After the Shock
Reform, Resilience, and Economic Transformation in MENA
ERF 32nd Annual Conference
June 14-16 | Cairo, Egypt

2026

# Casting Light on Africa's Shadow Economy

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ECONOMIC RESEARCH FORUM
منتدى البحوث الاقتصادية

Casting Light on Africa's Shadow Economy★

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**Abstract**

This paper develops a novel empirical framework integrating satellite imagery and machine learning to estimate the size and dynamics of the shadow economy across all African countries from 2000 to 2024. Addressing the inherent challenges of measuring hidden economic activity, especially in data-scarce and conflict-affected contexts, the study leverages multiple harmonized proxies and advanced econometric techniques to produce robust and granular estimates. We benchmark these results against traditional methods, revealing improved accuracy and new insights into regional heterogeneity between North Africa and Sub-Saharan Africa. Using local projections, we analyze informality's dynamic response to macroeconomic shocks, while machine learning identifies key drivers of shadow economic activity. Finally, we empirically assess how conflict events and instability affect informality. Our integrated approach delivers the most comprehensive and validated dataset of Africa's shadow economy to date, offering valuable guidance for policy and further research.

*Keywords:* Shadow economy, Informal sector, Africa, Satellite imagery, Machine learning, Conflict and instability, Macroeconomic shocks, Sub-Saharan Africa, North Africa, Economic measurement
*JEL*: O17, C55, E26, O55, D74

## 1. Introduction

Africa's shadow economy ranks among the largest worldwide, often comprising 30 to 50 percent of GDP in many countries Deléchat and Medina (2021). While informal activities sustain millions of livelihoods, they simultaneously undermine tax collection, distort markets, and challenge effective policymaking. Perceptions of informality have intensified amid growing economic and political instability across the continent, yet the relevance and impact of informality vary considerably between countries. Traditional measurement approaches—including surveys, Multiple Indicators Multiple Causes (MIMIC) models, and currency demand

★ The views expressed here are those of the authors and do not necessarily represent the views of the IMF, its Executive Board, or IMF management.

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analysis—provide broad estimates but lack precision in data-scarce and conflict-affected environments. In these contexts, weakened state capacity and unrecorded transactions lead to significant underreporting of economic activity. Moreover, conflict and geopolitical instability often fuel informality by diverting resources into unmonitored channels.

By its nature, measuring activities meant to remain hidden is inherently challenging, a task made even more difficult by the sparse and unreliable data prevalent in many African countries. This study proposes an integrated empirical framework that combines satellite imagery and machine learning to estimate the size and dynamics of the shadow economy across all African countries. The framework pays particular attention to heterogeneity by comparing North Africa and Sub-Saharan Africa, shedding light on regional variations in informal economic activity.

The core contributions of the paper include producing an updated, comprehensive map of informality in Africa, estimating the shadow economy's share of GDP in each country from 2000 through 2024. A central innovation lies in improved measurement within conflict-affected states; by incorporating conflict event data, the satellite and machine learning approach generates more accurate estimates precisely where formal data are weakest. This enables assessment of how instability and conflict drive informality, factors often overlooked by conventional models.

Methodologically, new estimates are benchmarked against existing datasets, including those from Elgin et al. (2021), demonstrating that machine learning models provide superior predictive accuracy, especially in fragile and data-scarce contexts. While confirming known patterns—such as greater informality in lower-income countries—the analysis also uncovers novel insights. Notably, it reveals that informal economic activity can expand during periods of rising conflict events.

The paper further explores the dynamic response of informality to macroeconomic shocks, specifically GDP and inflation fluctuations, using local projection techniques across the continent and within North African and Sub-Saharan African subregions. Machine learning methods identify key drivers, capturing heterogeneity across space and time. Finally, by integrating conflict and governance indicators, the study empirically quantifies the impact of instability on the shadow economy, offering critical evidence on how conflict shapes informality in fragile states.

Taken together, these contributions present the most robust and nuanced portrait of Africa's shadow economy to date. The approach provides a scalable tool for tracking informality in hard-to-survey settings and highlights that reducing informality requires not only regulation but also improvements in governance and political stability. This work informs both scholarly debates and policy design aimed at fostering inclusive economic growth.

The remainder of the paper is organized as follows. Section 2 overviews recent trends and estimates of the shadow economy. Section 3 reviews the literature. Section 4 describes the data sources and processing steps used in the analysis. Section 5 details the empirical methodology, including the construction of the shadow economy estimates and the machine learning framework. Section 6 presents the empirical results, covering benchmarking, dynamics of informality, and the impact of conflict and instability. Finally, Section 7 concludes, discussing policy implications.

## 2. The Shadow Economy's Trends and Estimates

The informal sector plays a vital role in many economies, encompassing activities, institutions, jobs, and workers operating outside formal regulatory and protective frameworks (Aktaruzzaman and Farooq, 2020; Salinas et al., 2023). In developing countries, the informal economy—or shadow economy—can account for up to 70% of GDP, compared to approximately 15% in developed nations. This aligns with evidence showing that higher economic development correlates with smaller informal sectors (La Porta and Shleifer, 2008, 2014). Nonetheless, considerable variation exists across regions and countries regarding the size and prevalence of informal activities.

Sub-Saharan Africa, Europe and Central Asia, Latin America, and the Caribbean exhibit some of the highest shares of the informal economy relative to GDP (Elgin et al., 2021). According to the International Labor Organization (ILO, 2025), over 60% of the global workforce and 80% of enterprises operate informally. Informal employment comprised roughly 57.7% of total employment worldwide in 2025, with substantial disparities by income level: 8.5% in high-income countries, 52.9% in upper-middle-income, 83.4% in lower-middle-income, and 90.2% in low-income countries. Regionally, informal employment rates reached 85.2% in Africa, 65.6% in Asia and the Pacific, 11.9% in Europe and Central Asia, and 34.5% in the Americas (ILO, 2025).

These figures have drawn significant attention from researchers and policymakers. On one hand, the informal sector is viewed as a barrier to economic development and effective public policy, undermining formal institutions, contributing to low productivity, and reducing tax revenue (La Porta and Shleifer, 2008, 2014; Ulyssea, 2020). For instance, an experimental study spanning 57 urban areas across 31 countries found that persistent informality impedes sustainable development and long-term growth (Elgin et al., 2021). On the other hand, the informal economy is recognized for providing essential employment opportunities, reducing unemployment, and fostering entrepreneurship and resilience, particularly in low-income settings

(Chen, 2012, 2014; Loayza, 2016). These contrasting perspectives underscore the importance of studying informality in African countries, where large informal sectors may offer lessons applicable to other low- and middle-income nations.

Africa's shadow economy ranks among the world's largest, comprising 30–50% of GDP in many countries (Deléchat and Medina, 2021). Estimates from the African Development Bank (AfDB, 2020) indicate that the informal sector employs about 80% of the continent's workforce and accounts for roughly 55% of Africa's GDP (Afful et al., 2025). While this sector sustains millions of livelihoods, particularly among women and youth, it also challenges tax collection, distorts markets, and complicates policymaking.

Rising economic and political instability—driven by conflicts and wars—has intensified perceptions of informality in Africa. In both MENA countries and Sub-Saharan Africa, disruptions caused by armed conflict have pushed many into informal livelihoods (Heintz and Valodia, 2008; Vorisek et al., 2022). Yet, the size and effects of the shadow economy vary substantially by country. Conflict and geopolitical instability further exacerbate informality by channeling resources into unmonitored activities. Crises such as the COVID-19 pandemic disproportionately affected informal workers (ILO, 2025; World Health Organization, 2020). Socioeconomic factors like poverty and inequality also heighten the vulnerability of informal households to shocks (Vorisek et al., 2022), driving further expansion of the informal economy as individuals evade formal restrictions.

This complexity complicates accurate measurement. Traditional approaches—including surveys, MIMIC models, and currency demand analyses—often provide imprecise estimates, especially in data-poor or conflict-affected contexts where state capacity is limited and transactions are unrecorded. Recognizing these challenges, the 21st International Conference of Labor Statisticians adopted a resolution in 2023 to update and enhance measurement standards for the informal economy (ILO, 2025).

## 3. Literature Review

The informal economy in Africa has attracted growing scholarly attention, reflecting both its large size and its implications for development, governance, and macroeconomic stability. Existing studies employ diverse methodologies—from survey-based approaches and currency-demand models to structural equation and MIMIC frameworks—to estimate the magnitude of informality and explore its determinants. While this literature provides valuable insights, traditional measurement approaches face well-documented limitations in data-scarce or fragile settings, where institutional capacity is weak, reporting is incomplete, and conflict disrupts formal economic activity. These gaps motivate recent efforts to incorporate satellite-based indicators, including nighttime lights, as more robust proxies for economic activity in low-information contexts.

Research consistently highlights a wide range of economic, social, and political factors shaping informality in Africa, including infrastructure quality, digital transformation, economic complexity, natural resource dependence, governance quality, demographic pressures, inequality, and energy poverty. This rich set of determinants also aligns with the machine-learning feature space used in this study, which integrates both structural characteristics and institutional indicators to capture nonlinear relationships affecting informality.

Using a structural equation model with latent variables, Abid (2016) estimated the size of the informal economy in 41 African countries over 2007–2013, finding an average of 42.9% of formal GDP with substantial regional variation. These findings underscore the persistent and heterogeneous nature of informal activity across the continent. Medina et al. (2017) advanced the literature by critiquing GDP's dual role as both cause and indicator in MIMIC models and introducing light-intensity data to improve identification. Their Predictive Mean Matching (PMM) estimates show persistently high informality across Sub-Saharan Africa, ranging from 20–25% in Mauritius, South Africa, and Namibia to 50–65% in Benin, Tanzania, and Nigeria.

Institutional quality and regulatory environments have also received considerable attention. The World Bank (2016) documented deteriorating regulatory frameworks, corruption, and weak public-sector capacity in North Africa, identifying these as key drivers of informal activity. At the country level, Etim and Daramola (2020) found that tax burdens, income inequality, unemployment, bureaucratic inefficiencies, and corruption contribute significantly to informality in South Africa and Nigeria.

Digitalization has emerged as a promising driver of formalization. Haruna and Alhassan (2022) showed that improvements in telecommunications infrastructure and expansion of government online services significantly reduce the size of the shadow economy in 42 African countries. Similarly, Ningaye and Ketu (2023) found that infrastructural development plays a critical role in decreasing informality across the continent.

Other work emphasizes deeper structural constraints. Vorisek et al. (2022) linked widespread informality to declining human capital, a large agricultural sector, weak institutions, and heavy regulatory burdens, while noting that conflict and instability exacerbate the shift to informal channels—highlighting a gap in the literature, as rigorous quantification of conflict–informality linkages remains limited. This gap directly motivates this study, which incorporates conflict indicators and geopolitical risk measures into a unified ML framework.

A growing strand focuses on natural resource revenues. Ajide and Ridwan (2023) showed that revenues from coal, natural gas, oil, forests, and minerals affect informality in nonlinear ways, with several thresholds below which resource revenues tend to expand the shadow economy. Kpognon (2022) similarly found a positive association between resource abundance and informal sector size in Sub-Saharan Africa, mitigated by strong institutions. Dada et al. (2024) further highlighted ethnic and religious diversity as additional channels through which informality responds to underlying socioeconomic conditions.

Energy poverty has also been identified as a key driver of informality. Ajide and Dada (2024) demonstrated that limited access to affordable, reliable energy deepens informal economic activity across 45 African countries. In related work, Afful et al. (2025) showed that financial development, trade openness, and economic growth reduce informality in Ghana, whereas high taxes increase it, emphasizing the need for financial inclusion and tax reform.

Finally, the broader implications of informality for development outcomes have been documented. Ajide et al. (2024) found that the shadow economy impedes sustainable development across African countries, while Ajide et al. (2025) reported that informality can reduce income inequality in West Africa, illustrating the complex and context-specific effects of informal activity.

Despite these advances, the literature remains constrained by measurement challenges, particularly in conflict-affected or data-sparse environments. Existing methods often struggle to capture shifts in informality during periods of institutional breakdown, conflict, or political instability—precisely when official statistics are least reliable. By integrating nighttime lights, macro-institutional indicators, conflict data, and machine-learning techniques, this study seeks to address these gaps and provide more accurate, scalable, and comparable estimates of informality across Africa from 2000–2024.

**4. Dataset**

This study assembles a harmonized annual panel dataset covering all African countries from 2000–2024. The dataset integrates four main categories of information: (1) satellite-based measures of economic activity, (2) macroeconomic and structural indicators, (3) governance, conflict, and uncertainty metrics, and (4) demographic and displacement statistics. Together, these variables provide a comprehensive foundation for estimating the size and determinants of the shadow economy across diverse economic and institutional contexts.

*Satellite Nightlights*

Nighttime light intensity is used as the core proxy for overall economic activity, capturing both formal and informal production. Following standard practice, raw DMSP-OLS (1992–2013) and VIIRS (2012–present) data were processed and harmonized to produce a continuous, comparable luminosity series. The resulting nightlight indicators—and their logarithmic transformations—serve as primary inputs into the machine-learning models. Details on sensor calibration, cross-platform scaling, and construction of the final harmonized series are provided in Appendix A.

*Macroeconomic Indicators*

Core macro variables are drawn from the IMF April 2025 WEO database, including real and nominal GDP, per-capita income, inflation, tax revenue, and fiscal balance measures. These indicators capture economic structure, cyclical conditions, and fiscal capacity—factors known to influence informality. Real GDP growth and tax-to-GDP ratios, in particular, help benchmark model estimates against traditional approaches to measuring informality.

*Structural and Institutional Quality Indicators*

Data from the World Development Indicators (WDI) include employment structure (agriculture, industry, services), vulnerable employment, urbanization, human capital (literacy and school enrollment), and access to energy and digital infrastructure. These variables reflect long-run drivers of formalization and structural transformation, and are incorporated as covariates in the ML framework. The Worldwide Governance Indicators (WGI) provide annual measures of corruption control, government effectiveness, rule of law, political stability, regulatory quality, and voice and accountability. These indicators are central to the analysis, given the extensive literature linking weak institutions to higher informality.

*Conflict, Fatalities, and Displacement*

To capture fragility and instability, the dataset includes annual conflict event counts and fatalities from ACLED, complemented by UNHCR data on refugees, internally displaced persons (IDPs), and asylum seekers. These variables help quantify how conflict and forced displacement alter economic activity and shift production into informal channels.

*Economic Uncertainty*

The World Uncertainty Index (WUI) provides a smoothed measure of macroeconomic and geopolitical uncertainty. This metric allows the analysis to capture how periods of heightened uncertainty shape incentives to engage in informal activity.

## 5. Methodology

This study develops an integrated empirical framework to estimate the size of the shadow economy that is applicable in all contexts but particularly valuable for data-scarce and conflict-affected countries. It extends the literature using the physical input method, which typically filters a single proxy of total economic activity to estimate shadow economy growth. For example, Abdel-Latif et al. (2017) shows that using energy consumption can address some critiques of the commonly used electricity consumption indicator. This paper further advances the approach by employing multiple proxies—including satellite imagery—which provide valuable data in contexts with limited or unreliable information. The framework combines these proxies with factor and machine learning models to produce comprehensive estimates. Using this approach, the study offers a dataset covering shadow economy estimates for all African countries from 2000 to 2024, including fragile and conflict-affected states.

Traditional approaches—such as MIMIC models, currency-demand regressions, and survey-based methods—face significant limitations in the African context, especially where national accounts data are unreliable or incomplete. Our framework offers a flexible and robust alternative by leveraging harmonized satellite data, accommodating structural heterogeneity, synthesizing multiple noisy proxies using factor models, and employing machine learning to generalize across countries and fill data gaps. Below, we outline the proposed methodology in detail.

*Step 1: Multiple Proxies for Total Economic Activity*

Following the physical-input tradition (e.g., Eilat and Zinnes (2002); Abdel-Latif et al. (2017)), observable proxies $Z_{i,t}$ are modeled as noisy indicators of the true total economic activity $Y_{i,t}^{\text{true}}$:

$$Z_{i,t} = \alpha_i + \beta_i Y_{i,t}^{\text{true}} + \gamma' X_{i,t} + \varepsilon_{i,t}, \tag{1}$$

where $X_{i,t}$ denotes structural determinants unrelated to output—such as energy prices, electrification rates, and demographic factors—and $\beta_i$ represents the output elasticity. The analysis employs four primary proxies chosen for their comprehensive spatial and temporal coverage across Africa. These include night-time lights (NTL) data from DMSP–OLS and VIIRS satellites, harmonized to ensure inter-satellite consistency; per capita energy consumption measured in kilograms of oil equivalent; electricity access rates; and the share of internet users, which serves as a proxy for digital economic activity. All proxies are converted into growth rates in line with the Modified Total Activity (MTA) approach of Abdel-Latif et al. (2017).

*Step 2: Filtering Proxy–GDP Relationships*

To isolate proxy-specific deviations from official GDP, we estimate, for each proxy, a fully modified ordinary least squares (FM-OLS) specification. The model expresses the growth rate of the proxy, $\Delta \ln Z_{i,t}$, as a function of the growth rate of official GDP, $\Delta \ln Y_{i,t}^{\text{official}}$, and a vector of structural controls, $\Delta X_{i,t}$:

$$\Delta \ln Z_{i,t} = \alpha_i + \beta_i \Delta \ln Y_{i,t}^{\text{official}} + \gamma' \Delta X_{i,t} + \eta_{i,t}, \tag{2}$$

where $\alpha_i$ denotes country fixed effects and $\eta_{i,t}$ captures the residual variation.

The structural controls $\Delta X_{i,t}$ encompass changes in sectoral employment shares across agriculture, industry, and services; electrification and urbanization indicators; demographic composition; and education proxies. These equations are estimated using fixed effects to control for country-specific heterogeneity. The residuals for each proxy are then computed as in Eq. 3. These residuals represent deviations between observed physical activity and official GDP figures and are interpreted as signals of shadow economic activity.

$$\widehat{\eta}_{i,t} = \Delta \ln Z_{i,t} - \widehat{\alpha}_i - \widehat{\beta}_i \Delta \ln Y_{i,t}^{\text{official}} - \widehat{\gamma}' \Delta X_{i,t}. \tag{3}$$

*Step 3: Dynamic-Factor Construction of a Latent Shadow-Economy Index*

Residuals from all proxies are combined using a state-space dynamic factor model. Formally, the model links the residuals $\widehat{\eta}_{k,i,t}$ for each proxy $k$ to a latent shadow-economy growth factor $S_{i,t}$ through

$$\widehat{\eta}_{k,i,t} = \lambda_{k,i} S_{i,t} + u_{k,i,t}, \tag{4}$$

$$S_{i,t} = \rho_i S_{i,t-1} + \xi_{i,t}, \tag{5}$$

where the subscript $k$ indexes proxies, including night-time lights, energy consumption, electricity access, and internet penetration. The latent factor $S_{i,t}$ represents the unobserved shadow economy growth, $\lambda_{k,i}$ are the corresponding factor loadings, and $u_{k,i,t}$ and $\xi_{i,t}$ denote idiosyncratic and state shocks, respectively. Estimation is conducted using the Kalman filter and smoother, facilitating the extraction of the latent factor despite noise and missing data. The resulting output is a country-year panel of the estimated latent shadow-economy growth, denoted as $\widehat{S}_{i,t}$.

*Step 4: Level Calibration Using External Benchmarks*

Since the dynamic factor model produces a *growth* series, we calibrate the levels by anchoring them to benchmark estimates from the World Bank Informal Economy Database Elgin et al. (2021). Specifically, we use two reference series: the Dynamic General Equilibrium (DGE) model estimates of informal output denoted as DGE_p, and the Multiple Indicators Multiple Causes (MIMIC) structural model estimates, labeled MIMIC_p. Let $\mathrm{DGE}_{i,0}$ and $\mathrm{MIMIC}_{i,0}$ represent these benchmark values for the base year (i.e., 1999). We define a country-specific baseline as the average of these two measures (i.e., $\mathrm{Base}_i = \frac{1}{2}(\mathrm{DGE}_{i,0} + \mathrm{MIMIC}_{i,0})$). For subsequent years, the shadow economy level $\widehat{SE}_{i,t}^{\text{constructed}}$ is obtained by chaining the latent growth rates:

$$\widehat{SE}_{i,t}^{\text{constructed}} = \widehat{SE}_{i,t-1}^{\text{constructed}} \cdot \left(1 + \frac{\widehat{S}_{i,t}}{100}\right).$$

*Step 5: Machine-Learning Estimation and Model Horserace*

The latent-based calibrated series remains incomplete for several countries, such as Libya and Somalia. To construct a comprehensive panel covering all African countries, we employ machine learning techniques to predict shadow-economy levels. The target variable for these predictions is the constructed shadow economy level, denoted as $\widehat{SE}_{i,t}^{\text{constructed}}$.

Predictor variables include harmonized night-time lights (NTL), key macroeconomic indicators such as GDP, consumer price index (CPI), tax-to-GDP ratios, and fiscal balances, as well as demographic and education metrics. We also incorporate governance indicators from the Worldwide Governance Indicators (WGI), conflict measures from ACLED, displacement data provided by UNHCR, and relevant structural variables, including sectoral employment shares and internet usage rates.

We evaluate four machine learning models: Random Forest, Gradient Boosting Regressor (GBR), Elastic Net regression, and Multi-Layer Perceptron (MLP) neural networks. To prevent overfitting and ensure that the models generalize well, especially to fragile states, the validation strategy includes group K-fold cross-validation with countries as groups, leaving one country out evaluation, training-time regularization using L1 and L2 penalties, feature standardization, as well as robustness checks across different model types. The results of the model comparison indicate that the Elastic Net consistently outperforms alternatives across metrics including mean absolute error (MAE), root mean squared error (RMSE).

*Step 6: Full-Panel Completion via Elastic-Net Prediction*

The Elastic Net model is retrained on all country-year observations with available constructed shadow economy levels:

$$SE_{i,t}^{\mathrm{ML}} = f(\mathbf{W}_{i,t}),$$

where $\mathbf{W}_{i,t}$ denotes the relevant predictors. This model is then used to predict shadow economy levels for all country-year pairs, completing the coverage. The final hybrid series is constructed by combining observed constructed estimates and machine learning predictions as follows:

$$SE_{i,t}^{\text{full}} = \begin{cases} \widehat{SE}_{i,t}^{\text{constructed}}, & \text{if available,} \\ SE_{i,t}^{\text{ML}}, & \text{otherwise.} \end{cases}$$

This process yields a complete panel dataset for all African countries—including those in North Africa and fragile states—spanning the period 2000 to 2024.

## 6. Empirical Results

### 6.1. *Shadow Economy Patterns in Africa (North Africa vs. SSA)*

This subsection presents our ML estimates of the shadow economy size in 53 African countries over 2000–2024. We make particular comparisons between *North Africa* and *Sub-Saharan Africa (SSA)*.[1] Table 1 summarizes the distribution of the index across regions. North African economies exhibit an average shadow sector of about 36 % of GDP—roughly six percentage points lower than the SSA average. Dispersion is also smaller in the north (interquartile range ≈ 3.8 percentage points) than in SSA (≈ 6.2 percentage points).

Table 1: Distribution of shadow economy index by region, 2000–2024

| Region | Observations | Mean | Median | IQR | Min | Max |
|---|---|---|---|---|---|---|
| North Africa | 150 | 35.67 | 36.21 | 3.75 | 32.34 | 39.11 |
| Sub-Saharan Africa | 1175 | 41.34 | 41.20 | 6.23 | 24.02 | 64.58 |

Figure 1 plots each country's trajectory based on our estimation along with other estimates from the literature which will be discussed in the following subsection. Considering the Shadow economy trajectory based on our estimation, North African countries cluster at lower levels (33–39 % of GDP), whereas several SSA economies—particularly Mauritania, Mauritius, Comoros and Equatorial Guinea—exhibit values exceeding 50 %. The trajectories differ: some SSA countries (e.g. Congo [Rep.], Guinea-Bissau, DRC, Liberia) show declines of 4–7 percentage points, while others (Mauritania, Mauritius) rise noticeably. North African countries generally change little over time: Morocco and Tunisia slightly decline, whereas Libya and Sudan rise modestly. Regional averages are consequently quite stable—North Africa's mean rises by only 0.42

[1] The North Africa group includes Algeria, Egypt, Libya, Morocco, Sudan and Tunisia. All other countries in the sample belong to SSA.

percentage points and SSA's falls by 0.15 over the sample period.

Figure 2 depicts smoothed regional averages using a 3-year centred moving mean. North Africa remains consistently below SSA, fluctuating around 35–36 %. SSA starts near 41.4 % in 2000, declines slightly in the mid-2000s, and ends at 41.2 % in 2024. The inter-regional gap persists at roughly 5–6 percentage points throughout. The spatial distribution is shown in Figure 3. Points are placed at approximate country centroids and scaled by each country's mean shadow economy share. North African countries (marked in red) have moderate marker sizes, whereas larger blue markers cluster in West and Central Africa, reflecting high informality (50–60 %). Smaller markers in southern and eastern Africa (e.g. Botswana, Namibia, Tanzania) indicate lower informal sectors.

These descriptive results show a persistent regional gap in informality. North Africa's smaller, less dispersed shadow economies align with higher industrialization and stronger state capacity. North African rankings remain relatively stable over time, with Tunisia and Morocco consistently the least informal. In SSA the distribution is wider and trends more heterogeneous—some countries (Congo [Rep.], Guinea-Bissau, DRC, Liberia) witness substantial declines, suggesting effective reforms or resource booms drawing activity into the formal sector, whereas others (Mauritania, Mauritius) experience increases that may reflect institutional deterioration or growing incentives to evade regulation.

### *6.2. Benchmarking Against Existing Studies*

To evaluate our shadow economy estimates, we benchmark the estimates against the two model-based series proposed by Elgin et al. (2021): the DGE-based measure (*dge*) and the MIMIC-based measure (*mimic*). All three series are expressed as a share of GDP. Table 2 summarizes the cross-section–time correlations and average deviations between our measure and the Elgin et al. (2021) benchmarks for all African countries, as well as separately for North Africa and Sub-Saharan Africa (SSA). Across the full African sample, our shadow series is strongly correlated with both external benchmarks, with Pearson correlation coefficients of about 0.82 vis-à-vis the DGE measure and 0.87 vis-à-vis the MIMIC measure. Rank correlations (Spearman) are similarly high (around 0.80–0.85), indicating that our approach broadly reproduces the cross-country ordering of informality implied by existing studies.

The comparison by region reveals interesting differences. For North Africa, the correlation between our estimate and the Elgin MIMIC series remains high (Pearson $\approx$ 0.82, Spearman $\approx$ 0.79), while the correlation with the DGE measure is more modest (Pearson $\approx$ 0.60, Spearman $\approx$ 0.57 ). In SSA, the correlation pattern is more symmetric across the two benchmarks: Our estimate co-moves closely with both DGE (Pearson $\approx$ 0.82 ) and MIMIC (Pearson $\approx$ 0.87), with rank correlations also in the 0.78˘0.83 range. These

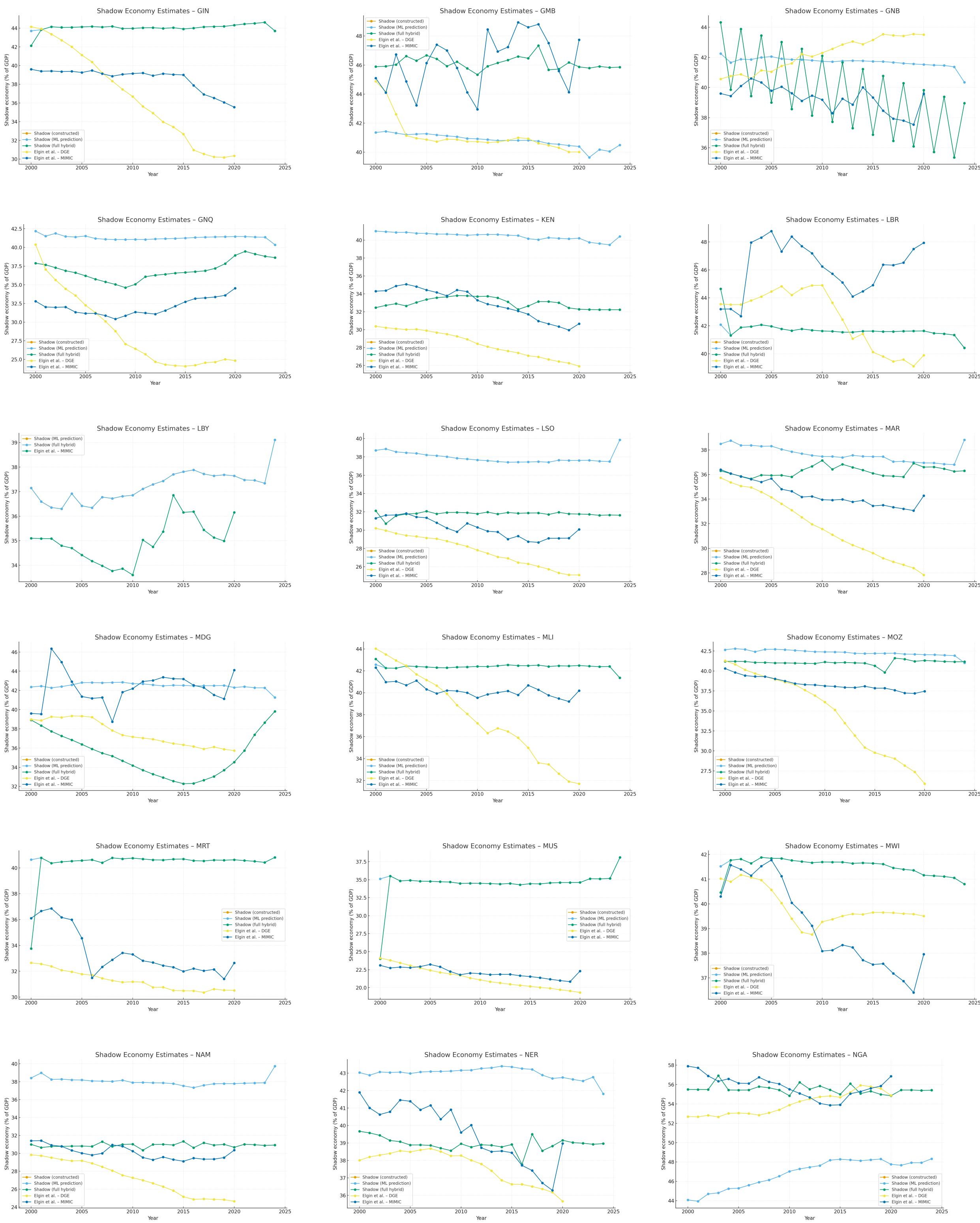
Figure 1: Shadow economy estimates for African countries (1/3)

(*Comparison of alternative measures*)


Source: Authors' calculations based on constructed shadow index, ML predictions, and Elgin et al. (2021).

Figure 1: Shadow economy estimates for African countries (2/3)

(*Comparison of alternative measures*)




Source: Authors' calculations based on constructed shadow index, ML predictions, and Elgin et al. (2021).

Figure 1: Shadow economy estimates for African countries (3/3)

(*Comparison of alternative measures*)


Source: Authors' calculations based on constructed shadow index, ML predictions, and Elgin et al. (2021).

Figure 2: Three-year rolling averages of the shadow economy index for North Africa and Sub-Saharan Africa.

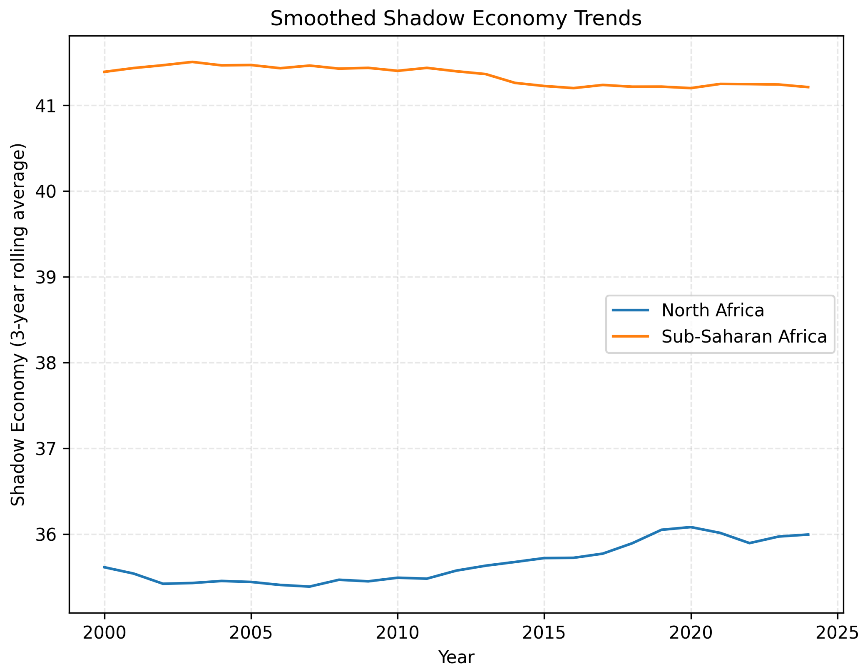
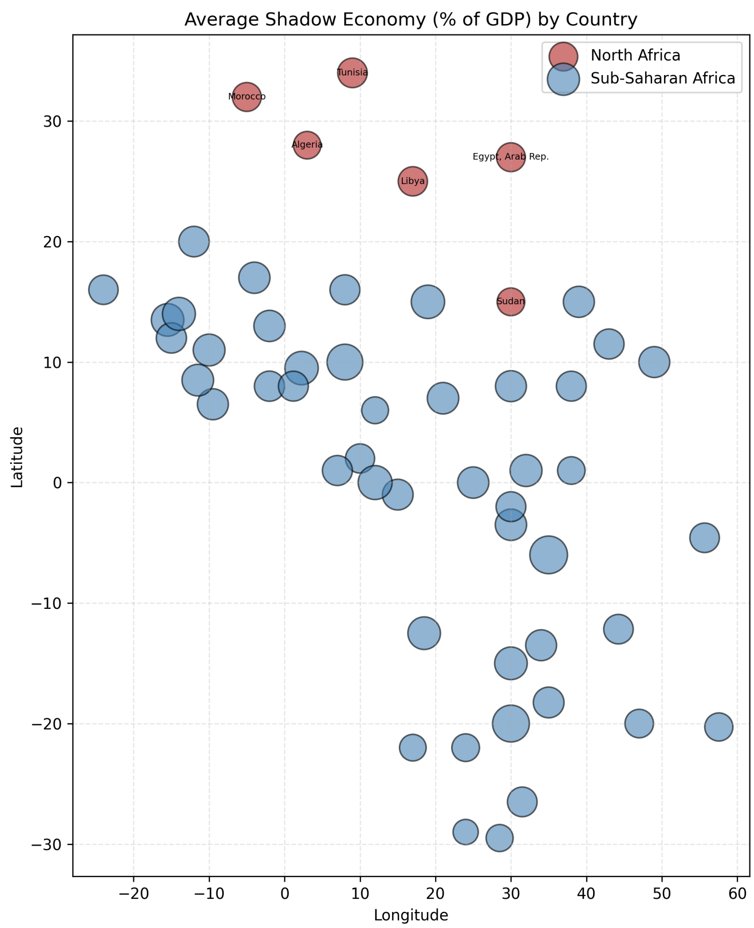



Table 2: Correlation and RMSE between our shadow economy measure and Elgin et al. (2021) benchmarks

| Region | Pearson full dge | Pearson full mimic | Spearman full dge | Spearman full mimic | RMSE full dge | RMSE full mimic |
|---|---|---|---|---|---|---|
| All Africa | 0.824 | 0.873 | 0.795 | 0.854 | 5.755 | 3.906 |
| North Africa | 0.603 | 0.818 | 0.573 | 0.786 | 4.148 | 1.948 |
| SSA | 0.818 | 0.866 | 0.777 | 0.830 | 5.886 | 4.077 |

*Notes:* The table reports Pearson and Spearman (rank) correlations between our shadow economy measure (`full`) and the DGE and MIMIC estimates of Elgin et al. (2021), as well as the root-mean-squared error (RMSE) of `full` relative to each benchmark, expressed in percentage points of GDP. "All Africa" includes all North African and Sub-Saharan African countries in the sample.

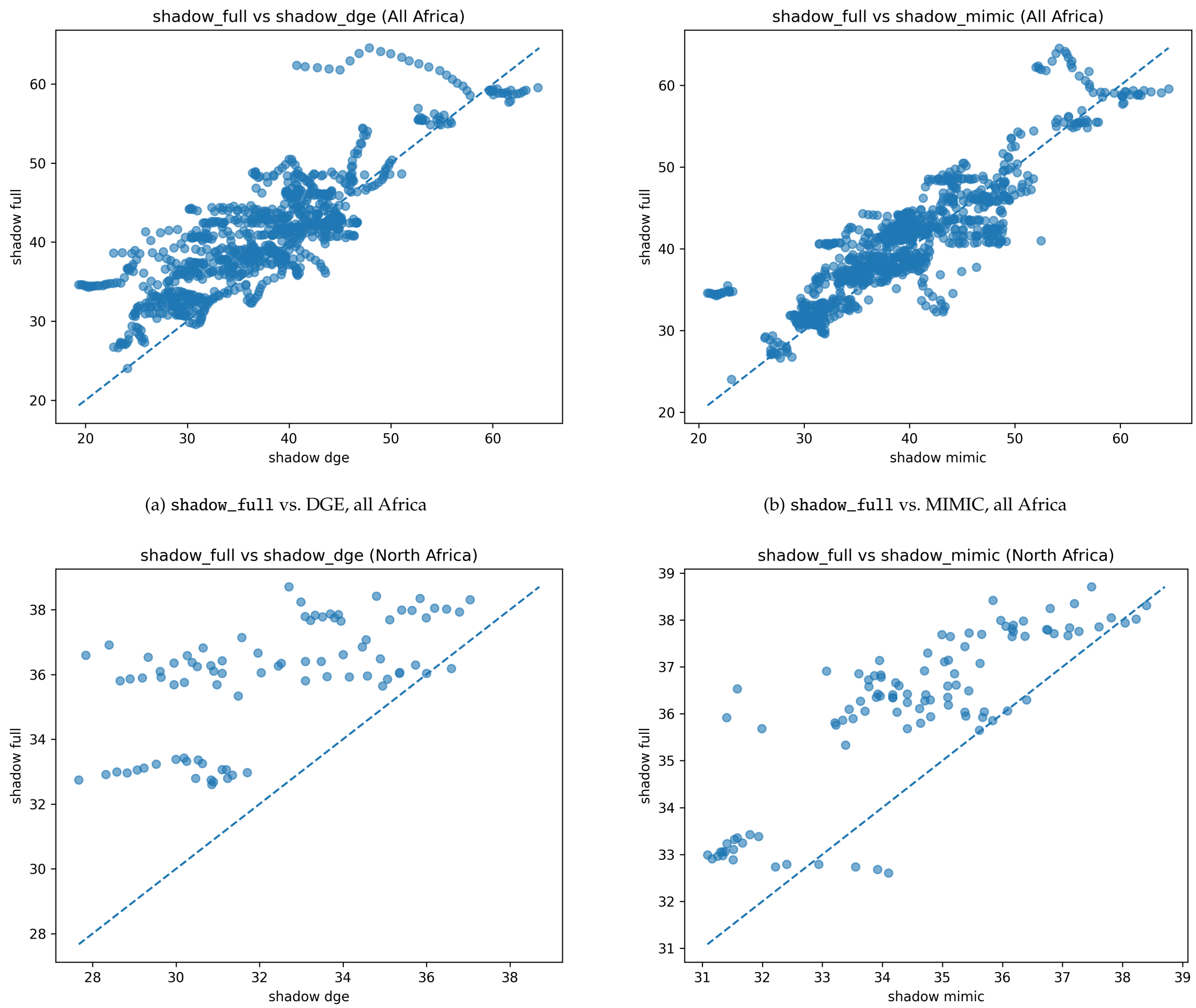
Figure 3: Average shadow economy share (2000–2024) by country.




Marker size is proportional to mean shadow economy share; color denotes region.

patterns suggest that our night-lights–based methodology is consistent with the broad patterns captured by the MIMIC and DGE models, while aligning somewhat more tightly with the MIMIC estimates in North Africa.

Figure 4: Benchmarking our shadow economy measure against Elgin et al. (2021)




(a) `shadow_full` vs. DGE, all Africa

(b) `shadow_full` vs. MIMIC, all Africa

(c) North Africa

(d) North Africa

*Notes:* The figure compares our shadow economy measure (`full`) with the DGE and MIMIC benchmarks of Elgin et al. (2021). The dashed line is the 45-degree line.

Scatter plots of our measures against each Elgin et al. (2021) measure (Figures 4) confirm these findings. For most countries, the point cloud is tightly distributed around the 45-degree line, indicating that our levels are comparable to those in the literature. Deviations from the line primarily arise in (i) conflict-affected SSA economies and (ii) more recent years beyond 2015, where our satellite-based estimates appear to respond more strongly to changes in economic and institutional conditions. In several such cases, the Elgin et al. (2021) estimates remain relatively flat while our measure series captures marked declines in informality during periods of macroeconomic stabilization or improvements in governance, and moderate spikes in informality during episodes of severe conflict or macroeconomic stress.

Overall, this benchmarking exercise shows that our approach is credible and coherent with existing global shadow economy datasets, while providing richer temporal resolution and greater sensitivity to recent structural changes, especially in data-scarce and conflict-affected environments. This added granularity is critical for the subsequent analysis of informality dynamics and the role of conflict and instability.

*6.3. Dynamics of Informality and Response to Shocks*

This subsection examines the response of the shadow economy to macroeconomic shocks—specifically GDP growth and inflation—across all African economies. As detailed in Abdel-Latif et al. (2017), the shadow economy's response to a slowdown in official GDP is ambiguous, as it depends on the relative strength of substitution and income effects. [2] Similarly, periods of high inflation are generally expected to drive economic agents into the informal sector.[3]

To capture these dynamics and quantify the shadow economy's response to macroeconomic shocks, we employ local projection regressions (Jordà, 2005). For each horizon $h \in \{0, 1, 2, 3\}$, the dependent variable is $\log y_{i,t+h} - \log y_{i,t-1}$, where $y_{i,t}$ is the shadow–economy index for country $i$ in year $t$. This outcome is regressed on contemporaneous GDP growth and inflation, their one-year lags, and the lagged dependent variable, controlling for country and year fixed effects. Standard errors are clustered at the country level to account for within-country correlation. Estimated coefficients are scaled by 100 so that a one-percentage-point shock corresponds to the cumulative percentage-point change in the shadow economy.

Regressions are conducted for the entire African continent as well as separately for North Africa and Sub-Saharan Africa to explore regional heterogeneity. The shadow economy across 53 African countries from 2000 to 2024 is measured using our machine learning–based index. Figure 5 presents the estimated impulse responses with 95% confidence intervals for the continent as a whole (first row), while the second row shows

[2] When official GDP growth accelerates unexpectedly, households and firms have stronger incentives to engage in the formal sector. Higher growth creates formal job opportunities and raises formal wages, reducing the need for informal work (income effect). Governments also collect more tax revenue and can devote greater resources to enforcing labor and tax regulations, which discourages informal activity. Structural transformation may accompany growth: sectors with higher productivity and larger firms—such as manufacturing and services—tend to be more formalized. On the other hand, during booms the opportunity cost of remaining informal rises as formal wages increase (substitution effect). The net impact of a growth shock on informality depends on the relative strength of these channels.

[3] Unexpected inflation erodes real incomes and savings, prompting households to seek unregulated income sources. Higher inflation raises the cost of complying with taxes and labor regulations, encouraging firms to operate underground to avoid price controls or currency shortages. In extreme cases, inflation can distort pricing mechanisms and undermine trust in the formal financial system, pushing transactions into cash and informal networks. While these forces can boost informality in the short run, households and firms may adapt over time, and the effect on the shadow economy may fade.

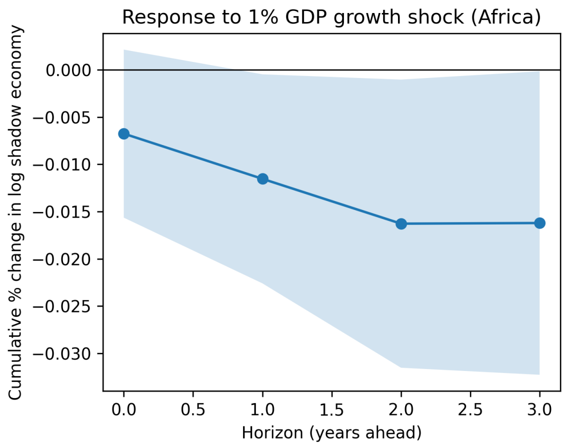
the responses for the two regions separately. These figures illustrate the cumulative response of the shadow economy to a 1 percentage-point shock in GDP growth and inflation, displayed both continent-wide and by region.

The results show that a positive GDP growth shock reduces informality: a 1 percentage point surprise lowers the log shadow economy by about 0.7 percentage points on impact, with the effect becoming more negative (approximately $-1.6$ percentage points) after two years. In contrast, a 1 percentage point inflation shock initially increases informality by roughly 0.22 percentage points, but the effect dissipates by the second year.

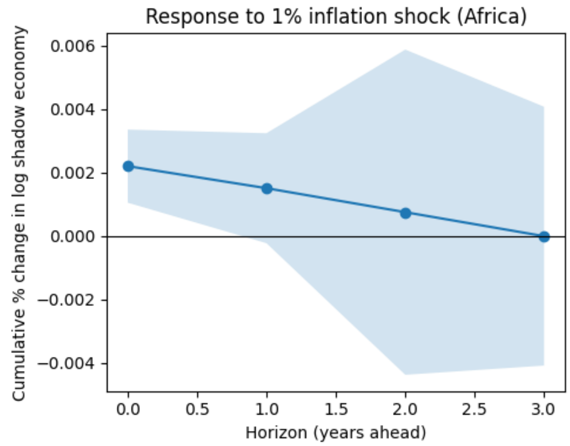
Moreover, growth shocks lead to a reduction in informality in both North Africa and Sub-Saharan Africa (SSA), with the negative effect intensifying over longer horizons and becoming statistically significant in North Africa after the first year. Inflation shocks, conversely, tend to increase informality in the short term, particularly in North Africa where the peak response at horizon two exceeds 0.7 percentage points; however, this effect diminishes and becomes slightly negative by the third year. Responses in North Africa are generally larger and more precisely estimated than those in SSA, which may be attributed to greater exposure to commodity price cycles and differences in labor-market institutions.

The impulse responses reveal several notable patterns. First, temporary increases in real GDP growth consistently reduce the shadow economy over subsequent years, with contemporaneous effects being small but strengthening over time. This suggests that sustained economic expansions, potentially through formal job creation, encourage a transition away from informal activities. Second, increases in inflation initially raise informality, with North Africa experiencing a more pronounced and prolonged effect compared to SSA, where the impact is weaker and fades more quickly. By the third year, inflation-driven effects on informality subside and may even reverse slightly as price shocks are absorbed. Finally, North Africa exhibits more pronounced fluctuations in informality in response to both growth and inflation shocks, while SSA's responses are more muted and less precisely estimated, likely due to factors such as varying exposure to commodity price variability and institutional distinctions across labor markets.

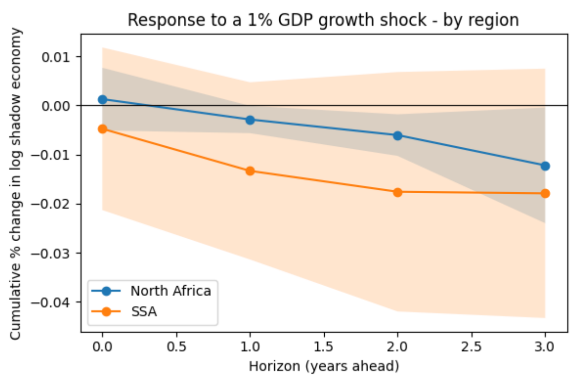
Figure 5: Shadow Economy Responses to Macroeconomic Shocks



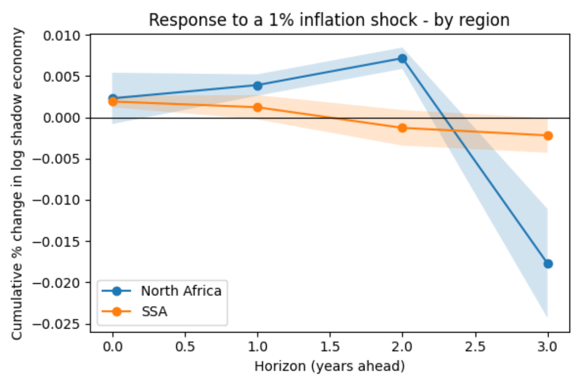

African sample: GDP growth shock




African sample: Inflation shock




Regional sub-samples: GDP growth shock




Regional sub-samples: Inflation shock

Impulse-response functions (IRFs) of the shadow economy to 1 percentage point GDP growth shocks (left) and 1 percentage point inflation shocks (right) for the full Africa sample (top row) and regional sub-samples (bottom row). Shaded areas show 95% confidence intervals based on clustered standard errors.

### 6.3.1. *Event Study*

Major global shocks generate abrupt movements in informality that complement the more gradual dynamics captured by the local-projection estimates. To quantify these discontinuities, the annual change in the log shadow economy is examined during three large global events: the 2008 commodity-price boom, the 2014 oil-price collapse and the 2020 COVID-19 pandemic. The results in Table 3 show that informality responds forcefully during these episodes but in ways that differ across Africa's regions. The continent as a whole experienced substantial increases in informality during 2008 and especially in 2020, reflecting the widespread reallocation toward informal employment during periods of acute macroeconomic stress. In contrast, the 2014 shock produced only a modest rise in informality at the continental level.

Regional patterns reveal more nuanced transmission. North Africa displays a small increase in informality during 2008, a pronounced uptick in 2014 following the end of the commodity super-cycle and a further rise during the COVID-19 shock. Sub-Saharan Africa shows a stronger response in 2008, a slight decline in 2014 and a sizable increase in 2020. These differences align with regional exposure to commodity markets, fiscal structures and labor-market institutions. The 2014 North African increase, for instance, is consistent with the region's reliance on hydrocarbon revenues, while the muted SSA response likely reflects more diversified shock-absorption patterns and different labor-market configurations.

Taken together, the event-study evidence reinforces the asymmetric nature of informality responses highlighted by the impulse-response functions. Global shocks trigger substantial shifts in the shadow economy, but the direction and intensity of these movements vary systematically across regions, mirroring differences in economic structure and sensitivity to global cycles.

Table 3: Average change in informality during major global shock years (percentage points)

| Region | 2008 (Commodity boom) | 2014 (Oil crash) | 2020 (COVID–19) | Notes |
|---|---|---|---|---|
| Africa (pooled) | 13.0 | 1.3 | 19.1 | Full sample average |
| North Africa | 0.01 | 0.20 | 0.13 | Regional average |
| Sub–Saharan Africa | 0.15 | −0.01 | 0.20 | Regional average |

Notes: Entries show the mean annual change in the log shadow economy multiplied by 100. A positive value denotes an increase in informality relative to the previous year.

#### *6.3.2. Drivers of Informality*

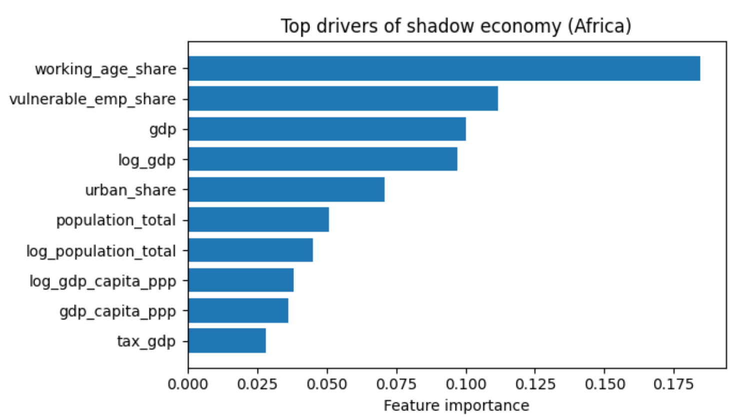
Understanding the structural forces that shape informality requires moving beyond macroeconomic shocks and examining the deeper characteristics that differ across countries. To this end, we use random-forest regressions to identify the most important predictors of the level of informality across Africa. The models are trained using a broad set of demographic, macroeconomic and governance variables, excluding conflict indicators, and are applied both to the pooled African sample and separately to North Africa and Sub-Saharan Africa. Figure 6 presents the importance ranking for the continent as a whole, while Figure 7 displays the top predictors for each region.

The Africa-wide results emphasize the central role of demographic structure and labor-market vulnerability in shaping informality. Countries with larger working-age populations and higher shares of vulnerable employment tend to exhibit systematically higher levels of informality. These variables dominate traditional macroeconomic drivers, although the level of income and urbanization also matter: informality tends to be higher in countries with lower GDP levels and slower structural transformation into urban and formal sectors. This pattern is consistent with evidence from firm-level and labor-market studies that link informality to under-employment, limited access to social protection and slow formal-sector absorption.

The regional analysis reveals additional layers of heterogeneity that align with the impulse-response and event-study results reported earlier. In North Africa, labor-market fragility and governance indicators play a prominent role. Vulnerable employment emerges as the most important predictor, followed closely by institutional variables such as rule of law and political stability. These findings suggest that in this region informality is shaped not only by labor-market segmentation but also by the credibility and enforcement capacity of public institutions. In SSA, demographic structure and economic scale dominate. The working-age share and the level of GDP consistently rank among the top predictors, indicating that the size of the economy and its capacity to absorb labor into formal activities are more influential than governance variables. In both regions population size and vulnerable employment remain among the strongest predictors, underscoring the structural character of informality across the continent.

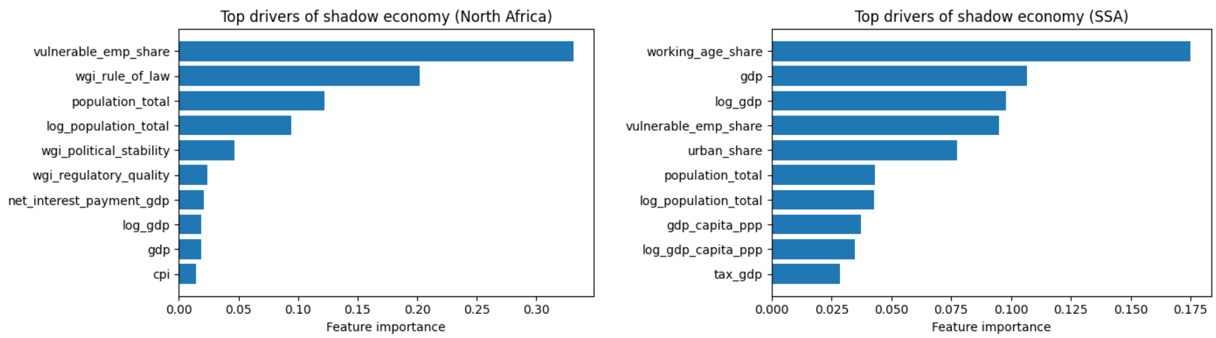
Taken together, the machine-learning evidence complements the dynamic patterns uncovered through the local-projection and event-study analyses. The cross-sectional determinants highlight persistent structural constraints—vulnerable labor markets, demographic pressure and uneven institutional quality—that shape the level of informality independently of short-run macroeconomic fluctuations. These results reinforce the broader conclusion from this subsection: reducing informality in Africa requires sustained macroeconomic stability as well as deeper reforms that improve labor-market resilience, strengthen institutional capacity and support the gradual transition of workers and firms toward the formal economy.

Figure 6: Drivers of Shadow Economy - Africa




Random–forest feature importance ranking for the pooled African sample. The figure shows the top ten variables that explain variation in the level of the shadow economy.

Figure 7: Drivers of Shadow Economy - Regional Sub-Samples




Random–forest importance of the top ten determinants of the shadow economy. Bars show the relative importance (summing to one) of each predictor in explaining the level of the shadow economy for the indicated region.

### *6.4. Conflict, Instability, and the Shadow Economy*

To assess how armed conflict and political instability shape Africa's shadow economy we utilize conflict intensity proxied by ACLED event counts while controlling for economic development and institutional quality and include country and year fixed effects. We estimate a dynamic logistic fixed-effects model in which the dependent variable is the logit transformation of the shadow-economy share and the key explanatory variable is the one-year lag of the natural logarithm of ACLED event counts. The regression includes other controls including log GDP per capita, institutional quality, and country and year fixed effects. The estimated coefficient on lagged conflict is positive and statistically significant at the 5% ($\approx 0.0047$; $p \approx 0.013$), indicating that increases in conflict intensity in the previous year are associated with a slight expansion of the size of the shadow economy. The estimated effect implies that a one-unit increase in the log of events raises the logit of the shadow-economy share by about 0.0047. Evaluated at the sample mean where the shadow economy is around 40 % of GDP, this translates into an increase of approximately 0.1 percentage points in the size of the informal sector.

Table 4: Dynamic logistic FE regression results

| Variable | Coefficient | *p*-value |
|---|---|---|
| Lagged log ACLED events | 0.0047 | 0.013 |
| Controls | log GDP per capita, night-time lights, institutional quality, country FE, year FE | |

The dynamic specification shows that conflict intensity has only a modest effect on the shadow economy once the temporal lag is taken into account. Nevertheless, the positive coefficient provides intuitive evidence that violence disrupts formal economic activity and pushes some transactions into informality. The small magnitude of the effect suggest caution in drawing strong conclusions from aggregate panels. Future refinement of this paper will explore additional conflict and political instability indicators.

## 7. Conclusion

This paper advances the empirical study of Africa's shadow economy by integrating satellite-based nightlight data and machine learning techniques to address persistent measurement challenges in data-scarce and conflict-affected contexts. The resulting harmonized panel dataset, covering all African countries from 2000 to 2024, enables a nuanced analysis of regional heterogeneity, with North Africa exhibiting a smaller and more stable informal sector relative to Sub-Saharan Africa.

Benchmarking against established methodologies, such as MIMIC and DGE models, demonstrates the robustness and enhanced accuracy of the proposed framework, particularly in fragile states where conventional data sources are unreliable. The dynamic analysis reveals that informality is sensitive to macroeconomic shocks: positive GDP growth reduces the shadow economy, while inflation and global crises, notably the COVID-19 pandemic, tend to expand informal activity. Machine learning models further elucidate the structural determinants of informality, highlighting the significance of demographic pressures, labor market vulnerability, and institutional quality. Notably, governance and political stability emerge as critical factors, especially in North Africa, while conflict intensity is shown to modestly increase the prevalence of informal economic activity.

Collectively, these findings underscore the complexity of informality in Africa and the necessity for multifaceted policy interventions. Effective strategies must extend beyond regulatory reforms to encompass improvements in governance, human capital development, and social protection. The methodological innovations presented herein offer a scalable and replicable approach for future research, facilitating more accurate monitoring of informality and informing evidence-based policy design in challenging environments.

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## Appendix A. Nighttime Lights Data

### *A.1 Data Sources and Coverage*

We construct an annual panel of satellite-based nighttime lights (NTL) for all sovereign African countries over the period 2000–2024. The dataset combines observations from two sensors:

- **DMSP–OLS (2000–2013).** Annual composites of the Defense Meteorological Satellite Program's Operational Linescan System are obtained from the NOAA Earth Observation Group. We use the "stable lights" product, which removes ephemeral light sources such as fires and lightning.
- **VIIRS DNB (2014–2024).** Monthly Day/Night Band radiance composites from the Visible Infrared Imaging Radiometer Suite (VIIRS) aboard the Suomi–NPP satellite are obtained from the NOAA Earth Observation Group. We use the monthly radiance product ("VCMSLCFG") and aggregate it to annual frequency using the median across months.

For VIIRS imagery, we floor all radiance values at zero to remove small negative artifacts occasionally present in the monthly composites. For both sensors, annual country-level NTL are computed as the mean radiance of all pixels intersecting each country's geometry. Because DMSP and VIIRS differ in radiometric resolution and dynamic range, the raw series are not directly comparable: DMSP values are typically higher due to sensor saturation and blooming effects, while VIIRS values are lower but more precisely measured.

### *A.2 Global DMSP–VIIRS Calibration*

To place DMSP observations on the same scale as VIIRS, we first estimate a global log–log calibration equation following standard practice in the literature (e.g., Li et al. (2020); Chen and Nordhaus (2015)). Specifically, for each country $c$ we construct a cross-section using the last year of DMSP (2013) and the first year of VIIRS (2014). Let $D_{c,2013}$ denote DMSP mean radiance and $V_{c,2014}$ the corresponding VIIRS mean radiance. We estimate:

$$\log(V_{c,2014}) = \alpha + \beta \log(D_{c,2013}) + \varepsilon_c.$$

The estimated coefficients $(\hat{\alpha}, \hat{\beta})$ are then used to convert all pre-2014 DMSP values into "VIIRS-equivalent" radiance:

$$\widetilde{V}_{c,t} = \exp(\hat{\alpha})\, D_{c,t}^{\hat{\beta}}, \qquad t \leq 2013.$$

### *A.3 Country-Specific Adjustment*

Although the global calibration corrects the bulk of the DMSP–VIIRS scale mismatch, residual discontinuities may remain due to country-specific patterns in electrification, spatial light distribution, or sensor noise. We therefore apply an additional country-specific multiplicative factor to ensure smoothness at the 2013–2014 transition. For each country $c$, we compute the ratio:

$$s_c = \frac{V_{c,2014}}{\widetilde{V}_{c,2014}},$$

where $V_{c,2014}$ is actual VIIRS radiance and $\widetilde{V}_{c,2014}$ is the globally calibrated DMSP prediction for 2014. The final harmonized NTL series is then:

$$\mathrm{NTL}_{c,t}^{\mathrm{final}} = \begin{cases} s_c \cdot \widetilde{V}_{c,t}, & t \leq 2013, \\ V_{c,t}, & t \geq 2014. \end{cases}$$

This approach fully eliminates sensor-induced level shifts while preserving genuine temporal variation. In our final data, 45 out of 45 countries with both 2013 and 2014 observations exhibit effectively zero discontinuity at the sensor switch (median relative jump: 0.0). The only exceptions are countries with VIIRS radiance equal to zero in 2014 (e.g., Eritrea and South Sudan), reflecting real-world low illumination rather than measurement error.

*A.4 Final Nighttime Light Dataset*

The final harmonized annual NTL dataset contains, for each country $c$ and year $t$, the variable $\mathrm{NTL}_{c,t}^{\mathrm{final}}$, a continuous VIIRS-scale measure of average nightlight intensity. We also provide the logarithmic transformation $\log(\mathrm{NTL}_{c,t}^{\mathrm{final}})$. This dataset is used as the primary luminosity-based proxy in the construction and modeling of the shadow economy index.

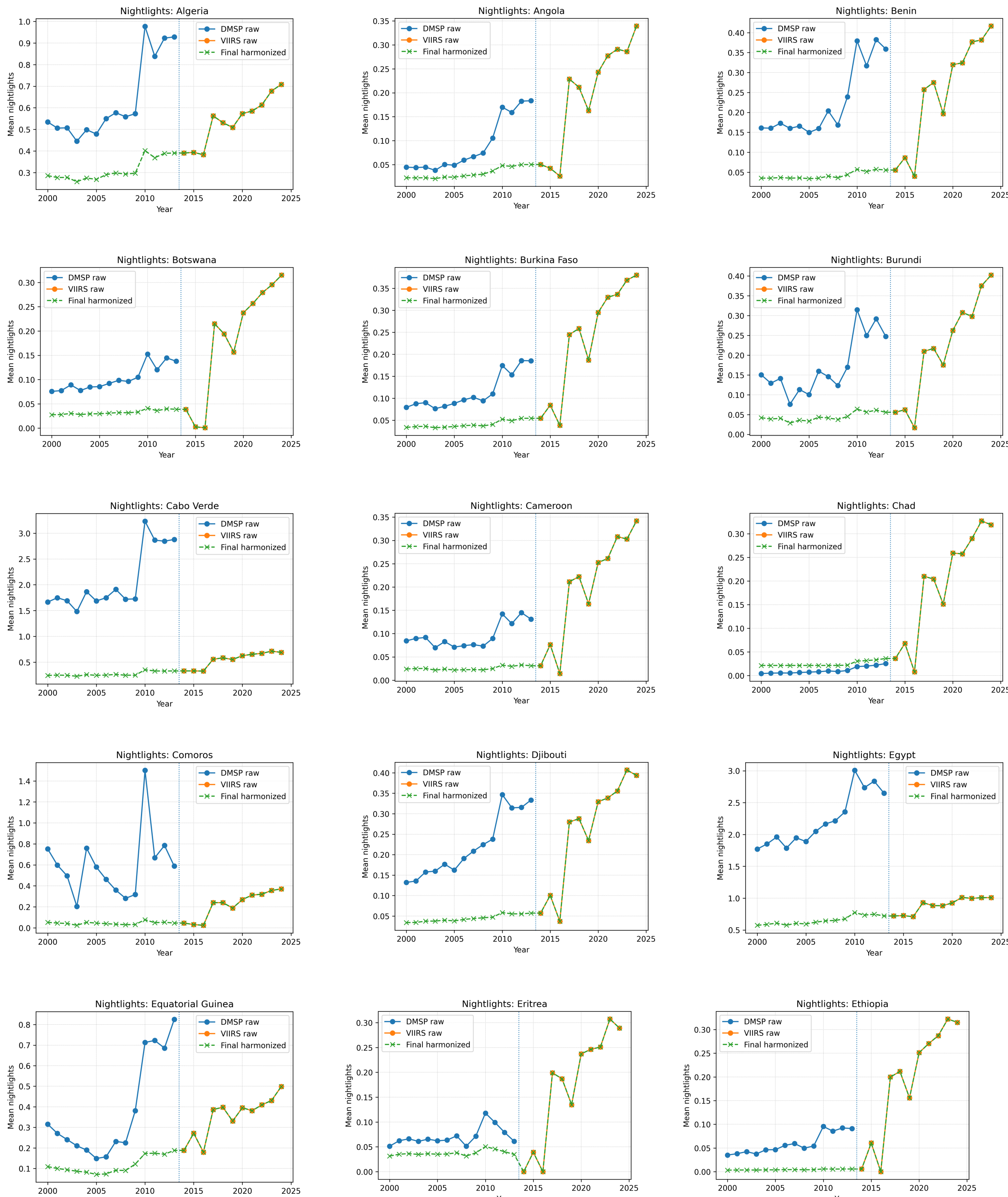
*A.5 Comparison of Calibrated NTL vs Harmonized NTL*

We compare our calibrated nighttime lights (NTL) series with the globally harmonized NTL dataset provided by Li et al. (2020). The harmonized dataset delivers radiometrically corrected composites at 1-km resolution for 1992–2024 and is designed to place DMSP-OLS and VIIRS-DNB observations on a consistent brightness scale. To evaluate potential differences, we aggregate the harmonized gridded data to the national level and juxtapose the resulting country-year series against our own calibrated DMSP-VIIRS series.

Figures below present these comparisons for all African countries. For each country, we plot (i) our calibrated series, (ii) the harmonized series, and (iii) the raw unscaled DMSP-VIIRS composite underlying our own processing. This allows visual inspection of level differences, trend deviations, and potential discontinuities arising from the DMSP-VIIRS transition.

Figure A.8: Nightlights time series for African countries (1/3)

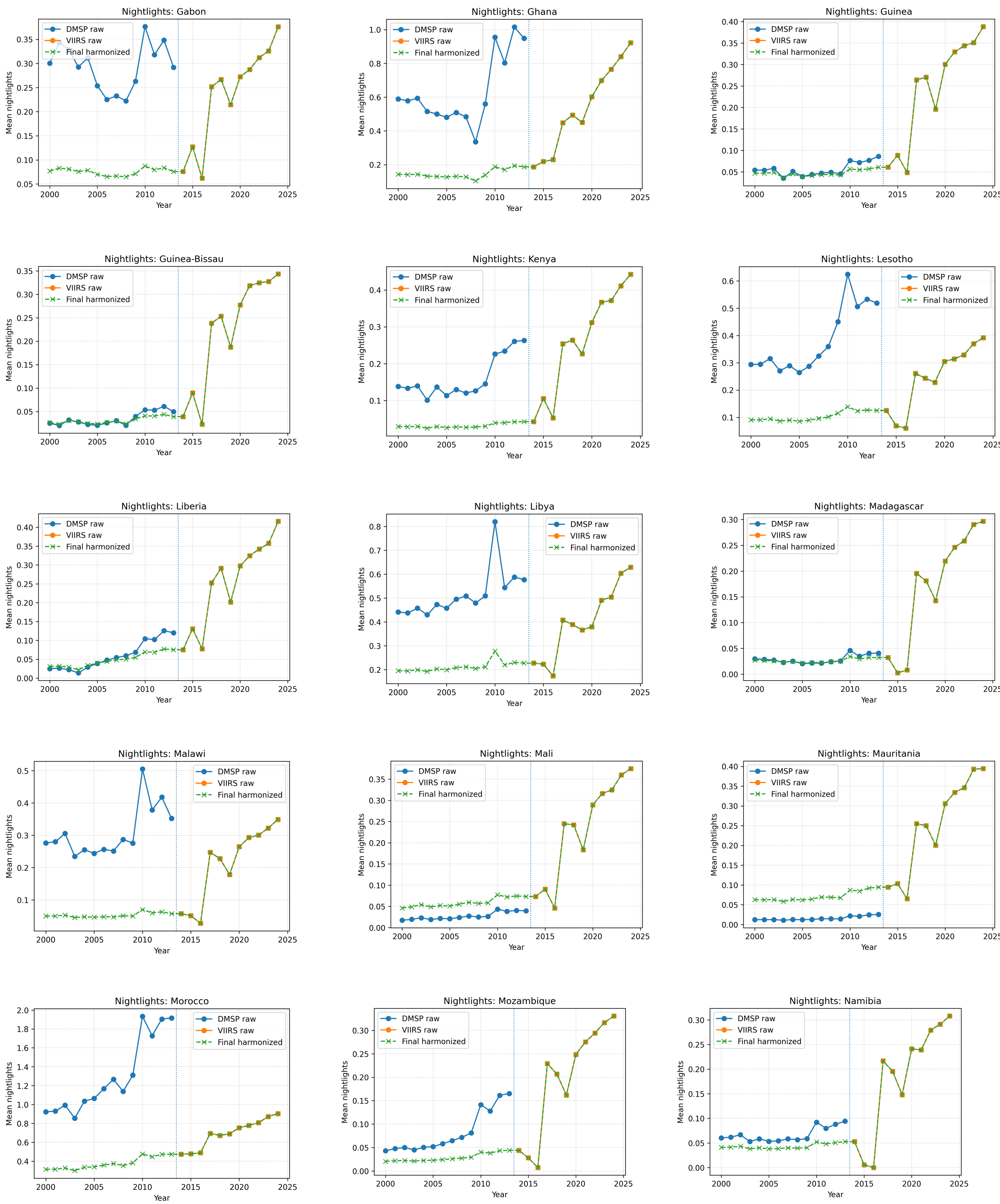
(*Harmonized*)




Source: DMSP–OLS, VIIRS DNB, and authors' calculations.

Figure A.8: Nightlights time series for African countries (2/3)

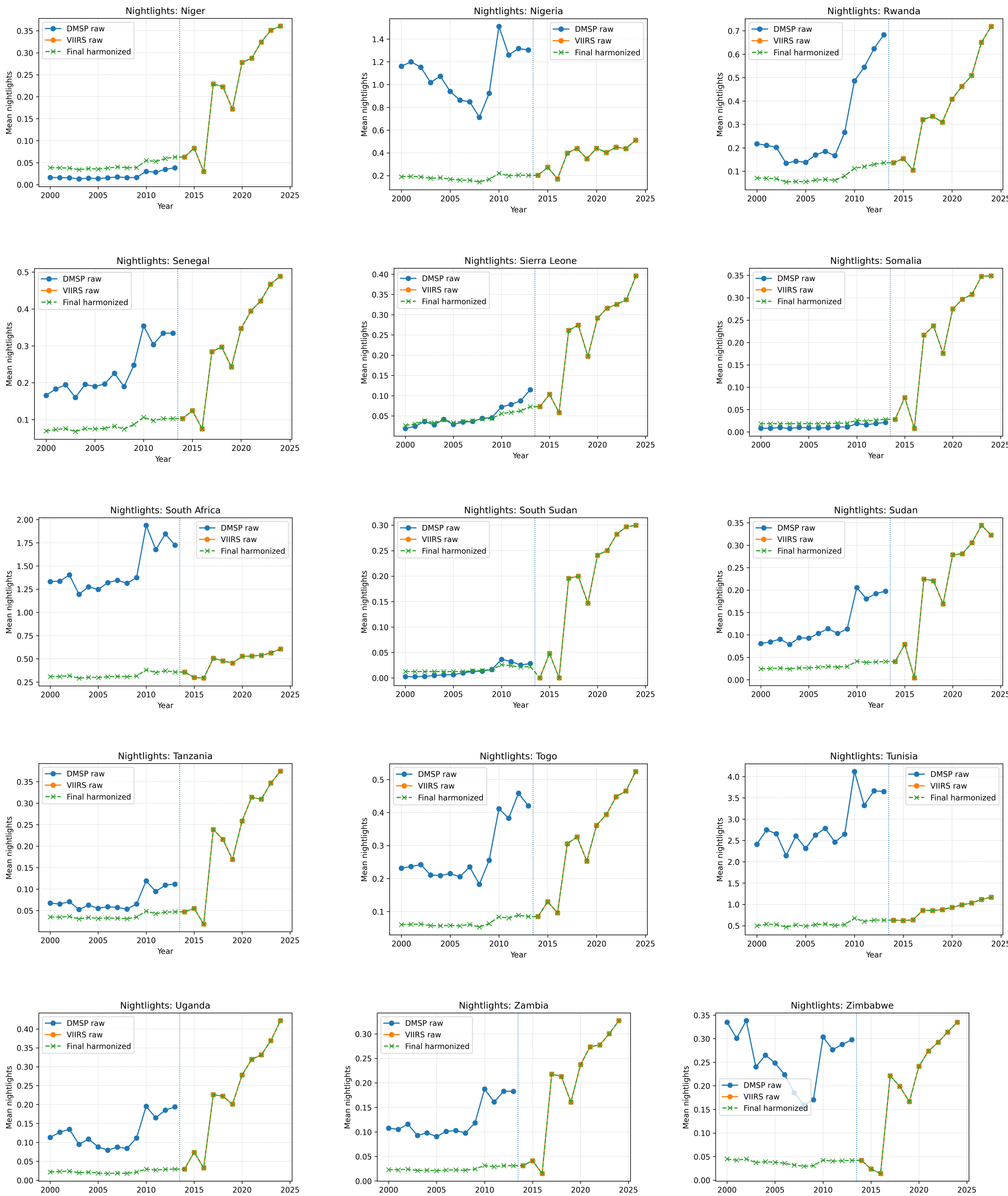
(*Harmonized*)




Source: DMSP–OLS, VIIRS DNB, and authors' calculations.

Figure A.8: Nightlights time series for African countries (3/3)

(*Harmonized*)




Source: DMSP–OLS, VIIRS DNB, and authors' calculations.

A key finding emerging from the comparison is that the harmonized dataset exhibits a systematic spike in the final year of DMSP-OLS (2013) across nearly all African countries. This spike is far too large to reflect actual economic or infrastructural changes and does not persist into 2014. It appears to reflect artifacts introduced by the cross-sensor radiometric regression used to map DMSP values onto the VIIRS scale. Because the harmonized dataset recalibrates all DMSP observations—including the final sensor-ageing-affected years—onto a brighter VIIRS radiance scale, 2013 frequently becomes an outlier, overstating brightness by factors of two to five depending on the country. These anomalies are particularly pronounced in small-island states and countries with very low baseline luminance, where noise is more influential.

In contrast, our calibrated series applies a transparent, country-specific linear scaling based on overlapping sensor-validity years, ensuring smooth continuity and preserving realistic growth patterns. The DMSP-VIIRS transition is handled carefully, avoiding artificial structural breaks. Post-2014, our series aligns closely with VIIRS raw radiance, while pre-2014 values retain the relative growth and intensity patterns present in the DMSP data without imposing upward-biased global rescaling. For macroeconomic applications—such as tracking national economic activity, growth, structural change, or energy use—smoothness, temporal coherence, and the absence of spurious discontinuities are far more important than achieving global radiometric comparability. For these reasons, our calibrated series provides a more reliable and policy-relevant measure of luminosity-based economic activity.

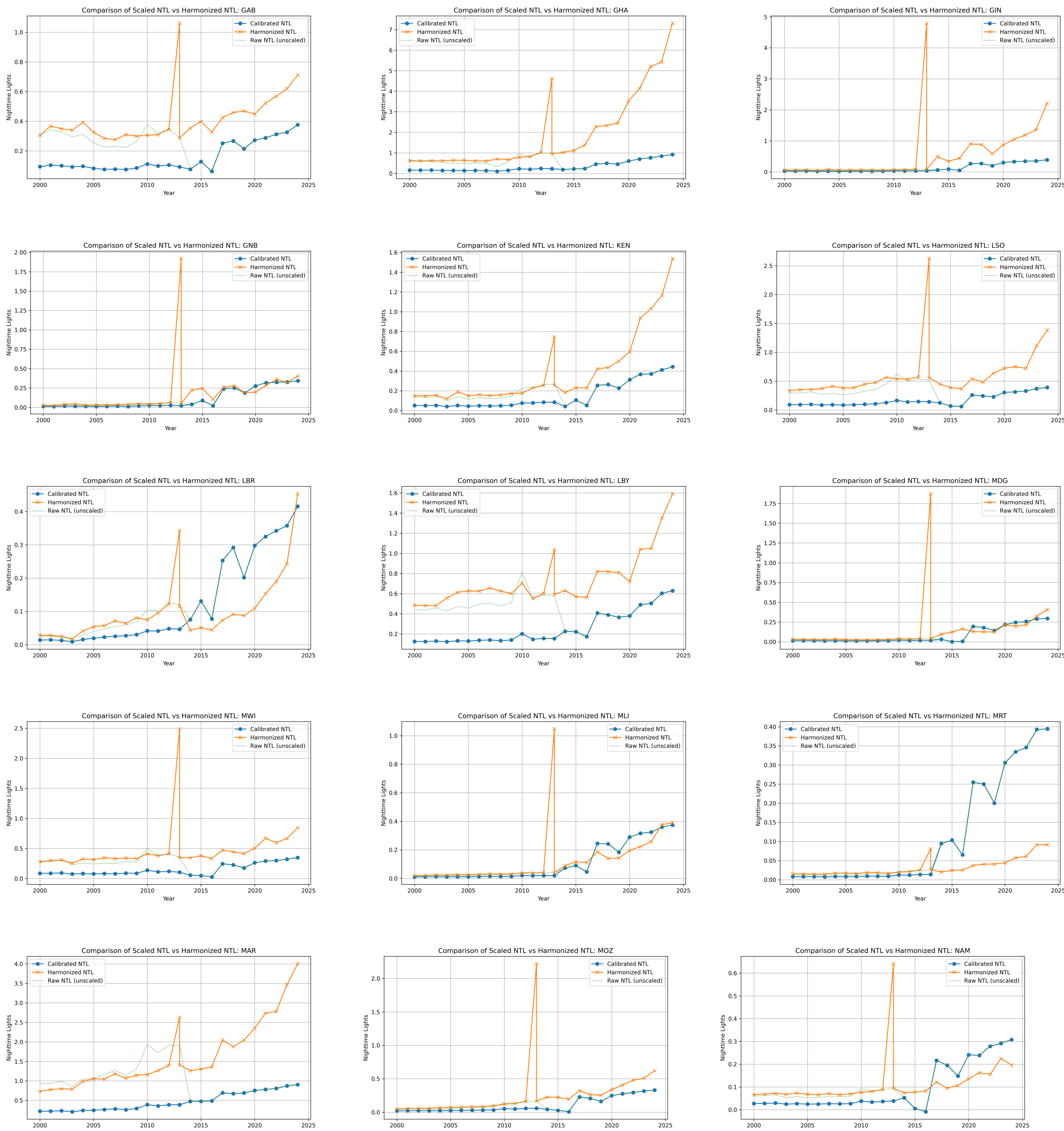
Figure A.9: Comparison of calibrated and harmonized nightlights (1/3)

(*Country-level means, DMSP–OLS and VIIRS*)


Source: DMSP–OLS, VIIRS DNB, harmonized NTL dataset, and authors' calculations.

Figure A.9: Comparison of calibrated and harmonized nightlights (2/3)

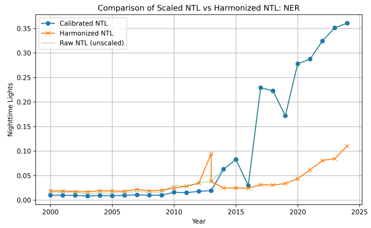
(*Country-level means, DMSP–OLS and VIIRS*)

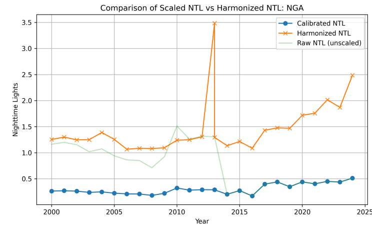


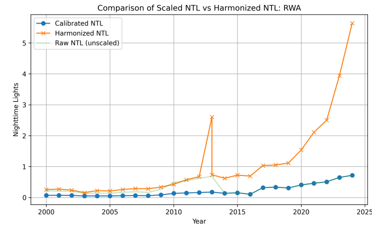

Source: DMSP–OLS, VIIRS DNB, harmonized NTL dataset, and authors' calculations.

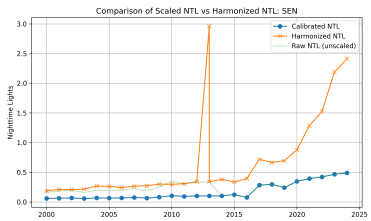
Figure A.9: Comparison of calibrated and harmonized nightlights (3/3)

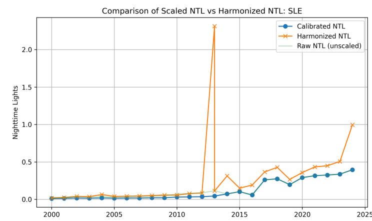
(*Country-level means, DMSP–OLS and VIIRS*)

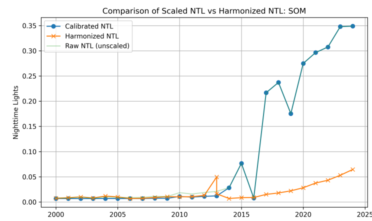


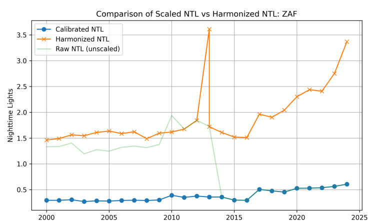

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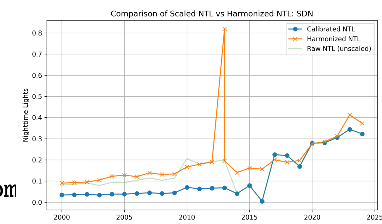


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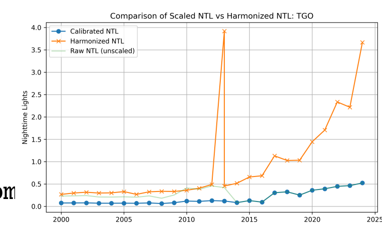


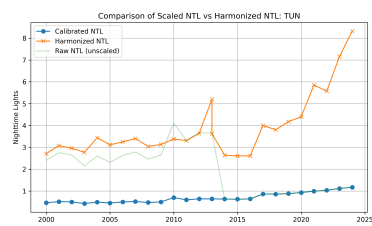


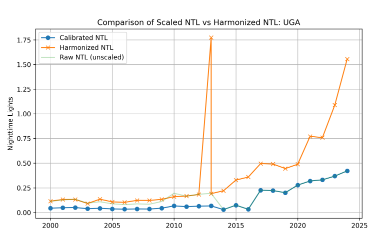


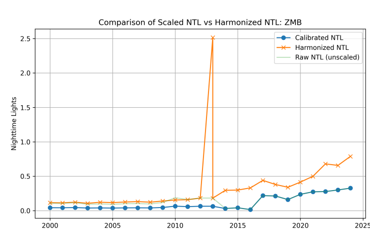


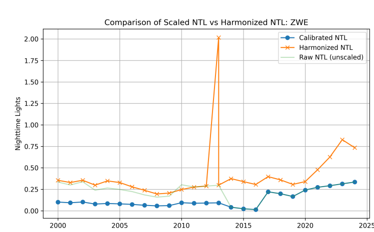


Source: DMSP–OLS, VIIRS DNB, harmonized NTL dataset, and authors' calculations.