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An abstract of

a thesis submitted to the Faculty of Emory College of Arts and Sciences

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Abstract

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The shadow economy constitutes a substantial portion of economic activities, especially in developing countries like Ethiopia, influencing public policy effectiveness and economic development. Understanding its scale and drivers is crucial for effective policy making and economic reforms. This study aims to estimate the size and identify key drivers of Ethiopia's shadow economy over the period 1995–2023, highlighting factors influencing its fluctuations and implications for policy. An Error Correction Multiple Indicators Multiple Causes (EMIMIC) model was utilized, integrating cointegration analysis to capture both long-run equilibrium relationships and short-run dynamics. The chosen specification is a MIMIC (6-1-2) model, refined with alternative calibration approaches to enhance robustness. The findings indicate that the average size of Ethiopia's shadow economy is approximately 47.46% of GDP, with a notable peak of 55.43% in 2020. Tax burden and government expenditure emerged as the most influential long-run determinants, each exhibiting a negative relationship with shadow economic activity. The study underscores the critical need for policymakers to address fundamental structural challenges alongside economic reforms. It cautions that recent reform initiatives may inadvertently expand the informal sector if these core structural issues remain unresolved.

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1 Introduction

The shadow economy which is also referred to as the informal economy, underground economy, hidden economy, parallel economy, subterranean economy, cash economy, black market, or non-observed economy, encompasses both legal and illegal economic activities that occur outside formal regulatory frameworks et al. [2002] (OECD). These activities can range from small-scale unregistered businesses to tax evasion by larger firms. On one hand, it plays a significant role in employment and income generation, especially in developing countries, but on the other, it poses challenges for tax collection, economic planning, and financial stability because it obscures the true scale of economic activity.

Measuring the shadow economy has presented significant challenges due to its nature. Feige [1979] notes that any attempt to quantify such an elusive sector is fraught with conceptual and empirical difficulties. Since direct measurement is not possible, estimates rely heavily on theoretical frameworks, which must be robust and well-justified to minimize errors. Despite these efforts, measurement inaccuracies are inevitable, as the shadow economy is deeply interwoven with the formal economy, making it difficult to establish clear boundaries between the two.

Nonetheless, scholars and policymakers agree that it is important to estimate the size of and understand the causes behind the shadow economy because it directly impacts the key insights used for policy decisions. For instance, when a country has a growing shadow economy, untaxed transactions lead to lower tax revenue. In response, the government might increase the tax rate, which in turn makes the shadow economy even more appealing, further fueling the cycle. But on the other side, it's known two-thirds of the income earned in the shadow economy is immediately spent in the official economy**?** (Schneider 2002), which overall has a positive effect on economic activity.

In a developing economy like Ethiopia, where the contribution of the shadow economy is higher than in many other countries **?**(scheider 2002), it is crucial to understand its magnitude so that appropriate measures can be taken.

This study aims to employ similar methods to estimate the size and causes of the Ethiopian shadow economy (1995 - 2023). Before presenting the empirical approach, it is essential to review existing definitions and methodologies, and past estimates of the shadow economy. The next section explores various conceptualizations of the shadow economy and discusses prior research relevant to this study.

2 Literature Review

2.1 Defining the Shadow Economy

One of the main challenges in studying the shadow economy is the lack of a universally agreed-upon definition. Scholars often use various terms such as informal economy, underground economy, or non-observed economy interchangeably. However, these terms frequently refer to different aspects or subsets of a broader phenomenon, raising an important question: are they truly equivalent?

A widely referenced framework comes from ISTAT (the Italian National Statistical Institute), as outlined in the et al. [2002]. This framework categorizes the non-observed economy (NOE) into three distinct types of production:Dell'Anno [2007]

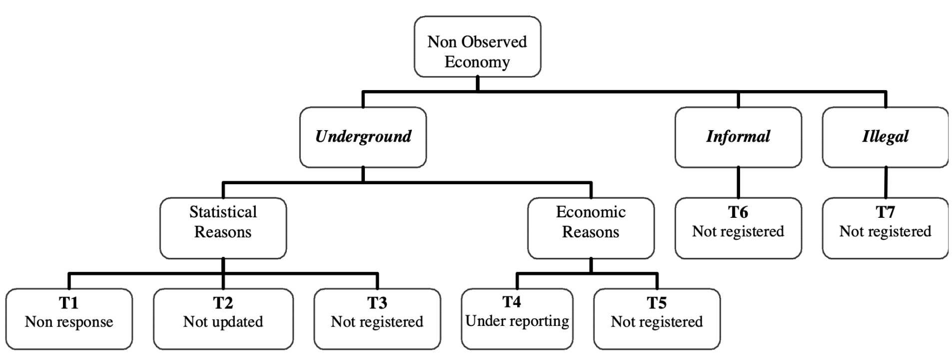

Figure 1: ISTAT Framework of the Non-Observed Economy

Underground Production: Activities that are both productive and legal but are intentionally concealed from authorities to evade taxes or regulatory compliance.

Informal Sector Production: Productive activities carried out by unincorporated household enterprises that remain unregistered or fall below a certain size threshold in terms of employment, yet still contribute to market production.

Illegal Production: Activities that either generate goods and services that are outright forbidden by law or involve normally legal activities carried out by unauthorized producers.

The different types of production are further clarified by the measurement challenges, which can be either *statistical* or *economic* in nature. For example, non-registration and outdated information occur when enterprises—especially those involved in illegal activities or operating on a small, informal scale—fail to register. This may be due to high turnover rates, inadequate legal mandates for statistical reporting, inefficiencies in data collection systems, or even deliberate avoidance of registration. Data quality is also undermined when enterprises or households choose not to respond to surveys, often because they are reluctant to reveal sensitive information, fear administrative consequences, or find the questionnaires overly burdensome. Additionally, even when responses are obtained, deliberate under reporting of income or overstating of expenses to reduce tax liabilities (or even unintentional errors) leads to systematic underestimation of the true economic activity.

For the purpose of this research, the shadow economy will be defined as the aggregation of four components: *T4*, which refers to the economic underground characterized by deliberate underreporting; *T5*, which represents the economic underground due to unregistered units; *T6*, which encompasses the informal sector composed of unregistered enterprises; and *T7*, which represents illegal activities that go unreported.

Past Studies

There have been numerous methods used to estimate the size of the shadow economy, which generally fall into two broad categories: direct and indirect approaches (Schneider 2018).

1. **Direct approach** :

   This approach relies on data collected directly from sources such as the System of National Accounts, often using surveys to capture micro-level insights into shadow economic activities and labor markets. These surveys typically explore public perceptions, actual participation in informal work, and attitudes toward shadow economy practices. Another form of direct measurement involves surveying business managers, who can provide estimates of under-reported income, unregistered employees, and off-the-books wages.

   Although these methods offer valuable insights into the structure and composition of the shadow economy, their main limitation lies in the reliance on self-reported data, which may be biased or inaccurate. Respondents may be unwilling to disclose truthful information about illegal or informal activities. Despite this flaw, direct approaches remain important because they capture details that are often missed by indirect, macro-level techniques Williams and Schneider [2016].

2. **Indirect Approach**: These are referred to as "indicator" approaches, are primarily macroeconomic in nature.

   - **Expenditure-Income Discrepancy**: This approach assumes that while shadow income may be hidden, expenditures remain visible. A consistent gap between national expenditure and income can therefore serve as a proxy for unreported activity, assuming accurate measurement and statistical independence between the two Feige [1979].

   - **Labor Force Discrepancy**: A decline in official labor force participation, assuming the total labor force remains constant, may indicate a shift into informal employment. However, this method is considered weak due to fluctuations driven by other factors like retirement, education, or economic cycles.

   - **Electricity Consumption Approach**: Since electricity usage tends to grow in line with GDP, a higher growth rate in electricity consumption compared to official GDP may signal shadow activity. However, not all informal activities rely on electricity, and this elasticity varies across time and regions Kaufmann and Kaliberda [1996].

- **Transaction Approach**: Using the quantity theory of money, this method links money supply, velocity, and prices to total (official plus shadow) economic activity. While theoretically sound, it relies on establishing a benchmark economy with no shadow sector, which is rarely feasible Feige [1979].
- **Currency Demand Approach (CDA)**: CDA assumes that informal transactions are predominantly cash-based. An unusually high demand for currency, after accounting for standard factors (like income and interest rates), may indicate shadow activity.Tanzi [1983] modeled this by including variables such as tax burden and regulatory complexity to isolate "excess" currency demand linked to informality.
- **Multiple Indicators, Multiple Causes (MIMIC) Approach**: Finally, the MIMIC approach explicitly incorporates several causes and multiple effects of the shadow economy. By analyzing the associations between observable causal variables and the effects (indicators) of an unobserved variable, this method estimates the size of the shadow economy itself Frey and Weck-Hanneman [1984].
- Recently, as **machine learning methods** have gained traction in economic forecasting, three notable studies have applied ML algorithms to predict the size of the informal economy with promising outcomes. These include the works of Shami and Lazebnik [2024], Ivașcu and Ștefoni [2023], Felix et al. [2025].

The MIMIC (Multiple Indicators, Multiple Causes) model is one of the most widely used approaches for estimating the size of the shadow economy. It has been applied in diverse contexts, including France, Australia, Portugal, and several cross-country studies. Over time, the model has evolved into several extensions such as EMIMIC (Error-Correction MIMIC), DYMIMIC (Dynamic MIMIC), and augmented factor models to better address issues like non-stationarity, short-run dynamics, and endogeneity.

One of the main advantages of the MIMIC approach is its ability to simultaneously incorporate multiple causes and indicators of the shadow economy within a single structural framework. It also allows researchers to produce time-varying indices that can be transformed into absolute estimates through calibration. However, the model is not without limitations. Its results are highly sensitive to variable selection, data quality, and calibration method. Moreover, since the shadow economy is a latent variable, its size cannot be observed directly and must be inferred from assumptions, which can introduce bias.

In the Ethiopian context, several studies have employed variations of the MIMIC model, often differing in the time period, type of data, variables used, and benchmarking approach. For instance, Mekonnen (2024) estimated that Ethiopia's shadow economy ranged from 39.8% to 62.42% of GDP between 1995 and 2022. On the other hand, Schneider and Medina (2018), using MIMIC in an IMF study covering 158 countries, found that Ethiopia's shadow economy declined from a peak of 40% in 2000 to a low of 24.47% in 2014, averaging 34.31%. Another study (source) used survey-based methods to explore the determinants of informality, focusing more on drivers like tax burden, regulation, and corruption rather than providing an absolute measure of size.

In this paper, I aim to build on and refine previous efforts by updating the model specification, using a different set of variables, applying the EMIMIC extension, and introducing an alternative calibration approach. These adjustments are intended to improve both the theoretical consistency and empirical accuracy of shadow economy estimates in the Ethiopian context.

3 Methodology

3.1 Error Correction Model (ECM)

In macroeconomic analyses, researchers frequently work with time series data, such as those utilized in the MIMIC model. These variables often display non-stationarity, meaning their statistical characteristics such as the mean, variance, and autocorrelation, vary over time. Traditional regression analyses using non-stationary data can yield spurious results, as persistent trends might falsely suggest correlations or causative relationships.

To overcome issues of non-stationarity, differencing is commonly applied. Differencing involves subtracting previous observations from current ones to remove inherent trends, in order to capture relationships between non-stationary series. The minimum number of times this process must be repeated to achieve stationarity determines the series' "order of integration," labeled I(d). A series is I(0) if it is already stationary, I(1) if it becomes stationary after differencing, etc.

Cointegration expands upon this by examining the long-term, stable relationships between multiple non-stationary variables despite their individual fluctuations. Mathematically, it means that a specific linear combination of these variables remains stationary. For instance, two individually non-stationary variables, y_t and x_t, may each trend independently yet combine into a stationary linear combination, represented as $y_t - \beta x_t$, illustrating their equilibrium relationship as described by **?**.

The Error Correction Model (ECM) specifically addresses cointegration by simultaneously capturing short-term dynamics and long-term equilibrium relationships. ECM incorporates an error correction term reflecting how quickly the variables adjust to equilibrium after deviating from it. Hence, an ECM effectively models immediate short-run changes while accounting for gradual adjustments towards long-run equilibrium.

Formally, for two cointegrated variables $I(1)$, y_t and x_t, with a cointegration vector $[1, -\beta]$, both the differences Δx_t and Δy_t, as well as the equilibrium relationship $y_t - \beta x_t$

are stationary . This relationship is captured by the equation:

$$\Delta y_t = \gamma \Delta x_t + \lambda u_{t-1} + w_t \tag{1}$$

Here, w_t is an error term, and u_{t-1} is the lagged error correction term representing the deviation from the long-run equilibrium in the previous period Buehn and Schneider [2008]. All components of this equation are stationary.

The ECM thus encapsulates changes in a dependent variable through its relationship with changes in independent variables and a lagged error correction term. This approach emphasizes the analysis of dynamic adjustments from equilibrium deviations and can easily be extended to scenarios involving multiple integrated variables and deterministic trends which is essential to the MIMIC model.

3.2 MIMIC Model

The Multiple Indicators and Multiple Causes (MIMIC) model is a type of structural equation model (SEM) designed to capture the relationships between a latent construct and its observable causes and indicators by minimizing the difference between the observed covariance matrix and the covariance matrix predicted by the model Buehn and Schneider [2008]. In this framework, observable variables are categorized into two distinct sets: causes, which influence the latent variable, and indicators, which reflect changes in the latent variable. Mathematically, the MIMIC model comprises two essential parts, the structural equation and the measurement equation.

In the structural model, the latent variable, η_t, is modeled as a linear function of a set of observable exogenous variables, x_t

$$\eta_t = \gamma' x_t + \zeta_t \tag{2}$$

In this formulation, $x_t = (x_{t1}, x_{t2}, \ldots, x_{tq})'$ represents a $1 \times q$ vector containing the observable variables at time t, each potentially influencing the latent variable η_t. The coefficient vector $\gamma' = (\gamma_1, \gamma_2, \ldots, \gamma_q)$ describes the magnitude and direction of these causal relationships. The error term ζ_t captures the variance in the latent variable not explained by the model. Critical assumptions include that all variables and errors are measured as deviations from their respective means, and that there is no correlation between the error term and the observed causes, formally stated as $E(\eta_t) = E(x_t) = E(\zeta_t) = 0$ and $E(x_t\zeta_t') = E(\zeta_t x_t') = 0$. The variance of ζ_t is denoted by ψ, while the covariance matrix of the causes x_t is denoted by Φ. Buehn and Schneider [2008]

The second equation specifies the measurement model, which relates the latent variable to a set of observed endogenous indicators, Y_t It is mathematically expressed as:

$$y_t = \lambda\eta_t + \varepsilon_t \tag{3}$$

Here, $y_t = (y_{t1}, y_{t2}, \ldots, y_{tp})'$ is a $1 \times p$ vector of observable indicator variables. The vector of disturbances $\varepsilon_t = (\varepsilon_{t1}, \varepsilon_{t2}, \ldots, \varepsilon_{tp})'$ consists of white noise error terms whose covariance matrix is denoted by Θ_ε. Here, λ is the vector (or matrix) of factor loadings that indicate how strongly each observed indicator reflects the latent variable, each component of the regression coefficient vector λ quantifies the expected change in an indicator for a one-unit shift in the latent variable. Similar to the structural model, indicators and errors are assumed to be measured as deviations from their means, and their errors are assumed uncorrelated with both the observed causes and the latent variable itself, stated as $E(y_t) = E(\varepsilon_t) = 0$, $E(x_t\varepsilon_t') = E(\varepsilon_t x_t') = 0$, and $E(\eta_t\varepsilon_t') = E(\varepsilon_t\eta_t') = 0$. Additionally, the error terms from the structural and measurement models must not correlate, implying $E(\varepsilon_t\zeta_t') = E(\zeta_t\varepsilon_t') = 0$ Buehn and Schneider [2008]

The structural disturbance ζ and ε and the measurement errors are assumed to follow a normal distribution, are mutually independent, and all variables are expressed as deviations from their means Dell'Anno [2007].

The covariance matrix is derived Σ of the MIMIC model Buehn and Schneider [2008].

This matrix illustrates how observed variables relate through their covariances, facilitating the decomposition of relationships between these observable variables and the latent (unobservable) variable in this context, the shadow economy. The resulting covariance matrix of the MIMIC model is expressed as:

$$\Sigma = \begin{pmatrix} \lambda(\gamma'\Phi\gamma + \psi)\lambda' + \Theta_\varepsilon & \lambda\gamma'\Phi \\ \Phi\gamma\lambda' & \Phi \end{pmatrix} \tag{4}$$

Here, Σ depends on parameters λ, γ, and the covariance matrices Φ, Θ_ε, and variance ψ. Since the latent variable itself is not directly observable, estimating its magnitude requires leveraging the relationships between observed variables' covariances and variances. Therefore, parameter estimation seeks values for λ, γ, Φ, Θ_ε, and ψ that closely approximate the observed covariance structure of the causal and indicator variables (x_t and y_t).

3.3 Error Correction Representation of the EMIMIC Model

The first step toward deriving the Error Correction MIMIC (EMIMIC) model involves substituting equation (2) into equation (3). Doing so yields the following relationship:

$$y_t = \Pi x_t + z_t \tag{5}$$

Here, the matrix $\Pi = \lambda\gamma'$ encapsulates the interactions between the observable causes and indicators, while the error term $z_t = \lambda\zeta_t + \varepsilon_t$ is a $p \times 1$ vector combining disturbances from both the structural and measurement equations. Specifically, $z_t \sim (0, \Omega)$, where the covariance matrix Ω is expressed as $\Omega = \lambda\psi\lambda' + \Theta_\varepsilon$. Equation (5) closely resembles a simultaneous regression model, with endogenous variables represented by the latent variable's indicators and exogenous variables represented by its observable causes, thus allowing for the application of cointegration analysis within the MIMIC framework.

As outlined earlier, the assumption of stationarity for every component z_{jt} is generally not valid if some observable causes x_{it} and indicators y_{jt} are integrated of order one, I(1). If x_t and y_t consist of I(1) series, each linear combination $y_{jt} - \pi_{j\cdot}x_t$ is also expected to be I(1), signifying the presence of trends and potential inconsistencies in equation (5). However, if there exists at least one linear combination $z_{jt} = y_{jt} - \pi_{j\cdot}x_t$ that is stationary (I(0)), the variables involved are considered cointegrated Engle and Granger [1987]. In such a case, the vector $[1, -\pi_{j\cdot}]$, where $\pi_{j\cdot}$ is the $1 \times q$ row vector from matrix Π, represents a cointegration vector. Typically, as each linear combination z_{jt} involves $q + 1$ variables, multiple cointegration vectors can exist, theoretically up to q independent vectors (Greene, 2007). For p indicators that are I(1), the maximum number of independent cointegration vectors is $p \cdot q$.

$$y_t = \Pi x_t + \mathrm{T} v_t + z_t \tag{6}$$

As indicated by equation (1), each cointegration relationship inherently involves an error correction mechanism, where long-term equilibrium relationships are maintained, and short-term dynamics are modeled explicitly (Engle & Granger, 1987). All macroeconomic variables are not necessarily I(1); some could be I(0) and so are included by the vector $v_t = (v_{t1}, v_{t2}, \ldots, v_{tr})'$. Thus, we express equation (6) in an error correction framework as follows:

$$\Delta y_t = A\Delta x_t + T v_t + K z_{t-1} + w_t \tag{7}$$

Here, $\Delta y_t = y_t - y_{t-1}$, $\Delta x_t = x_t - x_{t-1}$, and $z_{t-1} = y_{t-1} - \Pi x_{t-1}$. In this dynamic, short-run formulation, A, T, and K are coefficient matrices. Specifically, $A = \lambda\alpha'$ is the $p \times (q - r)$ coefficient matrix corresponding to the first differences of I(1) variables, while $T = \lambda\beta'$ is the $p \times r$ matrix for the stationary (I(0)) variables. The matrix $K = \lambda\kappa'$ is the $p \times p$ coefficient matrix capturing the adjustment to long-run equilibrium via the error correction term. The disturbance w_t is assumed to be white noise, $w_t \sim (0, \Omega)$.

Given that both y_t and x_t are vectors of I(1) variables, their differences are stationary, ensuring every term in equation (7) is also stationary, provided the cointegration condition for z_t is satisfied. Equations (6) and (7) collectively define the EMIMIC model structure. As the core idea behind the MIMIC approach is to minimize differences between the sample covariance matrix and the covariance matrix predicted by the theoretical model.

$$\Sigma = \begin{pmatrix} Var(y_t) & Cov(x_t, y_t) & Cov(v_t, y_t) \\ Cov(y_t, x_t) & Var(x_t) & Cov(v_t, x_t) \\ Cov(y_t, v_t) & Cov(x_t, v_t) & Var(v_t) \end{pmatrix} \tag{8}$$

Similarly the covariance matrix of the short-run error correction model is similarly structured as:

$$\Sigma = \begin{pmatrix} Var(\Delta y_t) & Cov(\Delta x_t, \Delta y_t) & Cov(v_t, \Delta y_t) & Cov(z_{t-1}, \Delta y_t) \\ Cov(\Delta y_t, \Delta x_t) & Var(\Delta x_t) & Cov(v_t, \Delta x_t) & Cov(z_{t-1}, \Delta x_t) \\ Cov(\Delta y_t, v_t) & Cov(\Delta x_t, v_t) & Var(v_t) & Cov(z_{t-1}, v_t) \\ Cov(\Delta y_t, z_{t-1}) & Cov(\Delta x_t, z_{t-1}) & Cov(v_t, z_{t-1}) & Var(z_{t-1}) \end{pmatrix} \tag{9}$$

Examining equations (8) and (9), compared with the traditional MIMIC covariance structure, clearly reveals the impact of incorporating cointegration. Specifically, the EMIMIC covariance matrix (9) includes adjustments for the long-run equilibrium error (via Ω) and error correction coefficients (K). Additional modifications isolate I(0) and I(1) causes, producing the sub-matrices Φ_2, Φ_3, and M. Because Σ remains a function of model parameters α, β, κ, and λ, estimation ensures a precise adaptation of the EMIMIC model's covariance matrix, suitable for empirical application. Buehn and Schneider [2008]

3.4 Variable Selection

This paper employs the general MIMIC 6-1-2 specification, consisting of six causal variables, one latent variable (the shadow economy), and two indicators, to estimate the evolution of the shadow economy in Ethiopia. The selection of variables is informed by prior empirical studies on the shadow economy in Ethiopia and comparable countries.

- **Interest Rate**: This study uses the average saving interest rate as a proxy for the overall interest rate environment. In theory, lower interest rates reduce the incentive to save formally by diminishing returns on deposits, thereby encouraging individuals to hold more cash or seek alternative investment options. These alternatives often exist in the informal sector, potentially expanding shadow economic activity. Conversely, higher interest rates are expected to reduce cash holdings and encourage formal saving. In the case of Ethiopia, the interest rate followed an upward U-shaped trend over the study period, which may reflect shifting monetary policies and financial sector reforms.

- Tax Burden: The tax burden is widely regarded in the literature as one of the most important determinants of the shadow economy Ogbuabor and Malaolu [2013]. The prevailing hypothesis is that higher taxes create strong incentives for individuals and businesses to operate informally, all else being equal. In this study, the tax burden variable is sourced from the Heritage Foundation, where it is measured as a composite index capturing marginal tax rates on both personal and corporate income, as well as the overall tax revenue as a percentage of GDP, including both direct and indirect taxes at all levels of government. In Ethiopia, the tax burden has shown a rising trend over the years, with a particularly sharp increase between 1999 and 2000, from 48% to 66%. In line with existing MIMIC model applications, this variable is consistently included as a causal factor of the underground economy and has historically demonstrated a direct impact on the size of the shadow sector.

- **Inflation**: Inflation plays a critical role in shaping the demand for cash and, by extension, the size of the informal economy. As prices rise, individuals often seek more affordable goods and services, which are frequently found in informal markets. As a result, higher inflation is generally associated with an expansion of informal economic activity. Additionally, inflation reduces the real value of money over time and can lead to what is known as "bracket creep." Mekonnen [2024] In this process, nominal wage increases can push individuals into higher tax brackets even if their purchasing power remains unchanged. This creates an incentive for taxpayers to shift to off-the-books or cash-based income in order to avoid additional tax burdens.

This issue is particularly relevant in Ethiopia, where inflation has been persistently high in recent years. According to the International Growth Centre, inflation is considered one of the country's most pressing policy challenges. In such an environment, the tendency to engage in informal transactions to maintain purchasing power and reduce tax liability is likely to be stronger.

- **Government Expenditure**: Government expenditure as a percentage of GDP is used as a proxy for the size of government and the degree of state intervention in the economy Ogbuabor and Malaolu [2013]. It is commonly argued that a larger public sector, often associated with increased regulation and bureaucratic oversight, may incentivize individuals and businesses to operate outside the formal economy. A positive coefficient would indicate that greater state presence encourages participation in the informal sector. In the period covered by this study, government expenditure in Ethiopia has been declining, which may signal a reduction in formal regulatory pressure.

- **Unemployment**: Unemployment, defined as the share of the labor force without work but actively seeking employment, has a complex and ambiguous relationship with the shadow economy. Higher unemployment may push individuals into informal work as a means of survival, potentially increasing the size of the informal sector. However, this depends on the interaction between two opposing effects: the income effect and the substitution effect. As explained by Buehn and Schneider [2008], Ogbuabor and Malaolu [2013], income losses reduce overall demand, including for informal goods and

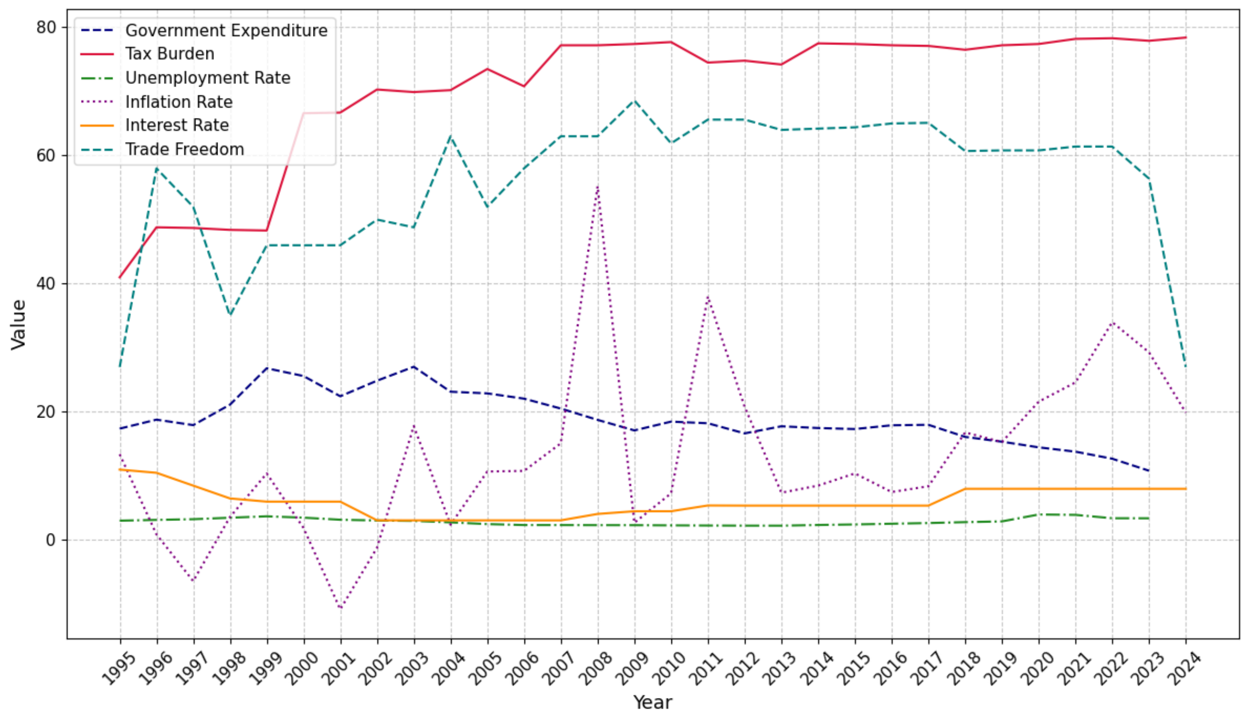

Figure 2: Economic Indicators Over Time (1995–2023)

services, while the substitution effect may lead people to seek lower-cost alternatives or informal employment. A negative relationship emerges when the income effect dominates, while a positive relationship occurs if the substitution effect is stronger.

Tedds and Giles [2007] highlight that although unemployment may reduce the size of the informal economy by lowering aggregate demand, some unemployed individuals may continue to participate in informal activities. This duality makes the net effect difficult to predict. Tanzi [1999] notes that the shadow economy includes a wide range of participants, such as unemployed individuals, retirees, undocumented workers, and others, making the official unemployment rate only loosely correlated with the size of the informal sector. Despite this ambiguity, studies such as Dell'Anno [2007] suggest that in many developing contexts rising unemployment is likely to lead to greater informal economic activity.

- **Trade Freedom**: Trade freedom is assessed as a composite index that reflects the extent of tariff and non-tariff barriers impacting the flow of goods and services across borders. As economies become more integrated into global markets, it can become more difficult to shift activities into the informal sector and to hide transactions from regulatory authorities. While trade openness is commonly expected to reduce shadow economic activity, there is empirical evidence supporting a positive relationship. Specifically, studies by **???** suggest that greater openness can lead to increased informal economic activities under certain conditions. However, greater openness may also create opportunities for illicit trade, such as the smuggling of contraband goods, which fuels the criminal component of the shadow economy. In contexts where regulatory enforcement is weak, increased trade liberalization may inadvertently expand informal economic activity. Therefore, a positive relationship between trade openness and the size of the shadow economy is expected in Ethiopia.

Two variables are used as indicators of the latent variable: the real GDP per capita and the realcurrency in circulation (M1), to measure the development of the SE

- **GDP per Capita**: Unfortunately, the literature does not offer a clear consensus on the relationship between the official and shadow economy. Some studies Frey and Weck-Hanneman [1984], Loayza [1996] argue that a downturn in the formal economy can lead to job losses and declining incomes, which may drive individuals into informal employment. Others Tedds and Giles [2007], **?**], **?**], Dell'Anno [2007] suggest that a contraction in GDP may reduce overall demand, including demand for goods and services in the informal sector, thereby offsetting the initial increase in informal activity. This ambiguity highlights the complex and context-dependent nature of interactions between the two sectors.

- **Currency in circulation**: Transactions in the informal economy are widely believed to be carried out using cash or funds withdrawn directly from current accounts, either to conceal them from authorities or because they are typically small-scale and cash-suited. Ogbuabor and Malaolu [2013] While some debate exists over whether the entire shadow economy operates in cash, there is general consensus that cash plays a dominant role. This is particularly true in Ethiopia, where 99% of all payment operations are conducted in cash, and only 46% of the population has access to a financial institution or mobile-money service provider, according to the World Bank. These conditions create an environment where informal transactions can thrive. Following Tedds and Giles [2007]and Buehn and Schneider [2008], this study employs real currency in circulation (M1) as an indicator of informal activity, with the expectation of a positive relationship between M1 and the size of the shadow economy.

Table 1: Summary of Variables, Sources, and Expected Signs

Variable	**Source**	**Expected Sign**
Interest Rate	National Bank of Ethiopia	−
Tax Burden	Heritage Foundation	+
Inflation	National Bank of Ethiopia	+
Government Expenditure	IMF	+
Unemployment	World Bank	Ambiguous
Trade Freedom	Heritage Foundation	+
Indicator Variables		
GDP per Capita	IMF	Ambiguous
Currency in Circulation	National Bank of Ethiopia	+

4 Applying the EMIMIC model

Both the long-run equilibrium relationship and the short-run error correction representation of the MIMIC model together constitute the EMIMIC framework applied in this study. The final dataset used for estimation consists of 28 annual observations, covering the period from 1995 to 2023, and includes all the variables outlined in the model specification.

To estimate the EMIMIC model using the selected variables, the first step involved pretesting the data for stationarity. An Augmented Dickey-Fuller (ADF) test was conducted on each series to determine whether a long-run equilibrium relationship could exist among the variables. The null hypothesis of the ADF test assumes that a series has a unit root (i.e., is non-stationary), while the alternative suggests stationarity. Failure to reject the null implies the need for first differencing to achieve stationarity.

In this analysis, all cause and indicator variables were found to be non-stationary, with the exception of Tax Burden, Trade Freedom, and Inflation, which were already stationary at I(0). This result is consistent with expectations, as most macroeconomic time series data are known to exhibit non-stationary behavior. After first differencing, all remaining variables became stationary, satisfying the requirements for proceeding with the EMIMIC estimation.

The next step is to check if all the causes are cointegrated with each indicator variable and for this the Engle and Granger two-step approach was used. The first step in this two step procedure is running cointegration regression, running a least squares regression of all the cause variables on each indicator variable.

$$
\begin{aligned}
\text{GDP} = {} & \alpha_1 \cdot \text{Interest Rate} + \alpha_2 \cdot \text{TaxBurden} + \alpha_3 \cdot \text{GovtExp} \\
& + \alpha_4 \cdot \text{Unemp} + \alpha_5 \cdot \text{Inflation} + \alpha_6 \cdot \text{TradeFreedom} + u_1 \\
\text{outBank} = {} & \alpha_1 \cdot \text{Interest Rate} + \alpha_2 \cdot \text{TaxBurden} + \alpha_3 \cdot \text{GovtExp} \\
& + \alpha_4 \cdot \text{Unemp} + \alpha_5 \cdot \text{Inflation} + \alpha_6 \cdot \text{Trade} + u_2
\end{aligned}
$$

Residuals u_1 and u_2 were tested for stationarity using the Augmented Dickey-Fuller (ADF) test. In both cases, the p-values were below the 0.05 threshold, indicating rejection of the null hypothesis of a unit root. This confirms that the residuals are stationary and that the variables are cointegrated, validating the existence of a stable long-run equilibrium relationship. A constant term was not included in the regression, as all variables were expressed as deviations from their means.

The MIMIC model requires the selection of a scale variable in order to estimate the remaining parameters relative to it. While the specific value assigned to this fixed parameter

Table 2: ADF Result for Residuals

Variable	**Test Statistic**	**5% Critical Value**	**Order of Integration**
Resid1 (U1)	-3.599	-2.994	I(1)
Resid2 (U2)	-3.454	-2.994	I(1)

is arbitrary, setting it to a positive (or negative) unit simplifies the interpretation of the relative magnitudes of other indicator variables.Dell'Anno [2007]. In this study, I fixed the coefficient of GDP per capita in both the long-run and short-run MIMIC estimations to serve as the scale variable which is common practice. By choosing this variable as the scale reference, the effects of the shadow economy are expressed in relation to official GDP.

Now the short run MIMIC model can be employed using the first difference of all causes and indicators including the lagged residuals. They're lagged because economic agents typically respond to past disequilibrium and I want it to measure how far the system was from equilibrium in the previous period. Then the long run MIMIC model is run to calculate the index which is calibrated using the average from different estimates.

5 Result

- **Interest rate**: The coefficients for Interest Rate were -0.51 in the short run and 0.23 in the long run, though neither coefficient was statistically significant. Only the short-run coefficient exhibited the expected negative sign, consistent with the theoretical notion that higher interest rates encourage savings in formal financial institutions and thus reduce incentives for shadow economic activities. However, given the insignificance of both coefficients, these findings suggest that interest rates do not play a statistically significant role in influencing shadow economic activities in Ethiopia, at least within the context and period analyzed.

- **Tax Burden**: As expected Tax Burden has a statistically significant coefficient in the long run of 0.67 at all conventional levels. While not significant the short run

Table 3: MIMIC Models and Parameter Estimates

	Long-run *MIMIC Model*	Short-run *MIMIC model*
Interest Rate	0.23	-0.51
	(1.61)	(1.60)
Tax Burden	0.67^{***}	-0.11
	(5.48)	(-0.86)
Inflation	0.048	0.24^{*}
	(0.69)	(1.74)
Government Expenditure	-0.39^{***}	-0.13
	(-3.03)	(-0.72)
Unemployment	0.14	-0.24^{*}
	(1.57)	(-1.77)
Trade	0.057	0.28^{**}
	(0.55)	(2.15)
u_1	–	0.18
		(1.04)
u_2	–	0.48^{***}
		(2.82)
Indicators		
GDP per capita	1.00	1.00
outBank	0.99^{***}	0.817^{***}
Statistics		
Chi-square	5018.97	9.29
Degree of Freedom	5	7
P-value	0.000	0.23
RMSEA	0.209	0.112

Note: Z-statistics are reported in parenthesis $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

has a negative coefficient which was surprising. This unexpected short-run negative relationship might suggest temporary compliance increases immediately following tax policy changes. Individuals and businesses may initially become more compliant due to increased scrutiny or enforcement activities. This heightened compliance might temporarily reduce shadow economic activity.

- **Inflation** Inflation was statistically significant at the 10% level in the short run, with a positive coefficient (0.24). This indicates that, in Ethiopia, short-term increases in inflation tend to stimulate shadow economic activities, likely by increasing incentives to seek cheaper informal goods or to avoid higher nominal taxes. In the long run, inflation retained the expected positive sign, but the coefficient was statistically insignificant, suggesting that inflation is not a robust determinant of Ethiopia's shadow economy in the long run.

- **Government Expenditure** Contrary to standard theoretical expectations, government expenditure showed a negative and significant relationship with Ethiopia's shadow economy, specifically in the long run. One plausible explanation is that increased government spending over the analyzed period prioritized essential public services (healthcare, education, social safety nets) institutional capacity, infrastructure, and social benefits, thereby improving the attractiveness and ease of operating within the formal economy. Providing public services reduces citizens' need to seek informal or unofficial alternatives, thus shrinking the shadow economy. This study which spans the history of Ethiopia under the leadership of the coalition of the Ethiopian People's Revolutionary Democratic Front who took over from a totalitarian socialist regime focused on the public services. For instance, the expansion of primary health care has been hailed as a model in sub-saharan Africa.

- **Unemployment**: Unemployment had a significant negative coefficient of -0.24 in the short run, indicating that short-term increases in unemployment actually decrease shadow economic activities. This result suggests that in the short run the income effect, exceeds the substitution effect. This implies that when unemployment rises in Ethiopia, the associated drop in income suppresses informal sector activity more significantly than unemployed workers can replace lost income through informal work. However, this effect does not persist in the long run, with unemployment showing a positive but statistically insignificant coefficient of 0.14.

- **Trade**: Trade exhibited a statistically significant positive short-run coefficient of 0.28, though the long-run coefficient 0.057 was positive but statistically insignificant. Increased trade openness without robust regulatory enforcement can allow economic actors to exploit loopholes, thereby expanding informal trade or illegal activities. Furthermore, greater openness often raises demand for foreign currency, particularly in economies experiencing currency instability or stringent foreign exchange regulations. This situation can significantly stimulate black market currency exchange activities, contributing directly to the growth of the shadow economy.

  In the Ethiopian context, this mechanism is particularly relevant due to the historical prevalence of currency black markets. Ethiopia's recent decision in July 2024 to float the birr highlights this phenomenon, reflecting prior currency market inefficiencies and widespread informal currency trading activities, which the policy aimed to curb.

In terms of model fit, the short-run specification demonstrated a better fit compared to the long-run model, which had an extremely high chi-square statistic indicating poor fit. To address this concern, I conducted a robustness check by re-estimating the long-run model, this time fixing the coefficient of the alternative indicator, currency outside banks, at 1 instead of GDP per capita. This adjustment substantially improved the long-run model fit, reducing the chi-square statistic significantly to approximately 11, while importantly maintaining both the magnitude and direction of the original coefficients. However, I ultimately chose to report the original long-run model specification with GDP per capita fixed at 1 because my primary interest is in expressing and interpreting the shadow economy explicitly as a percentage of GDP rather than as currency in circulation. Nonetheless, this robustness check confirms that the main findings and interpretations remain valid and stable regardless of indicator choice.

To calculate the long-run shadow economy index using the calibration method outlined above, 2001 was selected as the benchmark year, with the shadow economy size set at 41.85% of GDP. This benchmark value was determined by taking the average of estimates from the three prior studies on Ethiopia's shadow economy. Across these three studies, 2001 consistently emerged as the year closest to this average value, making it a suitable baseline for calibrating and interpreting the long-run estimates in this study. The long term index was calculated as follows:

$$\tilde{\eta}_t = 0.67(TaxBurden)_t + (-0.39)(GovtExp)_t$$

Following the benchmark strategy by Tedds and Giles [2007] the estimation for all the years were calculated as such:

$$\hat{\eta}_t = \frac{\tilde{\eta}_t}{\tilde{\eta}_{2001}} \times 41.85\%$$

Then the short run deviations from equilibrium are calculated in which the final estimation are derived. Below is a table summarizing the results

Due to the use of first differences and the inclusion of a lagged error correction term in the ECM specification, the first two years of data (1995 and 1996) are dropped from the estimation, as is standard in time series models of this kind.

Table 4: Shadow Economy Estimates and Adjustments (1995–2024)

Year	**Long-run**	**EMIMIC**	**Deviations**
1995	24.11	–	–
1996	29.55	–	–
1997	29.86	27.91	-1.95
1998	28.19	22.74	-5.44
1999	25.55	29.10	3.54
2000	40.35	40.46	0.11
2001	41.85	41.85	0.00
2002	43.56	44.85	1.29
2003	42.27	41.98	-0.30
2004	44.26	48.89	4.64
2005	46.94	43.44	-3.50
2006	45.21	47.20	1.99
2007	50.89	52.60	1.71
2008	51.68	51.75	0.07
2009	52.58	54.43	1.85
2010	52.20	50.21	-1.98
2011	49.82	51.15	1.33
2012	50.76	50.89	0.12
2013	49.80	49.43	-0.37
2014	52.49	52.68	0.19
2015	52.48	52.65	0.17
2016	52.06	52.35	0.29
2017	51.95	52.08	0.12
2018	52.34	51.02	-1.32
2019	53.22	53.29	0.07
2020	53.77	53.83	0.06
2021	54.70	54.96	0.26
2022	55.27	55.43	0.16
2023	55.80	54.32	-1.48

Applying the EMIMIC model to estimate the size of Ethiopia's shadow economy yields an increasing trend, with an average of 47.46% of GDP over the study period. The shadow economy reached its lowest point at 22.74% in 1998, and peaked at 55.43% in 2020. These estimates are broadly in line with prior studies on Ethiopia's informal sector, reinforcing the robustness of the MIMIC framework. However, unlike the findings of **?** and **?**, who observed a declining trend in the shadow economy, this study reveals a consistently upward trajectory, highlighting the growing significance of informal economic activities in recent years. This discrepancy could be attributed to differences in model specifications, choice of variables and span of this study.

One of the key challenges in this study is the limited number of observations which is a common constraint in time series analyses of developing countries. While the MIMIC model is designed to accommodate small samples, it remains sensitive to data quality and frequency, which may affect the stability of the estimates and the comparability across studies. The absence of high-frequency, standardized data for some of the variables used may introduce noise or obscure long-run relationships. Therefore, while the increasing trend observed here is empirically supported, it should be interpreted with caution and understood in light of these limitations.

To strengthen the robustness and reliability of future estimates, I believe there is a pressing need to improve the availability and quality of economic data in Ethiopia. Expanding data coverage such as quarterly data and consistency would allow for more nuanced modeling of informal sector dynamics. In future work, I hope to apply the EMIMIC model in a panel data setting, using data from comparable countries in the region to capture broader structural patterns and control for country-specific effects.

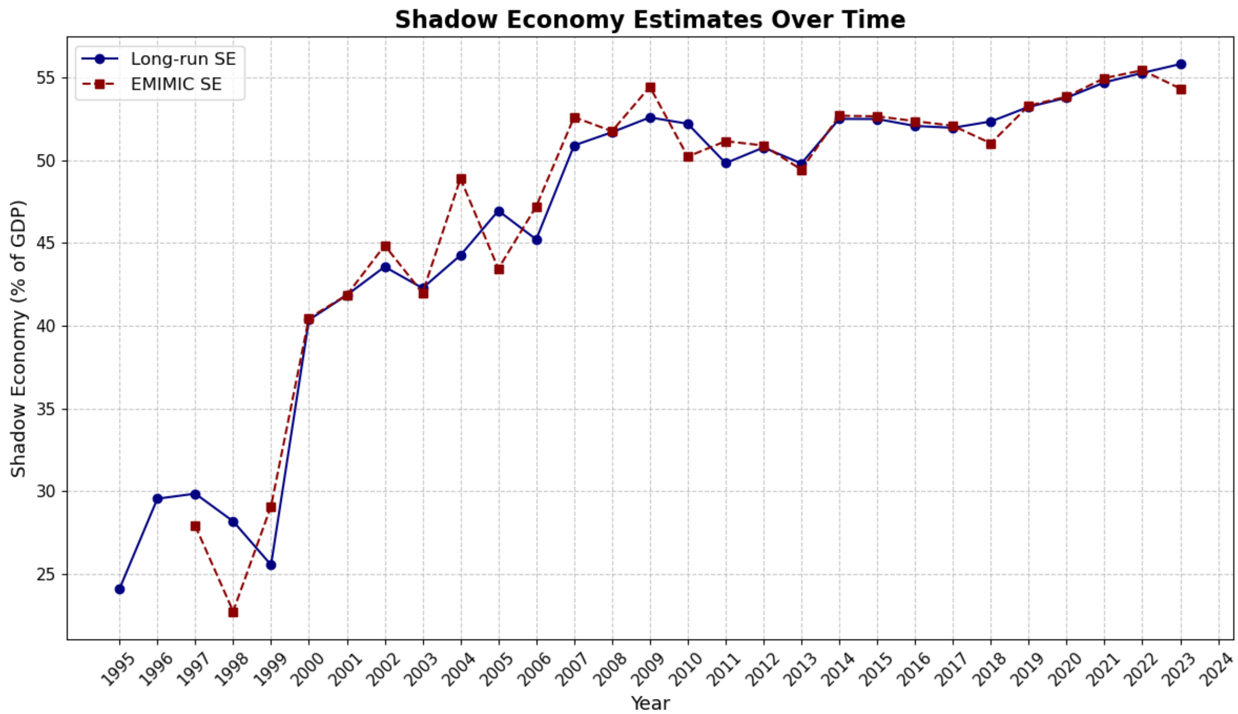

Figure 3: Size of the Ethiopian Shadow Economy (1995-2023)

6 Conclusion

Recent macroeconomic reforms in Ethiopia, such as floating the birr, raising tax rates, and aggressively expanding trade openness, have been implemented with the intention of stabilizing the economy, boosting transparency, and increasing government revenue. To address Ethiopia's low tax-collection rate which is largely attributed to the prevalence of informal economic activity, the government introduced new taxes. These reforms resulted in a short-term revenue boost, with a 65% increase in the first quarter of the 2024 fiscal year.

However, my results suggest that while tax burden may have a negative short-run impacts, it contributes to expanding the shadow economy in the long run. Increased taxation without parallel improvements in enforcement, institutional trust, or the ease of doing business risks pushing more individuals and enterprises into informality, thus achieving the opposite of the intended outcome.

Recently, the government has significantly increased expenditure aimed at beautifying cities to attract tourism and foreign investment, signaling greater trade openness. However, greater trade openness may expose fragile domestic industries to foreign competition, threatening their survival and further incentivizing informal practices. This issue is especially pertinent in developing economies like Ethiopia, where the informal sector serves as a critical source of employment and economic resilience. Recent reform initiatives may inadvertently expand the informal sector if these core structural issues remain unresolved.

To sustainably reduce the size of Ethiopia's shadow economy, policymakers must go beyond short-term revenue gains and address the structural drivers of informality. This means designing policies that lower the cost of formality, protect domestic industries during trade reforms, and improve access to finance and institutional trust. Reducing excessive tax burdens and improving the quality and visibility of public spending are the most effective levers, as evidenced by their significance in this study. A strategic balance of tax policy and developmental expenditure is essential for bringing economic activity into the formal fold.

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