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Does the Shadow Economy Cast a Cloud on Banking Sector Resilience?

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ABSTRACT

Employing 127 countries over the 1991–2017 period, we investigate whether the shadow economy affects banking sector resilience, as measured by bank non-performing loans, bank capital to total assets, and bank regulatory capital to risk-weighted assets. Using several different methodologies including System GMM, IV estimation, the High Dimensional Fixed Effects (HDFE) estimator, and Least Squares Dummy Variable (LSDV) estimation, we find that the shadow economy significantly negatively affects banking sector resilience. The Juodis et al. (2021) Granger non-causality tests further reveal a bi-directional causality between the shadow economy and bank non-performing loans and bank capital to total assets.

1 | Introduction

This study seeks to investigate the effect of the shadow economy on financial sector resilience. Financial sector resilience in this study is defined as bank capital adequacy and the proportion of non-performing loans (NPLs) (Feyen and Mare 2021). High levels of NPLs can strain a bank's financial health by eroding earnings and reducing liquidity. NPLs therefore, gauge financial sector resilience by reflecting the quality of a bank's loan portfolio and its ability to manage credit risk. The need to cover potential losses from NPLs can lead to a decrease in the bank's capital ratios potentially leading to higher borrowing costs or reduced access to capital, undermining investor, and market confidence, adversely affecting a bank's resilience and stability.

A lack of financial sector resilience can weaken monetary policy, cause capital flight, and increase the risk of financial crises, especially in countries with large shadow economies (Elgin and Uras 2013). These nations may struggle with financial stability due to inadequate disclosure and oversight, a situation that is especially problematic in light of the fact that some countries have shadow economies estimated to be as large as 71% (Medina and Schneider 2019). With growing attention on banking resilience since the financial crisis, understanding the impact of the shadow economy on financial stability is important.

Very few existing studies examine the impact of the shadow economy on the financial sector. Gobbi and Zizza (2007) examine the association between the shadow economy and the credit marke in Italy. They find that the shadow economy places significant limitations on the volume of borrowings by both firms and households. Elgin and Uras (2013), in a study of the relationship between sovereign default risk and the size of the shadow economy in a panel of countries, find a strong causal association between the size of the informal sector and indicators of a country's sovereign default risk and government indebtedness.

Several studies explore the converse, that is, how the financial sector affects the shadow economy. Stewart and Chowdhury (2021) find that banking sector stability, as measured by the banking z-score, enhances economic growth resilience and mitigates the negative impacts of banking crises. Ajide (2021) demonstrates that increased financial inclusion reduces the shadow economy's size. Colombo et al. (2016) reveal that during banking crises, the shadow economy expands, absorbing a significant portion of the decline in formal sector output.

The studies of Irani et al. (2021), Xiao (2020), Ferrante (2018) and Buchak et al. (2018) examine the effects of shadow banking. The findings of Irani et al. (2021) indicate that the entry of shadow banks can significantly impact credit availability and secondary market prices, especially during periods of increased overall uncertainty. Similarly, Buchak et al. (2018) observe that the market share of shadow banks doubled from 2007 to 2015, largely due to regulatory constraints imposed on traditional banks following the financial crisis. Xiao (2020) finds that shadow banks react to monetary policy in a manner opposite to commercial banks: while commercial banks contract, shadow banks tend to expand when the Fed tightens monetary policy. Ferrante (2018) notes that shadow banks tend to have higher endogenous leverage than traditional banks, which boosts credit availability. However, this increased leverage also heightens financial sector fragility due to the lower quality of the loans they finance and their vulnerability to bank runs.

There are also studies which suggest that financial market conditions are an important factor for choosing between operating in the formal and informal sector. For example, Straub (2005), employing a theoretical model within a moral hazard framework with credit rationing, shows how agents form their decisions by comparing the cost of entry into the formal sector with informal credit systems and associated institutional mechanisms.

Blackburn et al. (2012) argue that income disclosures improve with higher levels of financial development, finding that tax evasion is more prevalent at lower economic development stages, leading to a larger informal economy. Studying 137 countries from 1995 to 2007, Bose et al. (2012) observe that a more developed banking sector correlates with a smaller shadow economy and note the importance of both banking efficiency and depth in reducing its size. Similarly, Berdiev and Saunoris (2016) find that financial sector development diminishes the shadow economy, a conclusion also supported by Capasso and Jappelli (2013) and Beck and Hoseini (2014). Additionally, Jacolin et al. (2021) report that the adoption of mobile financial services significantly reduces the size of the informal financial sector.

While most studies highlight the negative impact of the shadow economy on the financial sector, some research presents a more positive view. Asea (1996) argues that the informal sector can expand markets, increase financial resources, foster entrepreneurship, and create a favorable environment for accumulation (as cited in Schneider 2000). Adam and Ginsburgh (1985) find a positive relationship between the growth of the shadow economy and the official economy in Belgium, attributing this to low entry costs and minimal enforcement, suggesting that expansionary fiscal policy benefits both sectors. Saunoris (2018), using data from 100 countries between 1970 and 2008, similarly finds that the shadow economy complements the official economy, providing positive externalities and higher productivity. Additionally, the corruption literature suggests that in countries with weak institutions, shadow economies can positively impact financial sector development by bypassing restrictive regulations.

While our study builds on existing literature, it extends upon previous research by exploring the impact of the shadow economy on financial sector resilience. The shadow economy, which encompasses economic activities that are not reported to the authorities and thus evade regulation and taxation, can significantly impact banking sector resilience in various ways. Banks exposed to loans tied to shadow economy activities may face increased credit risk and a higher likelihood of defaults, which can impact the quality of their loan portfolios and overall stability (Ferrante 2018). The shadow economy can undermine the formal financial sector's stability, as transactions in the shadow economy are not documented or regulated. They can distort the true picture of economic activity, making it difficult for banks to assess risk accurately and manage their financial stability (Williams and Beare 2003) This in turn can place pressure on their revenues and profitability. The presence of a substantial shadow economy can complicate regulatory oversight and enforcement and undermine the effectiveness of economic policies and financial regulations. For example, if a large portion of economic activity is outside the formal sector, monetary policy measures and financial regulations may not have the intended impact on the broader economy. Banks may similarly face challenges in mobilizing capital and liquidity, as they might not fully capture the breadth of economic activity. This can affect their ability to lend and manage their liquidity effectively.

The shadow economy can, therefore, increase bank (NPLs) (Cooray and Schneider 2018). As banks may struggle to accurately assess the creditworthiness of borrowers engaged in shadow economy activities, it could lead to a higher chance of loan defaults (Elgin and Uras 2013), thereby raising the level of NPLs. High shadow economy activities can limit the ability of banks to monitor and manage their exposure to high-risk sectors or borrowers effectively. Without proper oversight, the risk of loans becoming non-performing is heightened. Tax increases or reduced government spending, driven by a significant informal sector, can also diminish formal sector production, leading to an expanded shadow economy and greater government debt (Elgin and Uras 2013), which in turn can adversely affect the quality of bank assets and elevate non-performing loans. Higher credit demand from the informal sector can, moreover, reduce demand for formal sector credit, distorting fund allocation (Gobbi and Zizza 2007; Berdiev and Saunoris 2016) and potentially increasing the risk of non-performing loans while undermining capital adequacy through reduced lending opportunities.

Similarly, as loans extended to borrowers in countries with large shadow economies are often riskier due to the lack of transparency (Ferrante 2018), they could result in defaults, with banks writing off significant amounts, which reduces their capital base. Jiang et al. (2020) for example, show that shadow banks use twice as much equity capital as comparable traditional banks. To mitigate the risk of defaults, therefore, banks might need to set aside higher provisions for potential loan losses. These provisions are recorded as expenses and reduce the bank's profitability, which in turn diminishes retained earnings and, subsequently, the capital base. Reduced earnings affect the bank's ability to build up its capital reserves through retained profits, thereby impacting the capital-to-assets ratio. If a significant portion of the bank's assets is non-performing loans or other risky investments, it can decrease the asset value and affect the capital-to-total-assets ratio. A larger informal sector may similarly compel financial institutions to impose stricter capital regulations to mitigate risk, which can increase the cost of funds and strain capital adequacy (Gobbi and Zizza 2007; Berdiev and Saunoris 2016).

The shadow economy can similarly reduce a bank's regulatory capital-to-risk-weighted-assets (BRC) ratios. Loans and exposures associated with high shadow economies typically involve higher risk (Ferrante 2018). Regulatory frameworks often require banks to assign higher risk weights to these exposures, which increases the amount of capital needed to cover them (Flannery 2014). As a result, even if a bank's capital base remains unchanged, its risk-weighted assets will increase, thereby lowering the capital-to-risk-weighted-assets ratio. When loans become non-performing, their risk weight increases, and the capital required to cover these risks may also increase, potentially decreasing the BRC ratio.

Following from this discussion, we test the following hypotheses:

H1. *The shadow economy increases bank nonperforming loans to gross loans.*

H2. *The shadow economy reduces bank capital to total assets.*

H3. *The shadow economy reduces bank regulatory capital to risk-weighted assets.*

Employing panel data for 127 countries, we perform several robustness checks to test the validity of our results, including three measures of financial resilience, different methodologies involving fixed effects estimation, instrumental variable estimation, the System Generalized Method of Moments (GMM), and the novel Granger non-causality tests of Juodis et al. (2021). Our results suggest that shadow economies reduce banking sector resilience, as measured by bank non-performing loans and capital adequacy. Our dynamic Granger non-causality results strengthen these findings. Accordingly, there is causality between the shadow economy and the banking sector.

The rest of this paper is organized as follows. Section 2 describes the data, model, and methodology used in this study. Section 3 discusses the empirical results, and Section 4 concludes the paper.

2 | Data, Model and Methodology

2.1 | Data

We employ data for 127 countries (Appendix Table A) over the 1991–2017 period. Our dependent variables are the banking sector resilience variables which include bank non-performing loans to gross loans (%) (NPL), bank capital to total assets (%) (BC) and bank regulatory capital to risk-weighted assets (%) (BRC) as in Feyen and Mare (2021), Tölö and Virén (2021), Ari et al. (2019), among others. High levels of NPLs indicate increased credit risk and potential loan defaults. This, in turn, can affect a bank's earnings and liquidity, and the bank may need to set aside more provisions for potential losses (Feyen and Mare 2021). Elevated NPLs can erode investor and depositor confidence, potentially leading to a withdrawal of funds and contributing to market instability. NPLs are the ratio of loans overdue by 90 days or more to the total gross loan portfolio. The calculation includes the entire loan value recorded on the balance sheet, not just the overdue portion (World Bank 2024). Similarly, a higher capital adequacy ratio to total assets and regulatory capital to risk weighted assets indicates that a bank has more capital relative to its risk-weighted assets, which enhances its ability to absorb potential losses arising from risky exposures. BC to total assets is measured as the ratio of a bank's total capital and reserves to its total assets, including tier 1 capital. It also includes total regulatory capital, encompassing tier 2 and tier 3 capital, such as subordinated debt instruments designed to avoid repayment to maintain regulatory capital levels. Total assets are the sum of all non-financial and financial assets held by a bank. BRC assesses the capital adequacy of deposit-taking institutions, calculated as the ratio of a bank's total regulatory capital to its risk-weighted assets. Riskier assets require more capital to mitigate potential losses. This ratio ensures banks maintain adequate capital for their risk exposures. These data are obtained from the World Bank Global Financial Development Database.

Our main independent variable of interest is the shadow economy (SE). This data is from the shadow economy database compiled by Medina and Schneider (2019). The SE encompasses economic activities and income that escape government oversight, regulation, and taxation. This includes legal transactions, both monetary and non-monetary, that are unreported to evade taxes or regulatory compliance. Consequently, they are omitted from national accounts despite their contribution to a country's value added.[1]

We use several other control variables. GDP per capita (constant 2015 US$) to capture the country's level of development (lnGdp). As higher interest rates can lead to higher loan defaults and influence capital adequacy by affecting the value of a bank's assets and liabilities (Cecchetti and Kohler 2014), we thereforeinclude interest payments (% of revenue) (Int) on government debt, including long-term bonds, loans, and other debt instruments made to both domestic and foreign residents. La Porta et al. (2002) show that inefficient governments can lead to low financial sector growth. Therefore, government effectiveness (GE) is used to measure the efficacy of a government. GE gauges public service quality and civil service autonomy from political influence, policy development and execution, and government dedication to policies. The score ranges from −2.5 to 2.5. We use inflation, consumer prices (annual %) (inf) as measured by consumer prices to capture the efficiency of the banking system, as high inflation can lead to higher volumes of non-performing loans and lower bank capital adequacy. Similarly, high debt levels (debt) can adversely affect the banking sector, increasing the volume of non-performing loans and reducing capital adequacy; therefore, we include government debt as a percentage of GDP, which represents the total stock of debt liabilities issued by the government relative to the country's GDP. These control variables are sourced from the World Bank. Finally, we include a banking crisis dummy variable (crisis), a binary variable indicating the presence of a crisis (1 = banking crisis, 0 = no crisis). A crisis is classified as systemic if two conditions are met: (a) substantial evidence of financial distress in the banking system (as indicated by significant bank runs, losses in the banking system, and/or bank liquidations) and (b) significant banking policy intervention measures implemented in response to losses in the

TABLE 1 | Descriptive statistics.

	NPL	BC	BRC	SE	Gdp	Int	GE	Inf	Debt
Mean	6.799	9.421	16.02	29.84	14141.5	9.892	0.199	22.73	54.26
Median	4.000	8.900	15.40	28.97	5688.9	7.422	0.019	4.136	47.36
Maximum	54.54	30.60	48.60	70.52	112417.9	96.04	2.426	4734.9	277.53
Minimum	0.100	1.490	1.754	5.13	189.28	0.000	−2.137	−16.85	0.277
Std. Dev.	7.231	3.716	4.846	13.61	18163.01	9.819	0.952	173.7	34.31
Skewness	2.201	1.097	1.755	0.399	1.933	2.909	0.371	17.17	1.42
Swilk Test	0.764 (0.000)	0.942 (0.000)	0.881 (0.000)	0.975 (0.000)	0.972 (0.000)	0.749 (0.000)	0.959 (0.000)	0.086 (0.000)	0.911 (0.000)
Observations	1794	1731	1817	3402	3342	2259	2391	3205	2090

Note: p values are in brackets.

banking system. It is important to note that this variable encompasses the 2008 global financial crisis and the 2010–2013 sovereign debt crisis. In other words, the series is equal to 1 during these crisis periods. The crisis periods are sourced from the IMF.

Table 1 presents descriptive statistics for the variables used in the study.

The descriptive statistics indicate that the shadow economy has an average value of 29.84, with the minimum and maximum overall values being 5.13 (Switzerland, in 2014) and 70.52 (Bolivia, in 2001) respectively. NPL has an average value of 6.79, with the minimum and maximum overall values being 0.10 (Luxemburg and Sweden, in 2006 and 2007) and 54.54 (Ukraine, in 2017) respectively. For BC and BRC, the maximum and minimum values are recorded for Moldova and Nigeria. All variables are positively skewed. The Shapiro and Wilk test (Swilk test) indicates that all variables have *p* values less than 0.10, indicating that they are not normally distributed.

We also carry out unit root tests on the variables under study (Appendix Table B) employing the Im et al. (2003) *W* statistic (hereafter IPS), the Choi (2001) Fisher Chi (Fisher type) square test, and the Levin et al. (2002) *t* test. The IPS and Fisher-type unit root tests allow for unbalanced panel settings. In addition, the IPS is employed when $N \to \infty$, T fixed, and panel-specific applications. The Fisher type is useful for $N \to \infty$, T finite or infinite, and panel specific.

We find (in Appendix Table B) that NPL and BRC are stationary in levels I (0) according to the IPS, ADF, and LLC unit root tests. However, with BC, while the IPS test indicates stationarity in the first difference, the ADF and LLC tests show that BC is stationary in levels. We proceed based on the findings of the ADF and LLC tests, as they provide consistent conclusions.

2.2 | The Model and Methodologies

Our empirical model takes the following form:

$$y_{it} = \delta y_{i,t-1} + X'_{it}\beta + u_{it} \; (i = 1, \ldots, N; t = 1, \ldots, T), \tag{1}$$

Where δ is a scalar, y_{it} denotes non-performing loans to gross loans (NPL), bank capital to total assets (BC) and bank regulatory capital to risk weighted assets (BRC) for country i in period t and y_{it-1} is a lagged value of the dependent variable. Vector X'_{it} represents all exogenous variables ($1 \times$K), and β is K$\times$1, including the shadow economy and the control variables. u_{it} is assumed to follow a one-way error component model:

$$u_{it} = \mu_i + v_{it}, \tag{2}$$

where $\mu_i \sim IID\left(0, \sigma_\mu^2\right)$ and $v_{it} \sim IID\left(0, \sigma_\mu^2\right)$ independent of each other and among themselves.

The preliminary estimation is undertaken employing system GMM as all explanatory variables used in the empirical model are not strictly exogenous. This method enables controlling for the joint endogeneity of the explanatory variables by using internal instruments (Arellano and Bover 1995; Blundell and Bond 1998). Equation (3), which stands for the variables in levels, is combined with equation (4), which involves variables in first differences.[2] Equation (3) is instrumented by lagged first differences of the variables, while Equation (4) is instrumented by the lagged variables in levels.

$$y_{it} = \gamma y_{it-1} + X_{it}\beta + \varpi_i + \eta_t + \mu_{it} \tag{3}$$

$$y_{it} - y_{it-1} = \gamma\left(y_{it-1} - y_{it-2}\right) + \beta\left(X_{it} - X_{it-1}\right) + \eta_t + \left(\mu_{it} - \mu_{it-1}\right) \tag{4}$$

The variable definitions are the same as in equation (1) above. The GMM estimator is based on the assumption that the error terms are not serially correlated and that the explanatory variables are weakly exogenous and not significantly correlated with future realizations of the error terms (Roodman 2009). Therefore, the following moments condition applies to the first difference estimator:

$E[y_{it\text{-}s} \; (\mu_{it} - \mu_{it-1})] = 0$; $E[\boldsymbol{X}_{it\text{-}s} \; (\mu_{it} - \mu_{it-1})] = 0$; where $i = 1.....n$, $t = 3....$ T and $s \geq 2$.

As the levels' equation is instrumented with lagged first differences of the variables, it leads to an additional moment condition:

$E[\Delta y_{it\text{-}s}(\varpi_i + \mu_{it})] = 0$; $E[\Delta \boldsymbol{X}_{it\text{-}s}(\varpi_i + \mu_{it})] = 0$ for $s = 1$.

The system GMM estimator typically provides more effective predictors for endogenous variables, resulting in better performance than the difference GMM estimator when the series exhibit persistence.

Diagnostic tests, namely the Hansen test for over-identifying restrictions, under which the null hypothesis is that the instruments are not correlated with the residuals, and the Arellano-Bond test for second-order correlation in the first-differenced residuals are carried out. Here, the autocorrelation AR (1) and AR (2) tests are used to detect serial correlation with the error term. If the hypothesis of no second-order serial correlation is valid, autocorrelation will not occur (Roodman 2009). Roodman (2009) states that a Hansen test *p* value between 0.1 and 0.25 indicates reliable results for the endogenous variables. Roodman (2009) suggests that the number of instruments should be fewer than the number of units. To achieve this, one can limit the number of lagged instruments and collapse the instrument matrix (Roodman 2009). We use the Windmeijer-corrected standard errors, using the *xtabond2* Stata command developed by Roodman (2009). Moreover, to reduce the number of moment conditions, the collapse option is used.

We also use three additional estimators for checking the robustness of our results. The first is the high dimensional fixed effects estimator (HDFE) with heteroskedasticity adjusted model clusters to correct for the omitted variable bias developed by Correia (2014, 2016). The second test is the least squares dummy variable corrector (LSDVC) method, which has a dynamic unbalanced bias-corrected test developed by Bruno (2005). The last is the instrumental variable (IV) 2SLS approach, with robust VCE.

Using the HDFE linear estimator developed by Correia (2016), we employ specifications with fixed effects. This estimator is a feasible and computationally efficient solution for large and complex datasets. This method addresses the issue of downward bias in cluster-robust standard errors, although it results in a slight decrease in sample size. HDFE copes with potential heteroskedasticity and autocorrelation and provides better convergence, allowing for two or more levels of fixed effects, fixed slopes, two-way and multi-way clustering, and careful estimation of degrees of freedom, while considering the nesting of fixed effects within clusters and possible sources of collinearity within the fixed effects (Correia 2016).

To mitigate issues of correlation between fixed effects and the lagged dependent variable (Nickell 1981), Kiviet (1995), Judson and Owen (1999), Bun and Kiviet (2003), and Bruno (2005) propose the LSDVC method. The efficacy of this method depends on sample size. Bruno (2005) demonstrates that the LSDVC estimator exhibits greater efficiency than the GMM estimator when the sample size is small. In contrast to the conventional fixed effects method, the LSDVC estimator offers the advantage of resolving the potential endogeneity problems arising from the presence of the lagged dependent variable as an explanatory variable.

In order to correct for endogeneity, the instrumental variable estimation method is also carried out. From an economic perspective, the IV estimation decomposes the observed variations in the explanatory variables into exogenous and endogenous components, thereby isolating the effects of endogeneity. This is typically accomplished through an additional regression known as the "first-stage regression." One of the most frequently employed IV methods is two-stage least squares (2SLS) (Zaefarian et al. 2017). Given the difficulty in finding proper instruments, we use the initial levels of the shadow economy and initial levels of the independent variables in each model as instruments, as the initial levels of these variables are pre-determined compared to current values and are unlikely to affect the current values of the banking resilience variables (Cooray and Schneider 2016; Gupta et al. 2002), thus satisfying the exclusion restriction.

Finally, we use the novel Juodis et al. (2021) Granger non-causality (GNC) test to test for causality between the shadow economy and the banking sector resilience variables. The Juodis et al.'s (2021) GNC test fills the gap in the literature for panel data models with large cross-sectional (N) and time series (T) dimensions. According to the null hypothesis, the Granger causation parameters are assumed to be equal to zero, making them homogeneous. To test this, a pooled least-squares (fixed effects) estimator is used for the parameters. The test is undertaken in two stages. First, it uses the split-panel jackknife method to overcome the Nickell bias. The second stage produces a Wald test based on a bias-corrected estimator (Juodis et al. 2021). The GNC test can be applied to unbalanced panels with stationary data series to check for causality between the variables. The Half Panel Jackknife (HPJ) methodology, as developed by Dhaene and Jochmans (2015) in the context of the GNC approach, has the ability to rectify parameter biases and prevent size distortions. Using this feature, the Juodis et al. (2021) approach enables an examination of Granger causality within both homogeneous and heterogeneous panels. In addition, the GNC method can correct for scale and coefficient biases.

The system GMM and Granger non-causality estimators are preferable to the other baseline estimators for the following reasons. First, the statistical criterion that requires N (number of countries used) to be greater than T (time period) must be satisfied. In this case, there are 127 countries over 27 years (1991–2017). Second, the panel data structure will allow cross-country differences in specifications to be accounted for. Third, the common econometric problems mentioned above can be solved using internal instruments, allowing the inclusion of time-invariant indicators.

3 | Empirical Results

3.1 | System GMM

We first report our baseline results using system GMM. Table 2 reports results with bank non-performing loans to gross loans (NPL) as the dependent variable. Column 1 in the table reports estimates for the shadow economy (SE), GDP, and interest rate (Int). Note that the shadow economy has a positive and significant effect on bank non-performing loans, suggesting that the larger the shadow economy, the larger the non-performing loans. The positive coefficients indicate that an increase in non-performing loans can negatively impact banks by reducing the quality of assets and earning ability, thus reducing banking sector resilience. Surprisingly, a higher

TABLE 2 | System GMM estimation.

Dependent variable: NPL	Sys-GMM 1	2	3	4	5	6
NPL_{t-1}	0.790^{a} (0.0720)	0.687^{a} (0.1142)	0.708^{a} (0.1346)	0.940^{a} (0.2310)	0.946^{a} (0.0689)	0.909^{a} (0.1202)
SE	0.388^{b} (0.190)	0.590^{a} (0.1928)	0.387^{b} (0.188)	0.504^{b} (0.2224)	0.402^{c} (0.2177)	0.516^{c} (0.2892)
lnGdp	5.287^{a} (2.079)	7.15^{a} (2.398)	8.911^{a} (2.517)	13.042^{b} (5.521)	8.783^{b} (3.878)	12.90^{b} (5.624)
Int	0.214^{b} (0.094)	0.175 (0.1129)	0.224^{a} (0.0839)	0.137 (0.1148)	0.172 (0.1268)	0.412 (0.3328)
GE	—	—	−5.388^{b} (2.502)	−5.571^{b} (4.200)	−5.253^{c} (3.075)	−5.830^{b} (2.974)
Inf	—	—	—	—	0.0831 (0.1342)	0.077 (0.1200)
Debt	—	—	—	—	—	−0.051 (0.0557)
Crisis	—	3.916^{b} (1.828)	5.072 (3.282)	—	—	—
Constant	−59.83^{b} (24.199)	−81.677^{a} (27.173)	- 89.98^{a} (26.059)	−53.86^{a} (23.950)	−89.82^{b} (39.72)	−130.26^{b} (57.547)
Hansen test of over-identifying restrictions (*p* value)	0.168	0.245	0.140	0.191	0.259	0.326
AR(1) (*p* value)	0.011	0.025	0.030	0.059	0.015	0.034
AR(2) (*p* value)	0.200	0.166	0.141	0.212	0.182	0.155
OBS	976	985	983	1106	1022	960
Number of groups	81	81	83	97	93	80
Number of instruments	19	17	15	8	17	16
Mean VIF	1.90	1.68	2.73	3.14	2.80	31.5

Note: a, b, and c indicate statistical significance at 1%, 5%, and 10% respectively. Windmeijer corrected standard errors are reported in parentheses. The null hypotheses of the statistical tests are as follows: (1) The Arellano-Bond test for autocorrelation: H_0 = no autocorrelation; (2) The Hansen test: H_0 = the set of instruments is valid.

level of GDP per capita also leads to a greater volume of non-performing loans. This is possibly because the higher the level of GDP per capita in a country, the higher the ability of the banks in that country to lend, giving rise to a higher volume of NPLs. Similarly, the results indicate that higher interest rates lead to a higher volume of non-performing loans. Loan losses can increase as people face higher borrowing costs. Column (2) adds a banking crisis dummy variable to the model (crisis). Note that banking crises lead to a higher volume of non-performing loans, consistent with the literature. This suggests that the relationship between the shadow economy and non-performing loans (NPLs) is more pronounced during periods of banking crises, indicating that the adverse effects of informal economic activity on the banking sector become more apparent in these periods, and that during banking crises, the shadow economy may have a stronger influence on banks' credit risk. In column 3, banking crises are not significant. Note that in this column government effectiveness is statistically significant. It is perhaps due to the effectiveness of government regulations, which has a negative effect on NPL. This is consistent with the studies of La Porta et al. (2002) among others who argue that an inefficient government slows down financial sector growth. Column (5) incorporates inflation. Inflation is not statistically significant. Column (6) adds debt. Note that debt is also not statistically significant. Our main variable of interest, the shadow economy, has a positive and statistically significant effect on NPL in all columns, suggesting that a higher shadow economy contributes to a larger volume of NPL. Similarly, GDP per capita and government effectiveness have a statistically significant impact on NPL in all columns.

The Hansen test for over-identifying restrictions suggests that the instruments are valid at the 5% significance level. The Arellano-Bond test for second-order serial correlations in the first differences indicates the absence of second-order serial correlation between the first-differenced errors, thus supporting the consistency of the estimators.

TABLE 3 | System GMM estimation.

Dependent variable: BC	Sys-GMM					
	1	**2**	**3**	**4**	**5**	**6**
BC_{t-1}	0.847[a] (0.1425)	0.905[a] (0.0694)	−0.0023 (0.0611)	0.133 (0.1082)	0.084 (0.1003)	0.393[a] (0.1386)
SE	−0.087[b] (0.0603)	−0.115[b] (0.0509)	−0.213[b] (0.0843)	−0.211[b] (0.1073)	−0.190[b] (0.0903)	−0.152[c] (0.0879)
lnGdp	−0.924[a] (0.5819)	−1.125[a] (0.5493)	−3.129[c] (1.770)	−3.639[b] (1.672)	−1.115 (1.418)	0.6110 (1.815)
Int	−0.018 (0.0293)	−0.0155 (0.0208)	−0.155[a] (0.0577)	−0.123 (0.0906)	−0.152[b] (0.0658)	−0.086 (−0.0847)
GE	—	—	−1.412 (1.700)	−0.422 (3.507)	−3.617[b] (1.717)	−5.020[b] (2.301)
Inf	—	—	—	—	−0.040 (0.0373)	−0.079[c] (0.0451)
Debt	—	—	—	—	—	0.005 (0.0113)
Crisis	—	0.758 (1.070)	−0.161 (1.432)	—	—	—
Constant	12.290[a] (7.5036)	14.25[a] (6.4558)	45.567[a] (16.82)	48.037[a] (15.83)	26.70[a] (13.72)	6.709 (17.32)
Hansen test of over-identifying restrictions (*p* value)	0.137	0.192	0.300	0.169	0.287	0.272
AR(1) (*p* value)	0.000	0.000	0.421	0.695	0.235	0.006
AR(2) (*p* value)	0.772	0.752	0.701	0.690	0.516	0.340
OBS	1030	1015	1036	578	824	901
Number of groups	81	80	95	57	77	78
Number of instruments	18	18	17	16	19	16
Mean VIF	1.92	2.76	2.73	3.14	2.80	3.15

Note: a, b, and c indicate statistical significance at 1%, 5%, and 10% respectively. Windmeijer corrected standard errors are reported in parentheses. The null hypotheses of the statistical tests are as follows: (1) The Arellano-Bond test for autocorrelation: H_0 = no autocorrelation; (2) The Hansen test: H_0 = the set of instruments is valid.

Next, we re-run the estimation with bank capital to total assets as the dependent variable. The results are reported in Table 3. Note that the shadow economy has a negative and significant effect on bank capital to total assets in all columns, implying that the greater the shadow economy in a country, the greater the amount of capital the banks in a country must hold. Large informal economies can pose challenges to the capital of banks due to smaller formal sectors limiting their ability to raise funds. GDP per capita is negative and significant in the first four columns, implying that a higher level of GDP requires less bank capital. The interest rate is statistically significant only in column (3). Government effectiveness has a negative significant effect in all columns, suggesting that when a country has an effective government, banks require less capital to total assets, consistent with our previous results. Inflation and government debt are not statistically significant. The banking crisis dummy is statistically significant in column (2) and suggests that when there are more crises, banks must hold more capital.

Table 4 re-estimates the models with bank regulatory capital to risk weighted assets as the dependent variable. The shadow economy continues to have a statistically significant negative effect on bank regulatory capital to risk weighted assets implying that the larger the shadow economy, the larger the amount of bank regulatory capital to risk weighted assets banks need to hold, reducing baking sector resilience. GDP has a negative significant effect suggesting that banks in countries with higher per capita GDPs need to hold less regulatory capital. The coefficient on the banking crisis dummy variable is positive and significant in both columns suggesting that banking crises require more bank regulatory capital. Government effectiveness is statistically significant only in column (5).

In Tables 3 and 4, the Hansen test of over-identifying restrictions suggests that the instruments are valid at the 5% level of significance. The Arellano-Bond test for second-order serial correlations in the first differences indicates the absence of second-order serial correlation between the

TABLE 4 | System GMM estimation.

Dependent variable: BRC	Sys-GMM					
	1	2	3	4	5	6
BRC_{t-1}	−0.160[a] (0.0844)	0.223 (0.2575)	0.401 (0.0588)	−0.174[a] (0.0434)	−0.142[a] (0.0339)	−0.144[a] (0.0342)
SE	−0.406[a] (0.1773)	−.425[a] (0.0760)	−0.069[b] (0.0321)	−0.106[c] (0.0532)	−0.103[c] (0.0535)	−0.093[c] (0.0539)
lnGdp	−3.261[b] (1.599)	−3.813[a] (0.6104)	−0.186 (0.4553)	−0.582 (0.4537)	−2.189[b] (0.9365)	−2.066[b] (0.9581)
Int	−0.122 (0.1127)	−0.132 (0.0867)	−0.060[b] (0.0294)	−0.163 (0.0232)	−0.103[c] (0.0616)	−0.109[c] (0.0615)
GE	—	—	−0.410 (0.8174)	−0.881 (0.7093)	−3.377[c] (1.953)	−3.181 (1.989)
Inf	—	—	—	—	−0.033 (0.0477)	−0.031 (0.0484)
Debt	—	—	—	—	—	0.006 (0.0139)
Crisis	—	8.874[b] (3.547)	9.065[a] (1.421)	—	—	—
constant	59.158[a] (19.35)	58.24[a] (18.40)	13.75[a] (4.131)	12.27[a] (5.1758)	41.53[a] (7.536)	40.038[a] (7.874)
Hansen test of over-identifying restrictions (*p* value)	0.115	0.113	0.147	0.238	0.164	0.136
AR(1) (*p* value)	0.844	0.190	0.113	0.069	0.281	0.282
AR(2) (*p* value)	0.271	0.892	0.288	0.372	0.184	0.178
OBS	1172	971	394	902	394	395
Number of groups	96	78	40	77	40	40
Number of instruments	16	20	23	17	22	22
Mean VIF	1.93	1.70	2.75	3.18	2.83	3.15

Note: a, b, and c indicate statistical significance at 1%, 5%, and 10% respectively. Windmeijer corrected standard errors are reported in parentheses. The null hypotheses of the statistical tests are as follows: (1) The Arellano-Bond test for autocorrelation: H_0 = no autocorrelation; (2) The Hansen test: H_0 = the set of instruments is valid.

first-differenced errors, thus supporting the consistency of the estimators.

3.2 | Robustness Checks

We employ three additional estimators to check the robustness of our findings. The first is the high-dimensional fixed-effects (HDFE) linear estimator, the second is a dynamic unbalanced bias-corrected test, and the third is the IV estimator. Next, we re-estimate the models by employing fixed effects to correct for the omitted variable bias. The linear panel data model estimator, which incorporates fixed effects, enables us to create controls for constant, time-invariant unobserved heterogeneity specific to individuals or groups of individuals.

As we have three dependent variables, we continue to report only the results for NPL in Table 5. Note the results for bank capital to total assets and bank regulatory capital to risk weighted assets are consistent with those obtained above.

The HDFE results reported in Table 5 show that the coefficients on the shadow economy continue to be positive and statistically significant, although most other variables are not statistically significant. The estimation process may be affected by the presence of an omitted variable; however, the shadow economy coefficient remains consistent across the models. As OLS, random effects, and fixed-effect estimators do not fully account for the bias of the fixed-effect estimator, resulting in less robust outcomes, we utilize the LSDVC model. This estimator is a dynamic unbalanced bias-corrected

TABLE 5 | HDFE estimation.

Dependent variable: NPL	Panel HDFE 1	2	3	4	5	6
NPL_{t-1}	0.774[a] (0.000)	0.752[a] (0.000)	0.766[a] (0.000)	0.776[a] (0.000)	0.775[a] (0.000)	0.770[a] (0.000)
SE	0.181[a] (0.005)	0.165[b] (0.010)	0.144[b] (0.032)	0.154[b] (0.023)	0.158[b] (0.021)	0.218[a] (0.001)
lnGdp	−0.928 (0.618)	−0.860 (0.626)	−1.75 (0.384)	−1.860 (0.394)	−1.981 (0.363)	0.062 (0.974)
Int	0.074[c] (0.054)	0.056 (0.118)	0.061 (0.148)	0.083[c] (0.067)	0.080 (0.198)	−0.058 (0.459)
GE	—	—	1.22[c] (0.080)	1.188[c] (0.099)	1.256 (0.102)	1.323 (0.124)
Inf	—	—	—	—	−0.006 (0.839)	−0.010 (0.779)
Debt	—	—	—	—	—	0.053[a] (0.006)
crisis	—	2.10[a] (0.005)	2.03[b] (0.010)	—	—	—
constant	4.61 (0.796)	4.50 (0.791)	12.59 (0.511)	13.20 (0.522)	14.24 (0.487)	−7.70 (0.670)
F test Prob	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
R^2	0.8731	0.8784	0.8739	0.8690	0.8693	0.8777
OBS	1290	1290	1200	1200	1184	988
Number of clusters (id)	95	95	95	95	94	78

Note: a, b, and c indicate statistical significance at 1%, 5%, and 10% respectively. Parentheses indicate the *p* value.

approach, developed by Bruno (2005). Dynamic panel data modeling requires the inclusion of a lagged dependent variable as an independent variable. GMM and Instrumental Variable (IV) estimators are commonly used techniques for this purpose; however, they may not be efficient for small sample sizes and can suffer from biases in certain situations. Bruno (2005) proposed a bias-corrected LSDVC procedure to address these limitations. Monte Carlo simulations have shown that LSDVC outperforms other dynamic estimators in terms of smaller variances and provides more accurate estimates in all finite sample cases. Results for BC and BRC as dependent variables are also consistent with the results obtained under system GMM (not reported).

Table 6 replicates the estimation in Table 2 with non-performing loans as the dependent variable, employing the LSDVC method.

These findings are consistent with the system GMM results. The results suggest that an increase in the shadow economy leads to an increase in NPLs. Moreover, an increase in lnGdp and interest rate payments continues to lead to an increase in NPLs. The rate of inflation is insignificant, as in the system GMM findings. Government effectiveness and debt are statistically significant only in column (6) and banking crises have a positive and significant effect on non-performing loans.

As a further robustness check, we also estimate the models employing the IV estimator. Table 7 presents the results. As stated above, we use the initial levels of the shadow economy and initial levels of the independent variables in each model as instruments, as the initial levels of these variables are pre-determined compared to current values and are unlikely to affect the current values of the banking resilience variables (Cooray and Schneider 2016; Gupta et al. 2002).

These findings are consistent with that obtained above. The shadow economy continues to have a significant positive impact on non-performing loans. Similarly, lnGdp leads to an increase in NPLs. An increase in government effectiveness leads to a decrease in NPL. Interest rate payments have a positive effect on non-performing loans. Inflation and debt are not significant, and the banking crisis dummy is positive and significant suggesting that bank crises increase NPLs. The results of the two-step system GMM estimator are verified by Hansen's J test for instrument validity in Table 7. The model accuracy test results (robust score chi^2, robust regression *F*, Endogenous R^2) show that the instrumental variables are valid.

In addition, we employ the test developed by Olea and Pflueger (2013) to assess the presence of weak instruments. This methodology is applicable for evaluating weak instruments in linear IV regression models in the post-estimation

TABLE 6 | Dynamic unbalanced bias corrected estimation.

Dependent variable: NPL	Dynamic unbalanced bias corrected (LSDVC) 1	2	3	4	5	6
NPL_{t-1}	0.792[a]	0.777[a]	0.797[a]	0.793[a]	0.796[a]	0.753[a]
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
SE	0.1075[b]	0.121[b]	0.090[c]	0.109[b]	0.089[c]	0.118[b]
	(0.026)	(0.010)	(0.082)	(0.029)	(0.084)	(0.047)
lnGdp	1.65[c]	1.91[b]	1.76[c]	2.069[b]	1.61[c]	−0.137
	(0.051)	(0.020)	(0.062)	(0.025)	(0.093)	(0.900)
Int	0.067[a]	0.053[b]	0.075[b]	0.056[b]	0.068[b]	–.075[b]
	(0.001)	(0.010)	(0.001)	(0.015)	(0.017)	(0.039)
GE	—	—	0.439	0.610	0.452	1.063[c]
			(0.395)	(0.224)	(0.385)	(0.066)
Inf	—	—	—	—	−0.026	−0.015
					(0.212)	(0.530)
Debt	—	—	—	—	—	0.063[a]
						(0.000)
crisis	—	0.053[b]	—	2.435[a]	—	—
		(0.000)		(0.000)		

Note: a, b, and c indicate statistical significance at 1%, 5%, and 10% respectively. Parentheses indicate the *p* value.

phase as well as in two-stage least squares (TSLS) estimation and the limited-information maximum likelihood (LIML) method with a single endogenous regressor. Under the condition of strong instruments, the TSLS and LIML estimators are asymptotically unbiased. However, this property does not hold in the presence of weak instrumentation. The weak-instrument test examines the null hypothesis of weak instruments. Upon rejection of the null hypothesis, we conclude that the instruments are strong and proceed with a standard inference (Pflueger and Wang 2015).

Table 8 reports the Olea and Pflueger (2013) F statistic of 25.133 for weak instruments. The TSLS critical value and LIML critical value are 13.253 for $\tau = 5\%$, suggesting that the null of weak instruments for TSLS or for LIML for a weak instrument threshold of $\tau = 5\%$ can be rejected.

3.3 | Granger Non-Causality

We employ the following model to test for causality between the shadow economy and banking sector:

$$NPL_{i,t} = \sigma_{0,i} + \sum_{p=1}^{P} \sigma_{p,i} NPL_{i,t-p} + \sum_{p=1}^{P} \beta_{1p,i} SE_{i,t-p} + \mu_{i,t}, \quad (4)$$

for $i = 1, \ldots, N(127)$ and $t = 1, \ldots, N(27)$.

The null hypothesis that the time series $SE_{i,t}$ does not Granger-cause $NPL_{i,t}$ and can be formulated as a set of linear restrictions on the β_1's in Equation (4). This can be adapted to the other two banking sector variables. Apart from these, we also investigate reverse causality for the feedback approach (NPL Granger-cause SE, etc.). Table 9 reports results for the Juodis et al. (2021) Granger non-causality test.

The null hypothesis that SE does not Granger-cause NPL is rejected at the 5% level of significance. The results reveal bi-directional causality between the shadow economy and NPLs and bank capital to total assets. Studies show that a stronger banking sector reduces the size of the shadow economy (Bose et al. 2012). Therefore, the existence of large informal sectors can lead to higher NPLs and lower bank capital, weakening the banking sector and further increasing the size of the shadow economy. The results reveal unidirectional Granger causality from the shadow economy to bank regulatory capital to risk-weighted assets.

4 | Conclusion

Analyzing data for 127 countries between 1991 and 2017, we investigate the impact of the shadow economy on banking sector resilience, using non-performing loans, bank capital to total assets, and regulatory capital to risk-weighted assets. Our findings, using the System GMM, IV estimation, HDFE, and LSDV methods, show that the shadow economy significantly undermines banking sector resilience. The Juodis et al. (2021) Granger non-causality tests reveal a bi-directional relationship between the shadow economy and both non-performing loans and bank capital to total assets. High NPLs reduce asset quality and earning capacity, potentially necessitating higher capital adequacy ratios and further weakening the banking sector.

Additionally, we find that higher GDP per capita correlates with increased NPLs, possibly because wealthier countries can afford more lending, resulting in more NPLs. Interest rates and bank

TABLE 7 | IV estimation (VCE robust version of IV-2SLS).

Dependent variable: NPL	IV-2SLS 1	2	3	4	5	6
SE	0.194[a] (0.000)	0.165[a] (0.000)	0.076[b] (0.012)	0.095[a] (0.006)	0.107[a] (0.002)	0.206[c] (0.064)
lnGdp	2.72[a] (0.000)	2.20[a] (0.000)	4.81[a] (0.001)	6.265[a] (0.000)	7.051[a] (0.000)	15.057[c] (0.051)
Int	0.077[a] (0.005)	0.058[b] (0.022)	0.085[b] (0.027)	0.117[a] (0.007)	0.135[a] (0.002)	0.3884 (0.112)
GE	—	—	−4.98[a] (0.000)	−6.378[a] (0.000)	−7.34[a] (0. 000)	−15.19[b] (0.042)
Inf	—	—	—	—	−0.070 (0.234)	−0.171 (0.151)
Debt	—	—	—	—	—	−0.042 (0.252)
Crisis	—	1.97[a] (0.001)	1.66[a] (0.010)	—	—	—
Constant	−30.77[a] (0.000)	−25.10[a] (0.000)	−44.13[a] (0.001)	−57.36[a] (0.000)	−64.20[a] (0.000)	−136.09[c] (0.051)
R^2	0.7607	0.7963	0.7252	0.6325	0.5766	(0.249)
Robust score chi^2	0.7607 (0.0000)	18.6257 (0.0000)	16.2809 (0.001)	19.437 (0.0000)	25.2691 (0.0000)	9.79859 (0.0017)
Robust regression F	26.15 (0.000)	20.7164 (0.0000)	17.6338 (0.000)	22.0626 (0.0000)	26.7163 (0.0000)	4.7157 (0.0301)
Endogenous R^2	0.6768[a] (0.000)	0.6793[a] (0.0000)	0.8287[a] (0.0000)	0.8277[a] (0.0000)	0.8277[a] (0.0000)	0.8277 (0.5588)
Score chi^2	13.7569 (0.0081)	11.8448 (0.0185)	11.897 (0.0181)	11.5101 (0.0214)	8.17956 (0.0424)	2.01974 (0.3643)
Hansen J p value	0.9128	0.9161	0.9643	0.9046	0.9931	0.9586
OBS	1012	976	944	944	944	944

Note: a, b, and c indicate statistical significance at 1%, 5%, and 10% respectively. Parentheses indicate the p value. Initial values of the independent variables in each model are used as instruments.

TABLE 8 | Olea and Pflueger robust weak instrument test.

Effective F statistic	**25.133**	
Confidence level alpha:	5%	
Critical Values (% of worst-case Bias)	TSLS	LIML
tau = 5%	13.253	13.253
tau = 10%	8.525	8.525
tau = 20%	5.898	5.898
tau = 30%	4.930	4.930

Note: This post's estimations are based on Column 1 of Table 7.

crises also increase NPLs while reducing bank capital, whereas government effectiveness lowers NPLs and increases bank capital.

The large informal sectors in many developing economies significantly impact financial sector resilience, highlighting the need for effective policies and a robust property rights system. Strong institutions and effective governance are crucial for promoting financial sector development, limiting informal economies, and supporting long-term economic growth.

Endnotes

[1] Medina and Schneider (2019) use a Multiple Indicators Multiple Causes (MIMIC) model to estimate the shadow economy variable. The model identifies specific causes and indicators that influence the shadow economy. The primary causes include (i) tax burden, where higher taxes incentivize operating outside the formal sector; (ii) institutional quality, where weaker institutions, characterized by law disrespect or high corruption, encourage informality; (iii) openness, measured by trade openness, suggesting greater economic interconnectedness complicates hiding informal activities from authorities; and (iv) unemployment, where higher rates push individuals into the informal economy because of limited formal opportunities. The MIMIC model also uses key indicators to measure the shadow economy, including: (i) currency as a fraction of broad money, reflecting reliance on cash

TABLE 9 | Judois et al. (2021) Granger non-causality test results.

Causality direction	HPJ Wald Stat	HPJ *p* value	Cross-sectional heteroskedasticity-robust variance estimation			
			Coef.	Stand. errors	*p*	Results
SE Granger-cause NPL	7.735	0.0518	0.207	0.079	0.009	Yes
SE Granger-cause BC	7.239	0.0646	−0.046	0.0191	0.015	Yes
SE Granger-cause BRC	18.318	0.0004	−0.122	0.039	0.002	Yes
NPL Granger-cause SE	20.588	0.0001	−0.146	0.0374	0.000	Yes
BC Granger-cause SE	14.092	0.0028	0.213	0.079	0.007	Yes
BRC Granger-cause SE	3.711	0.1564	0.005	0.031	0.857	No

Note: H_0: Selected covariates do not Granger-cause; H_1: X variables do Granger-cause Y variables for at least one panel var. HPJ Wald; Half-Panel Jackknife Wald test, *p* value HPJ; Half-Panel Jackknife *p* values. Lag selection by BIC.

transactions; (ii) labor force participation, where a decrease may indicate a shift to informal employment; and (iii) the size of the economy, providing context for the shadow economy's relative scale (Medina and Schneider 2019, 4–5).

[2] The system GMM estimator may not correct for the potential omitted variable bias. We attempt to correct for this by including the lagged values of the dependent variable as a regressor in the estimation, as past values of the dependent variable can influence current values. The system GMM estimator, however, permits correction for potential endogeneity. We also use the fixed effects estimator to correct for the omitted variable bias by taking into account fixed effects.

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Appendix A

TABLE A | List of Countries.

Albania	Jamaica	Cabo Verde	Pakistan	Denmark	Norway
Argentina	Kazakhstan	Cambodia	Papua New Guinea	Estonia	Oman
Armenia	Libya	Cameroon	Philippines	Finland	Poland
Azerbaijan	Malaysia	Congo, Rep.	Senegal	France	Portugal
Belarus	Mauritius	Egypt, Arab Rep.	Sri Lanka	Germany	Qatar
Belize	Maldives	Ghana	Tanzania	Greece	Romania
Bosnia and Herzegovina	Mexico	Guinea	Tunisia	Guyana	Saudi Arabia
Botswana	Moldova	Haiti	Ukraine	Hong Kong SAR, China	Singapore
Brazil	Namibia	Honduras	Ukraine	Hungary	Slovak Republic
Bulgaria	Paraguay	India	Vietnam	Iceland	Slovenia
China	Peru	Jordan	Zambia	Ireland	Spain
Colombia	Russian Federation	Kenya	Zimbabwe	Israel	Sweden
Costa Rica	South Africa	Kyrgyz Republic	Australia	Italy	Switzerland
Dominican Republic	Suriname	Lao PDR	Austria	Japan	United Arab Emirates
Ecuador	Thailand	Lebanon	The Bahamas	Korea, Rep.	United Kingdom
El Salvador	Türkiye	Lesotho	Bahrain	Kuwait	United States
Equatorial Guinea	Algeria	Mauritania	Belgium	Latvia	
Fiji	Angola	Mongolia	Canada	Lithuania	
Gabon	Bangladesh	Myanmar	Chile	Luxembourg	
Georgia	Benin	Nepal	Croatia	Malta	
Guatemala	Bhutan	Nicaragua	Cyprus	Netherlands	
Indonesia	Bolivia	Nigeria	Czech Republic	New Zealand	

TABLE B | Unit root test results.

	Individual unit root process intercept and trends		**Common unit roots process intercept and trends**
Variables	**Im, Pesaran and Shin *W*-stat**	**ADF-Fisher Chi-square**	**Levin, Lin and Chu *t****
NPL	−4.57534 (a)*	349.065 (a)*	−27.6954 (a)*
BC	−0.95585 (b)*	285.179 (a)**	−7.26248 (a)*
BRC	−6.22506 (a)*	315.011 (a)*	−64.7002 (a)*
Se	−3.17901 (a)*	319.375 (a)**	−3.17901 (a)*
lnGdp	−1.72253 (a)**	346.199 (a)*	−1.87342 (a)**
Int	−2.32196 (a)**	353.866 (a)*	−5.25082 (a)*
Ge	−5.81959 (a)*	412.997 (a)*	−10.6464 (a)*
Enf	−162.417 (a)*	3273.87 (a)*	−723.051 (a)*
Debt	−4.31713 (a)*	270.920 (a)*	1.66571$^{(n)}$

Note: **, and * denote 5%, and 1% statistical significance levels, respectively; a and b are stationarity in levels, and the first difference, respectively. Automatic lag length selection based on SIC: 0 to 3 Newey-West automatic bandwidth selection and Barlett kernel. Results include an individual intercept and trends. ^{n}indicate that LLC findings have an individual intercept and trends, and the series is non-stationary in the first and second differences.