DISCUSSION PAPER SERIES

IZA DP No. 17557

Long-Run Estimates of the Global Informal Economies and New Insights for 152 Countries over 1997 to 2022 Using an Enhanced MIMIC Approach

Alban Asllani
Roberto Dell'Anno
Friedrich Schneider

DECEMBER 2024

I Z A Institute
of Labor Economics
Initiated by Deutsche Post Foundation

DISCUSSION PAPER SERIES

IZA DP No. 17557

Long-Run Estimates of the Global Informal Economies and New Insights for 152 Countries over 1997 to 2022 Using an Enhanced MIMIC Approach

Alban Asllani
University of East London

Roberto Dell'Anno
University of Salerno

Friedrich Schneider
Johannes Kepler University Linz and IZA

DECEMBER 2024

ISSN: 2365-9793

IZA – Institute of Labor Economics

Schaumburg-Lippe-Straße 5–9
53113 Bonn, Germany

Phone: +49-228-3894-0
Email: publications@iza.org

www.iza.org

ABSTRACT

Long-Run Estimates of the Global Informal Economies and New Insights for 152 Countries over 1997 to 2022 Using an Enhanced MIMIC Approach*

Using an enhanced MIMIC method, this paper presents new and long-run estimates of the Informal Economy (IE) for 152 countries from 1997 to 2022. We address several limitations found in previous estimates of the IE, notably issues surrounding the missing values, time-invariant country characteristics, and calibration issues with exogenous variables. We enhance the MIMIC model by including fixed effects for country-specific characteristics of IE, thereby providing more reliable and long-run estimates. This approach allows us to control for time-invariant effects across countries by incorporating fixed effects through a transformation of observed variables, thereby holding constant both observable causes and unobserved structural factors unique to each country. Our findings show a significant variation in the key drivers of IE between high-income and not-high-income countries, exhibiting distinct causal effects on the IE depending on different economic developments. In terms of normative implications, our results highlight the need for specific and tailored policies in dealing with the formalisation of informal activities in countries with different levels of income.

JEL Classification: O17, C39, H26

Keywords: informal economy, shadow economy, Structural Equation Modelling, MIMIC approach

Corresponding author:
Alban Asllani
Business, Entrepreneurship, and Finance Department
Royal Docks School of Business and Law
University of East London
London, E15 1NF
United Kingdom

E-mail: a.asllani@uel.ac.uk

* The authors have no relevant financial or non-financial interests directly or indirectly related to this article to disclose. The authors thank the anonymous reviewers for their invaluable contributions.

1. INTRODUCTION AND BACKGROUND

Over the last three decades, attention to the Informal Economy (IE hereafter) has grown significantly, predominantly focusing on four key areas: defining what constitutes it;[1] estimating its size and impact through various approaches, analysing its main drivers, causes, and effects, and finally, proposing potential policy measures that governments can implement to transition it into the formal economy. Estimating IE in a country can be challenging since the agents involved in informal activities purposefully hide from being identified to avoid taxes and regulations imposed by the government (Gerxhani, 2004; Buehn and Schneider, 2012; Medina and Schneider, 2021). The existence of the IE, however, is known and it is more common in developing nations (ILO, 2018) and can affect the reliability of the official economic data, which consequently affects other socio-economic indicators based on that official data (Schneider and Enste, 2000; Dell'Anno and Schneider, 2003). This evidence usually comes from surveys of leading organisations, such as the World Bank and the International Labour Organisation (ILO). Their accuracy, on the other hand, is questionable because surveys tend to produce biased results, as participants may not fully disclose their involvement (Gerxhani, 2004).

The IE can have many political, social, and economic implications. It can reduce market efficiency, weaken institutions, decrease tax revenues, and limit public spending on key areas such as infrastructure, education, and healthcare – thereby affecting the main objectives of social and economic policymaking (Dell'Anno, 2021; 2022; Arby et al., 2012). The size of the IE can also indirectly impact society, and its presence can indicate regulatory burdens or government-induced distortions (Dell'Anno, 2023). However, it also provides additional value that can be spent in the official economy. It acts as a social buffer by offering opportunities for low-skilled workers, particularly in less developed economies with high unemployment (de Soto, 1989; Chen, 2012).

This paper focuses on the measurement issue, with emphasis on the Multiple-Indicators and Multiple-Causes (MIMIC) model, which is a widely used but often controversial method. The MIMIC model was first used by Zellner (1970) and Goldberger (1972) and later adopted by Frey and Weck-Hanneman (1984) – who are considered the pioneers in its application. While National Accounts (NA) methods are generally seen as the most reliable for estimating the size of the IE, they

[1] We have adopted the narrower definition of the IE as suggested by Pedersen (2003) and Kazemier (2003). They define the IE as all market-based legal production of goods and services deliberately concealed from public authorities for tax evasion and avoidance. The definition of the IE can also vary depending on the terminology employed to describe it. Terms such as the hidden economy (Frey and Pommerehne, 1984), IE (Andrews et al., 2011; Dell'Anno, 2022), Shadow Economy (Feige, 2016; Williams and Schneider, 2016; Schneider, 2023), black economy (Thomas, 1999) and underground economy (Bajada, 1999) use various definitions of the IE, but they are predominantly similar – that is tax evasion and avoidance.

have several limitations (Dell'Anno, 2023; Dybka et al., 2019). NA estimates are often delayed, vary in reliability across countries, lack detailed data access for external researchers, and are not peer-reviewed, which raises concerns about transparency. Additionally, NA estimates may not be easily comparable across countries or periods. Therefore, econometric methods like MIMIC offer valuable complementary approaches (although there are still controversies, as discussed later) to estimate the size of the IE. The MIMIC model requires calibration using exogenous values of the IE, with NA estimates being the best candidates for this. Conversely, NA methods can benefit from MIMIC in sectors or periods lacking data.

We present a novel approach to measuring the size of the IE and estimates for 152 countries worldwide by employing an enhanced MIMIC model, which accounts for multiple interactions between the latent variable, causes, and indicators rather than focusing solely on causes and effects. We use the MIMIC model because it offers a more robust framework for assessing the drivers that affect the IE compared to direct or indirect methods. Cassar (2001) highlights that the MIMIC approach does not rely on restrictive or unreasonable assumptions, except for the requirement to employ an exogenous variable to calibrate the estimates of the IE. As a result, the model is more flexible and broadly applicable in various contexts. Zhou and Oostendorp (2014) show that compared to direct and indirect techniques, the MIMIC model provides a relatively more accurate estimation. This implies that the precision of the model is influenced by its capacity to capture complex data.

However, while the MIMIC model has some advantages, it still faces some criticism and challenges in the validity and reliability of its estimates, necessitating further investigation and methodological improvements. Breusch (2005, 2016), Feige (2016), Kirchgässner (2016), Slemrod and Weber (2012), and later Dybka et al. (2019) and Dell'Anno (2023) express doubts about the robustness of the specifications and results of the MIMIC model. They contest the results' generalisability across various datasets and situations, arguing that its predictions might not always hold under specific circumstances. This debate underscores the need for a cautious approach to interpreting MIMIC estimates, with some scholars (Dybka et al., 2019; Dell'Anno, 2023) suggesting that further refinement in methodology and variable selection is required to enhance the model's predictive accuracy and reliability.

With this in mind, we thoroughly examine some criticism of the earlier, widely used MIMIC methodology and make several significant methodological contributions. Firstly, a key contribution of this paper is that we control for time-invariant effects across countries, by incorporating fixed effects by a within transformation of observed variables. This MIMIC specification allows for interpreting the effect of a one-unit change in a covariate on the informality ratio while holding constant not only other observable causes (e.g., self-employment, corruption, poverty, economic development, etc.) but also the unobserved, time-invariant characteristics specific to each country that influence informality. In other words, by including time-invariant country characteristics in the MIMIC model, we account for unobserved "structural" factors like culture, religion, tax morale, the structure of the economy, and the average efficiency of tax inspections—factors that do not significantly vary over the period studied but still impact informality. Thus, our MIMIC model estimates the extent to which changes in causes result in deviations in the IE ratio from its long-term level. This step is taken before applying a calibration approach in the panel dataset, allowing for more accurate cross-country comparisons over time. Secondly, the approach contributes to the literature by addressing the issue of missing values (MVs) through an innovative replacement method, thereby enhancing the robustness of the analysis and mitigating potential biases caused by incomplete data. Thirdly, the study presents exogenous estimates derived from reliable official data, including those from the International Labour Organisation (ILO) and national accounts (NA). By calibrating the MIMIC estimations, these parameters enhance the model's validity and precision. Furthermore, we use a consistent statistic for the reference indicator of the MIMIC (i.e. an index of IE ratio) by adjusting the statistics used in the model for the different definitions of informal economy used by the ILO and NA approach to estimate the IE. This maintains consistency in measuring, enabling more apparent comparisons and accurate data interpretations in different situations. These methodological innovations strengthen the study's analytical rigour and provide a more nuanced understanding of the subject matter.

The paper is organised as follows: first, we present a brief literature review on the various methods used to estimate the IE, outlining arguments for and against each approach. Second, we examine the fundamental driving forces of informality – justifying their inclusion in our model. Third, we detail our new methodology and explain the calibration process in a longitudinal dataset. The fourth section presents our results and economic interpretation of the estimated coefficients, offering insights into the findings. Finally, we summarise the key outcomes and provide recommendations for future research.

2. LITERATURE REVIEW

This section offers a general overview of the existing literature on estimating the size and evolution of the IE using various approaches. It presents the advantages and drawbacks of each approach and discusses the theoretical underpinnings of the main drivers of informality. The growing literature on the IE underpins one key observation: the size of the IE, however measured, will always be merely an estimate at best.

2.1. Methods to Estimate the IE

The IE cannot be measured directly, so different methods have been generated to estimate its magnitudes (Breusch, 2005). The measurement is not an easy task either (Schneider and Enste, 2000; Dell'Anno and Schneider, 2003), and yet it is critical to measure the IE since its size around the world has been reported to be of significant size (Alm and Embaye, 2013; Hassan and Schneider, 2016; Elgin et al, 2021; Dybka et al., 2019; Schneider, 2023; Dell'Anno, 2023). Different methodologies often yield varying results, with a margin of error of around +/- 10 to 15 per cent (Schneider, 2014). Despite these challenges, once the IE is defined, its size is typically measured using three main approaches. A clear definition is crucial to avoid ambiguities and controversies in the estimation process (Schneider et al., 2010). Based on the definition of IE, one applies the three primary approaches to measurement, which are direct, indirect, and statistical modelling, with the latter treating the IE as an unobserved variable. Later, Dybka et al. (2019) emphasised hybrid approaches, too.

The direct approach to measuring the IE includes surveys and tax auditing approaches. The survey asks respondents about their economic activities through multiple-choice, closed-ended questions. These surveys, often part of labour force surveys conducted annually in many countries, aim to capture data on informal sector workers (Abdih and Medina, 2013; Vuletin, 2008). One primary benefit of surveys is their ability to yield insightful first-hand information (Medina and Schneider, 2021). However, the data is unreliable and perhaps biased because accuracy depends on respondents' willingness to disclose undeclared work (Schneider and Enste, 2000; Gerxhani, 2004; Medina and Schneider, 2021). Additionally, survey results provide only a snapshot of informal activity and are influenced by how questions are framed (Pedersen, 2003; Feld et al., 2012), often not capturing all informal activities. The tax auditing method estimates the IE by comparing declared income with income uncovered through audits (Thomas, 1992; Schneider, 2008). Recent software advances have improved the ability to detect undeclared income (Alderslade et al., 2006; Asllani and Schneider, 2024), but results can still be biased, and in many cases, most developing countries lack funding for such effective monitoring. Furthermore, audits are often not random but targeted at tax returns suspected of fraud (Schneider, 2008, 2014; Schneider and Buehn, 2017). This method only captures the portion of the IE that tax authorities detect, usually a tiny fraction (Alderslade et al., 2006). Thus, it is not suitable for long-term trend analysis.

The indirect methods, on the other hand, use economic, social, and other indicators to estimate the IE over time (Schneider and Enste, 2000; Abdih and Medina, 2013; Medina and Schneider, 2021). One such method is the Labour Force Discrepancies[2]. This approach examines gaps between official employment rates and the actual labour force. A declining labour force participation rate in the formal sector may signal an increase in informal work (Schneider, 2014; Schneider and Buehn, 2017). However, this method risks double-counting workers involved in both formal and informal economies (Alderslade et al., 2006). Transactions Method, based on Feige's (1996) work, assumes a constant relationship between official Gross Domestic Product (GDP) and total transactions over time. The gap between these two variables may reflect the size of the IE. However, it relies heavily on assumptions, such as the velocity of money and a base year without informal activity, which can lead to unreliable estimates (Schneider, 2008; Dybka et al. 2019). Another indirect method is the Currency Demand Approach (CDA)[3]. This method, enhanced by Tanzi (1980, 1983), assumes that informal transactions use cash. By comparing the demand for currency under low tax rates with current demand, one can estimate the size of the IE (Alm and Embaye, 2013). However, this method does not account for non-cash transactions or key factors like tax morality and government trust (Blades, 1982; Feige, 1996). Finally, the Electricity Consumption Method, developed by Kaufmann and Kaliberda (1996), uses electricity consumption to indicate overall economic activity. The difference between electricity consumption and GDP growth is attributed to the IE. While simple, this method assumes all economic activities require electricity, which is not always true (Lackó, 1998).

The direct and indirect approaches are limited in that they need to account for multiple factors influencing the size and development of the IE. Moreover, a vital drawback of the direct approach is its inability to provide estimates of the IE's growth and development over extended periods. A further significant criticism of the direct and indirect methods is that the causes determining the size of the IE are only considered in some monetary approach studies, which often focus on a single factor, such as the burden of taxation, rather than the multiple causes that could influence changes in the size and development of the IE (Dell'Anno et al., 2007; Schneider, 2008).

Due to these limitations of direct and indirect methods, the MIMIC model, based on the Structural Equation Modelling approach (SEM), has become widely used (Dell'Anno and Schneider,

---

[2] The National Accounts Discrepancies approach, which compares income and expenditure statistics, is no longer applied in IE estimation as a direct method. This method also captures errors and omissions in national accounts, making it unreliable (Schneider, 2007).

[3] Cagan (1958) made an early contribution to the development of CDA, observing that changes in the ratio of cash to a broader monetary aggregate may reflect the evolution of the IE. Later, Gutmann (1977) provided a more simplified CDA method, which observed an increased ratio and deduced that this growing 'surplus' of cash in circulation was linked to the IE. For a detailed discussion on the evolution of the CDA method and its drawbacks, see Dybka et al. (2019).

2006). The MIMIC model treats the IE as a latent variable, explained by observable causes and indicated by observable indicators. This model provides a more comprehensive overview of the IE by accounting for multiple causes and indicators (Buehn and Schneider, 2012; 2017). The MIMIC model can be applied to both time series and panel data and is the central method used in this research. However, this approach is open to criticism too. Breusch (2005; 2016) and Dybka et al. (2019) are some of the strongest critics of using the MIMIC approach, as outlined in the following section. Dybka et al. (2019) propose a new hybrid approach to measure the IE over time. This approach combines CDA and MIMIC methods into one. Dybka et al. (2019) claim that this hybrid model addresses the long-standing identification problem in the MIMIC model, clearly defining the scale and unit of measurement, avoiding obscure ad-hoc adjustments, and constructing a sensible confidence interval. Dell'Anno (2023), using a Monte Carlo simulation, provides general conclusions on the reliability and limitations of the MIMIC approach to estimate the IE. He also proposes a calibration approach that addresses the most important shortcoming of the MIMIC approach, i.e. how to convert the index of the latent variable to the actual measure of the IE. Even though the MIMIC model and related approaches are still being debated, they nevertheless offer a thorough framework for analysing the dynamics of the IE because they consider a variety of variables and indicators, including public sector governance and economic conditions (Schneider and Enste, 2000).

2.2. Potential issues with the MIMIC model approach

Several potential problems and limitations can arise when using the MIMIC approach (Breusch, 2016; Dybka et al., 2019). The first problem faced when using the MIMIC model is the completeness, availability and quality of data. This problem is particularly evident when dealing with panel datasets, which constitute many countries. For many countries, reliable data is either unavailable or incomplete, with several missing data points across many countries and over many years. For many countries, updating and collecting data regularly can be challenging and costly (Dybka et al., 2019).

Most literature on measuring the IE for large panel datasets avoids discussing this fundamental data missing issue, and often, in publications, this is not raised. One solution applied to treat missing data in this context was that of Medina and Schneider (2021), who used predictive mean matching (PMM). However, PMM assumes data is missing at random (MAR) (Sinharay et al., 2001). However, economic data is generally not missing at random (data is MNAR), making the imputation unreliable (Lang and Little, 2016). PMM can face several other challenges when applied to panel data. One key issue is that it may fail to preserve the temporal correlations within subjects, leading to inconsistencies in how values are imputed across time (Lee et al., 2016; Cai et al., 2022). PMM also tends to ignore individual-specific effects, which are essential for panel data and struggles with unbalanced panels where missingness patterns vary across time (Sinharay et al., 2001). Moreover, it may not capture time-dependent relationships like autocorrelation, leading to biased imputations in time-varying covariates (Cai et al., 2022; Kleinke, 2018). These limitations can distort the natural structure of panel data, making the imputed values less reliable. We address this by applying a panel regression imputation method to replace the missing values with predicted values.

The second issue is the model specification. The construct of the MIMIC model relies on identifying and reasonably justifying observable causes and indicators of the IE. If the wrong causes or indicators are selected or important ones are omitted, it can lead to biased or inaccurate estimates. Breusch (2005; 2016) argues that the MIMIC model is flawed in its specification, particularly in identifying the IE as a latent variable. He claims that the model's causes and indicators are often selected arbitrarily, leading to weak identification and specification. The lack of a robust theoretical foundation may make it difficult to determine whether the MIMIC specification captures the actual size of the IE or whether the specification produces just statistical noise. With our model specification, we justify the use of each variable as a cause and indicator and provide robust connections between each cause, indicator and latent variable.

Third, there are concerns with endogeneity. The relationship between causes and indicators might be more complex than the model assumes, leading to biased estimations (Dybka et al., 2019; Medina and Schneider, 2021). For example, some of the indicators used may also influence the causes. Moreover, there may be a measurement error since indicator variables such as the unemployment rate, taxation burden, or the labour market participation rate may not fully account for the IE's hidden nature, leading to various measurement errors (Dybka et al., 2019). This could give rise to confusion about the causality of some of the causes and indicators used in the MIMIC specification. Breusch (2016) argues that while the MIMIC model does evaluate potential correlations between variables used as causes and indicators in the model specification, it may not always capture causality. The identification of variables that are either causes or indicators can be challenging and open to discussion, which may also give rise to reverse causality issues. We deal with this issue by also including a direct effect of some causes on indicators in order to control for interactions among observed variables that are not mediated by the latent construct (i.e. the IE).

The fourth issue concerns the theoretical underpinnings and assumptions made with and within MIMIC models. The MIMIC approach relies on assumptions about the relationship between the IE and its indicators, which may not hold in every context. For instance, the exact causes might not lead to the same informal economic behaviours across different countries or regions (Dybka et al., 2019). The causes and indicators of informal economies can vary significantly from country to country (Breusch, 2005; Dybka et al., 2019; Dell'Anno, 2023). Applying a single MIMIC model across multiple countries can produce inconsistent results that are not fully comparable due to differences in institutional structures, tax regimes, economic behaviour and society's attitudes towards the IE and the state in general. We account for this by clustering the dataset into high-income and not-high-income countries.

Fifth is the issue of the definition of IE and the absence of a model that would directly measure informality or IE (Gerxhani, 2004; Losby et al., 2002). The MIMIC model treats the IE as an unobservable (latent) variable in the MIMIC model, meaning the estimates are based purely on indirect observations. This may lead to higher uncertainty with results not accurately reflecting the actual size of the IE. Furthermore, depending on the definition used, different key drivers of informality could be applied (Schneider et al., 2010). We test our model with various exogenous variables to capture different definitions of informality and estimation approaches. We use a definition and measurement approach of the IE that accounts for the prevalent nature of informality across countries. Precisely for not high-income countries, we link the latent construct to the ILO statistics because they focus on informal employment. In contrast, for high-income countries, we use as a reference indicator a proxy of the IE that includes underground production, informal production, and illegal production.

Finally, there is generally an issue with the benchmarking procedures or calibration of the latent scores to meaningful values where the IE is usually presented as a percentage of official GDP (Dybka et al., 2019). The MIMIC model needs to be calibrated using an external reference (e.g., surveys or other estimates of the IE). If the calibration is inconsistent or outdated, it may lead to distortion of the overall estimates. Different calibration methods often yield different results and, at times, have high degrees of variance (Breusch, 2005; 2016; Dell'Anno, 2022; 2023). This calibration is usually based on independent studies or expert opinions, introducing substantial subjectivity into the estimation process. Breusch (2005; 2016) criticises that the final estimates are susceptible to these calibration choices, making the results unreliable. Several benchmarking procedures use an exogenous value of the IE as the base year, calibrate the index values generated from the MIMIC results into absolute values of the IE, and convert them into percentages (Buehn and Schneider, 2012). Some prefer that the exogenous base value of the IE be taken from the first year of the dataset to understand and capture the dynamics and development of the IE across the periods in the dataset (Schneider et al., 2010; Buehn and Schneider, 2012). Others (such as Dell'Anno and Schneider, 2003; Dell'anno, 2023) use the last available exogenous values to calibrate the intercept. The idea is that the most recent values are more reliable than the oldest. There is no clear consensus in the literature regarding which of the above benchmarking procedures can be used to calculate the absolute values of the IE from the MIMIC results (Buehn and Schneider, 2012). Our methodology, adapting Dell'Anno's (2023) calibration approach to a longitudinal dataset, addresses most of these challenges to provide more robust and reliable estimates of the IE.

2.3. Main causes and indicators of the IE

The main drivers of the IE have been extensively studied in the literature. General macroeconomic conditions play a significant role in the expansion of the IE across many countries worldwide. These include the unequal distribution of income and higher levels of poverty (Dell'Anno, 2024), lower levels of GDP per capita (Feld and Schneider, 2010; Schneider et al., 2010; Medina and Schneider, 2021), high inflation or cost of living, and elevated unemployment rates (Elgin et al., 2021; Dybka et al., 2019; Dell'Anno, 2024) all contribute towards increased IE activities. Fiscal policy drivers, such as the tax burden, government expenditure, and the size of the government, alongside social security contributions, are also critical determinants of informality (Kelmanson et al., 2019; Schneider, 2023; Asllani and Schneider, 2024). Excessive regulation and administrative bureaucracy incentivise engagement in informal economic activities. Regulatory indicators such as the burden of the regulation (Kelmanson et al., 2019), bureaucratic red tape for business activities, and the quality of regulatory enforcement are critical drivers towards greater informality (Enste, 2010; Buehn and Schneider, 2012; Schneider, 2023). Furthermore, judicial and rule of law factors, including government effectiveness in monitoring and enforcement, are also significant (Schneider, 2023; Dybka et al., 2023). Strong government effectiveness and the rule of law can lead to lower levels of the IE.

Additionally, social factors such as the level of education and human development indicators (e.g. HDI) are countercyclically influential (Medina et al., 2017). High levels of poverty and inequality, alongside vulnerable employment (Dell'Anno, 2023; 2024), self-employment (Mai and Schneider, 2016; Dell'Anno, 2024), and higher employment in agriculture (Dybka et al., 2019), are crucial determinants shaping labour market dynamics and leading towards greater levels of the IE. Lastly, trust in institutions plays a vital role, with factors such as a higher level of corruption, lower tax morale (Giles et al., 2002; Schneider, 2005; Torgler and Schneider, 2009; Kirchgässner, 2011), and lower political and governmental stability being important procyclical drivers of the IE (Canh et al., 2021).

Conversely, IE's size change may be reflected in indicators (Schneider, 2005; Dell'Anno and Schneider, 2003; Medina and Schneider, 2021). Such effects are the development of monetary indicators because additional monetary transactions are required if activities in the IE rise (Mai and

Schneider, 2016; Schneider, 2023). Development in the labour market can indicate how large the IE will be (Dell'Anno, 2023). Increasing workers' participation in the IE results in a decrease in participation in the official economy, thus increasing the level of IE employment and vulnerable employment for both men and women (Dell'Anno, 2024). Developments in the production market may also indicate a country's informality level. An increase in the IE means that factors of production (especially labour) move out of the formal economy, and this displacement might harm the official growth rate of the official economy (Dell'Anno, 2003; Chaudhuri et al., 2006; Dell'Anno et al., 2007; Dell'Anno, 2007; Schneider et al., 2010; Feld and Schneider, 2010; Buehn and Schneider, 2012; Barbosa et al., 2013; Nchor and Adamec, 2015; Medina and Schneider, 2019).

Given the above discussion, we include most of these causes and indicators within our model and aim to directly and indirectly test several hypotheses, as outlined in Table 1. These hypotheses are designed to examine the key drivers of informality, as previously identified, and assess their marginal effects on the size and development of the IE.

Table 1. Hypothesis on the leading causes and indicators of the IE.

Causes:	**(Expected sign) Hypothesis**
Fiscal Policy Drivers	(+) The higher the tax burden, the larger the size of the IE, ceteris paribus * (+) The higher the level of social security contributions, the larger the size of the IE, ceteris paribus. (+) The more significant the central government spending, indicating the larger the size of the government, the more significant the IE, ceteris paribus.
Official Macroeconomic indicators	(+) The higher the unemployment, the larger the size of the IE, ceteris paribus. (-) Conversely, the higher the employment rate, the lower the size of the IE, ceteris paribus. (+) The higher the cost of living, the larger the size of the IE, ceteris paribus. (-) Higher GDP per capita leads to lower informal economic activity, ceteris paribus.
Regulatory framework	(+) The more intensive the regulatory burden is, the larger the size of the IE, ceteris paribus. * (+) Higher levels of bureaucracy in doing business can lead to higher levels of IE, ceteris paribus.
Institutional Quality	(-) The more robust the institutional framework, the more willing people are to pay taxes and reduce their participation in the IE, ceteris paribus. (-) Greater government effectiveness leads to lower levels of the IE, ceteris paribus. (+) Higher levels of corruption lead to higher levels of IE, ceteris paribus. * (-) The stronger the rule of law and judiciary system, the lower the IE, ceteris paribus. (-) Higher tax morale leads to lower levels of the IE, ceteris paribus.
Social Factors	(+) The higher the level of income inequality, the higher the level of the IE, and vice versa, ceteris paribus. (+) Higher poverty levels can boost the size of the IE, ceteris paribus. * (-) An enhanced education system and human development indicators can lead to lower levels of IE, ceteris paribus. *
Labour market structural characteristics	(+) The higher the self-employment rate, the larger the size of the IE, ceteris paribus. * (+) The more significant the employment rate in the agriculture sector, the larger the IE, ceteris paribus. * (-) Greater labour freedom, lower IE, ceteris paribus. *
Political stability	(-) Greater government and political stability, the lower the size of the IE, ceteris paribus.
Economic and Social Disruptions	(-) Economic and social disruptions (i.e. pandemics, and financial crises) can negatively impact the informal and formal sectors of the economy. *
Indicators:	
Informal Sector Employment/Income	(+) A higher IE needs higher workforce levels, thus increasing the informal sector's employment and income generation. *
Currency in Circulation	(+) The higher the IE, the greater the currency in circulation/currency held by the public, ceteris paribus.
Official economic distortions	(-) The higher the IE, the lower the GDP per capita and GDP growth, ceteris paribus. (-) The higher the IE level, the lower the labour force participation rate, ceteris paribus.
Labour market structural characteristics	(+) The larger the size of the IE, the higher the vulnerable-employment rate, ceteris paribus. *
*Confirmed or partly confirmed with our results. See section 4 for discussion.	

3. AN ENHANCED MIMIC APPROACH TO ESTIMATE THE IE

The estimation of informality consists of three main steps: The first step deals with preparing the dataset and replacing missing values. The second step involves selecting the more reliable model specification and estimating coefficients. The third step explains how we assign a unit of measure to the latent scores, the so-called calibration procedure.

3.1 First step: Variable selection and treatment of missing data

According to the MIMIC approach, the IE is a "latent" variable that is both affected by a set of observed variables (the so-called structural model) and affects other observable indicators (i.e. the measurement model). We refer to the former variables as causes or drivers of the IE, while the latter are typically referred to as indicators, hence the MIMIC construct. Accordingly, following the ample economic literature on drivers of informality (e.g., Andrews et al. 2011; Schneider and Enste 2013; Goel and Nelson 2016; Pham 2017; Dell'Anno 2022; Zhanabekov 2022; Dell'Anno 2024 and others), we collect twelve variables to account for potentially relevant drivers of Informality as a percentage of official GDP. Specifically, we include in the structural equation: Tax revenue as a percentage of GDP (*TaxRev*); Index of Labor Freedom (*LabFreed*); Employment in agriculture as a percentage of total employment (*EmplAgric*); Self-employed, total as a percentage of total employment (*SelfEmpl*); Employment rate (*Empl*); Index of Corruption (*Corrupt*); an index of bureaucracy quality (*BureacrQ*); an index that accounts for the change and level of actual standards of life of the population: the Human Development Index (*HDI*); Poverty headcount ratio at national poverty lines as a percentage of the population (*Poverty*); A linear time-trend (*LinTrend*) to control for spurious relationships that might arise due to the presence of non-stationarity and an index of public investment in human capital measured by the share of expenditure on tertiary education to total government expenditure on education (*ExpTertEdu*) and a dichotomic variable for Covid Pandemic (*Covid*=1 if *year* is 2020 and 0 otherwise). The latter variables (*ExpTertEdu, Covid*) are also included in three measurement equations as a covariate to control for the direct effect (i.e. not mediated by the IE) of human capital on male and female vulnerable employment and the income generated by employment in the informal sector.

We collect four potential indicators of the IE (i.e. measurement equations). The most relevant indicator (hereinafter reference indicator, i.e. the observed variable with the highest correlation with the latent construct) is *IE_Index*. It is calculated considering the different nature of informality between developed and developing countries. Accordingly, for high-income and European countries, we employ the projections of the estimates of Non-Observed Economy (NOE) provided by the National Institutes of Statistics (as estimated by Dell'Anno (2024, Online Appendix D)[4] and Fernandes (2022, Table A.1 and A.2)[5]. For non-high-income countries, we estimate the income generated by informal employment by multiplying the size of informal employment, as estimated by the ILO (2019, Appendix B, Table B.1), by the expected informal wage that we assume is equal to 90% of the household's final consumption per population in working age (15-64 years old).[6] To combine the two measures of informality ratio based on NA and ILO sources into the same metric, i.e., IE/observed economy, we convert the projections of NOE adjustments that are reported as a ratio between unobserved and total (i.e., unobserved + observed) economy, into a ratio of unobserved (or IE) and observed GDP.[7]

The second and third indicators of the latent construct are the ratios between male vulnerable employment[8] and male employment (*VulnMal*) and female vulnerable employment and female employment (*VulnFem*).

The fourth indicator is a proxy for income generated by the informal sector calculated as total employment outside the formal sector and 90% of the final consumption of households and Non-Profit Institutions Serving Households per population in working age (*InfSectInc*).

---

[4] Dell'Anno's (2024) estimates are adjusted by adding country-specific constants ($_{neg}^{N}\hat{\beta}_i^c$) that the author suggests to use in order to solve the issue of negative projections in NOE adjustments in some countries.

[5] Precisely, Table A.1: Allowances for exhaustiveness in the national accounts in the EU-28 and EFTA (1997-2008) (% GDP) and Table A.2: Allowances for exhaustiveness in the national accounts in the EU-28 and EFTA (2009-2019) (% GDP). From these tables we extract data for countries not included in Dell'Anno (2024), and Central Eastern European countries. Detailed information are provided in Appendix D.

[6] According to Ohnsorge and Yu (2022: p. 133): "*estimates of the formal sector wage premium vary widely but, in the meta-analysis of the 18 studies conducted here, amount to just under 20 percent of informal wages*". Assuming that on average (net) wages are close to household's final consumption per working age population, we apply a 10% reduction to the wages of informal workers. Consequently, if the formal wage premium is 20%, then informal wages are 10% below the average, and formal wages are 10% above the average of household's final consumption estimated at country level in real terms.

[7] We apply the following formula: $\frac{IE}{OE} = \left[\left(\frac{IE}{IE+OE}\right)^{-1} - 1\right]^{-1}$.

[8] ILO defines vulnerable employment as the sum of the employment status groups of own-account workers and contributing family workers. They are less likely to have formal work arrangements and are therefore more likely to lack decent working conditions, adequate social security and a 'voice' through effective representation by trade unions and similar organizations. Vulnerable employment is often characterised by inadequate earnings, low productivity and difficult conditions of work that undermine workers' fundamental rights (see: http://www.ilo.org/global/about-the-ilo/newsroom/features/WCMS_120470/lang--en/index.htm).

The second part of this data collection involves replacing missing values in the dataset to preserve the quality of predictions and include as many countries as possible in our worldwide analysis. Appendix A explains the applied approach in detail.

3.2 Second Step: the MIMIC Model

3.2.1 The MIMIC model specification

The basic intuition of the MIMIC model is that the IE as a percentage of the official GDP is an endogenous (i.e. related to a set of variables that explain them) latent construct ($\eta_1 = IE$). In symbols, the widest structural equation assumes that IE depends on a linear combination of twelve observable causes:

$$IE_{it} = const_0 + \sum_{j=1}^{12} \gamma_j x_{it}^j + \mathrm{c}_4 Covid + \mathrm{c}_i country_i + \zeta_{it}, \qquad (1)$$

Where: $i = 1, \ldots, 152$; $\mathrm{t} = 1997, \ldots, 2022$; and f_i are country fixed-effects.[9]

As far as the measurement model is concerned, the four indicators (y_h) of the IE are as follows:[10]

$$IE\_Index = const_1 + \beta_1 IE_{it} + \mathrm{c}_i country_i + \varepsilon_{it}^1 \qquad (2)$$

$$VulnMal_{it} = const_2 + \mathrm{c}_1 ExpTertEdu_{it} + \mathrm{c}_2 Covid + \mathrm{c}_i country_i + \varepsilon_{it}^2 \qquad (3)$$

$$VulnFem_{it} = const_3 + \mathrm{c}_3 ExpTertEdu_{it} + \mathrm{c}_4 Covid + \mathrm{c}_i country_i + \varepsilon_{it}^3 \qquad (4)$$

$$InfSecInc_{\mathrm{it}} = const_4 + \mathrm{c}_5 ExpTertEdu_{it} + \mathrm{c}_6 Covid + \mathrm{c}_i country_i + \varepsilon_{it}^4 \qquad (5)$$

To address the omitted variables problem, we remove unobserved time-invariant (country-specific) effects in the model specification by centring (i.e. demeaning) all the observed variables at the country level. Since the latent construct (IE) metric depends on observed variables, this implies that the IE is also measured as a deviation from its country's means.[11] This data transformation works in structural equation modelling (SEM) as a (within) fixed-effects estimator in the standard panel data regression.[12] In conclusion, following the

---

[9] We also test for unobserved country-invariant effects, e.g., time-fixed effects or two-time dummies (The Great Recession and COVID-19), and a deterministic linear time trend. Although we often have problems with the SEM algorithm's non-convergence, the only statistically significant variable is the linear time trend.

[10] We also allow to covariate the measurement errors of measurement equations that account for the income of informal employment in an informal sector (i.e. $\mathrm{Cov}(\varepsilon_{it}^1 \varepsilon_{it}^4)$), and covariances among causes (see figure 1) to control for multicollinearity in the structural equation.

[11] Precisely, we transform all observed variables: $x_{\mathrm{it}}^{\mathrm{j}} = \mathrm{x}_{\mathrm{it}}^{\mathrm{j}} - \bar{\mathrm{x}}_{\mathrm{it}}^{\mathrm{j}}$,

[12] The advantage of within transformation respect to the inclusion of i-1 dummy variables is that the former transformation saves the degrees of freedom (e.g. by constraining intercepts of structural and measurement equations equal to zero (const=0 in eqs 1-5).

usual conventions to graph SEM models,[13] the MIMIC representation of the selected model MIMIC 12 (causes) – 1 (latent construct) – 4 (indicators) is described by the path diagram of Figure 1.

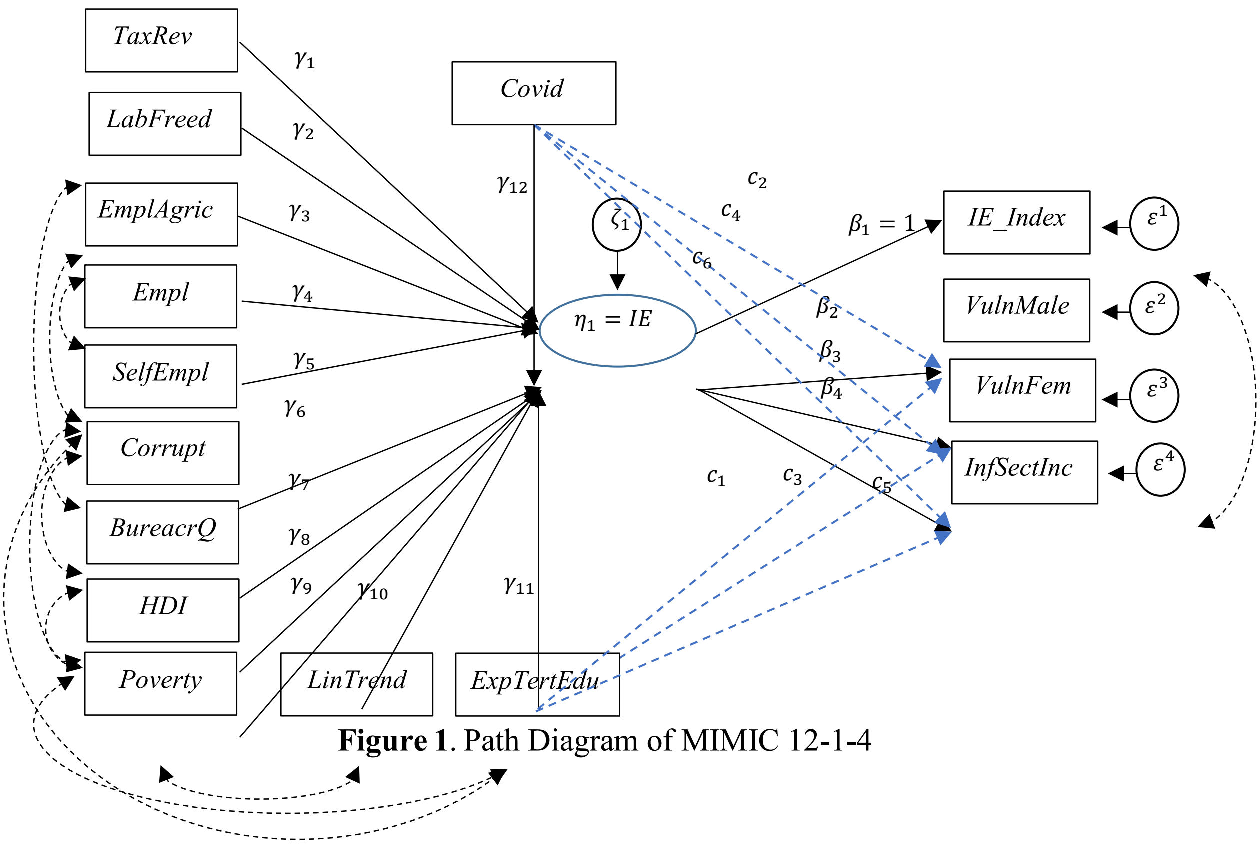

Figure 1. Path Diagram of MIMIC 12-1-4

3.2.2 The MIMIC estimates

To select the best estimator of the SEM model, we test if the observed variables are not multivariate normally distributed. Indeed, the standard estimator (i.e. Likelihood-ratio test comparing the fitted model with the saturated model, from now on ML) is derived assuming that the observed variables are normally distributed. If they are not, the ML estimator produces biased standard errors and an ill-behaved χ^2 test of the overall model fit indexes. Because of that, we apply four tests for multivariate normality,[14] and all suggest rejecting the null hypothesis of multivariate normality. In this case, the literature suggests applying Satorra

[13] Specifically, we indicate observed variables as rectangles, the latent variables and error terms by circles or ovals, paths or loadings (or regression effects) that connect variables or error terms as single-headed arrows. The covariances (double-headed arrows) are shown if they are estimated in the MIMIC (i.e. we are not constrained to be equal to zero), and this occurs if, in an initial estimation of the model where all the covariances are unconstrained, they are not statistically different from zero. This specification of covariances among the "causes" of the latent construct makes it possible to control for multicollinearity in the structural model.

[14] Doornik-Hansen (2008) omnibus test, Henze-Zirkler's (1990) consistent test, Mardia's (1970) measure of multivariate kurtosis and multivariate skewness.

and Bentler's (1994) rescaled Likelihood ratio χ^2 test statistics adjustments to obtain standard errors and goodness-of-fit statistics that are robust to nonnormality.

A further contribution of this research is that we implement in the econometric model the theoretical argument that considers the qualitative differences in the composition of IE across developed (i.e. High-income countries) and developing economies (not high-income countries) (See among the others Dell'Anno 2022, Goel and Nelson, 2016). In particular, marginal effects of the IE determinants are estimated separately between developed and developing countries, i.e. (107 Low and medium-income countries as "Not-High income" and 45 high-income countries according to World Bank classification; see Appendix A for the list of countries included in two sub-samples).

As the first step, we estimate the model simultaneously in both groups and constrain the parameters to be equal between groups. Then, we replicate the estimation fitting the MIMIC for not high-income and high-income country groups.

Table 2 reports estimates based on demeaning variables comparing coefficients based on the whole sample and two groups. We perform a likelihood-ratio test to compare if the estimated coefficients differ between groups of countries. In particular, we test the statistical significance that structural and measurement coefficients and covariances among structural errors are different between groups against the alternative hypothesis that they should be constrained (i.e. "all countries" estimated in the same sample) and verify if the differences between structural ($\gamma_j^d$and γ_j^z) and measurement coefficients ($\beta_h^d$and β_h^z) are statistically significant.[15] In Table 2, we complete this analysis by reporting the p-values of *Score tests* that compare the single structural and measurement coefficients.[16]

[15] The LR $\chi^2(17)$ = 2901 with a p-vale equal to 0.000 suggests that there is a statistically significant difference between high-income and not high-income countries in the structural, measurement coefficients and structural error.

[16] Results of these tests should be considered with caution because this test is based on the $\chi2$ test that assumes normal distribution, and this hypothesis does not hold for our variables.

***Table 2**: Score tests for group invariance: Not High-income vs. High-income Countries*

Structural Eq. (2) - Dep. Var: IE (latent var.)	χ^2
TaxRev	10.116***
LabFreed	3.154*
EmplAgric	30.188***
Empl	15.354***
SelfEmpl	7.479***
Corruption	1.661
ExpTertEdu	2.477
BureacrQ	4.846**
HDI	32.830***
Poverty	0.450
LinTrend	39.052***
Covid	1.311
Measur. Eq. (3) - Dep. Var: IE_Index	
IE (latent)	18.282***
Measur. Eq. (4) - Dep. Var: VulnEmpl_Mal	
IE (latent)	8.009***
ExpTertEdu	0.089
Covid	2.078
Measur. Eq. (5) - Dep. Var: VulnEmpl_Fem	
IE (latent)	0.214
ExpTertEdu	0.533
Covid	0.042
Measur. Eq. (6) - Dep. Var: Inf_Sect_inc	
IE (latent)	0.770
ExpTertEdu	4.334**
Covid	4.153**

*Notes: ***, **, * represents p-values<1%, 5% and 10%.*

Based on these results, we conclude that splitting the sample into two groups improves the explanatory power of the MIMIC model because (at the 5% level) estimating two different structural and measurement coefficients significantly improves the model's fitting rather than one coefficient for all countries. This difference is not statistically significant for the index of Labour Freedom, the proxy of human capital, the index of Poverty and control for the Covid.

Table 3 reports the estimates of two MIMIC models (with and without HDI) based on the whole sample "All countries" and "Two groups". [17]

[17] Appendix B reports the estimates based on MIMIC 12-1-4 (1 group and 2 groups) and, as a robustness check, provides the estimates based on Maximum Likelihood with Missing Values (MLMV) and robust standard errors instead of ML and Satorra Bentler standard errors. This method includes observations with missing values in the analysis rather than omitting them (listwise deletion). This approach assumes that the data are either missing completely at random or missing at random and requires the data to be multivariate normal.

Table 3: Estimates MIMIC 12-1-4 Estimator ML – All sample Vs two groups

Sample Composition	All countries	All countries	Two groups
Structural Eq. (2) - Dep. Var: IE	12 - 1 - 4	11- 1 - 4	12 - 1 - 4
TaxRev	0.014***	0.015***	
Not High-income Countries			0.021***
High-income Countries			-0.024***
LabFreed	-0.013***	-0.014***	
Not High-income Countries			-0.013***
High-income Countries			-0.005
EmplAgric	0.072***	0.076***	
Not High-income Countries			0.071***
High-income Countries			0.187***
Empl	0.033***	0.035***	
Not High-income Countries			0.046***
High-income Countries			0.015**
SelfEmpl	0.235***	0.246***	
Not High-income Countries			0.227***
High-income Countries			0.254***
Corruption	0.161**	0.161**	
Not High-income Countries			0.169**
High-income Countries			-0.079
ExpTertEdu	0.202***	0.202***	
Not High-income Countries			0.249***
High-income Countries			0.037***
BureacrQ	-0.373***	-0.399***	
Not High-income Countries			-0.489***
High-income Countries			-0.154*
HDI	-0.266	0 *(constr.)*	
Not High-income Countries			-0.409**
High-income Countries			-3.998***
Poverty	0.037***	0.039***	
Not High-income Countries			0.045***
High-income Countries			0.005
LinTrend	0.038***	0.038***	
Not High-income Countries			0.055***
High-income Countries			0.036***
Covid	-11.837***	-11.598***	
Not High-income Countries			-14.062***
High-income Countries			-4.596***
Measur. Eq. (3) - Dep. Var: IE_Index			
IE	1 (constr.)	1 (constr.)	
Not High-income Countries			1 (constr.)
High-income Countries			1 (constr.)
Measur. Eq. (4) - Dep. Var: VulnEmpl_Mal			
IE	2.421***	2.309***	
Not High-income Countries			2.565***
High-income Countries			1.759***
ExpTertEdu	-0.44***	-0.417***	
Not High-income Countries			-0.591***
High-income Countries			-0.011
Covid	27.334***	25.463***	
Not High-income Countries			34.847***
High-income Countries			6.69***
Measur. Eq. (5) - Dep. Var: VulnEmpFem			
IE	2.418***	2.31***	
Not High-income Countries			2.445***
High-income Countries			2.315***
ExpTertEdu	-0.466***	-0.444***	
Not High-income Countries			-0.59***

High-income Countries			-0.04**
Covid	27.081***	25.261***	
Not High-income Countries			32.804***
High-income Countries			8.88***
Measur. Eq. (6) - Dep. Var: InfSectInc			
IE	0.589***	0.519***	
Not High-income Countries			0.631***
High-income Countries			0.272***
ExpTertEdu	-0.042***	-0.028**	
Not High-income Countries			-0.068***
High-income Countries			0.017***
Covid	1.169	0 *(constr.)*	
Not High-income Countries			1.969
High-income Countries			-1.183***
# observations	3,951	3,951	3951
# countries	152	152	107/45
χ^2(SB)	5,250.75	4,420.90	8,096.77
p-value(χ^2(SB))	0	0	0
degrees of freedom	104	95	208
CD	0.995	0.995	0.997/0.984
R^2 (IE)	0.973	0.973	0.979/0.938
mc (IE)	0.986	0.986	0.990/0.967

Notes: ***, **, * represents p-values<1%, 5% and 10%. (s.e. are not reported for the sake of space, but they are shown in Appendix B (Table B.1). We apply Satorra Bentler with ML; CD is the coefficient of determination; R^2(IE) indicates the R^2 concerning the latent variable (IE); mc reports the correlation between the dependent variable (IE) and its prediction. "(constr.)" indicates that we fix the coefficients equal to zero (because it is not statistically significant). Additional constraints on covariances, means, and variances are applied to save degrees of freedom (see Figure 1).

Regarding overall model evaluation, the χ^2 test is statistically significant and is not an ideal result (i.e. our model-implied covariance matrix fails to reproduce the databased covariance matrix). However, this is not a conclusive negative evaluation of our MIMIC specification for several reasons. First, the χ^2 test is sensitive to sample size; the larger the sample size, the greater the chances of obtaining a statistically significant χ^2, and with more than 3,950 observations, this may affect the result. Second, our MIMIC models have complex specifications considering the multifaceted nature of latent construct (IE). Although we drop out the statistically insignificant variables from the final models, we do not modify the model to increase the goodness of fitting if the statistical parameters (e.g. suggested by modification indexes) have no economic meaning. This is because by modifying the model, we alter the economic meaning of the latent construct (i.e. IE) and the risk of measuring different macroeconomic variables rather than informality (e.g. socio-economic development). Accordingly, in the trade-off between better statistical fitting and a consistent definition of the meaning of the latent variable, we prioritise the second one. Finally, due to the predictive aim of this model, we are interested in explaining mainly the latent construct rather than the overall fitting of the model and the estimated measurement equations of the MIMIC. In this sense, looking at the indexes of the explanatory power of structural equation (i.e. coefficient of determination, i.e. CD, the R^2 of the latent construct, and the correlation between the dependent variable and its prediction, i.e. *mc*) have major relevance than other statistics of overall model evaluation. That being stated, we find that the structural equation has satisfactory performance in terms of prediction and degree of variance explanation of the latent variable (i.e., the *IE*).

3.3 Third Step: Identification and Calibration of the MIMIC model

The third step of analysis deals with the most controversial issue of the MIMIC approach, i.e., how SEM estimates can be converted into actual values of IE. A complete treatment of this issue is outside the scope of this paper, so we refer to Dell'Anno (2023). In brief, this issue is strictly related to the identification issue that generates an indeterminacy of the estimated parameters in SEM. Generally, each latent variable needs a scale, and the most popular scaling method uses a scaling or reference indicator. We select a proxy of the IE (*IE_index*) as a reference indicator of the IE based on two primary sources. For European and high-income countries, we use Dell'Anno's (2024) projections and Fernandes's (2022) collection of the estimates of the NOE as calculated by national institutes of statistics, while for not high-income countries, we use our estimation of income generated by informal employment based on ILO (2019) estimates of informal employment (see Appendix D). This variable is selected as the reference indicator because, in line with Bollen et al.'s (2022) recommendation, it is expected to have the highest positive correlation with the latent variable. Consequently, we fix equal to unit the measurement coefficient of the latent variable with this indicator. As demonstrated by Dell'Anno (2023), this anchoring approach does not "solve" the indeterminacy of MIMIC estimates - because all the absolute values of parameters are still arbitrary - but they make it possible to estimate the SEM by fixing a (unknown) scale for all the parameters of the model. To obtain the latent variable's fundamental metric, the MIMIC model's latent scores must be calibrated by estimating a "factor of scale" to adjust estimated SEM coefficients and, consequently, predict the latent scores.

In particular, considering that the source of bias of the MIMIC coefficients is the constraint on the coefficient of scale ($\beta_1 = 1$), the first method "adjusts" the identification bias of structural coefficients ($\hat{\gamma}_j^d$) to predict the IE in its real metric. In the following sections, we report the steps applied to calibrate the best model specification MIMIC 12-1-4. Following Dell'Anno's (2023) taxonomy: the first method aims to adjust structural coefficients, and the second method seeks to adjust structural coefficients based on the measurement equation of the reference variable.

3.3.1 Adjusting structural coefficients by estimating the structural equation of the MIMIC

We calibrate structural coefficients by rescaling the MIMIC structural coefficients (i.e. ${}^{1d}\hat{\gamma}^{*}_{ij} = \hat{\gamma}^{d}_{j}/\hat{\beta}^{*}_{i1}$) by an exogenous (OLS) estimate of the coefficient of scale (i.e. ${}^{1}\hat{\beta}^{*}_{i1}$). Once all the structural coefficients are rescaled, the IE is predicted by multiplying them by the centred observed causes (${}^{d}\mathrm{x}^{j}_{it}$). The step-by-step procedure follows Dell'Anno (2023):

<u>Step 3.1</u> - Computing "first-stage" latent scores through structural coefficients:

$${}^{FS}\widehat{IE}^{d}_{it} = \sum_{j=1}^{12} \hat{\gamma}^{d}_{j}\, {}^{d}\mathrm{x}^{j}_{it}, \qquad \text{with } j=1,\dots,12;\ i=1,..,152;\ t=1997,\dots 2022 \quad (8)$$

<u>Step 3.2</u> - Estimating the "coefficients of scale" by auxiliary OLS regressions:

Defining the exogenous estimate of the IE as ${}^{exog}IE^{d}_{it^*}$, we centre the exogenous estimates with the country mean to have the same metric of the latent scores (i.e. eq. 8) ${}^{exog}IE^{d}_{it^*} = {}^{exog}IE^{d}_{it^*} - {}^{exog}\overline{IE}^{d}_{t^*}$. This variable is used as a dependent variable of OLS regressions that, separately for each i-th country, estimate the (inverse of) "true" value of the coefficient of scale, i.e. ${}^{1}\hat{\beta}^{*}_{1}$ by the following 152 regressions:

$$\forall i = 1, \dots, 152: \qquad {}^{exog}IE^{d}_{it^*} = {}^{ols}\hat{\rho}_{i1}\, \overbrace{{}^{FS}\widehat{IE}^{d}_{it}}^{eq.8} + \varepsilon_{it^*}, \qquad \text{with } t^* \quad (9)$$

Where the estimated coefficient of scale is equal to ${}^{1}\hat{\beta}^{*}_{i1} = 1/{}^{ols}\hat{\rho}_{i1}$ and t^* indicate the years with available exogenous estimates of the IE. To increase the reliability of exogenous values, ${}^{exog}IE^{d}_{it^*}$ includes the estimates based on NA projections (i.e. extracted by Dell'Anno 2024) and ILO (2019) only for the years with available official estimates of the NOE published by the NA institutes of statistics or with available estimates of informal employment published by ILO (2019). If these values are lower than three, therefore the reliability of OLS estimates is weak; we include the four closer values to t^* (i.e. two years before and two years later of the year with available official estimates of NOE or informal employment Finally, we use all the IE values (i.e., $t^* = t$) for countries without official estimates of the IE but where all the estimates of exogenous estimates are imputed according to the imputation approach based on clustering explained in Appendix A.[18] As a robustness check, we calibrate our model by using alternative exogenous estimates of the IE such as Elgin et al. (2021, i.e. DGE and MIMIC1) and Medina and Schneider (2021, i.e. MIMIC2).[19]

Step 3.3 - "Adjusting" SEM coefficients -

we rescale the structural coefficients in each country ${}^{1d}\hat{\gamma}^{*}_{ij}$ by dividing the estimated coefficients ($\hat{\gamma}^{d}_{j}$) by ${}^{1}\hat{\beta}^{*}_{i1}$ estimated by step 2:

$$ {}^{1d}\hat{\gamma}^{*}_{ij} = \frac{\hat{\gamma}^{d}_{j}}{{}^{1}\hat{\beta}^{*}_{i1}}, \tag{10}$$

Step 3.4 - Calculating the "adjusted" latent score:

$$ {}^{LS}\widehat{IE}^{\mathrm{d}}_{it} = {}^{1d}\hat{\gamma}^{*}_{ij}\ {}^{\mathrm{d}}\mathrm{x}^{\mathrm{j}}_{\mathrm{it}}, \tag{11}$$

Step 3.5 - Estimating the intercepts for each country (i.e. fixed effects) of the structural model (${}^{1}\hat{\gamma}^{*}_{\mathrm{i0}}$) -

For each country, the intercept is calculated as the value that equalises the most recent exogenous estimate of the IE based on the NA approach or ILO estimates of informal employment[20] and the transformed values of the IE as estimated by eq. 11:[21]

$$ {}^{1}\hat{\gamma}^{*}_{\mathrm{i0}} = {}^{exog}IE^{d}_{it^{\max}} - {}^{LS}\widehat{IE}^{\mathrm{d}}_{it^{max}}. \tag{12}$$

Step 3.6 - Calculating the "absolute" values of the IE:

Predicting the IE by using transformed latent scores of step 4 and the intercept of step 5:

$$ \widehat{\mathrm{IE}}^{m\_1}_{it} = {}^{1}\hat{\gamma}^{*}_{\mathrm{i0}} + {}^{LS}\widehat{IE}^{\mathrm{d}}_{it}. \tag{13}$$

---

[18] E.g. Let's assume that for the j-th country, there is only one exogenous estimate of the IE based on NA approach or ILO informal employment in 2010, then we replace missing from 2008 to 2009 and from 2011 and 2012, i.e. $t^{*}\epsilon[2008, 2012]$; if there are 2 (or 3) exogenous values (e.g. 2010 and 2015), we replace the following missing values 2009, 2011, 2014, 2016). For countries without NA's or ILO's exogenous values we use the reference indicator for calibration (i.e. ${}^{exog}IE^{d}_{\mathrm{t}} = IE\_Index_{t}$).

[19] As explained by Dell'Anno (2023), calibration methods may lead to a biased estimate of the factor of scale, which may cause an inverted trend of the predicted values. To take into account this issue, we use the absolute value of the coefficient of scale (${}^{ols}\hat{\rho}_{\mathrm{i1}} = 1/\left|{}^{1}\hat{\beta}^{*}_{i1}\right|$) in order to prevent the inverted trend at the country level (i.e. the estimate of ${}^{ols\_est}\hat{\rho}_{1}$ has a negative sign).

[20] For Exogenous values based on DGE, MIMIC1 and MIMIC2, we use the most recent available values.

[21] Alternative hypotheses can be possible, e.g. equalize the mean between exogenous and adjusted latent scores.

3.3.2 Adjusting structural coefficients by estimating measurement coefficient of reference factor

This method is applied to twelve countries because the first calibration approach generates some negative IE estimates.[22] According to this second method, we estimate the measurement coefficient at the country level (${}^{2}\hat{\beta}^{*}_{i1}$) by regressing the exogenous estimate of the IE (${}^{exog}IE^{d}_{it^{*}}$) on the reference indicator ($IE\_Index^{d}_{it^{*}} = IE\_Index^{d}_{it^{*}} - \overline{IE\_Index^{d}_{t^{*}}}$). Later, we calculate the intercepts of the structural model as the differences between first-stage latent scores and an exogenous value of the IE.

The step-by-step procedure is:

<u>Step 3.7</u> - Estimating the "coefficient of scale" by auxiliary OLS regressions -

Estimating the "coefficient of scale" (i.e. ${}^{2}\hat{\beta}^{*}_{i1}$) through the first measurement equation (eq. 2*)* after replacing the (unobserved) latent variable with the external estimate (i.e. ${}^{exog}IE^{d}_{it^{*}}$) by the following 152 regressions:

$$\forall i = 1, \ldots, 152: \quad IE\_Index^{d}_{it^{*}} = {}^{2}\hat{\beta}^{*}_{i1}\, {}^{exog}IE^{d}_{it^{*}} + \varepsilon_{it^{*}} \tag{14}$$

<u>Step 3.7</u> -"Adjusting" SEM coefficients -

Rescaling the MIMIC coefficients $\hat{\gamma}^{d}_{j}$ by using the coefficient of scale estimated by eq. 14:

$${}^{2d}\hat{\gamma}^{*}_{ij} = \frac{\hat{\gamma}^{d}_{j}}{{}^{2}\hat{\beta}^{*}_{i1}} \qquad \text{with } j = 1, \ldots, 12; \text{ and i=1,...,152} \tag{15}$$

<u>Step 3.8</u> - Computing "first-stage" latent scores by adjusted structural coefficients:

To compute "first-stage" latent scores (${}^{FS}\widehat{IE}^{d}_{it}$) using ${}^{2d}\hat{\gamma}^{*}_{ij}$ we apply the same approach as the first method:

$${}^{FS}\widehat{IE}^{d}_{it} = {}^{2d}\hat{\gamma}^{*}_{ij}\, {}^{d}\mathrm{x}^{j}_{it}, \tag{16}$$

<u>Step 3.9</u> - Estimating the intercepts for each country (i.e. fixed effects) of the structural model (${}^{2}\hat{\gamma}^{*}_{i0}$) -

The intercepts are calculated as the values that equalise, in each country, the first-stage latent scores (${}^{FS}\widehat{IE}^{d}_{it^{**}}$) and the exogenous estimates at the t^{**} (${}^{exog}IE^{d}_{it^{**}}$), where t^{**} indicates the period with available exogenous estimates of the IE published by the national institutes of statistics for the NA approach or ILO (2019) for the estimate of income generated by informal employment. For the exogenous values extracted from academic sources, t^{**}

[22] See Dell'Anno (2023) for a general discussion of this issue.

corresponds to the most recent available exogenous estimates published by Elgin et al. (2021) or Medina and Schneider (2021). In symbols:

$$ {}^{2}\hat{\gamma}_{\mathrm{i}0}^{*} = {}^{exog}IE_{it^{**}}^{d} - {}^{FS}\widehat{IE}_{it^{**}}^{d}, \tag{17} $$

Step 3.10 - Calculating the "absolute" values of the IE -

Predicting the IE by using latent scores of step 3 (eq. 16) and the intercepts of step 4 (eq. 17):

$$ \widehat{\mathrm{IE}}_{it}^{m\_2} = {}^{2}\hat{\gamma}_{\mathrm{i}0}^{*} + {}^{FS}\widehat{IE}_{it}^{\mathrm{d}}. \tag{18} $$

3.4 Estimates of the IE

This section presents estimates of the IE as a percentage of observed GDP, derived from the MIMIC 12-1-4 model estimated using the ML estimator, with Satorra-Bentler adjustments for non-normality and based on separate estimations of the sample's MIMIC coefficients in two groups (third column of Table 3): 45 high-income countries and 107 not-high-income countries, as classified by the World Bank. The estimates include the exogenous estimates if available $({}^{exog}IE_{it^{*}}^{d})$ And, for 140 countries, we use the first calibration method, while the second calibration method is applied when the first method generates at least a negative predicted value. According to this criterion, we apply the second method to 12 countries. See appendix D for details.

For brevity, we report only the three-year average estimates obtained using the NA approach and ILO estimates to calibrate the latent score. Detailed annual estimates and alternative exogenous calibration values - such as those from Elgin et al. (2021) using the DGE and MIMIC approaches and Medina and Schneider (2021) using the MIMIC model - are provided in Appendix C.

Table 4: Estimates (average 3-year) – MIMIC 12-1-4; 2 groups based on NA and ILO

Country	'97-'99	'00-'02	'03-'05	'06-'08	'09-'11	'12-'14	'15-17	'18-'20	'21-'22
Albania	45.25	43.97	41.88	41.17	41.03	41.44	40.00	35.48	48.56
Algeria	29.77	28.07	25.98	24.38	23.05	21.47	20.12	17.04	25.65
Angola	23.35	23.33	23.69	23.42	24.22	23.48	23.37	23.15	24.46
Argentina	16.58	16.57	18.35	17.84	17.88	18.26	17.95	17.60	19.79
Armenia	23.32	23.31	22.99	22.84	27.23	29.96	21.99	20.78	27.51
Austria	3.82	5.96	6.29	6.20	3.35	3.37	3.25	4.38	3.83
Bahamas, The	5.43	5.43	5.42	5.35	5.39	5.44	5.45	5.23	5.51
Bangladesh	35.58	35.59	35.52	35.51	35.63	35.29	35.67	35.39	36.32
Barbados	4.24	4.49	5.22	5.23	5.90	6.80	7.02	6.07	9.10
Belarus	39.06	38.55	37.50	36.52	34.75	34.52	34.20	30.83	42.75
Belgium	5.66	7.22	7.18	6.50	6.37	6.38	5.95	7.03	5.66
Belize	34.42	34.09	34.05	34.12	34.73	35.98	36.35	34.72	47.89
Benin	44.42	44.47	44.11	43.47	45.10	44.31	42.42	36.34	58.76
Bhutan	49.47	48.49	46.94	45.85	44.76	44.11	44.02	40.18	53.60
Bolivia	42.24	36.66	41.64	41.96	39.35	37.44	34.53	37.43	42.63
Bosnia_Herz.	36.44	35.31	35.09	35.24	34.99	34.75	34.48	31.66	40.20
Botswana	32.42	34.14	36.27	38.12	40.06	41.36	42.58	42.33	47.99
Brazil	16.59	16.64	16.57	16.44	16.95	16.59	16.73	16.96	17.14
Brunei Dar.	3.57	3.60	3.62	3.63	3.69	3.66	3.91	3.81	3.89
Bulgaria	13.16	14.09	12.52	11.67	11.49	11.45	11.86	9.99	20.06
Burkina Faso	37.47	37.45	37.35	37.40	37.35	38.65	37.02	36.59	39.27
Burundi	56.82	57.61	53.21	54.96	52.93	54.84	52.58	47.84	69.77
Cambodia	48.68	48.59	48.48	48.38	48.27	48.21	47.86	47.73	48.31
Cameroon	49.86	48.37	48.46	47.58	46.36	43.69	41.99	36.79	57.17
Canada	2.78	2.75	2.76	2.77	2.79	2.79	2.79	2.71	2.80
Central Afr.R.	55.83	56.17	56.53	56.85	57.17	57.53	57.92	57.22	62.15
Chad	39.16	39.43	39.64	39.70	38.79	41.63	41.10	39.97	49.49
Chile	10.50	10.50	10.45	10.04	9.93	9.91	10.09	10.14	9.79
China	12.71	13.15	13.54	13.87	13.86	13.76	13.68	13.28	13.51
Colombia	24.53	24.68	24.50	24.96	27.09	26.88	25.81	24.85	26.86
Comoros	39.89	40.18	37.61	39.75	38.27	36.96	37.02	35.12	45.20
Congo Dem.R.	58.80	59.77	58.40	55.17	49.05	42.10	40.48	29.14	80.72
Congo, Rep.	26.92	26.05	25.44	24.50	23.62	22.75	22.03	20.78	24.24
Costa Rica	13.74	14.04	13.93	13.91	12.73	14.38	14.28	13.71	17.01
Cote d'Ivoire	32.64	32.67	32.67	32.72	32.68	34.07	33.68	32.28	33.20
Croatia	12.06	11.33	11.30	9.83	10.09	8.07	6.83	4.93	6.57
Cuba	35.89	36.50	37.24	37.42	38.13	39.75	40.64	40.13	45.92
Cyprus	8.07	12.25	14.48	11.97	5.71	2.59	5.39	5.90	5.18
Czechia	9.52	9.88	9.89	9.83	9.70	9.77	9.80	9.04	10.02
Denmark	0.73	3.55	4.93	3.29	1.66	1.51	0.93	1.96	0.81
Djibouti	8.51	8.41	8.30	8.20	8.08	7.96	7.81	7.49	8.29
Dominican R.	33.90	33.32	30.08	22.82	21.56	21.87	22.84	22.71	32.60
Ecuador	16.96	22.14	31.31	29.13	24.55	21.60	24.03	24.74	33.00
Egypt, Arab	20.74	20.70	20.73	19.65	18.43	19.43	19.89	19.02	21.02
El Salvador	32.47	32.44	32.44	32.50	32.76	32.87	33.36	32.02	34.79
Equatorial G.	61.97	58.28	53.91	50.12	47.61	46.03	45.86	43.03	55.45
Eritrea	51.48	52.05	53.19	54.32	55.44	56.57	57.01	55.95	56.81
Estonia	5.21	3.70	4.18	4.07	5.60	5.53	5.36	5.47	5.21
Eswatini	16.05	15.59	15.62	15.23	14.90	14.76	14.30	12.51	17.74
Ethiopia	64.80	64.89	64.99	65.05	65.12	65.13	65.16	65.07	65.78
Finland	2.64	5.34	5.20	4.28	2.12	1.40	2.61	3.05	2.60
France	3.57	3.55	4.66	4.55	3.37	3.31	3.16	3.96	3.55
Gabon	32.42	32.50	32.57	32.67	32.76	32.83	32.96	32.94	33.83
Gambia, The	39.29	39.13	38.38	37.86	37.49	35.84	37.25	36.08	39.34
Georgia	51.39	52.70	53.25	52.58	51.71	51.53	50.36	48.43	54.32
Germany	7.23	7.29	7.54	7.64	6.81	7.57	7.42	6.19	7.40
Ghana	37.72	36.93	37.29	39.25	35.87	39.27	35.22	33.57	41.36

Greece	35.93	29.22	23.36	20.98	22.97	25.56	22.85	15.15	24.96
Guatemala	37.80	39.48	39.88	39.37	38.92	39.10	38.78	36.01	50.30
Guinea	49.20	49.24	48.42	49.52	50.51	49.78	50.07	45.67	57.94
Guinea-Bissau	40.86	40.76	40.52	40.19	39.90	39.69	39.36	38.16	42.32
Guyana	32.48	30.45	29.78	29.13	28.11	26.58	25.99	21.01	22.21
Honduras	41.77	41.07	40.18	31.15	34.30	35.05	35.98	35.71	39.03
Hungary	15.99	13.03	12.11	10.98	12.28	10.53	10.20	7.45	12.53
Iceland	5.36	5.90	7.38	6.10	0.86	2.61	2.76	2.18	3.14
India	24.64	24.67	24.65	24.68	24.77	24.58	24.70	24.65	25.00
Indonesia	30.04	30.04	30.04	30.03	30.03	30.03	30.28	30.07	30.04
Iran, Isl. Rep.	14.93	16.44	16.00	17.12	17.12	17.78	19.27	17.65	28.29
Ireland	4.19	4.06	3.95	3.88	3.92	3.91	3.88	3.59	3.79
Israel	5.85	5.83	5.84	5.84	5.86	5.85	5.86	5.75	5.89
Italy	15.19	18.50	20.18	19.08	15.61	13.67	13.45	13.42	13.40
Jamaica	29.76	29.16	27.83	27.40	29.36	28.58	28.29	25.59	42.72
Japan	8.58	8.21	7.98	7.65	7.39	7.21	7.03	5.88	7.23
Kazakhstan	40.81	39.55	38.11	37.83	37.11	36.04	34.11	30.41	41.50
Kenya	34.94	35.51	35.91	36.64	35.66	35.58	33.79	29.11	45.58
Korea, Rep.	10.70	10.59	10.33	10.12	9.90	9.79	9.62	9.27	9.63
Kyrgyz Rep.	29.96	29.95	29.93	29.87	29.81	29.46	29.74	28.67	29.88
Lao PDR	45.12	45.23	44.17	43.58	44.57	39.79	39.36	34.37	56.74
Latvia	18.42	15.74	15.46	15.20	15.16	15.18	15.24	14.87	15.31
Lebanon	20.47	20.87	21.02	20.81	20.36	21.38	21.21	18.79	35.36
Lesotho	33.72	32.10	33.91	34.34	31.27	30.61	29.64	25.67	37.91
Liberia	56.22	51.93	50.40	48.20	46.01	43.21	40.72	35.85	49.51
Libya	24.08	23.42	22.11	20.82	19.45	18.99	18.38	15.30	23.95
Lithuania	23.30	22.55	23.27	23.21	23.17	23.19	23.19	23.14	23.18
Luxembourg	1.17	3.17	5.21	5.30	1.81	1.72	2.83	3.52	3.46
Madagascar	57.42	57.01	56.99	57.18	57.20	57.02	55.79	54.75	58.68
Malawi	48.94	49.29	49.79	50.03	50.43	50.17	50.14	49.49	55.45
Malaysia	20.68	19.92	19.84	20.05	20.22	18.80	17.84	15.85	25.52
Maldives	19.71	19.06	18.36	17.61	17.85	19.83	20.64	19.17	37.19
Mali	44.08	44.13	44.03	44.16	45.58	47.10	48.46	43.16	58.00
Malta	2.11	2.27	2.29	2.51	3.08	3.06	3.39	2.56	4.08
Mauritania	20.66	20.71	20.66	20.57	20.51	21.22	20.49	20.04	22.25
Mauritius	21.99	21.98	21.98	21.93	21.93	21.25	21.45	21.69	22.23
Mexico	24.32	24.22	25.13	23.37	23.51	23.68	23.44	22.66	26.69
Moldova	16.49	17.00	16.85	16.80	16.77	17.15	17.74	15.78	19.46
Mongolia	16.96	16.92	16.89	16.84	16.78	17.50	16.61	16.25	16.99
Montenegro	40.06	39.90	39.73	39.81	39.50	39.56	39.81	39.27	41.67
Morocco	33.49	34.16	34.68	33.54	33.85	33.79	33.06	30.55	40.28
Mozambique	49.10	48.53	47.69	47.03	46.53	46.07	45.12	42.91	49.60
Myanmar	58.17	55.12	50.89	47.12	43.71	40.10	35.00	30.66	50.40
Namibia	16.75	17.05	17.17	17.23	17.90	16.75	20.06	18.46	20.92
Nepal	31.04	28.60	27.45	28.50	25.97	25.19	23.50	17.94	36.79
Netherlands	2.34	3.88	4.57	5.72	4.20	3.19	3.41	3.82	2.99
New Zealand	7.31	7.22	6.82	6.40	6.26	6.10	6.46	5.83	7.24
Nicaragua	34.40	34.05	33.72	33.05	32.55	32.52	30.96	29.29	33.44
Niger	23.00	24.45	26.39	28.94	36.73	32.70	36.63	33.68	58.04
Nigeria	43.44	42.75	41.46	41.15	40.63	41.12	40.53	36.12	54.93
North Maced.	49.62	50.01	45.68	44.97	42.48	40.06	39.41	31.11	43.75
Norway	6.55	3.51	5.83	7.06	7.08	8.16	6.33	6.80	6.54
Pakistan	34.20	34.16	33.95	31.32	31.65	32.96	33.35	32.72	37.24
Panama	15.82	16.18	16.87	13.59	16.89	14.77	16.25	17.05	27.03
Papua New.	35.15	35.20	34.53	33.75	32.72	32.18	31.40	28.92	38.27
Paraguay	30.09	30.36	30.32	30.74	30.65	30.28	29.18	29.64	31.64
Peru	35.33	34.79	36.41	35.94	36.36	33.89	33.16	32.68	38.96
Philippines	35.71	35.06	34.60	33.79	33.14	31.76	29.97	26.59	36.04
Poland	18.10	19.12	19.18	18.42	18.23	18.02	17.76	16.91	17.65
Portugal	10.38	10.53	11.43	10.68	6.48	3.78	4.01	4.99	4.76

Romania	51.55	43.19	46.41	43.76	44.21	45.45	39.63	36.17	35.08
Russian Fed.	27.96	29.08	29.20	29.90	29.47	29.64	29.75	27.61	38.98
Rwanda	33.36	33.31	33.21	33.13	32.99	34.62	32.10	30.61	33.06
Saudi Arabia	8.88	8.78	8.60	8.41	8.19	7.96	7.56	6.55	7.69
Senegal	29.82	29.62	29.33	29.23	29.20	29.16	27.66	28.42	32.18
Serbia	42.51	42.49	42.04	40.99	40.72	40.85	40.96	39.02	46.34
Sierra Leone	40.11	40.07	40.10	41.01	41.12	40.38	42.92	42.49	45.68
Slovak Rep.	20.46	17.40	20.43	21.86	22.39	24.50	24.52	19.02	27.35
Slovenia	12.77	10.30	9.36	10.17	9.38	10.55	8.56	5.68	7.70
South Africa	14.28	14.31	13.16	12.98	8.94	8.65	9.46	9.31	20.13
Spain	12.66	12.60	12.58	12.56	12.55	12.56	12.55	12.47	12.55
Sri Lanka	21.63	21.63	21.62	21.63	21.63	21.63	22.58	21.36	21.71
Sudan	75.40	75.29	75.26	75.18	75.07	74.97	74.76	73.43	78.80
Suriname	24.31	24.11	23.97	24.40	24.41	24.70	25.13	20.95	38.30
Sweden	2.93	5.43	6.54	4.76	3.35	2.66	2.49	2.41	3.03
Switzerland	4.52	4.34	4.28	4.09	3.90	3.97	3.90	2.66	4.06
Tajikistan	30.10	30.07	28.16	27.87	27.52	26.95	25.97	22.87	32.51
Thailand	23.94	23.82	23.73	23.70	23.57	25.03	26.15	23.11	23.98
Timor-Leste	29.31	29.02	28.75	28.56	28.32	27.61	27.13	26.23	28.35
Togo	39.28	39.06	39.03	38.95	39.21	37.79	36.85	35.41	40.59
Trinidad_Tob.	6.96	6.86	6.46	6.31	6.44	6.43	6.67	6.30	6.83
Tunisia	14.77	15.57	17.58	17.55	18.86	17.31	15.64	10.67	35.20
Turkiye	15.14	15.03	13.91	13.04	11.68	10.61	9.83	9.13	17.12
Turkmenistan	47.37	47.29	47.20	47.10	46.98	46.87	46.76	46.56	47.05
Uganda	40.46	40.45	40.46	40.46	40.21	41.84	40.34	39.41	44.08
Ukraine	25.38	29.35	30.30	31.29	32.18	31.81	30.28	28.37	43.76
United King.	2.18	1.99	2.27	2.29	2.49	3.02	3.22	2.16	3.41
United States	2.51	2.49	2.61	2.65	2.78	2.79	2.88	1.98	3.73
Uruguay	9.80	11.08	11.62	12.16	11.93	10.45	10.64	8.71	12.10
Uzbekistan	48.74	47.85	47.07	46.24	45.14	44.96	44.29	41.79	49.42
Venezuela,RB	43.94	43.87	43.62	43.29	43.04	42.88	42.91	42.76	42.92
Viet Nam	32.67	32.41	31.82	33.11	32.19	33.06	32.93	29.67	30.89
Yemen, Rep.	25.42	22.81	19.57	18.78	18.80	20.07	21.91	19.47	40.24
Zambia	25.21	24.88	25.14	24.69	23.98	23.39	22.50	20.86	26.93
Zimbabwe	37.46	37.28	37.14	36.99	37.69	37.57	35.67	33.98	37.67

Note: Annual estimates for each country and for various exogenous calibration values are provided in Appendix C.

4. DISCUSSIONS ON ESTIMATED COEFFICIENTS

As stated in previous sections, our model incorporates time-invariant characteristics (i.e. fixed effects at country level); therefore, the coefficients reflect the effect of a covariate on the dependent variable based on within-country changes over time. Unlike how coefficients are usually commented on in a MIMIC model (similar to pooled models, that is, a specification that does not use the information on the longitudinal structure of the dataset), in the proposed model, the coefficients are always interpreted as the effect of a one-unit change in the covariate on the dependent variable (IE/GDP), holding everything else constant, with the difference that, in this case, what is kept constant is not only the covariates (self-employment, HDI, size of agriculture sector, corruption, etc.) but also the unobserved, time-invariant characteristics of each country that affect the informality. In other words, if we consider these country-specific characteristics such as the "structural or long-term" components of the IE/GDP ratio (which depend on factors like culture, religion, tax morale, the country's economic structure, etc.), the structural coefficients of our MIMIC then describe how much a change in the causes makes the IE/GDP ratio deviate from its long-term level.

Consequently, our findings show a significant variation in the key drivers of IE between high-income and not-high-income countries, exhibiting distinct causal effects on IE depending on different economic developments. These results highlight the inherent complexity and rigidity in altering historical levels of the IE using policy interventions that target specific causes of informality. The presence of IE in a country is deeply rooted in the very structural and cultural fabrics of the society in many economies, which are often shaped by fundamental socio-economic factors (such as weak institutional and legal frameworks, inadequate education systems, lack of social protection etc) (Schneider and Enste, 2000; Zhanabekov, 2022). These act as barriers to reducing informality with short-run policy measures. Additionally, any attempt to reduce the size of the IE in a country is often complicated by the fact that in some countries, particularly low-income countries, many people's livelihoods depend on informal activities (Williams, 2014; Berdiev et al. 2020). Even for high-income countries, reducing levels of informality may be a slow process, as some industries or sectors might favour informal labour practices due to fluctuations in economic conditions, cost-saving practices, or taking advantage of potential regulatory loopholes (Loayza, 2018). This necessitates a more nuanced, multifaceted and longer-term approach by governments, as targeted short-term policy measures can face resistance from economic agents involved in informal activities.

Our study has produced mixed findings regarding labour market characteristics across two groups of countries. The Labour Freedom Index (*LabFreed*) has differing effects on these groups, though the causality remains consistent. For non-high-income countries, labour freedom has a significant negative impact on informality, suggesting that greater labour market freedom reduces informality and promotes formalisation. However, in high-income countries, where labour markets are already well-regulated, the effect of labour freedom on the IE is insignificant, albeit with the same causal direction.

There is a significant positive relationship between the level of agricultural employment (*EmplAgric*) and the IE, implying a larger agricultural workforce is linked to higher informality worldwide. A very strong positive effect is seen for high-income countries (Schneider et al., 2023), indicating that employment in agriculture drives informality more in these countries than in less wealthy countries. The model also reveals a significant positive relationship between self-employment (*SelfEmpl*) and the IE. This suggests that higher levels of self-employment in an economy may lead to an increase in informal economic activities (Torrini, 2005; Cabral et al., 2012; Hassan and Schneider, 2016; Dell'Anno, 2023). This finding highlights a reliance on informal self-employment, often due to limited formal job opportunities. Similarly, the positive and significant results observed in high-income countries indicate that self-employment continues to contribute to informality, even in these contexts.

Our model incorporates the Human Development Index (*HDI*). The findings show a significant relationship indicating that countries with higher levels of human development experience lower levels of informality across the sample. In advanced economies, high HDI levels are particularly effective in reducing informality. This underscores the importance of investing in education and in health development as a long-term strategy to address informality. However, focusing solely on tertiary education does not necessarily lead to greater formalisation. Our results reveal a significant positive relationship between expenditure on tertiary education (*ExpTertEdu*) and informality with a significantly stronger effect in non-high-income countries compared to high-income countries. Other studies also identify a significant positive relationship between education and tax non-compliance behaviour, suggesting that higher education may contribute to increased tax evasion and, consequently, higher levels of informality (Alm and Torgler, 2006; Torgler, 2006). Nevertheless, we do find a negative and significant effect of *ExpTertEdu* in Male Vulnerable Employment, indicating that higher education spending reduces male and female vulnerable employment globally, who are more likely to operate informally.

Poverty impacts only not-high-income countries positively. This indicates that higher levels of poverty lead to greater informal activities, as economic agents look for opportunities in the informal sector to secure incomes in the absence of such opportunities in the formal sectors of the economy (Chen, 2005). The informal sector offers opportunities for those who are poor to escape their poverty (Williams, 2014). On the other hand, poverty has no significance in the model for the high-income countries sample. This might be a result of lower levels of poverty and stronger welfare states in wealthier countries.

A country with a higher level of corruption (*Corruption*) tends to have higher levels of informality. We use the Control of Corruption index from the World Bank Governance Indicators in our model. This ranges between -2.5 to 2.5, with +2.5 indicating the highest level of corruption. This is due to public mistrust in government institutions and their services, which can potentially influence an economic agent's decision to seek informal opportunities to avoid dealing with corrupt or less efficient public services and institutions (Alm and McClellan, 2012; Elgin, 2020; Dell'Anno and Teobaldelli, 2015). However, for high-income countries, this variable has a negative but non-significant, indicating little or no impact in advanced economies.

The quality of bureaucratic burden, as measured by the Bureaucratic Quality Index (*BureacrQ*) from ICRG, exhibits a significant negative impact on the IE, indicating that better bureaucratic quality reduces the size of the IE (Schneider and Enste, 2013) and suggesting that improving bureaucracy is critical to reducing informality. For high-income countries, the results show a smaller effect, likely due to already high bureaucratic efficiency.

As already established in the literature, our results show that for not-high-income countries samples, there is a positive and significant, relationship between the tax revenue (*TaxRev*) and the IE globally. However, in contrast to previous literature, our study has shown that tax revenue, which we proxy to capture the tax burden, is negative and significant for the high-income countries sample. Gaspareniene and Remeikiene (2015) argue that a high tax burden is not always associated with higher informality, providing results that countries with a high tax burden have small informality (such as Scandinavian countries), while some developing countries have low tax rates, but large informal sectors. This suggests better tax compliance, enforcement and governance in high-income countries. Similarly, the results for the employment rate are somewhat unexpected too. We observe a positive and significant impact on the employment rate in IE, particularly for not-high-income countries, indicating that higher employment levels correlate with greater informality globally. This may be due to underemployment, where people may be employed only part-time, leading to an increase in the employment rate.

Our rationale for including the linear trend (*LinTrend*) in our MIMIC model is that it captures the broader structural transformations in the economy and production systems over the past 25 years. Specifically, we observe widespread trends such as increasing agricultural productivity per worker, a growing share of value added in the services sector relative to manufacturing in advanced economies, and a rise in manufacturing relative to agriculture in low-income countries. Additionally, phenomena such as increased globalisation, higher female labour force participation, greater labour market vulnerability, digitisation, and the proliferation of electronic payments have emerged (Dybka et al., 2019). Although these variables undoubtedly impact the size of the informality, they are not explicitly included in the model due to data unavailability. Thus, the inclusion of a linear trend can be considered a second-best approach. It functions as a "black box" that captures the cumulative effects of these unmeasured variables. We find that the linear trend is significant and positively related to the size of the IE in all countries of the sample, with a stronger trend in the less wealthy nations.

Particularly noteworthy is the strong negative effect of the COVID-19 pandemic on the informality ratio, where the non-observed economy (i.e., the numerator) contracted more sharply than the observed economy (the denominator). This effect has been especially pronounced in non-high-income countries compared to high-income ones. Several hypotheses can explain this differentiated impact, rooted in structural and institutional differences between these economies. The first explanation lies in the distinct sectoral composition between non-high- and high-income economies. Informal activities are likely to be heavily concentrated in sectors particularly vulnerable to the pandemic, such as retail trade, transportation, food services, construction, and personal care services that are relatively more important in employment and value-added in non-high-income countries. These sectors rely significantly on physical mobility and direct customer interaction, both of which were severely curtailed by lockdowns and other public health measures. In contrast, high-income economies are characterised by a greater share of advanced tertiary sectors and public services, which are less dependent on physical presence and may thus be comparatively less affected by pandemic-related restrictions. Another major factor is the weaker social protection infrastructure in middle- and low-income countries. Informal workers in these economies faced greater exposure to the negative economic shocks of the pandemic, as they often lacked access to unemployment benefits or emergency financial support provided to formal workers during the crisis. The absence of such safety nets intensified the adverse effects on income and consumption for informal workers, magnifying the pandemic's economic impact on these countries.

Finally, the limited access to digital technologies, network infrastructure, and digital literacy in many non-high-income countries further exacerbated the challenges faced by the informal sector. While workers and businesses in high-income countries could leverage online platforms and remote work to sustain economic activity, such opportunities were largely inaccessible to informal workers and businesses in less developed economies. This technological divide curtailed income-generating opportunities in the informal sector, contributing to a more pronounced decline in informality.

These combined factors - sectoral vulnerability, insufficient social protection, and limited digital access - explain why the pandemic's impact on the informality ratio was significantly more severe in non-high-income countries. The findings underscore the structural inequalities in how different economies (informal versus formal activities and non-high income versus high-income countries) respond to global crises, shedding light on the vulnerabilities of informal workers in the face of systemic shocks.

The results also show a positive and significant increase in male vulnerable employment due to the pandemic across all groups. Globally, the impact is substantial, with a stronger effect in non-high-income countries, likely due to greater economic disruption. In high-income countries, the increase is smaller, reflecting the mitigating role of stronger fiscal support systems.

On the other hand, a large IE is strongly and positively associated with vulnerable employment for both males and females (*VulnEmplMal* and *VulnEmplFem*) across all country samples. Covid-19 has played a significant role in amplifying this relationship, while expenditure on tertiary education (*ExpTertEdu*) helps mitigate it, underscoring the importance of education in enhancing formal employment opportunities and reducing informality globally. Additionally, there is a positive relationship between the IE and informal sector income (*InfSectInc*) in non-high-income countries but a negative relationship in high-income countries. This suggests that in high-income countries, informal sector income is minimal due to the nature and quality of informal jobs, whereas in non-high-income countries, the informal sector offers higher quality opportunities and greater availability of informal work.

5. Conclusions

Compared to the existing literature dealing with the measurement issue of IE, our study has offered several contributions while addressing various existing methodological limitations. Firstly, our study provides robust estimates of the IE ratio in 152 countries of the sample for the longest period (from 1997 to 2022). Secondly, we provide a novel approach to dealing with missing data to measure the IE using the MIMIC approach and mitigate potentially biased estimates with an incomplete dataset. Unbalanced datasets are particularly an issue in less developed countries. Since a large sample of our countries is not high-income countries, the treatment of missing values is essential to ensure robust and more reliable estimates.

Thirdly, we demeaned all the variables used in the MIMIC specification to account for time-invariant and country-specific characteristics such as cultural, religious and economic structures. This has ensured that these various country-specific characteristics do not interfere with the cross-country comparisons. This approach, we believe, provides more robust and reliable estimates of the IE across diverse levels of economic development, and in particular between high-income and not-high-income countries.

Fourth, our MIMIC model with fixed effects highlights that, even after controlling for country-specific factors, the potential to reduce informality levels in the short term significantly remains limited due to the strength and persistence of the long-term component (such as tax morale, geography, culture, social capital, etc.). The methodological improvement of the MIMIC specification proposed in this research enables us to obtain unbiased estimates of the marginal effects of the causes of informality, which provides more reliable country estimates at the international level.

Fifth, the MIMIC model is theoretically constructed to account for the multifaceted characteristics of the IE, where we account for multiple interactions between the latent variable, causes and indicators, but also between the causes and indicators themselves. This is a new approach, which we believe is enhanced when estimating the IE using the MIMIC model. Additionally, the inclusion of the linear trend in our model provides us with insights into the development of the IE in all our sample countries.

We show that the size of the IE is still significant in both developed and less developed countries (on average, 9.5% in high-income countries and 33.5% in not high-income countries). Our model distinguishes between high- and not high-income countries, thus providing insights that factors that affect the size of the IE positively or negatively cannot be assumed to be homogenous. We test that this approach improves the explanatory power of the MIMIC model and the accuracy of the estimates because estimating two distinct sets of structural and measurement coefficients significantly enhances both the overall model fit statistics and the precision of marginal effects, compared to assuming the same coefficients for both groups of countries.

From our results and estimates, we can state that the relatively low variation in the IE estimates within individual countries (owing to the low absolute values of the structural coefficients) reflects how complex and rigid it is to alter historical levels of informality through interventions targeting specific causes. While these causes are statistically significant, their impacts tend to affect the size of informality marginally. From a positive viewpoint, it may explain why countries with similar economic structures can exhibit significantly different IE levels over time despite having similar underlying drivers (MIMIC causes).

Overall, we conclude that factors like self-employment levels, labour freedom, and employment in the agriculture sector can significantly increase the IE for high-income countries. At the same time, control of corruption and bureaucratic quality decreases it.

For not high-income countries, factors like poverty levels, the level of agriculture employment, and the control of corruption positively influence the IE, while labour freedom, education spending, and higher HDI reduce it. Such nuanced differences highlight the need for specific and tailored long-term policies in dealing with the formalisation of economic informality in countries with different levels of development.

From a normative viewpoint, the low variation in the IE/GDP within individual countries (due to the low marginal impacts relative to the country average) indicates the complexity of modifying the historical levels of informality through simple interventions on one or only a few, causes of informality (e.g. tax revenue, labour regulation, etc). Indeed, these causes are statistically significant, they have generally minor impacts. This result also helps explain why, historically, countries with similar economies have IE/GDP levels, one double that of the other, even though the drivers (MIMIC causes) are not so different between them.

What our MIMIC model with fixed effects does is precisely to make visible that while controlling for country-specific effects (such as geography, culture, etc.), the possibilities of changing IE levels are quite limited because the "long-term component" is very strong and ultimately decisive. This is another contribution that we offer with this paper.

REFERENCES

Abdih, M. Y., & Medina, L. (2013). Measuring the Informal Economy in the Caucasus and Central Asia. WP/13/137, IMF Working Paper, International Monetary Fund, Washington DC, USA

Alderslade, J., Talmadge, J., & Freeman, Y. (2006). Measuring the Informal Economy: One neighbourhood at a time. Discussion Paper, The Brooking Institution Metropolitan Policy Program, Washington D.C., September 2006.

Alm, J., & Torgler, B. (2006). Cultural differences and tax morale in the United States and in Europe. *Journal of Economic Psychology*, *27*(2), 224-246. doi.org/10.1016/j.joep.2005.09.002

Alm, J., & McClellan, C. (2012). Tax morale and tax compliance from the firm's perspective. *Kyklos*, *65*(1), 1-17. doi.org/10.1111/j.1467-6435.2011.00524.x

Alm, J., & Embaye, A. (2013). Using dynamic panel methods to estimate informal economies around the world, 1984–2006. *Public Finance Review*, 41(5), 510-543. doi.org/10.1177/1091142113482353

Andrews, D., A. Caldera Sánchez and Å. Johansson (2011), "Towards a Better Understanding of the Informal Economy", OECD Economics Department Working Papers, No. 873, OECD Publishing, Paris. doi.org/10.1787/5kgb1mf88x28-en.

Arby, Muhammad Farooq, Muhammad Jahanzeb Malik, and Muhammad Nadim Hanif. (2012). The size of the IE in Pakistan. *Finance Research*, Vol1 No2, April 2012, ISSN: 2165-8226 mpra.ub.uni-muenchen.de/id/eprint/22617

Asllani, A., & Schneider, F. (2024). A review of the driving forces of the Informal Economy and policy measures for mitigation: an analysis of six EU countries. *International Tax and Public Finance*, 1-35. doi.org/10.1007/s10797-024-09842-z

Bajada, C. (1999). Estimates of the underground economy in Australia. *Economic Record*, 75(4), 369-384. doi.org/10.1111/j.1475-4932.1999.tb02573.x

Bajada, C., & Schneider, F. (2005). The informal economies of the Asia-Pacific. *Pacific Economic Review*, 10(3), 379-401. doi.org/10.1111/j.1468-0106.2005.00280.x

Berdiev, A. N., Saunoris, J. W., & Schneider, F. (2020). Poverty and the shadow economy: The role of governmental institutions. *The World Economy*, *43*(4), 921-947. doi.org/10.1111/twec.12917

Blades, D. (1982). The Hidden Economy and the National Accounts. OECD, Occasional Studies.

Bollen KA, Lilly AG, Luo L. Selecting scaling indicators in structural equation models (sems). *Psychological Methods.* 2022 Oct 6. doi.org/10.1037/met0000530

Breusch, T. (2005). Estimates of the underground economy in Australia. *Economic Record*, 81, 394–403.

Breusch, T. (2016). Estimating the underground economy using MIMIC models. *Journal of Tax Administration*, 2(1), 1–29. ideas.repec.org/p/wpa/wuwpem/0507003.html

Buehn, A., & Schneider, F. (2012). Shadow economies around the world: novel insights, accepted knowledge, and new estimates. *International Tax and Public Finance*, 19, 139-171. doi.org/10.1007/s10797-011-9187-7

Cai, M., van Buuren, S., & Vink, G. (2022, July). Generalizing Univariate Predictive Mean Matching to Impute Multiple Variables Simultaneously. In Science and Information Conference (pp. 75-91). Cham: Springer International Publishing. doi.org/10.1007/978-3-031-10461-9_5

Cabral, A. C. G., Gemmell, N., & Alinaghi, N. (2021). Are survey-based self-employment income underreporting estimates biased? New evidence from matched register and survey data. *International Tax and Public Finance*, *28*, 284-322. doi.org/10.1007/s10797-020-09611-8

Cassar, A. (2001). An Index of The Underground Economy in Malta. *Bank of Valletta Review*, No. 23, Spring 2001.

Chen, M. (2005). The business environment and the informal economy: Creating conditions for poverty reduction. In *Background paper for the Committee of Donor Agencies for Small Enterprise Development Conference on "Reforming the Business Environment,"* November, 2005.

Chen, M. (2012). The Informal Economy: Definitions, Theories and Policies, WIEGO Working Paper No. 1, ISBN: 978-92-95095-41-0

Cling, J.P., Razafindrakoto, M. and Roubaud, F., (2010). Assessing the potential impact of the global crisis on the labour market and the informal sector in Vietnam. *Journal of Economics and Development*, 38, pp.16-25.

Colombo, E., Onnis, L., and Tirelli, P. (2016). Informal economies at times of banking crises: Empirics and theory. Journal of Banking and Finance, 62, 180-190. doi.org/10.1016/j.jbankfin.2014.09.017

De Soto, H. (1989). The other path: The invisible revolution in the third world. Development Southern Africa, Volume 6, 1989 - Issue 3, pp. 390-392

Dell'Anno, R. (2021). Inequality and informality in transition and emerging countries. *IZA World of Labor*. doi.org/10.15185/izawol.325.v2

Dell'Anno, R. (2022). Theories and definitions of the Informal Economy: A survey. *Journal of Economic Surveys*, 36(5), 1610-1643. doi.org/10.1111/joes.12487

Dell'Anno, R. (2023). Measuring the unobservable: estimating the Informal Economy by a structural equation modelling approach. *International Tax and Public Finance*, 30(1), 247-277. doi.org/10.1007/s10797-022-09742-0

Dell'Anno, R. (2024). Integrating national accounting and macroeconomic approaches to estimate the underground, informal, and illegal economy in European countries. *International Tax and Public Finance,* 1-40. doi.org/10.1007/s10797-024-09835-y

Dell'Anno, R., & Schneider, F. (2003). The Informal Economy of Italy and other OECD Countries: What do we know? *Journal of Public Finance and Public Choice*, 21(2-3), 97-120. doi.org/10.1332/251569203X15668905422009

Dell'Anno, R., & Schneider, F. G. (2006). Estimating the underground economy by using MIMIC models: A Response to T. Breusch's critique (No. 0607). Working paper. hdl.handle.net/10419/73283

Dell'Anno, R., Gómez-Antonio, M., & Pardo, A. (2007). The Informal Economy in three Mediterranean countries: France, Spain and Greece. A MIMIC approach. *Empirical Economics*, 33, 51-84. doi.org/10.1007/s00181-006-0084-3

Dell'Anno, R., & Teobaldelli, D. (2015). Keeping both corruption and the shadow economy in check: the role of decentralization. *International Tax and Public Finance*, *22*, 1-40. doi.org/10.1007/s10797-013-9298-4

Djankov, S., Glaeser, E., La Porta, R., Lopez-de-Silanes, F., and Shleifer, A. (2003). The new comparative economics. *Journal of Comparative Economics*, 31(4), 595-619. doi.org/10.1016/j.jce.2003.08.005

Doornik, J.A. and Hansen, H. (2008). An Omnibus test for univariate and multivariate normality. *Oxford Bulletin of Economics and Statistics*, 70, 927-939. doi.org/10.1111/j.1468-0084.2008.00537.x

Dybka, P., Kowalczuk, M., Olesiński, B., Torój, A., Rozkrut, M. (2019). Currency demand and MIMIC models: towards a structured hybrid method of measuring the IE. *International Tax and Public Finance* 26, 4–40. doi.org/10.1007/s10797-018-9504-5

Dybka, P., Olesiński, B., Rozkrut, M., Torój, A. (2023). Measuring the model uncertainty of shadow economy estimates. *International Tax and Public Finance* 30, 1069–1106. doi.org/10.1007/s10797-022-09737-x

Elgin, C. (2020). The informal economy: Measures, causes, and consequences. Routledge.

Elgin, C., M. A. Kose, F. Ohnsorge, and S. Yu. (2021). "Understanding Informality", C.E.P.R. Discussion Paper 16497, Centre for Economic Policy Research, London.

Feige, E. L. (1996). Overseas holdings of US currency and the underground economy. Exploring the Underground Economy. Kalamazoo, Michigan, 5-62.

Feige, E. L. (2016). Reflections on the meaning and measurement of unobserved economies: what do we really know about the 'Shadow Economy'? *Journal of Tax Administration* (2016) Vol, 2. No. 1., Available at SSRN: ssrn.com/abstract=2728060

Feld, L. P., Larsen, C., Feld, L. P., & Larsen, C. (2012). Defining and measuring undeclared work. In Defining and measuring undeclared work. In Undeclared work, deterrence and social norms (pp. 7–13). Springer 7-13. doi.org/10.1007/978-3-540-87401-0_2

Fernandes, A. (2022). The non-observed economy in the national accounts. "To be or not to be" on the agenda of national accountants, policymakers and academics, Working Paper, Leuven: HIVA - KU Leuven. (https://hiva.kuleuven.be/en/news/docs/working-paper-the-non-observed-economy-in-the.pdf)

Frey, B. S., & Pommerehne, W. W. (1984). The hidden economy: state and prospects for Measurement. *Review of Income and Wealth*, 30(1), 1-23. doi.org/10.1111/j.1475-4991.1984.tb00474.x

Frey, B. S., & Weck-Hanneman, H. (1984). The hidden economy as an 'unobserved' variable. *European Economic Review*, 26(1-2), 33-53. doi.org/10.1016/0014-2921(84)90020-5

Gaspareniene, L., & Remeikiene, R. (2015). Evaluation of the shadow economy influencing factors: Comparative analysis of the Baltic States. *Academic Journal of Interdisciplinary Studies*, 4(3), 653–659. doi.org/10.5901/ajis.2015.v4n3s1p653

Gerxhani, K. (2004). The informal sector in developed and less developed countries: A literature survey. *Public Choice*, 120(3), 267-300. doi.org/10.1023/B:PUCH.0000044287.88147.5e

Goel, R. K., and Nelson, M. A. (2016). Shining a light on the shadows: Identifying robust determinants of the Shadow Economy. *Economic Modelling*, 58(C), 351–364. doi.org/10.1016/j.econmod.2016.06.009

Goldberger, A. S. (1972). Structural equation methods in the social sciences. *Econometrica: Journal of the Econometric Society*, 979-1001. doi.org/10.2307/1913851

Hassan, M. & Schneider, F. (2016). Size and development of the shadow economies of 157 worldwide countries: Updated and new measures from 1999 to 2013. *Journal of Global Economics*, 4(3), 1-15. doi.org/10.4172/2375-4389.1000218

Henze, N., Zirkler, B. (1990). A class of invariant consistent tests for multivariate normality. *Communication in Statistics - Theory and Methods*, 19:3595–3617. doi.org/10.1080/03610929008830400

ILO (International Labour Organization), (2018). Women and men in the Informal Economy: A statistical picture. Third edition.

Johnson, S., D. Kaufmann and A. Shleifer, (1997), “The Unofficial Economy in Transition,” Brookings Papers on Economic Activity, Fall, Washington D.C. Johnson, S. doi.org/10.2307/2534688

Johnson, S., Kaufmann, D., and Zoido-Lobaton, P. (1998). Regulatory Discretion and the Unofficial Economy. *American Economic Review*, 88(2):387-92. jstor.org/stable/116953

Kaufmann, D., & Kaliberda, A. (1996). An" Unofficial" Analysis of Economies in Transition an Empirical Framework and Lessons for Policy (No. 294375). Harvard University, Kennedy School of Government. doi.org/10.22004/ag.econ.294375

Kazemier, Brugt (2005). The Underground Economy: A Survey of Methods and Estimates. Discussion Paper, Statistics Netherlands, Voorburg, Netherlands

Kelmanson, M. B., Kirabaeva, K., Medina, L., Mircheva, M., & Weiss, J. (2019). Explaining the Shadow Economy in Europe: size, causes and policy options. Working Paper No. 2019/278. International Monetary Fund.

Kirchgässner, G. (2016). On estimating the size of the Shadow Economy. *German Economic Review*, 18(1), 99–111. doi.org/10.1111/geer.12094

Kleinke, K., Reinecke, J., Salfrán, D., & Spiess, M. (2020). Applied multiple imputations. Berlin/Heidelberg, Germany: *Springer International Publishing*. doi.org/10.1007/978-3-030-38164-6

Lackó, M. (1998). The hidden economies of Visegrad countries in international comparison: A household electricity approach. Hungary: Towards a market economy. ed. László Halpern, and Charles Wyplosz. Cambridge: Cambridge University Press, p. 128-152.

Lang, K. M., & Little, T. D. (2018). Principled missing data treatments. *Prevention Science*, 19(3), 284-294. doi.org/10.1007/s11121-016-0644-5

Lee, K. J., Roberts, G., Doyle, L. W., Anderson, P. J., & Carlin, J. B. (2016). Multiple imputation for missing data in a longitudinal cohort study: a tutorial based on a detailed case study involving imputation of missing outcome data. *International Journal of Social Research Methodology*, 19(5), 575-591. doi.org/10.1080/13645579.2015.1126486

Losby, J. L., Else, J. F., Kingslow, M. E., Edgcomb, E. L., Malm, E. T., & Kao, V. (2002). Informal Economy literature review. ISED Consulting and Research, 1, 55. Available at: aspeninstitute.org/wp-content/uploads/2017/04/InformalEconomyLiteratureReview.pdf (accessed 26.09.2024)

Loayza, N. (2018). Informality: why is it so widespread, and how can it be reduced? *World Bank Research and Policy Briefs*, (133110). ssrn.com/abstract=3360124

Mardia, K. V. (1970). Measures of multivariate skewness and kurtosis with applications. *Biometrika*, 57(3), 519-530. doi.org/10.1093/biomet/57.3.519

Medina, L., and Schneider, F. (2021). The evolution of shadow economies through the 21st century. The Global Informal Workforce: Priorities for Inclusive Growth, IMF, Washington DC, USA, S. 10–6.

Mehrotra, S. (2009). The impact of the economic crisis on the informal sector and poverty in East Asia. *Global Social Policy,* 9(1 suppl), pp. 101-118. doi.org/10.1177/1468018109106887

Pedersen, S. (2003). The IE in Germany, Great Britain and Scandinavia: A Measurement Based on Questionnaire Service. The Rockwell Foundation Research Unit, Copenhagen, Study 10.

Pham, T. H. H. (2017). Impacts of globalisation on the informal sector: Empirical evidence from developing countries. *Economic Modelling*, 62, 207-218. doi.org/10.1016/j.econmod.2017.01.001

Satorra, A., & Bentler, P. M. (1994). Corrections to test statistics and standard errors in covariance structure analysis. In A. von Eye & C. C. Clogg (Eds.), Latent variables analysis: Applications for developmental research (pp. 399-419). Thousand Oaks, CA: Sage Publications.

Schneider, F. (2008). Shadow Economy. *Readings in public choice and constitutional political economy*, 511-532. doi.org/10.1007/978-0-387-75870-1

Schneider, F. (2014). Work in the shadow: Micro and macro results. *International Economic Journal*, 28(3), 365-379. doi.org/10.1080/10168737.2014.936924

Schneider, F. (2023). Do different estimation methods lead to implausible differences in the size of non-observed or shadow economies? A preliminary answer. *Annual Review of Resource Economics*, 15(1), 257-277. doi.org/10.1146/annurev-resource-090822-114308

Schneider, F., & Buehn, A. (2017). Estimating a Shadow Economy: Results, methods, problems, and open questions. *Open Economics*, 1(1), 1-29.

Schneider, F., & Enste, D. H. (2000). Shadow economies: Size, causes, and consequences. *Journal of Economic Literature*, 38(1), 77-114. doi.org/10.1257/jel.38.1.77

Schneider, F., & Enste, D. H. (2013). The Shadow Economy: An international survey. Cambridge University Press.

Schneider, F., Buehn, A., & Montenegro, C. E. (2010). Shadow economies all over the world: New estimates for 162 countries from 1999 to 2007. In Handbook on the Shadow Economy. Edward Elgar Publishing. doi.org/10.4337/9780857930880.00007

Sinharay, S., Stern, H. S., & Russell, D. (2001). The use of multiple imputations for the analysis of missing data. *Psychological methods,* 6(4), 317-329. doi.org/10.1037/1082-989X.6.4.317

Schneider, F., Morkunas, M., & Quendler, E. (2023). An estimation of the informal economy in the agricultural sector in the EU-15 from 1996 to 2019. *Agribusiness*, *39*(2), 406-447. doi.org/10.1002/agr.21774

Slemrod, J., & Weber, C. (2012). Evidence of the invisible: toward a credibility revolution in the empirical analysis of tax evasion and the Informal Economy. *International Tax and Public Finance*, 19, 25-53. doi.org/10.1007/s10797-011-9181-0

Tanzi, V. (1980). The underground economy in the United States: Estimates and implications. *PSL Quarterly Review*, 33(135).

Tanzi, V. (1983). The underground economy. Finance and Development, 20(4), 10-13.

Thomas, J., (1992). Informal Economic Activity. In: LSE, Handbooks in Economics, London: Harvester Wheatsheaf.

Thomas, J., (1999). Quantifying the black economy: measurement without theory yet again? *The Economic Journal*, 109(456), pp.381-389. doi.org/10.1111/1468-0297.00441

Torgler, B. (2006). The importance of faith: Tax morale and religiosity. *Journal of Economic Behaviour & Organization*, *61*(1), 81-109. doi.org/10.1016/j.jebo.2004.10.007

Torgler, B., & Schneider, F. (2006). Shadow Economy, institutions, and tax morale. In Proceedings. Annual conference on taxation and minutes of the annual meeting of the National Tax Association (Vol. 99, pp. 204-210). National Tax Association. jstor.org/stable/prancotamamnta.99.204

Torrini, R. (2005), "Cross-Country Differences in Self-Employment Rates: The Roles of Institutions". *Labour Economics*, 12(5), pp. 661-683. doi.org/10.1016/j.labeco.2004.02.010

Vuletin, G. J. (2008). Measuring the Informal Economy in Latin America and the Caribbean (No. 8-102). International Monetary Fund. ISBN/ISSN: 9781451869637/1018-5941

Williams, C. (2014). The Informal Economy and Poverty: evidence and policy review. *Report prepared for Joseph Rowntree Foundation, York*. ssrn.com/abstract=2404259

Williams, C. C., & Schneider, F. (2016). Measuring the Global Shadow Economy: the prevalence of informal work and labour. Edward Elgar Publishing.

Zellner, A. (1970). Estimation of regression relationships containing unobservable independent variables. *International Economic Review*, 441-454. doi.org/10.2307/2525323

Zhanabekov, S. (2022). Robust determinants of the Shadow Economy. *Bulletin of Economic Research*, 74(4), 1017-1052. doi.org/10.1111/boer.12330

Zhou, F., & Oostendorp, R. (2014). Measuring true sales and underreporting with matched firm-level survey and tax office data. *Review of Economics and Statistics*, 96(3), 563-576. doi.org/10.1162/REST_a_00408