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A photograph of the interior of the Central Bank of Malta building. The space is characterized by a high ceiling with a dramatic, colorful sky (orange, red, and blue) projected onto it. The walls are made of light-colored stone blocks. In the foreground, there are long, curved, light-colored stone benches. To the right, there are rows of white, rectangular, three-dimensional architectural elements that resemble a grid or a series of steps. In the background, there is a large, arched stone doorway leading to another part of the building. The overall atmosphere is modern and architectural.

CENTRAL BANK OF MALTA DISCUSSION PAPER



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An updated estimate of the size of Malta's underground economy

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Abstract

The underground, or shadow, economy – comprising legal and productive activities concealed from authorities for monetary, regulatory, or institutional reasons – poses challenges to fiscal governance, labour protection, and market competition. This paper provides an updated estimate of the size of Malta's underground economy over the period 1995–2024, employing a Multiple Indicators and Multiple Causes (MIMIC) model estimated on quarterly data. The specification includes four causal variables (tax burden, government expenditure, self-employment, and unemployment) and three indicators (currency-to-GDP ratio, real GDP growth, and labour force participation). All variables except government expenditure are statistically significant and display the expected signs. Increases in the tax burden, self-employment, and unemployment are associated with higher shadow-economy activity. The estimated trajectory of the shadow economy over the sample period suggests that the underground economy's share of GDP rose modestly until 2009 and declined thereafter, reaching 15.3% in 2024. The findings are robust to alternative specifications and consistent with the empirical tendency for informality to decline with economic growth, as well as with increased institutional capacity focused on reducing tax evasion and other aspects of the informal economy in Malta.

JEL Classification: C32, E26, H26, O17.

Keywords: Shadow economy, Underground economy, Tax evasion, MIMIC model, Malta.

Table of Contents

Abstract	2
Executive Summary	4
1. Introduction	5
2. Literature Review	6
2.1. Methods	6
2.2. MIMIC models and variable choice.....	7
2.3. Estimates of the size of Malta's shadow economy	9
3. Methodology & Data	10
4. Results	11
4.1. Main results.....	11
4.2. Sensitivity Analysis.....	12
5. Conclusion	14
References	16

Executive Summary

Although there is no broad consensus surrounding its definition, the underground, or shadow, economy is generally taken to constitute legal and productive economic activities that are hidden from official authorities or misreported, for monetary, regulatory, and institutional reasons. A large shadow economy poses challenges to policymakers across multiple fronts, including distortions to national accounts figures, eroding government budgets, and fostering an environment which could undermine labour protection and fair competition. These consequences explain the sustained interest within policy and academic circles in quantifying the size and evolution of underground economies, despite the measurement challenges arising from their unobservable nature.

This study provides an updated estimate of the size of Malta's underground economy. Building on previous work by Abela, Gauci and Rapa (2022), we employ a Multiple Indicators and Multiple Causes (MIMIC) model estimated on quarterly data from 1995 to 2024. The MIMIC framework – widely adopted in the empirical literature concerned with quantifying the shadow economy – treats the underground economy as a latent, or unobserved, variable that is influenced by a set of observed 'causes' and reflected through a set of 'indicator' variables. Our model specification utilises four causal variables and three indicators. On the causes side, the model includes the tax burden, recurrent government expenditure, the self-employment rate, and the unemployment rate. The indicator variables comprise the ratio of currency in circulation to GDP, the growth rate of real GDP, and the labour force participation rate.

All variables in our model, with the exception of the government expenditure ratio, are found to be statistically significant and display the theoretically expected signs. Increases in the tax burden, self-employment, and unemployment are associated with increased activity in the shadow economy, which is in turn reflected in a higher currency-to-GDP ratio and a lower labour force participation rate. Using an external benchmark equating the shadow economy to 21.0% of GDP in 2013, we transform the values of the latent variable estimated through the model to a series of the ratio of the underground economy to GDP. Our estimates suggest that the share of the underground economy rose modestly between 1995 and 2009, before declining steadily thereafter. Focusing on recent developments, the shadow economy is estimated to have decreased from 18.3% of GDP in 2019 to 15.3% in 2024. The results are robust across three alternative model specifications. The downward trajectory aligns with stylised facts documented in the literature, notably the tendency for the relative size of the shadow economy to decline with higher economic development, as well as with increased institutional capacity focused on reducing tax evasion and other aspects of the informal economy in Malta. The results carry notable policy implications, not least that efforts to refine the incentives implied by tax frameworks, facilitate compliance for self-employed and small businesses, and maintaining low unemployment rates whilst reducing potential labour market frictions, are likely to favourably complement monitoring and enforcement measures in reducing the prevalence of underground economic activity.

MIMIC-based estimates such as those produced in this study are subject to limitations regarding variable selection, identification, and benchmarking, meaning that exact point estimates should be treated with a degree of caution. Nonetheless, these estimates provide valuable insights into the dynamics of the underground economy in Malta and provide useful guidance to policymakers. Whilst regular and robust measurement of the shadow economy is essential for effective policy design, reducing informality also requires a deeper understanding of the drivers and channels through which underground activities proliferate, an avenue that can be explored by future research. More broadly, greater use of multi-method approaches could be a promising opportunity to obtain increasingly robust estimates of the shadow economy and other transactions that escape statistical detection.

1. Introduction

Although there is no broad consensus surrounding its definition, the underground, or shadow, economy is generally taken to constitute legal and productive economic activities that are hidden from official authorities or misreported, for monetary, regulatory, and institutional reasons (e.g. Schneider, Buehn, & Montenegro, 2010; Medina & Schneider, 2018; Asllani & Schneider, 2024). Sometimes also referred to as undeclared work (European Commission, 1998; Horodnic et al., 2024), the shadow economy is a subset of the broader statistical concept of the non-observed economy (Eurostat, 2014; Eurostat, 2021; Fernandes, 2025; UNECE, 2008), which also encompasses illegal production, household own-production, and other measurement gaps which prevent national accounts statistics from exhaustively capturing all productive activities carried out in an economy.

Naturally, the underground economy is associated with several adverse effects that go beyond the accuracy of measurements of economic activity. Evaded taxes negatively impact the government budget and therefore the quality of the services provided by the public sector, whilst creating revenue pressures that governments may seek to alleviate by further raising taxes, potentially setting off a feedback loop. Additionally, businesses that do not operate in line with regulations could pose risks to their employees and customers, whilst distorting the competitive landscape of the markets in which they participate.

Over the last half century, there has been considerable interest in measuring the shadow economy. While Kazemier (2005) places the earliest documented attempts as far back as Helfferich (1914), the academic literature on the topic is generally taken to date back to Cagan (1958), who attempted to infer unreported income in the United States from a measure of “excess” currency holdings. Research in this area started to grow more rapidly following the stagflationary period of the 1970s. Gutmann (1977) and Feige (1979) are early examples of such work. Similarly to Cagan (1958), these papers are broadly based on the observation of currency holdings (or, in the case of Feige (1979), an estimated volume of transactions) which are in excess of what is explained by recorded economic activity.

Apart from the role of currency as the predominant medium of exchange in unrecorded transactions, these early papers identify tax evasion as the primary motivation for economic agents to conceal otherwise legal economic activities, two elements that continue to feature in modern conceptual frameworks of the underground economy. By failing to declare their operations or part of their transactions, businesses and individuals operating in the underground economy circumvent the need to pay taxes on income, value added, as well as other levies such as social security contributions. In other cases, tax evasion is a byproduct of informal activities that are unreported for other reasons, such as bypassing labour regulations (related to, for example, pay or worker safety) or other administrative procedures.

The methods employed by Cagan (1958), Gutmann (1977), and Feige (1979) were the first iterations of a class of methods referred to as ‘indirect methods’, which attempt to trace developments in the shadow economy based on the movements in some observed indicator given a hypothesised relationship between this indicator and undocumented activity. Though indirect methods are still occasionally used, a variety of other methods have been developed and employed to estimate the size of the shadow economy since the 1970s (Schneider & Buehn, 2018; Horodnic et al., 2024). Some more recently developed methods, such as the so-called ‘direct methods’, harness wider availability of survey data and do not require strong simplifying assumptions, whilst model-based methods, which have been more widely applied since the turn of the century, are comparatively easy to implement as they primarily rely on readily available macroeconomic data (Franić, 2019). However, estimating the shadow economy remains inherently difficult, and all available methods have limitations which need to be kept in mind when drawing conclusions.

This study provides an updated estimate of the size of the shadow economy relative to GDP in Malta. Building on earlier work by Abela, Gauci, & Rapa (2022), who estimated the size of Malta’s underground

economy, we employ a similarly specified Multiple Indicators and Multiple Causes (MIMIC) model estimated on quarterly data from 1995 to 2024. Consistent with Abela et al. (2022), we find that the ratio of the shadow economy to GDP exhibits a slight upward trend between 1995 and 2009, before declining steadily thereafter. Focusing on results beyond 2019, the latest available data point in our previous study, the estimated ratio continued to decline at a pace comparable to that observed over the preceding decade. Although point estimates should be treated with a degree of caution and more focus should be placed on the estimated trajectory of the ratio, our results suggest that the size of the underground economy in Malta fell from an average of 18.3% of GDP in 2019 to 15.3% in 2024, compared to a high of 22.8% in 2005. This downward trajectory is consistent with stylised facts from the literature, including the tendency of the shadow economy to fall with increased levels of national income and development. Our results are also shown to be insensitive to changes in the model specification and to the sample period of the estimation.

This paper proceeds as follows. The next section reviews the literature, focusing on methods used to estimate the shadow economy, its theoretical and empirical drivers and indicators, and previous estimates of the size of the shadow economy in Malta. Section 3 presents the MIMIC model employed in this study and the data used. Section 4 outlines the results, whilst section 5 concludes.

2. Literature Review

2.1. Methods

Because of its inherently unobservable nature, researchers have proposed a number of approaches to estimate the size of the underground economy, all of which are subject to varying degrees of uncertainty. In their exhaustive literature review, Horodnic et al. (2024) categorise available methods into four groups: indirect methods, direct methods, discrepancy methods, and model-based methods.

Indirect methods hypothesise a relationship between some (often macroeconomic) indicator and the size of the shadow economy, with deviations in this relationship which are not explainable through relevant observable variables being attributed to unrecorded activities. The most common strand of these models links a growing shadow economy to higher currency holdings. Among these, the most widely adopted has perhaps been the currency demand approach (Tanzi, 1980, 1983), which explicitly estimates an equation for currency holdings and derives the size of the underground economy from estimated excess currency in circulation. Other indicators used in this class of models have included energy consumption (Kaufmann & Kaliberda, 1996), the volume of transactions in the economy (Feige, 1979), and labour force participation (Contini, 1981). Indirect methods are, however, limited by their underlying simplifying assumptions. Most of these methods require the implicit assumption of a fixed relationship between the chosen indicator and the shadow economy, limiting their accuracy when producing estimates over prolonged periods of time. Some other assumptions that are commonly required by indirect methods, for instance that all transactions in the shadow economy are carried out in cash, and that such transactions take place solely due to the burden of taxation, have also been criticised (Giles, 1999; Schneider & Buehn, 2018).

Direct methods rely on surveys of the taxpaying population and on audits by tax authorities. Since the latter imply significant time and resource costs, questionnaires have been more widely used, including by the European Commission, which has carried out three EU-wide surveys on undeclared work in the bloc (European Commission, 2007, 2014, 2020). The main downside of these methods is that they rely on the willingness of individuals and businesses to admit their involvement in activities they usually strive to conceal. As a result, estimates from direct surveys are often markedly lower than those obtained through other approaches.

Discrepancy methods can be described as a bridge between the direct and indirect approaches, as they seek to identify inconsistencies between sources of data on the same concept, one of which is

typically survey data. Horodnic et al. (2024) distinguish between demand-based and supply-based discrepancy methods. As an example of a demand-based discrepancy method, household survey data on expenditure is reconciled with business revenues, with inconsistencies being ascribed to unreported income. This approach assumes that households have little incentives to under-declare expenditure in surveys, allowing survey data to serve as an accurate measure of expenditure, whereas businesses might have incentives to underreport revenues for tax avoidance purposes. On the supply-based side, the labour input method, for instance, takes labour force surveys as an accurate representation of labour inputs in an economy. This is then used to identify excess labour supply over that reported by employers. Discrepancy methods therefore combine survey data that has a purported lower risk of under-declaration by respondents, with measures that are more likely to be mis-reported, in an effort to identify possible under-declaration of business activity. The robustness of discrepancy methods depends on the quality of the data used for these comparisons, and on the methods used to account for other potential sources of discrepancy. As such, discrepancy methods still imply substantial data requirements and implementation challenges (Horodnic et al., 2024).

Such factors, combined with econometric developments, particularly since the turn of the century, have rendered model-based methods the most commonly used tool in both the academic and policy literature (Dybka et al., 2019; Franić, 2019; Horodnic et al., 2024). Although not without their own drawbacks, model-based methods are generally favoured for doing away with the strong simplifying assumptions of indirect methods, and the complexity and relatively high implementation costs of direct and discrepancy methods (Franić, 2019). In turn, the most popular among model-based methods are Multiple Indicators and Multiple Causes (MIMIC) models, which specify the underground economy as an unobservable variable that is driven by a set of observable causes while developments in this unobservable construct are reflected in a set of indicator variables (Horodnic et al., 2024). In comparison to indirect approaches, MIMIC models have the advantage of incorporating movements in several indicators and causes to extract developments in the underground economy, rather than tying them to a single variable.

2.2. MIMIC models and variable choice

MIMIC models are a particular type of structural equation model (SEM), based on the theories developed by Zellner (1970) and Jöreskog and Goldberg (1975). MIMIC models relate closely to the unobserved component literature, in that they can be cast in a state space representation in which the underground economy is specified as a latent variable that is determined by a set of causes in a structural equation, and which is simultaneously reflected in a set of indicator variables through a measurement equation (Giles and Tedds, 2002; Breusch, 2016). Along with the growth in popularity of the MIMIC methodology, a large body of research (e.g. Asllani & Schneider, 2024; Buehn & Schneider, 2012; Dell'Anno, Gómez-Antonio, & Pardo, 2007; Dell'Anno, 2007; Medina & Schneider 2018; Schneider & Enste, 2000; Schneider & Buehn, 2007; Schneider, Buehn, & Montenegro, 2010; Zhanabekov, 2022) has examined the theoretical and empirical drivers and indicators of the underground economy.

In line with the long-standing view that evading taxation is the main motivation for participating in the underground economy, the tax burden in an economy is generally considered to be the primary cause variable in MIMIC models. A wider wedge between pre-tax and post-tax income, as well as a complex tax framework, strengthens the incentive for businesses and individuals to conceal or under-declare activities that generate taxable income. Most studies measure the tax burden as the share of tax revenue in GDP (e.g. Asllani, Dell'Anno, & Schneider, 2024; Dell'Anno & Schneider, 2003) or alternatively include the share of individual tax components (i.e., direct taxes, indirect taxes, and social security contributions) in GDP or total tax revenue (e.g. Medina & Schneider, 2018; Schneider, 2022; Schneider & Buehn, 2007).

Several papers also include the burden of regulations, including labour market, trade and other market regulations, as another incentive to operate in the shadow economy. In the absence of comprehensive indices measuring regulatory burden, this variable is often proxied by measures of government involvement in the economy, such as the level of public employment or government recurrent expenditure (e.g. Dell'Anno et al., 2007; Dell'Anno, 2007). A higher incidence of self-employment relative to the total workforce is also associated with a larger shadow economy, since it is generally easier for self-employed individuals to avoid declaring the true extent of their economic activities. Therefore, *ex-ante*, the size of the shadow economy is expected to be positively related to all these variables. Lastly, the underground economy is also generally believed to be positively associated with the unemployment rate, however this relationship is less clear-cut. A high unemployment rate reflects adverse economic conditions that may lead some individuals to seek compensation for lost income by carrying out undeclared work. However, Giles and Tedds (2002) point out the opposing view that if a decline in formal economic activity spills over into the shadow economy, then the shadow economy could be negatively linked to the unemployment rate. Nevertheless, most studies tend to hypothesise a positive relationship between unemployment and the size of the shadow economy (e.g. Asllani et al., 2024; Dell'Anno et al., 2007).

In terms of indicators, it is generally assumed that transactions in the shadow economy are predominantly conducted in cash as a means of avoiding detection. As a result, a measure of cash use in the economy is commonly included as an indicator variable in MIMIC specifications. This is typically measured as the ratio of currency in circulation, either to measured GDP or to some monetary aggregate. Changes in official economic output are inextricably linked to changes in the shadow economy. *Ceteris paribus*, undeclared economic activity that would have otherwise taken place in the formal economy dampens officially measured GDP. Additionally, foregone tax revenue could dampen economic growth through lower quality of public services (see e.g. Dell'Anno, 2007; Dell'Anno et al., 2007; Schneider & Enste, 2000). On the other hand, some theoretical arguments and empirical results suggest that a positive relationship between the underground economy and the formal economy may hold in certain circumstances (Schneider & Enste, 2000). For instance, a large proportion of undeclared income is subsequently spent in the formal economy, contributing positively to formal economic activity, whilst by extension of the argument put forward by Giles and Tedds (2002), a downturn in economic activity could be reflected in lower demand for goods and services provided underground.

A third indicator commonly included in MIMIC models is a measure of participation or employment in the formal economy. A priori, it is typically hypothesised that higher participation in the informal economy comes at the expense of participation in the official labour force, *ceteris paribus*, which would suggest a negative relationship between the shadow economy and the official participation or employment rates (Asllani et al., 2024; Buehn & Schneider, 2012). This effect may be dampened, however, if undeclared activities are undertaken by individuals who are simultaneously employed (or registered unemployed) in the regular economy, for example by working outside the hours of their regular employment (Bajada & Schneider, 2005). That said, many studies find a statistically significant negative relationship between the shadow economy and the labour participation rate (e.g. Dell'Anno et al., 2007; Schneider et al., 2010; Medina & Schneider, 2018).

An additional aspect of MIMIC model estimation is the requirement to apply a benchmarking procedure to the fitted values of the latent variable, in order to infer developments in the size of the underground economy from the dynamics of the fitted variable (Dell'Anno, 2007; Medina & Schneider, 2018). Several approaches have been proposed in the literature (see e.g. Dell'Anno & Schneider, 2009, and Breusch, 2016 for a detailed discussion). A typical approach is the multiplicative approach attributed to Giles and Tedds (2002), where the level of the estimated latent variable is pegged to an external estimate of the size of the shadow economy (relative to GDP) at a particular point in time, and changes in the latent index relative to that point in time are interpreted to reflect proportional changes in the size of the shadow economy. Alternative approaches, such as that adopted by Bajada & Schneider (2005), instead interpret changes in the latent variable as growth rates of the underground economy and combine these with exogenous benchmark estimates to derive a time series for the size of the shadow economy. The

choice of benchmarking procedure depends on the specification and underlying assumptions of the estimated model and, accordingly, different approaches have been adopted across the literature (Dell'Anno & Schneider, 2009; Medina & Schneider, 2018).

2.3. Estimates of the size of Malta's shadow economy

The first known estimates of the size of the Maltese shadow economy were produced by Micallef (1988) and Briguglio (1989), both using the currency demand approach. Micallef (1988) estimates that the size of the shadow economy in Malta increased rapidly from 3.3% of Gross National Product (GNP) in 1970 to a stable level ranging between 20% and 24% over the period 1979-1985. Consistently, Briguglio (1989) estimates a stable ratio of 25-26% of GDP over the period 1979-1987. Cassar (2001) estimates a MIMIC model for the period between 1971 and 1997, finding that the underground economy grew from 16% to 25% of GDP between 1980 and 1997.

Besides Abela et al. (2022), more recent estimates of the Maltese shadow economy have been published in cross-country studies. These estimates have typically been higher than those discussed above. Schneider et al. (2010) estimate the size of the shadow economy for up to 162 countries over the period 1999-2007 using a MIMIC model, with the average estimate for Malta over that period being 27.7% of GDP. Across all EU countries, the average size of the shadow economy over the period covered by this study is 22.9%, ranging from 9.7% in Austria to 35.3% in Bulgaria. For a set of 158 countries and also using a MIMIC model, Medina & Schneider (2018) calculate the average size of the underground economy in Malta between 1991 and 2015 at a slightly higher 29.8% of GDP, fluctuating between 27% and 33% with a gradually declining path, whilst the average value across the EU-27 is found to be 20.6%. More recently, Schneider (2022) presents a slightly declining profile for the size of the underground economy in Malta, from around 27% of GDP in the mid-2000s to 23% between 2020 and 2022, again relying on a MIMIC model. The average estimate for 2022 across the 27 EU countries in this study stands at 17.7%. Lastly, using the labour input method, Franić et al. (2023) estimate the share of undeclared work in all EU countries in 2019. For Malta, the share of undeclared work is estimated at 23.4% of Gross Value Added (GVA), with the mean value across the sample of countries being 14.8%.

That said, most cross-country studies using MIMIC models carry some drawbacks that affect both the reliability of their estimates for individual countries, and their comparability with results estimated in both Abela et al. (2022) and in this study. The main limitation is that models in these papers are not estimated at the individual country level. Coefficients are instead estimated for panels of between 36 (in the case of Schneider, 2022) and 158 (in Medina & Schneider, 2018) countries and applied *ex-post* to data of individual economies. Given the large number of countries included, no details are given on data availability for individual countries, nor whether data for some countries was partially or fully excluded in the estimation phase. Additionally, differences in the choice of benchmarking method could further limit comparability across studies; in the case of Medina & Schneider (2018) and Schneider (2022), the benchmarking method used is not explicitly discussed, further complicating the comparison of these estimates with those of Abela et al. (2022) and the figures published in this study. Such comparability concerns extend to Franić et al. (2023), a study which uses a different estimation method altogether and provides an estimate for a single year.

This study therefore contributes to the literature estimating the size of the shadow economy in Malta. Building on the work of Abela et al. (2022), we estimate a MIMIC model for the Maltese shadow economy based entirely on country-specific data for Malta, introducing two innovations. First, this work extends available estimates to 2024, providing the most updated estimates in the literature to date. Second, it does so by using a higher-frequency, quarterly time series database.

3. Methodology & Data

In a standard MIMIC framework, the underground economy is specified as a latent variable that is linked to a set of observed cause and indicator variables. In the structural equation, the underground economy, or the latent variable denoted by η_t , is linearly determined by a vector of i observed cause variables, denoted by x_t . In the measurement equation, the underground economy linearly determines a set of j indicator variables denoted by y_t . The MIMIC model can thus be written as follows:

$$\eta_t = \boldsymbol{\gamma}'x_t + \zeta_t$$

$$y_t = \boldsymbol{\lambda}\eta_t + \epsilon_t$$

where $\boldsymbol{\gamma}$ and $\boldsymbol{\lambda}$ are $i \times 1$ and $j \times 1$ vectors of estimated coefficients, respectively, whilst ζ_t and ϵ_t are uncorrelated zero-mean error terms with variances given by ψ and Θ . The variance-covariance matrix Θ is further assumed to be diagonal, i.e., the error terms of the measurement equation of each indicator variable are not correlated. The model can be estimated by maximum likelihood under the assumption that the error terms ζ_t and ϵ_t are normally and serially independently distributed.

The model specification used in this study employs four causal variables and three indicator variables which are widely agreed upon in the literature and are also consistent with the variables chosen in Abela et al. (2022). On the causes side, we use the overall tax burden in the economy, measured as the ratio of government tax revenue to GDP, together with the ratio of recurrent government expenditure to GDP, the self-employment rate, and the unemployment rate. Government tax revenue includes revenue from taxes on income and wealth, social security contributions, taxes on production and imports, and capital taxes, whilst recurring expenditure is composed of intermediate consumption, compensation of employees, subsidies, property expenditure, taxes, social benefits and other current transfers. Both revenue and expenditure data are sourced from Government Finance statistics. Self-employment and unemployment rates are based on Jobsplus records. Our indicator variables are the ratio of currency in circulation to GDP, the growth rate of real GDP, and the labour force participation rate. Currency in circulation refers to the sum of notes and coins issued by the Central Bank of Malta and the Treasury, less currency balances held by banks.² Lastly, the labour force participation rate is also sourced from administrative data. All data series are seasonally adjusted using the Census-X12 procedure implemented in EViews. We estimate the model using quarterly data from 1995Q1 until 2024Q4.

For the MIMIC model to be identified, the estimated latent variable needs to be scaled to some observed variable in the model, since it otherwise has no natural scale or defined unit of measurement. Identification is usually achieved by fixing the coefficient on one of the indicator variables to either 1 or -1. In line with Abela et al. (2022), as our identifying assumption we impose a negative unit loading on the relationship between the estimated shadow economy index and GDP growth, following Dell'Anno et al. (2007) and Dell'Anno (2007).³ Once the model is identified, the latent variable obtained – given the theoretical structure imposed – reflects developments in the size of the shadow economy relative to GDP over time, but does not directly provide such estimates in percentage terms, presenting the need for the use of an external benchmark. As in Abela et al. (2022), we use the multiplicative benchmarking method suggested by Giles and Tedds (2002) and rescale the index such that the shadow economy as a share of GDP is on average 21.0% in 2013, an estimate derived in Abela et al. (2022) using the currency demand approach:

² From 2008 onwards, banknotes issued by the Central Bank of Malta include the notional value of banknotes issued by the Bank in line with its ECB capital key and any excess or shortfall issuance with respect to this value. It is important to note that, since then, due to the interchangeability of euro banknotes and coins across the euro area, currency issued in Malta and not held by banks is not a measure, but rather a proxy, of actual currency in circulation in Malta.

³ The choice of the sign in front of the numeraire variable does not change the dynamics of the latent variable estimated by the MIMIC model.

$$\left(\frac{\widehat{SE}_t}{GDP_t}\right) = \frac{\hat{\eta}_t}{\overline{\hat{\eta}_{2013}}} * 21.0\%$$

where $\left(\frac{\widehat{SE}_t}{GDP_t}\right)$ denotes the estimated ratio of the shadow economy to GDP at time t in percentage terms, whilst $\overline{\hat{\eta}_{2013}}$ is the average value of $\hat{\eta}_t$ in 2013.

4. Results

4.1. Main results

Table 1 below shows the results obtained from the main MIMIC specification. All variables included in the model are statistically significant, with the exception of the government expenditure ratio. Additionally, all variables are linked to the shadow economy with the expected signs. Higher tax burdens, self-employment rates and unemployment rates are all associated with an increase in the size of the shadow economy. In turn, a larger shadow economy is estimated to be reflected in a higher currency-to-GDP ratio and a lower official labour force participation rate, with the coefficient on the GDP growth rate fixed to -1 as an identifying assumption. The magnitudes of the coefficients, however, are not directly interpretable in terms of impacts on the size of the shadow economy (or, in the case of coefficients on indicator variables, in terms of the effects of the shadow economy on the indicator), since they relate to the values of the estimated index prior to benchmarking. The benchmarked series, and thus the implied path of the shadow economy as a share of GDP expressed in annual terms between 1995 and 2024, is shown in Chart 1. For ease of comparison, the chart also plots the estimates in Abela et al. (2022) for the period 1995-2019.

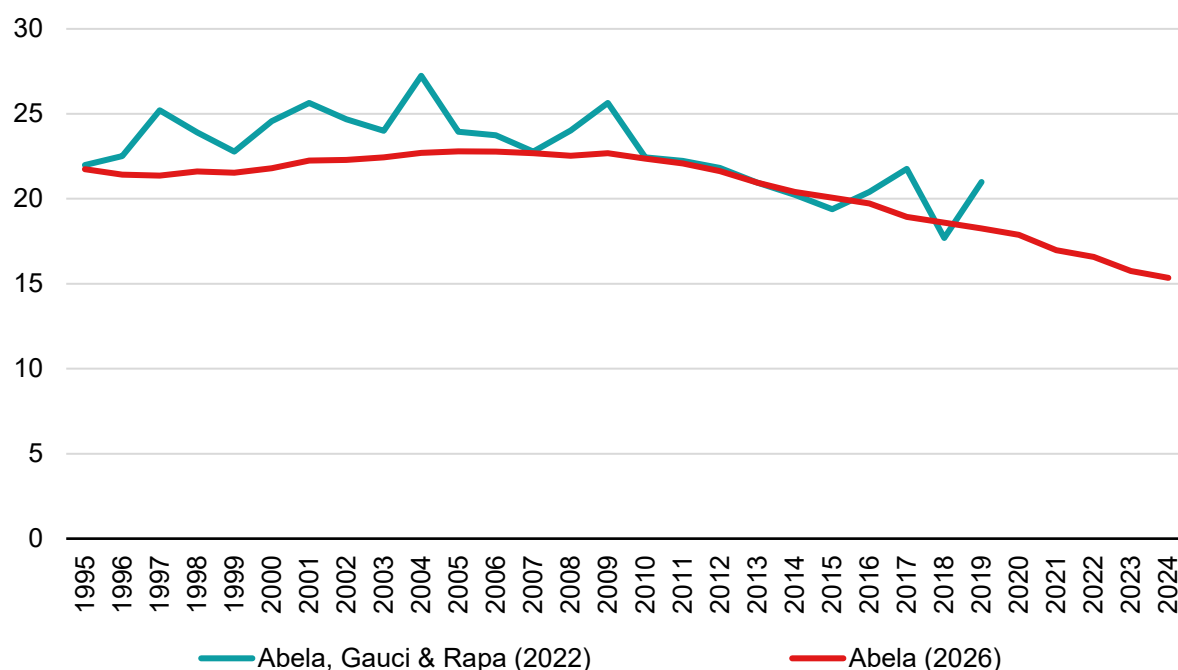
In terms of the trajectory of the size of the shadow economy as a ratio to GDP, the new estimates are consistent with the estimates of Abela et al. (2022). The ratio of the shadow economy to GDP was stable with a slight upward trend between 1995 and 2009, and declined steadily thereafter. Reassuringly, the estimated magnitudes are very close throughout the overlapping period, particularly if the slight volatility seen in the estimates of Abela et al. (2022) is set aside. Importantly, the estimates suggest that the relative size of the shadow economy continued to decline steadily beyond 2019. Our results suggest that the shadow economy fell from an average of 18.3% of GDP in 2019 to 15.3% in 2024. As commented in Abela et al. (2022), this downward trajectory is consistent with stylised facts from the literature, including the tendency of the share of the shadow economy to decline with higher levels of economic development.

Table 1: MIMIC model results

Causes	Coef.	Std. dev.	z	p > z
Tax burden	0.136	0.037	3.657	0.000
Government expenditure/GDP ratio	-0.017	0.027	-0.639	0.523
Self-employment rate	0.969	0.273	3.552	0.000
Unemployment rate	0.867	0.186	4.667	0.000
Indicators	Coef.	Std. dev.	z	p > z
Currency/GDP ratio	3.094	0.838	3.694	0.000
GDP growth rate	-1			
Labour force participation rate	-3.284	0.686	-4.787	0.000

Source: Author's calculations.

Figure 1: Size of the Maltese shadow economy



Source: Author's calculations.

Notes: Size of the shadow economy is measured as a % of nominal gross domestic product.

4.2. Sensitivity analysis

Although MIMIC models have been widely applied in the literature, it is worth noting that they are subject to some limitations which should be considered when using results derived using this methodology. For instance, results may be sensitive to the choice of variables and data periods, whilst the choice of benchmarking technique also introduces a degree of subjectivity (see e.g. Buehn & Schneider, 2012; Breusch, 2016). Moreover, a few caveats concern the econometric estimation of MIMIC models and its underlying assumptions (e.g. Breusch, 2016; Dybka et al., 2019). In an effort to obtain estimates that are as robust as possible, we carry out a number of sensitivity tests.

The first sensitivity specification tested replaces the proxy for government involvement in the economy – government expenditure as a ratio to GDP under the baseline – with the share of public sector employment in total employment. As above, data on public sector employees is sourced from administrative sources. The second sensitivity test replaces the currency-to-GDP ratio with currency in circulation per capita as the measure of cash intensity in the Maltese economy. We focus on the proxy for government involvement and the measure of cash intensity as they tend to show the most variability in terms of definitions used across studies. The alternative measures chosen for these sensitivity tests are likewise grounded in variables that are commonly employed in the MIMIC literature. In a third sensitivity specification, results are estimated using only data from 2005 onwards, to assess sensitivity to the choice of sample window.⁴

⁴ For the third sensitivity test, the model's coefficients are estimated using a sub-sample of the available data. The latent variable, however, is estimated over the full sample period using the coefficients obtained from that sub-sample.

Table 2: Sensitivity analysis

Test (i)				
Causes	Coef.	Std. dev.	z	p > z
Tax burden	0.118	0.044	2.70	0.007
Share of public sector employment	0.198	0.064	3.10	0.002
Self-employment rate	0.065	0.265	2.44	0.015
Unemployment rate	0.355	0.122	2.91	0.004
Indicators	Coef.	Std. dev.	z	p > z
Currency/GDP ratio	1.546	0.695	2.23	0.026
GDP growth rate	-1			
Labour force participation rate	3.799	1.056	3.60	0.000
Test (ii)				
Causes	Coef.	Std. dev.	z	p > z
Tax burden	0.148	0.058	2.52	0.012
Government expenditure/GDP ratio	-0.075	0.032	-2.33	0.020
Self-employment rate	1.110	0.432	2.57	0.010
Unemployment rate	0.622	0.225	2.77	0.006
Indicators	Coef.	Std. dev.	z	p > z
Currency per capita	-0.948	0.341	2.78	0.005
GDP growth rate	-1			
Labour force participation rate	-4.394	1.560	-2.82	0.005
Test (iii)				
Causes	Coef.	Std. dev.	z	p > z
Tax burden	0.172	0.064	2.69	0.007
Government expenditure/GDP ratio	-0.067	0.031	2.17	0.030
Self-employment rate	1.188	0.436	2.72	0.006
Unemployment rate	0.690	0.228	3.02	0.003
Indicators	Coef.	Std. dev.	z	p > z
Currency/GDP ratio	1.579	0.762	2.07	0.038
GDP growth rate	-1			
Labour force participation rate	-3.928	1.279	-3.07	0.002

Source: Author's calculations.

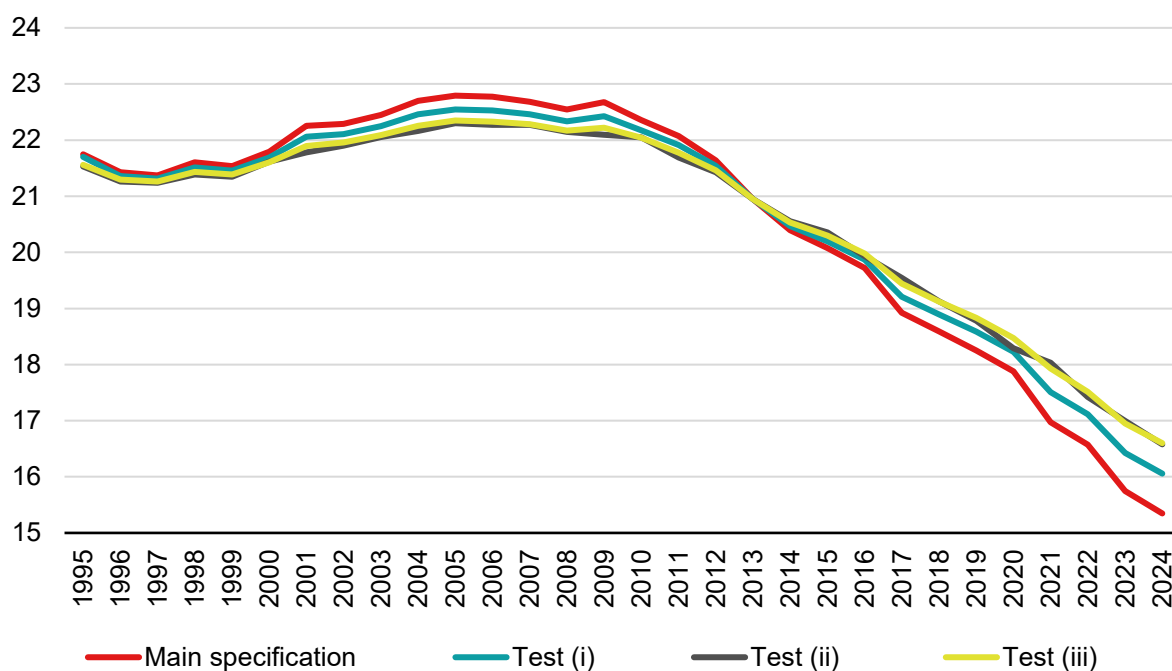
Results from the three sensitivity tests described above are displayed in Table 2, whilst the implied trajectory of the size of the shadow economy is plotted in Chart 2 together with the main estimate displayed in Chart 1. Test (i) and Test (ii) refer to the sensitivity tests that replace the proxy for government involvement and currency use, respectively, while Test (iii) is the sensitivity check relating to the sample period. These tests show that the results are highly robust to these model specification adjustments, with the general trajectory of the size of the underground economy remaining virtually unchanged across all model versions. This in turn suggests that the estimated dynamics are not driven by any single proxy variable or by the inclusion of earlier observations in the sample.

In the case of Test (ii), replacing the currency-to-GDP ratio with currency in circulation per capita produces a statistically significant coefficient with the opposite sign to that predicted by the standard cash-demand interpretation of shadow economy activity. This potentially reflects the fact currency per capita could be influenced by broader set of factors beyond informal economic activity, including

population growth, nominal income developments, tourism-related cash demand, and changes in payment behaviour. In contrast, the currency-to-GDP ratio more directly measures the intensity of cash usage relative to recorded economic activity and is therefore conceptually closer to the theoretical framework commonly underpinning MIMIC estimates of the shadow economy. Importantly, despite the change in sign, the implied trajectory of the benchmarked shadow economy series remains largely unchanged, suggesting that the estimated dynamics are not being driven solely by the choice of monetary proxy, but rather reflect the broader covariance structure captured by the model.

It is also reassuring that the magnitude of the estimated ratio of the underground economy to GDP is also not materially affected by alternative specifications. Taken together, the sensitivity analysis increases confidence that the estimated series reflects persistent underlying relationships in the data, rather than being an artefact of particular modelling assumptions or variable definitions. Nevertheless, it would be prudent to exercise caution whenever interpreting results obtained through the MIMIC approach. In particular, more focus should rather be placed on the estimated dynamics of the shadow economy over time rather than on the absolute level of the point estimates.

Figure 2: Sensitivity tests



Source: Author's calculations.

Notes: Size of the shadow economy is measured as a % of nominal gross domestic product.

5. Conclusion

This study provides an updated estimate of the size of the shadow economy relative to GDP in Malta for the period 1995-2024. We specify a MIMIC model where the shadow economy is a function of the level of tax burden in the economy, a proxy for government involvement, the self-employment rate, and general economic conditions proxied by the unemployment rate. In turn, we use a measure of currency in circulation, the real GDP growth rate, and the labour force participation rate as variables that reflect developments in the underground economy.

All variables in our model show statistically significant links to the shadow economy, except for the ratio of government expenditure to GDP. The results suggest that higher tax burdens, self-employment rates

and unemployment rates are associated with an increase in the size of the shadow economy, whilst a larger shadow economy translates into a higher currency-to-GDP ratio and a lower official labour force participation rate. Through a benchmarking process, we transform the index obtained from the model into a time series of the size of the shadow economy as a ratio to nominal GDP. We find a slight upward trend in the ratio over the first half of our sample period, which declines steadily following 2009. Focusing on recent developments, our point estimates suggest that the shadow economy fell from an average of 18.3% of GDP in 2019 to 15.3% in 2024, although precise point estimates should be treated with caution and more focus should be placed on the broader trend. The results are robust to a series of sensitivity checks.

A sustained decline in the share of the underground economy relative to the official economy is consistent with the significant growth recorded in the Maltese economy over the last decade. Over this period, and especially in recent years, there have also been increased efforts by Government to clamp down on tax evasion. A notable example lies in the use of artificial intelligence systems to increase detection of noncompliance with Value Added Tax (VAT); a system that will gradually be applied to other taxes (Fenech, 2023). This was followed by amendments to key tax and revenue laws implemented in 2025, aiming to strengthen investigative and enforcement powers of tax administration bodies, together with larger penalties for infringements (Government of Malta, 2025; Act No. XXX of 2025). In tandem with such measures by authorities, awareness campaigns and engaging stakeholders remain important tools to increase participation in the formal economy. Such initiatives aim to increase compliance by shifting perceptions over time. These efforts are more likely to bear fruit in the presence of transparent government operations and efficient public services (Horodnic et al., 2024; Zhanabekov, 2022).

Policy measures to address the shadow economy necessarily require regular, robust measurements of its size and an understanding of the drivers and channels through which underground activities proliferate. Our results suggest that the tax burden, self-employment rate, and unemployment rate are all significant drivers of the shadow economy. Given the well-known role of tax burdens, optimising taxation regimes and monitoring their implications on incentives is a potential avenue which, in line with recent tax cuts (see e.g. Abela & Debattista, 2025; Ministry for Finance, 2025), is likely to encourage higher compliance and potentially increase acceptance of stronger enforcement measures. In terms of the role of self-employed individuals, streamlining processes and facilitating compliance, such as through the development of a National Business Portal (see European Labour Authority (2024)) is important, particularly in an economy where the vast majority of businesses operate at a micro scale. This may be complemented by further targeted compliance and reporting frameworks in sectors characterised by a higher prevalence of cash transactions. Policies aimed at maintaining the low unemployment rates experienced in recent years, not least through a continued focus on job creation, reducing job search frictions, and strengthening labour market attachment, are also expected to contribute to a lower prevalence of underground economic activity.

Model-based estimates, such as those presented in this study, serve to provide an approximation of the trajectory of the shadow economy over time. However, they are unable to shed light on, for example, the exact pathways and legislative shortcomings through which tax frameworks drive economic activity underground, and which segments of the population are most likely to be involved. A holistic and multi-method approach is likely needed in this regard. As argued by Horodnic et al. (2024), more widespread and transparent applications of frameworks such as Eurostat's Tabular Approach to Exhaustiveness (TAE) – under which national statistical institutes are required to estimate and transmit the effect of several factors, including the shadow economy, on the comprehensiveness of National Accounts aggregates – could be a promising avenue, enabling the use of multiple methods and data sources to obtain increasingly robust estimates of the shadow economy and other transactions that escape statistical detection.

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