [10]. This study applies the approach proposed by Dell'Anno [11] by adopting the ISTAT framework and limiting the definition of the shadow economy to the aggregation of T4, T5, and T6 classifications.

The estimation of the shadow economy is conducted through two primary approaches: direct and indirect approach [16]. Direct approaches typically involve survey methods and the analysis of discrepancies in national accounts. Direct approach is highly dependent on the planning process and data collection as input for estimation activities. This approach limited to provide a general overview, such as the classification of shadow economy activities, public perception of the shadow economy, public participation in the shadow economy, and the structure of the shadow economy. Indirect approaches use of theoretical frameworks such as DGE model and statistical techniques including the CDA and the MIMIC model. Indirect approach offers significant advantages in measuring the shadow economy, particularly through its ability to ensure cross-country comparability and to facilitate time-series analysis.

2.2. MIMIC Model

The Multiple Indicators and Multiple Causes (MIMIC) model is a theory-based analytical framework used to examine the impact of exogenous causal variables on a latent construct, in this case the shadow economy, and to evaluate the subsequent effects of that construct on selected macroeconomic indicators. A critical preliminary phase in utilizing this model involves developing a theoretical framework that elucidates the relationships between the exogenous variables and the latent variable. Consequently, the MIMIC model is regarded as a confirmatory approach rather than an exploratory one [15]. MIMIC model represents a specialized form of structural equation modeling (SEM).

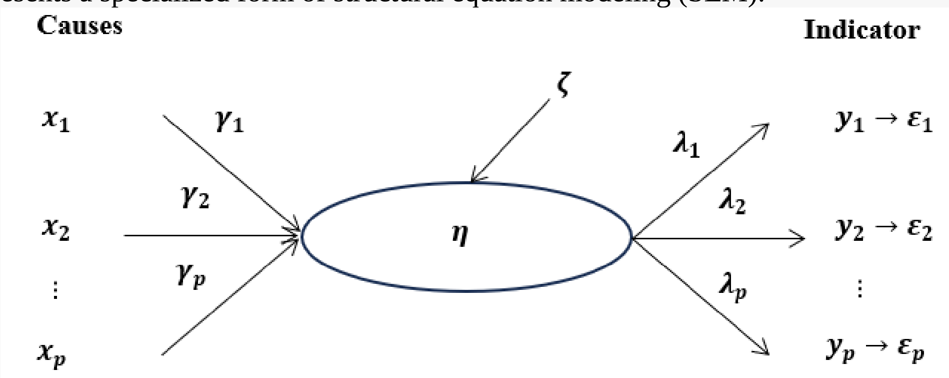

Figure 2. The general equation of MIMIC Model

The MIMIC model comprises two components: the structural model and the measurement model as shown in figure 2. Generally, the MIMIC model incorporates a single latent factor, which allows it to be characterized as a unidimensional or one-factor MIMIC model. The shadow economy acts as a latent variable whose relationship with observed variables is analysed through a covariance matrix [15]. The left side of the path diagram contains exogenous causal variables included in the structural model, while the right side includes observed indicators that form part of the measurement model. The general form of the MIMIC model can be expressed below [22].

$$y = \mathbf{\Lambda_y}\eta + \epsilon \quad (1)$$
$$\eta = \mathbf{B}x + \zeta \quad (2)$$

Equation 1 represents the measurement model, which describes observable variables as reflections of latent constructs. y denotes vector of indicator variables representing the impact of the latent variable denoted by η. While $\mathbf{\Lambda_y}$ is a matrix of loadings factor representing coefficients relating y to η. Lastly, ϵ denotes vector of measurement error for y. The basic concept of a measurement model is confirmatory factor analysis (CFA). The measurement model uses factor loadings as the link between latent variables and observed variables.

Structural model as describe in Equation 2 is a model used to construct latent variables and describe the relationships within them. x is a set of observable variables acting as causal variables for the latent variable. **B** is a matrix of regression coefficients representing the variation in the latent variable following a one-unit change in the causal variable. While ζ is latent errors in the equations. The basic concept of a structural model is regression. But SEM solves the measurement error problem that may occur when regression models use latent variables. To obtain consistent parameter estimates, structural errors are assumed to be uncorrelated with the exogenous variables in the model.

SEM emphasises the use of covariance rather than individual cases. SEM will minimise the difference between sample covariance and covariance predicted by the model. Residuals in SEM are the difference between predicted covariance and measured covariance. The fundamental hypothesis in the SEM procedure is that the covariance matrix of the population data (**Σ**) is equal to the covariance matrix derived from the model (**Σ(θ)**). With the correct model specification and estimable parameters, the population covariance matrix can be accurately reproduced. Thus, the residuals are expected to be as minimal as possible or zero.

The initial stage in estimating the MIMIC model involves validating the hypothesized relationships between the shadow economy, as a latent construct, and its associated causes and indicators. Model identification is then undertaken to ensure that the system yields a unique solution and to determine whether it is identified or overidentified. Following the estimation of parameters, the model outputs are employed to construct a relative index of the shadow economy. Model evaluation is subsequently conducted to assess the validity of the estimation at the measurement level, the structural level, and the overall model level. Finally, a benchmarking procedure is implemented using existing estimates to establish a base year value, which serves as the reference point for calculating the absolute size of the shadow economy.

2.3. Data Collection Method

This study estimates the size of the shadow economy in ten ASEAN member states, specifically Brunei Darussalam, Cambodia, Indonesia, Lao PDR, Malaysia, Myanmar, the Philippines, Singapore, Thailand, and Vietnam, over the period 2000 to 2023. The data are obtained from several macroeconomic indicators provided by the World Bank and the Asian Development Bank (ADB). The list of variables used in this study is presented in table 1.

Table 1. Research data with its sources and its references.

Variables	Metrics	Sources	References
(1)	(2)	(3)	(5)
Inflation (*INFP*)	Percentage	World Bank	(Macias & Cazzavillan, 2010; Schneider et al., 2010)
Unemployment rate (*UNMP*)	Percentage	World Bank	(Elgin et al., 2021; Macias & Cazzavillan, 2010; Medina & Schneider, 2018; Schneider et al., 2010)

Per capita GDP (*GDPC*)	US Dollar	World Bank	(Elgin et al., 2021; Kelmanson et al., 2019; Medina & Schneider, 2018; Schneider et al., 2010)
M2 growth (*GM2*)	Percentage	ADB	(Macias & Cazzavillan, 2010)
Economic growth (*GGDP*)	Percentage	World Bank	(Macias & Cazzavillan, 2010; Schneider et al., 2010)

2.4. Analysis Method

The shadow economy estimation derived from MIMIC model using SEM. The formulation of the MIMIC model involves a sequence of stages, including specification, identification, estimation, and assessment of model fit. The model applied in this study is outlined as follows.

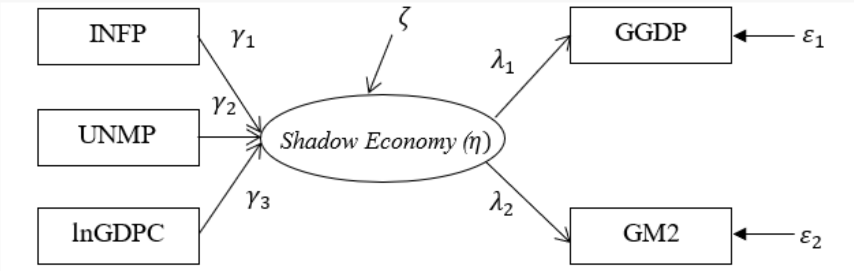

Figure 3. Path diagram for the MIMIC model

Description:

η : Latent variable (shadow economy)
$\gamma_1, \ldots, \gamma_3$: Coefficient of structural model
INFP : Inflation (percent)
lnGDPC : Natural Logarithm of GDP per capita (percent)
UNMP : Unemployment rate (percent)
ζ : Structural model error
λ_1, λ_1 : Coefficient of measurement model
GGDP : GDP growth (percent)
GM2 : M2 growth (percent)
ϵ_1, ϵ_2 : Measurement model error from each indicator

The next stage is the benchmarking procedure, which is conducted to derive the absolute value of the shadow economy. This procedure employs estimates from previous studies as the reference point for establishing the base year value. This study uses shadow economy estimates by Medina & Schneider [15] for ten AMS in 2000. Shadow economy estimates can be obtained using the following equation.

$$\hat{\eta}_t = \frac{\tilde{\eta}_t}{\tilde{\eta}_{2000}} \eta^*_{2000} \quad (3)$$

Description:

$\hat{\eta}_t$: Shadow economy estimation for year t
$\tilde{\eta}_t$: Relative shadow economy index for year t
$\tilde{\eta}_{2000}$: Relative shadow economy index at base year (2000)
η^*_{2000} : Shadow economy estimation at base year (2000)

3. Result and Discussion

The shadow economy, treated as a latent construct, is estimated indirectly through the MIMIC model. Estimation is carried out using the Maximum Likelihood Estimation (MLE) method, which necessitates the assumption of multivariate normality across all observed variables. Multivariate normality will be examined using the Multivariate Mardia test, which is based on skewness and kurtosis calculations. The multivariate normality test using the Mardia Skewness test and Mardia Kurtosis test is considered the most stable and reliable [17]. Based on the results of the multivariate normality test in Table 2, the p-value for multivariate skewness and kurtosis is less than 0.05. With a significance level of five percent, it can be concluded that the observed variables are not normally distributed or, in other words, the assumption of multivariate normality is violated.

Tabel 2. Mardia multivariate normality test.

Multivariate Mardia Test	Skewness	Kurtosis
(1)	(2)	(3)
z-value	365.3142	15.0267
p-value	0.0000	0.0000

Observed variables that are not normally distributed multivariate produce large differences in Chi-square testing and are of limited use [18]. An alternative method to address this condition is Robust Maximum Likelihood (RML). This method modifies the original variables through transformation, then analyzes the transformed data using MLE estimation [19]. The path diagram of the MIMIC model estimated with the Robust Maximum Likelihood (RML) method together with its notation expressed through structural and measurement equations, is outlined as follows (figure 4).

Table 3. Structural model estimation using RML.

Path	Coefficient	t-value	Decision
(1)	(2)	(3)	(4)
$INFP \rightarrow SE$	0.27	3.81	Significant
UNMP→ SE	-0.99	-3.68	Significant
LnGDPC→ SE	-3.72	-7.34	Significant
$Error\ Variance$	16.68		
R^2	0.76		

Based on Table 5, the M2 growth indicator variable has a coefficient value of +1. The coefficient value restriction in the measurement model is done to identify the system and make it easier to compare parameter estimates [16]. The MIMIC model that has been obtained is then evaluated in terms of data suitability and model estimation.

Table 4. Overall model evaluation metrics.

Fit indices	Criteria	Estimation result	Decision
(1)	(2)	(3)	(4)
Chi-square Prob	Chi-square has small value (*P-value* > 0.05)	$\chi^2 = 0.99$ (P-value = 0.62)	failed to reject H_0 (good fit)
NCP	NCP has small value	0.00	*Good Fit*
GFI	GFI ≥ 0.9	1	*Perfect Fit*
RMR	Standardized RMR ≤ 0.05	0.0081	*Good Fit*
RMSEA	RMSEA ≤ 0.08 (good fit)	0.00	*Good Fit*
EVCI	EVCI has small values close to the saturated model	M* = 0.12; S* = 0.13; I* = 1.73	*Good Fit*
AGFI	AGFI ≥ 0.9	0.99	*Good Fit*
NNFI	NNFI ≥ 0.9	1	*Perfect Fit*
NFI	NFI ≥ 0.9	1	*Perfect Fit*
IFI	IFI ≥ 0.9	1	*Perfect Fit*
CFI	CFI ≥ 0.9	1	*Perfect Fit*
RFI	RFI ≥ 0.9	0.99	*Good Fit*
AIC	AIC has small values close to the saturated model	M* = 26.99; S* = 30; I* = 412.62	*Good Fit*
CAIC	CAIC has small values close to the saturated model	M* = 85.24; *S** = 97.21*;* I* = 435.03	*Good Fit*
CN	CN ≥ 200	2225.27	*Good Fit*

Description: M* (Model); S* (Saturated Model); and I* (Independence Model)

Measurement models based on CFA need to be evaluated in terms of their validity. Validity in SEM models is measured by standard factor loadings. This measure indicates the extent to which observed variables contribute to the construction of unobserved latent variables. In the LISREL 8.80 program, standard factor loadings can be displayed using the standardize solution feature (figure 4). Each indicator variable, namely GDP growth and M2 growth, has standard factor loadings of 0.54 and 0.73, respectively (figure 4). Hair [21] states that a variable is considered to have adequate validity if the standard factor loading value reaches or exceeds 0.50, indicating a significant contribution to the measured construct [20]. Thus, both indicator variables can be considered valid for constructing the latent variable of the shadow economy.

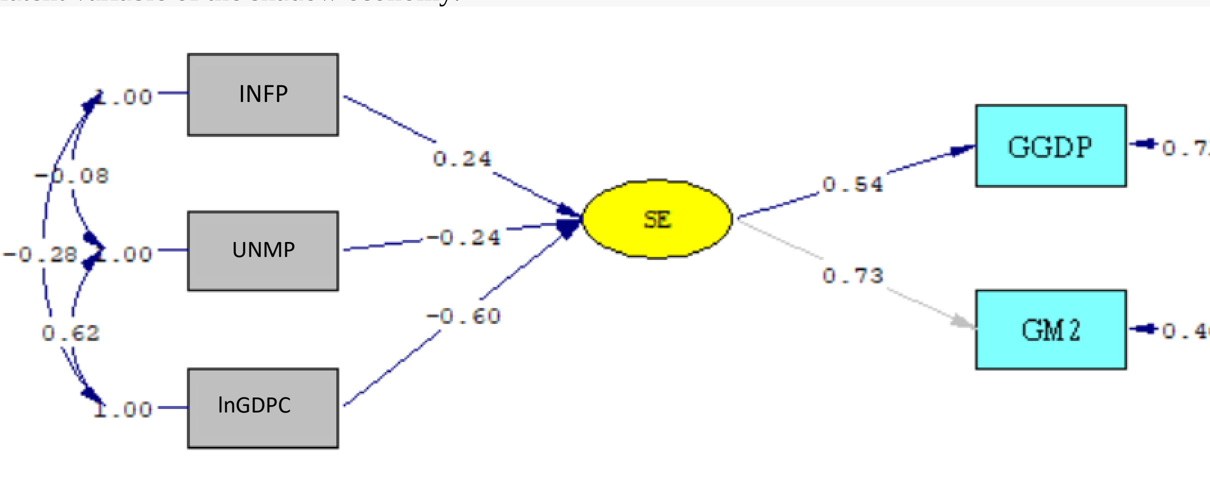

Figure 4. MIMIC Model (standardized solution)

The structural model fit test is based on the significance test of the coefficients for each causal variable and examines the suitability of the direction of the relationship formed with the given hypothesis. Table 5 shows a summary of the coefficients, t-test results, and significance of the three causal variables.

Table 5. Structural model estimation using RML.

SE → *Indicator*	Standardized loading factor	t-value	Validity
(1)	(2)	(3)	(4)
GM2	0.73	**	Good validity
GGDP	0.54	6.40	Moderate validity

Description: ** M2 growth does not have a t-value because its coefficient is fixed at +1

At a significance level of five percent, the critical value of the t-statistic is 1.96. Since the calculated t-statistics for all variables exceed this threshold, it can be concluded that each variable is statistically significant. Based on Table 5, the absolute t-calculated values for all three variables are greater than 1.96. This indicates that each causal variable is significant in influencing the occurrence of the shadow economy. However, there is one variable whose direction of relationship does not align with the hypothesis, namely the unemployment rate variable.

Estimates of the shadow economy cannot be derived directly from the structural equations and therefore require a benchmarking procedure. This procedure, implemented in accordance with Equations 3 and 4, produces estimates of the shadow economy expressed as a percentage of GDP. For the base year, the benchmark values are drawn from the shadow economy estimation by Medina and Schneider [15]. The resulting estimates for the ten ASEAN member states over the period 2000 to 2023 are provided in the appendix, while the dynamics and growth of the shadow economy in these countries are illustrated in the following figure.

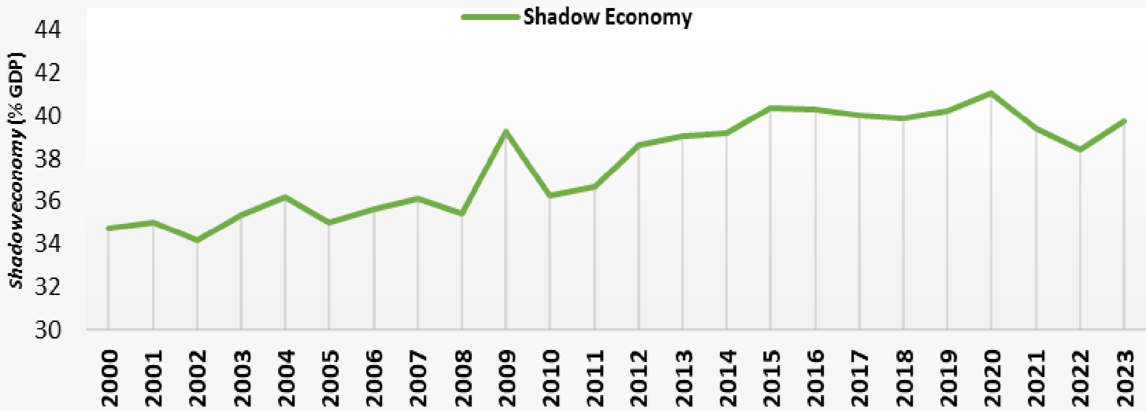

Figure 5. ASEAN's average shadow economy estimation, 2000-2023

In general, the average shadow economy rate in ASEAN during the research period showed a positive trend (figure 5). This finding is in line with the shadow economy estimates for eight AMS conducted by Vo & Ly for the period 1995-2014 [9]. The growing shadow economy is believed to be due to the fact that ASEAN member countries are dominated by developing countries with low-income levels. This confirms the findings of Medina & Schneider who explain that developing countries with low-income levels tend to have higher shadow economy rates compared to high-income countries [15]. The growth of the shadow economy exhibits a fluctuating pattern, suggesting that annual increases are generally modest, with the exception of specific periods such as times of economic crisis.

Figure 5 illustrates a marked increase in the average size of the shadow economy in 2009. This development coincided with the Asian financial crisis, which generated severe disruptions in both the formal and informal sectors of the economy. A similar surge is observed in the growth rate of the shadow economy during the same year. The crisis placed considerable strain on households and firms, prompting greater reliance on informal activities as an alternative source of income and a means of economic resilience. This expansion of informal sector activity contributed directly to the rise of the shadow economy. A similar difficult period recurred in 2020 with the COVID-19 pandemic crisis. During this period, ASEAN reached its highest shadow economy level in the study period, accounting for 41% of GDP. However, the shadow economy level tends to vary when broken down by country.

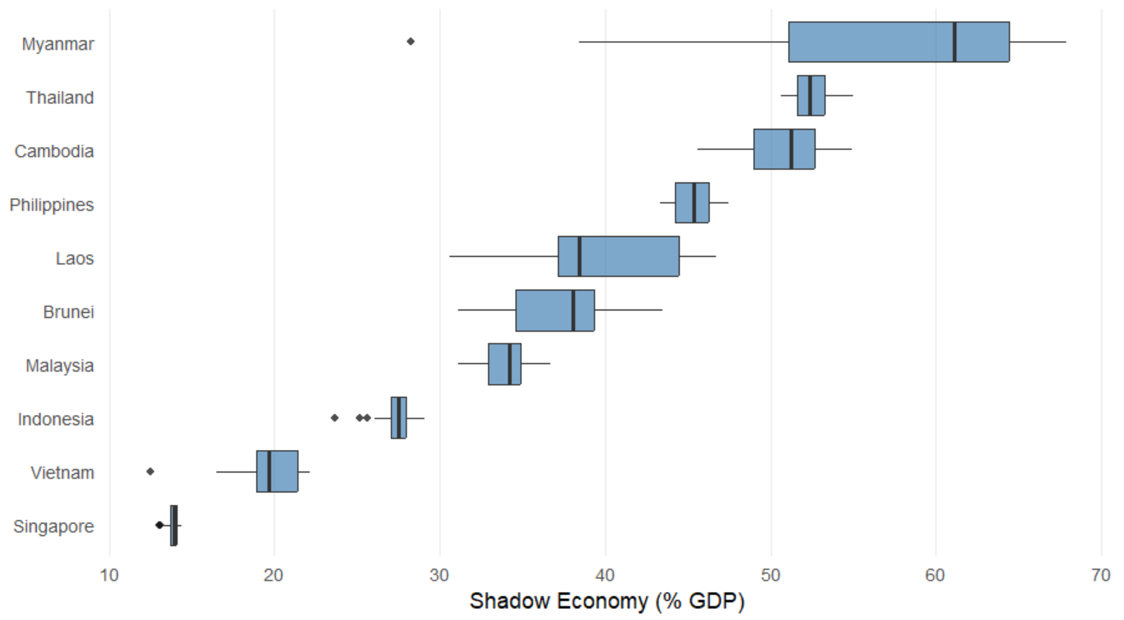

Figure 6. Boxplot of ASEAN's average shadow economy estimation, 2000-2023

There is a large gap between the levels of shadow economy in each AMS (figure 7). Singapore has the lowest level of shadow economy among other ASEAN members. Over the past three decades, the size of shadow economy in Singapore has remained relatively stable, as indicated by the narrow boxplot. Singapore is the only developed country in ASEAN with an average GDP per capita of USD 58,127.837 annually. High income, dominated by contributions from the trade and services sectors, has enabled Singapore to suppress the informal sector and maintain a narrow size of shadow economy. Conversely, Myanmar has the highest shadow economy rate among AMS, averaging 55.49 percent of GDP. This result differs by 4.1 percent from the estimates of Medina & Schneider [15], who also place Myanmar as the ASEAN member country with the highest shadow economy rate. This is, of course, with the caveat that the research periods used are different.

The shadow economy rate shows a strong correlation with a country's level of development. Myanmar, as a developing country with an unstable political climate, has a high informal sector, which impacts its high shadow economy rate. Philippines, Cambodia, Thailand, and Myanmar record the highest levels of shadow economy activity (figure 6). This result is consistent with the findings of Schneider et al [12], who identified these same countries as having the largest shadow economies among ASEAN member states [11]. A high shadow economy rate has various impacts, one of which is causing macroeconomic indicators to be underestimated. A high shadow economy rate in a country can affect the quality of economic information, such as economic growth data used by policymakers to make decisions [16]. In fact, an increase in the shadow economy has occurred in almost all ASEAN member countries.

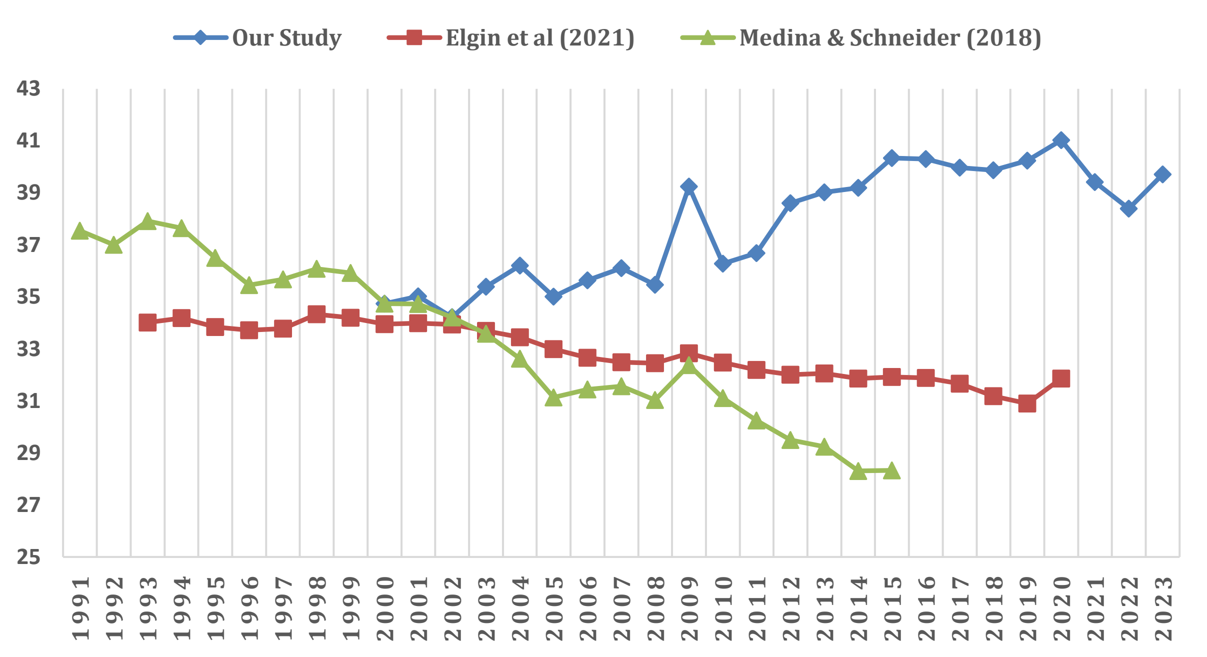

Figure 7. Comparative trends in the estimated size of the shadow economy in ten AMS, 1991–2023.

The average shadow economy estimates from this study indicate an upward trend during the period 2000–2023, which contrasts with the declining patterns reported in the two comparative studies (figure 7). The estimates by Medina and Schneider [15] exhibit a more pronounced downward trend compared to those by Elgin et al [13]. These differences in trends are likely due to the sensitivity of shadow economy estimates to model specifications. Previewer studies employ global samples with extended time spans, which may lead to different aggregate patterns compared to the present study that focuses exclusively on ten AMS. Nevertheless, a similar increasing trend in the shadow economy among ASEAN countries was also reported by Vo and Ly [10], although their analysis excluded Singapore and Brunei and covered a shorter period from 1995 to 2014. The sensitivity of model specifications has been previously acknowledged by Medina and Schneider [15], who emphasized that estimated coefficients vary considerably with changes in model design, country coverage, and time span. ASEAN member states, most of which are developing economies with extensive informal sectors, exhibit a high propensity for shadow economic activities. The dominance of informal employment within the labour market further contributes to the persistence of unrecorded economic transactions, making accurate measurement particularly challenging.

4. Conclusion

Based on the results and discussion in the previous section, the estimated shadow economy in ten ASEAN member countries for the period 2000-2023 shows an average shadow economy of 37.75% of GDP. Myanmar recorded the highest shadow economy rate of 55.8% and Singapore the lowest at 11.88%. The results of the MIMIC model demonstrate that all causal variables exert a significant influence on the latent construct of the shadow economy. Mitigating shadow economy activities requires stronger oversight of transactions occurring outside the formal banking system to ensure that informal and illicit activities are appropriately captured. A sustained reduction in the shadow economy is more likely under conditions of macroeconomic stability and low inflation. The policies that emphasize in maintaining price stability, promoting inclusive economic growth, and expanding formal employment opportunities remain essential to mitigate the expansion of the shadow economy. Future research may benefit from incorporating causal variables and indicators that more accurately reflect the dynamics of the shadow economy.

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