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Remote sensing the lie: Corruption and economic data distortion

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ABSTRACT

This paper investigates how corruption contributes to economic data overstatement by comparing officially reported GDP figures with satellite-recorded nighttime light intensity in post-Communist countries, where national accounts have historically been vulnerable to strategic misreporting. Using harmonized nighttime light data from 1996 to 2020 as an external and objective proxy for economic activity, we apply fixed-effects panel estimations to quantify discrepancies between reported and observed performance. The results show that corruption is associated with significant overstatement in official GDP statistics. A one–standard deviation improvement in control of corruption reduces the gap between the two measures by 32% on average, indicating that more effective corruption control is associated with closer alignment between reported GDP and satellite-based measures. This discrepancy is especially pronounced in non-EU post-Communist countries, while EU member states show little evidence of systematic divergence between reported GDP and nightlight-based measures. These findings highlight the importance of institutional quality in limiting both corruption and data distortion and demonstrate the usefulness of satellite-based indicators for assessing economic performance in low-transparency environments.

1. Introduction

Corruption is often studied for its impact on economic performance, but less attention has been paid to its effect on the credibility of the data used to measure that performance. In environments with weak institutions, official statistics—especially GDP—may not simply be inaccurate, but strategically manipulated. This concern is particularly relevant in post-Communist countries, where state control over information and legacies of data falsification remain embedded in institutional practices. While these tactics were once overt under central planning, they may persist today in more subtle but equally consequential forms.

Against this backdrop, we examine whether corruption affects the integrity of economic reporting itself. In high-corruption environments, weaker oversight and greater political discretion may increase both the incentives and the capacity to manipulate official statistics. Specifically, we investigate whether countries with weaker control of corruption exhibit larger gaps between reported GDP and satellite-based measures, proxied by nighttime light intensity.

Drawing on harmonized data from the DMSP and VIIRS programs between 1996 and 2020, we use nightlight luminosity as an objective, externally generated indicator of real economic output. Previous research has shown that satellite light data captures economic activity particularly well, especially in countries with questionable national accounts (Henderson et. al. 2012), and provides

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further advantages, such as increased access to otherwise difficult-to-obtain information, high spatial resolution, and extensive geographic coverage (Donaldson and Storeygard, 2016). The intuition is clear: nighttime light activity reflects strong economic activity due to corresponding urbanization, industrial expansion, and commercial activity.

Our analysis centers on the World Bank's "Control of Corruption" indicator, drawn from the Worldwide Governance Indicators (WGI) database.[1] Using fixed-effects panel estimations, we examine how variation in corruption control relates to the discrepancy between official GDP and satellite-based measures of economic activity. This approach allows us to assess whether higher control of corruption is associated with greater alignment between the two measures. We focus on post-Communist countries, where the legacy of data misreporting under central planning raises the question of whether such practices persist in subtler forms today, more than 30 years after the collapse of the USSR, and how corruption plays into this tendency. The region's institutional divergence—particularly the split between countries that joined the European Union and those that did not—also provides an opportunity to examine the role of institutions in mitigating the effects of corruption on the misreporting of economic data.

The results reveal a consistent and systematic relationship between corruption and the divergence between official and satellite-based measures of economic activity. In more corrupt countries, reported GDP tends to exceed what would be expected based on nightlight data, suggesting possible overstatement of official figures. As control of corruption improves, this gap narrows—by as much as 30% on average—and reported GDP becomes more closely aligned with satellite-based estimates. These findings suggest that corruption may influence not only governance outcomes, but also the credibility of official economic statistics.

This paper makes several contributions to the literature. First, it advances the literature on institutions, governance, and macroeconomic outcomes by shifting attention from how corruption affects economic performance to how it affects the credibility of the statistics used to measure performance. A large comparative panel literature shows that institutional quality and governance shape macroeconomic and financial outcomes (e.g., Farzanegan and Witthuhn, 2017; Khalid and Shafiullah, 2021; Khan et al., 2022; Gandjon Fankem and Ndzana, 2025). We complement this work by focusing on a distinct but consequential margin which is the reliability of official macroeconomic reporting.

Second, we extend the emerging literature on data manipulation and political economy. Existing research shows that authoritarian regimes may distort economic statistics (Martinez, 2022) and that institutional arrangements such as decentralization or openness can affect reporting incentives (Briviba et al., 2024). We identify corruption as a significant driver of economic data distortion.

Third, we contribute to the literature on corruption and macroeconomic performance by introducing an empirical strategy that distinguishes between officially reported output and independently observed economic activity. Prior studies examine how corruption affects growth (e.g., Song et al., 2021; Uberti, 2022), typically relying on official macroeconomic statistics. We instead benchmark reported GDP against satellite-recorded nighttime lights, following Henderson et al. (2012). By combining governance indicators with externally generated measures of economic activity, we directly assess whether improvements in corruption control are associated with closer alignment between official and independently observed output. This approach allows us to identify distortions in reported GDP rather than conflating reporting bias with real economic effects. Substantively, the post-Communist context provides a setting where legacies of centralized reporting coexist with divergent institutional reforms, allowing us to assess how improvements in corruption control are associated with closer alignment between official and satellite-based measures of economic activity.

The rest of this paper is organized as follows. Section 2 reviews the relevant literature. Section 3 outlines the data and estimation strategy. Section 4 presents the empirical results followed by robustness checks in Section 5. We conclude with a broader discussion of limitations and implications in Section 6.

2. Literature review

2.1. Data manipulation, corruption and the credibility of official statistics

The manipulation of economic data is neither new nor rare. Governments have long altered official statistics to serve political ends, a pattern well-documented throughout modern history. During the Cold War, for example, the CIA developed its own independent estimates of Soviet economic output after concluding that official Soviet statistics were systematically manipulated by the leadership for political reasons.[2] More recently, The Economist (2015, 2020) and the Financial Times (2024) have raised concerns about the accuracy of official economic indicators in countries such as China and others with opaque data practices.[3]

While anecdotal evidence is widespread, systematic investigation into the drivers of statistical manipulation remains relatively recent. Aragão and Linsi (2022) examined different cases in Greece, Brazil and Argentina with the common goal of shielding governments from the political fallout of underperformance, and categorized the distortion into four distinct types: (1) outright falsification of known figures to meet political needs; (2) politically motivated estimations when data are lacking; (3) selective use of statistical methods that yield favourable outcomes; and (4) indirect interference with the raw data before the application of statistical methodologies. A growing body of research further demonstrates that politically constrained environments, such as democracies, tend to produce more credible national statistics, while unconstrained settings, such as autocracies, exhibit systematic divergence between

[1] We also use alternative corruption variable namely the Corruption Perceptions Index (CPI) produced by Transparency International (TI) in our robustness check.

[2] Accessed on October 9, 2024 at https://www.cia.gov/readingroom/docs/CIA-RDP90T00114R000800310001-6.pdf

[3] Manipulation of data is not only limited to economic statistics, but also involves economic news (Rozenas and Stukal, 2019), election outcomes, media publications, and even COVID-19 death statistics (Kofanov et al., 2023).

official performance indicators and external benchmarks (Magee and Doces, 2015; Martinez, 2022).

Corruption, defined as the abuse of public office for private gain (Treisman, 2000), could shape both the incentives and opportunities to distort official statistics. From a political economy perspective, corruption operates through rent extraction and discretionary allocation, creating incentives to obscure underperformance and misallocation (Shleifer and Vishny, 1993; Mauro, 1995; Aidt et al., 2008). Using Herrera and Kapur's (2007) framework, which links data quality to actors' incentives and capabilities, we argue that corruption undermines statistical credibility through a mechanism that varies systematically across high- and low-corruption environments. We outline a step by step process connecting corruption to statistical distortion, specifying how shifts in incentives, institutional constraints, and measurement discretion generate observable discrepancies in macroeconomic data.

One channel could operate through heightened incentives to distort performance indicators. In high-corruption settings, political survival and elite cohesion often depend more heavily on maintaining rent-generating arrangements and protecting connected networks. In such contexts, credible reporting of weak performance can increase political costs by exposing misallocation, intensifying public discontent, and increasing external scrutiny by donors, creditors, and international organizations. This generates a stronger incentive to manage macroeconomic narratives and performance indicators. Evidence consistent with this logic appears in studies showing systematic overstatement of economic performance in autocracies when compared to democracies (Magee and Doces, 2015; Martinez, 2022). Furthermore, a study by Rozenas and Stukal (2019) on information control suggests that autocrats strategically manage economic information when it has political consequences. By contrast, in low-corruption environments, stronger institutional constraints and reputational costs reduce both the incentives and the expected benefits of manipulating official statistics.

A second mechanism concerns institutional constraints. Corruption is typically associated with weaker accountability institutions and greater political discretion over public agencies. When oversight bodies, judicial constraints, and independent media are weaker, the expected probability of detection and sanction declines (Besley and Prat, 2006). As a result, the space for political or bureaucratic interference in statistical production expands. Importantly, manipulation need not involve crude falsification; it can operate through subtle interventions across the statistical pipeline, including selective methodological choices, politically motivated revisions, or interference at early data-collection stages (Aragão and Linsi, 2022). Recent evidence also shows that the quality of the institutional setting shape the feasibility of official-statistics manipulation, reinforcing the broader claim that institutions matter for data credibility (Briviba et al., 2024).

Third, corruption can further weaken data credibility indirectly by encouraging informal economic activity. Firms facing predatory extraction may respond by underreporting output, shifting activity off the books, or using informal arrangements that reduce traceability. A well-established empirical literature links corruption and institutional weakness to the size of the shadow economy (Dreher and Schneider, 2010; Johnson et al., 1998). A larger informal sector complicates national accounts measurement by increasing reliance on indirect estimation, extrapolation, and imputation, which expands discretion in aggregation. This does not imply that discretion always leads to manipulation; however, in high-corruption environments, greater discretion can lower technical barriers to strategic adjustment and increase plausible deniability, making distortion both easier and harder to detect (Aragão and Linsi, 2022; Herrera and Kapur, 2007).

Fourth, distortion can arise from both top-down and bottom-up processes. These channels imply two broad levels at which distortion may occur. First is a top-down mechanism where political leaders or senior officials could pressure statistical institutions, directly or indirectly, to present favorable macroeconomic indicators to sustain credibility or legitimacy (Aragão and Linsi, 2022). A bottom-up mechanism, on the other hand, local officials and firms could distort administrative and survey data at the point of collection, shaping the inputs that national statistical offices aggregate in corrupt environments. Empirical studies of subnational reporting provide evidence that when career incentives and accountability are weak, local political actors may cause overstatement of economic performance (Wallace, 2016; Chen et al., 2021) by pressuring locally listed firms to inflate earnings to increase local GDP numbers (Cai et al., 2022). In practice, both levels may interact and corruption can induce enterprise-level underreporting and also weaken the institutional environment that would otherwise detect and correct distortions, especially in countries with weak oversight and underdeveloped business environments.

Taken together, these mechanisms could imply that in high-corruption environments, stronger incentives to distort and weaker constraints on doing so would increase the likelihood that official GDP deviates from externally generated proxies of economic activity. We do not claim that every observed discrepancy reflects deliberate falsification; rather, our argument is that higher corruption systematically increases the likelihood and feasibility of strategic distortion relative to low-corruption settings. Satellite-based nighttime lights have been shown to track economic activity and to be especially useful when official statistics are noisy or strategically distorted (Henderson et al., 2012; Martinez, 2022).

2.2. Use of satellite data

The primary challenge to identify this manipulation is alleviated by the alternative independent data source which is nighttime lights (NTL) data. We approach this problem by contrasting the government reported GDP statistics to night-time light captured by satellites from outer space. Access to satellite images and high computing technology have endorsed social scientists to utilize nighttime lights (NTL) data for studying interesting research questions previously difficult to investigate due to the hardships in accessing the reliable information in poor countries (Nordhaus and Chen, 2015). This trend becomes more salient within socio-economic studies after seminal paper by Henderson et al. (2012) who explored the possible use of satellite data as a proxy for economic activity. They have shown that NTL data is particularly useful at the subnational level and in countries where economic data at a detailed spatial level is thought to be either unavailable or unreliable. Following these justifications, the number of studies has grown significantly (for a review of papers using satellite data see Gibson et al., 2020)

Recently, the enhanced quality and greater accessibility of NTL data have encouraged scholars from various fields to explore a diverse array of phenomena linked to human economic activities (Shapiro et al., 2023), including informal and shadow economy (Tanaka and Keola, 2017), ethnic inequality (Alesina et al., 2016), role of national institutions on subnational development in Africa (Michalopoulos and Papaioannou, 2014), realization of Chinese aid programs (Isaksson and Kotsadam, 2018), the effect of insurance on urban earthquake recovery (Nguyen and Noy, 2020) and higher education (Castelló-Climent et al., 2018).

Having reviewed literature on the use of NTL data for economic analysis, in this article we also utilize NTL data as a proxy for economic activity in the empirical setting for two reasons. First, self-reported and government provided economic performance data is politically sensitive data and could be vulnerable for manipulation by governments. Its use for analysis may endanger the validity of the results. NTL data would alleviate this weakness with its inherited objectivity as it is captured from outer space. Second, measuring corruption activities is inherently a difficult task as it is a hidden and illegal activity. This in turn might encourage reduced transparency in human economic activities. Hence, promised and planned economic activities, which are reported to be as an economic figure, might not take place due to the embezzlement of public fund, for example. Satellite imagery might enable us to compare the outputs of reported and captured economic activities.

2.3. Geographical scope: post-communist countries

Our study focuses on countries once dominated by Communist regimes, where corruption persisted as a crucial institutional weakness.[4] To situate this analysis, we draw on existing literature on institutional legacies, such as the colonial origins of good and bad institutions (e.g., Acemoglu et al., 2001). Similarly, the institutional legacies of Communist rule continue to shape the formal institutions of currently independent states. Historical examples illustrate how past institutions can leave enduring marks. Becker et al. (2016), for instance, examined whether formal institutions from the Habsburg Empire continue to influence cooperative attitudes, such as trust and corruption practices, in present-day Eastern European countries like Poland, Ukraine, Romania, Serbia, and Montenegro. Their findings show that respondents in former Habsburg territories exhibit higher trust in courts and a lower propensity to engage in bribery. These results suggest that historical institutions, whether colonial or Communist, can leave lasting legacies through cultural norms and by shaping interactions between citizens and the state.

"Corruption is the greatest obstacle to progress in post-communist countries" Rose (2001, p 105). This assertion has been backed up several scholars to date. Sandholtz and Taagepera (2005) has put forward that communism established structural incentives that encouraged corrupt behaviours, making corruption so pervasive that it became ingrained in the culture of these societies—specifically, in the social norms and practices that characterized communist regimes. Several studies propose various factors, which are highly associated with the communist past, powerful to explain the persistence of corruption in post-Communist countries such as high barriers to new business entry (Broadman and Recanatini, 2002), a centralised administrative system and historical path-dependency of communist regime (Iwasaki and Suzuki, 2012); low level of economic development (M⊘ller and Skaaning, 2009), the natural resource curse, absence of small-scale privatisation and the long history of underdevelopment (Cieślik and Goczek, 2018).

Recent studies have attempted to examine the role of legacies of the Communist party on the current institutional weaknesses, such as corruption at the macro level and corrupt behaviour at the micro level. Macro-level evidence has been presented in the study of Libman and Obydenkova (2013) that focuses on the persistence of corruption as a result of Communist legacy across the Russian regions between 1970 and 2010. They have found that high shares of Communist party members in the 1970s are related to higher levels of corruption in 2010. This suggests that historical legacies of the Communist regime could still be influential in the persistence of corruption not only in Russia but also in other members of the Communist bloc.

On the other hand, a study by Ivlevs and Hinks (2018) has investigated the possible role of Communist party members in the bribing behaviour of individuals in the current time. Their study found that having links to former Communist Party members, as well as their children and relatives, increases the probability of paying bribes today. Indeed, their findings suggest that there is a possibility of the intergenerational transmission of corrupt practices among former Communist party members, creating a favourable environment for the persistence of corruption within a society over time.

Following the collapse of the Communist regime, each state pursued its own path of reform and development, leading to considerable divergence in their current socio-economic and political environments. Some countries adopted institutional reforms and regulatory frameworks that enabled them to join the European Union, while others retained weak institutional structures inherited from the Communist era. Our research focuses on this divergence, comparing post-Communist countries that have taken distinct institutional trajectories. In the first group—non-EU member states—pervasive corruption across both public and private sectors may incentivize government officials to manipulate publicly available economic data. In contrast, the second group—EU member states—undertook more stringent institutional reforms, particularly in the area of corruption control, fostering conditions that promote accurate reporting and adherence to the high statistical standards required by the EU. This study contributes to the literature by providing empirical evidence on the role of corruption in shaping discrepancies between reported and actual economic performance in post-Communist countries.

[4] Countries in our empirical analysis: Albania, Armenia, Azerbaijan, Bosnia and Herzegovina, Belarus, Bulgaria, Croatia, Czechia, Estonia, North Macedonia, Georgia, Hungary, Kazakhstan, Kyrgyzstan, Kosovo, Latvia, Lithuania, Montenegro, Moldova, Mongolia, Poland, Romania, Russia, Serbia, Slovak Republic, Slovenia, Tajikistan, Turkmenistan, Ukraine, Uzbekistan. By following Henderson et al. (2012), Serbia, Montenegro, Kosovo are removed from final sample due to border changes. In total, we process satellite images of these 30 countries in order to produce measurements of economic activity.

3. Data

In this section we describe our data sources in greater detail and provide some descriptive analysis. To conduct our research, we need measures of reported real GDP and nightlights; the former we obtain from the World Bank. The latter comes from the harmonized DMSP VIIRS nighttime lights data (V6) provided by Li et al. (2020), who calibrate the DMSP's (Defense Meteorological Satellite Programme) nighttime lights data from 1992 to 2013, and the VIIRS (Visible Infrared Imaging Radiometer Suite) Nighttime lights (VNL) from the Earth Observation Group from 2014 to 2020, so that the two can be used together as a continuous panel. For our main explanatory variable—a uniform measure of corruption—we rely on the World Bank once again, particularly its Worldwide Governance Indicators (WGI) database.

3.1. Description of data

There are two different panel datasets of nighttime lights that can used for studying economic activity: the DMSP-OLS from 1992 to 2013, and the VIIRS VNL from 2014 – present. However, due to the different types of satellites and methodology, the two datasets could not be used as a continuous panel from the year 1992 to present. Henderson et al. (2012) and the more recent Martinez (2022) rely on the DMSP panel, while Briviba et al. (2024) use the VIIRS VNL, which come with their limitation. Fortunately, Li et al. (2020) have published a harmonized dataset which calibrates the VIIRS annual nighttime lights data, to the same scale as the DMSP dataset, so that researchers can use the all the information at hand.

Henderson et al. (2012) provides an extensive description of the DMSP nightlights, and Li et al. (2020) describes their methodology on how the VIIRS datasets were converted to the same scale as DMSP. We emphasize here that the final version of the nighttime lights that researchers use for studying human activity are thoroughly processed to remove images that capture auroral activity, forest fires, the bright half of the lunar cycle, cloud coverage etc. to leave stable, predominantly "man-made" lights. As in the original DMSP dataset, a datapoint in the harmonized DMSP-VIIRS dataset from Li et al. (2020) measures the intensity of the nightlights in a grid of length 30 arc seconds (approximately 0.86 square kilometres at the equator); this intensity is reported by a digital number between 0 and 63, with the former detecting no light and the latter capturing the greatest intensity, top-coded.[5]

As per convention in the literature that uses the nightlights measure (Henderson et al., 2012; Martinez, 2022) and spatial data more generally, we re-project the nightlights data to equal area using Q-GIS software to remove distortions from the curvature of the earth; this ensures that the amount of light luminosity captured by each pixel is comparable, regardless of its location. Then we use the area of the country and the number of pixels per country to obtain the area-weighted average light luminosity digital number per country per year.[6] Because the data is right-skewed, we take the natural logarithm transformation.

The measure that captures the level of corruption within a country comes from the Worldwide Governance Indicators (WGI) Database (Kaufmann and Kraay, 2024). Developed by Kaufmann and Kraay, the "Control of Corruption (CC)" estimate is a composite score (on a standard normal distribution) that averages the data from various underlying sources.[7] The WGI project draws from household/firm surveys, commercial business information providers, NGOs and public sector organisations in order to get a complete picture. The variable captures "perceptions of the extent to which public power is exercised for private gain, including both petty and grand forms of corruption, as well as "capture" of the state by elites and private interests" ("Control of Corruption," WGI, World Bank). Since the estimate is normalized, most of the observations range from −2.5–2.5, where −2.5 indicates practically no control of corruption and 2.5 indicates high control of corruption. This estimate is available from 1996 to 2022, biannually until 2002 and then annually thereafter.

We obtain our official GDP measure from the World Development Indicators (WDI), also collected by the World Bank; specifically, we use the natural-logarithm transformation of constant local-currency GDP in this paper. Our control variables also come from the WDI database and include sectoral level net value added (as a % of GDP) in each of the four sectors: Agriculture and Forestry, Manufacturing, Industry, and Services. We also include the Dynamic General Equilibrium (DGE) Model estimates for informal economy as a share of GDP from the *World Bank Informal Economy* database (World Bank, 1990–2018). The last control variable, Freedom Index, comes from the *Freedom in the World* database, and is the average of the two measures—Civil Liberties and Political Rights—and ranges from 0 to 7, with higher numbers indicating less freedom (Freedom House, 2024).

3.2. Summary statistics

Table 1 on the following page provides the summary statistics table for the variables used in our paper. We create three variables

[5] The luminosity digital number reported is not exactly proportional to "true radiance" or physical amount of light received by the satellites due to sensor saturation and a scaling factor performed in the data-cleaning process. However, Henderson et al. (2012) perform an experiment for one year that shows that the difference between the two is minor and does not affect results.

[6] For visual representations of night lights in the years 1996 and 2020 see Figure S1a, S1b.

[7] A complete description of the methodogly can be found here Kaufmann et al (2010).

Table 1
Descriptive statistics.

	Post Communist Countries (29)				EU Countries Only (11)				Non-EU Countries Only (18)			
VARIABLES	N	Mean (SD)	Min	Max	N	Mean (SD)	Min	Max	N	Mean (SD)	Min	Max
Control of Corruption (CC)	717	-0.316 (0.673)	-1.53	1.58	264	0.347 (0.440)	-0.65	1.58	453	-0.703 (0.447)	-1.53	0.83
Low CC ($CC < -0.5$)	717	0.432 (0.496)	0	1	264	0.0152 (0.122)	0	13	453	0.675 (0.469)	0	1
Med CC ($-0.5 < CC < 0.5$)	717	0.425 (0.495)	0	1	264	0.633 (0.483)	0	1	453	0.305 (0.461)	0	1
High CC ($CC > 0.5$)	717	0.142 (0.350)	0	1	264	0.352 (0.479)	0	1	453	0.0199 (0.140)	0	1
ln(real GDP)	797	26.34 (2.913)	21.12	32.71	297	25.90 (2.366)	23.00	31.42	500	26.61 (3.167)	21.12	32.71
Area-weighted mean NTL	841	9.078 (20.98)	0.019	210.4	319	14.90 (30.20)	0.098	210.4	522	5.524 (10.95)	0.019	94.35
ln(Lights)	841	0.925 (1.206)	-3.95	2.99	319	1.638 (0.659)	-2.32	2.99	522	0.488 (1.255)	-3.95	2.62
ln(real GDP/Lights)	724	25.36 (3.250)	19.54	33.82	275	24.15 (2.137)	21.52	29.44	449	26.11 (3.577)	19.54	33.82
Informal Economy (%)	775	33.73 (10.61)	14.78	66.34	341	26.46 (5.550)	15.89	39.72	434	39.44 (10.14)	14.78	66.34
Agriculture NVA (%)	844	10.56 (8.663)	1.54	52.35	316	4.355 (3.227)	1.54	20.99	528	14.28 (8.769)	2.93	52.35
Manufacturing NVA (%)	750	14.84 (6.069)	3.72	44.60	283	17.69 (3.657)	9.60	30.03	467	13.11 (6.572)	3.72	44.60
Industry NVA (%)	844	28.54 (8.335)	12.19	66.58	316	27.49 (4.537)	16.21	43.14	528	29.16 (9.889)	12.19	66.58
Services NVA (%)	841	49.76 (9.501)	15.47	79.44	316	56.21 (5.126)	29.71	65.93	525	45.88 (9.417)	15.47	79.44
Freedom Index	891	2.45 (1.94)	0	6	205	0.405 (0.519)	0	2	543	3.649 (1.519)	0.5	6

Notes: The variable of interest 'Control of Corruption' is obtained from the *World Bank Governance Indicators* and is on a scale from −2.5–2.5, where −2.5 indicates non-existent control of corruption and 2.5 is complete control of corruption. The three binary 'CC' variables are derived from the original control of corruption estimate. Official GDP measures come from the *World Development Indicators* (WDI) database. Real GDP is in local currency constant units. 'Area-weighted mean Lights' is the area-weighted mean of light luminosity observed from space and is a value between 0 and 63; our dataset includes both the DMSP lights until 2013, and then the VIIRS lights measurement from 2014 to 2020 (harmonized by Li et. al. (2020) to be used a single time-series). 'ln(Lights)' is the log transformation of the area-weighted average of light luminosity. The deviation between the official GDP measures and the lights measure is captured by ln(real GDP/lights). Informal Economy is the DGE estimate of the share of informal economy in a country and is provided by the *World Bank Informal Economy* database. Sectoral-level GDP measurements are the net value added in each sector—Agriculture and Forestry, Manufacturing, Industry, and Services—as a percentage of GDP and is also from the WDI database. 'Freedom Index' is a binary variable from the *Freedom in the World* database and is the average of political rights and civil liberties, ranging between 0 and 7.

from the original WGI 'Control of Corruption' (CC) estimate: Low CC, Medium CC and High CC. Low CC is a dummy variable which is 1 when the control of corruption estimate is below −0.5 inclusive. Medium CC is a dummy variable which is 1 when control of corruption is between −0.5 and 0.5 inclusive. High CC is 1 when CC is greater than 0.5.

Our sample is limited to post-communist countries, which we further divide into two subsamples: EU and non-EU countries.[8] From the table, we can see that the mean Control of Corruption (CC) is positive in EU countries (0.347), but negative in the non-EU countries (-0.703). Further concentrating on the three dummy CC variables, we observe that most of the observations in the EU countries fall in the Medium and High categories of controlling corruption (with about two-thirds of them in the medium range and one-third in the high). In contrast, in the non-EU subsample they are mainly in the Low and Medium levels of controlling corruption, but now two-thirds of the observations in the Low CC level, while only one-third are in the medium.

Turning to measures of economic activity and the elasticity between the two, note that the mean of the area-weighted average lights luminosity digital number in the EU subsample is almost three times higher than the non-EU subsample mean (14.9 v. 5.52). We further observe that the mean difference between the two growth measures of economic activity—ln(GDP/lights) = ln(GDP) − ln (lights)—is lower in the EU subsample than in the non-EU and the whole sample.

In Fig. 1 above, we divide the countries in our sample into two categories—country-year observations with positive v. negative Control of Corruption—and obtain the annual mean divergence between real GDP and nightlights in those countries. As we can see, for

[8] The 11 EU post-communist countries considered in this paper are: Bulgaria, Croatia, Czechia, Estonia, Hungary, Latvia, Lithuania, Poland, Romania, Slovakia and Slovenia. The 16 non-EU post-communist countries in our sample are Albania, Armenia, Azerbaijan, Bosnia and Herzegovina, Belarus, North Macedonia, Georgia, Kazakhstan, Kyrgyzstan, Moldova, Mongolia, Russia, Tajikistan, Turkmenistan, Ukraine and Uzbekistan. Serbia, Montenegro and Kosovo are dropped due to changing borders, which would compromise the NTL measure.

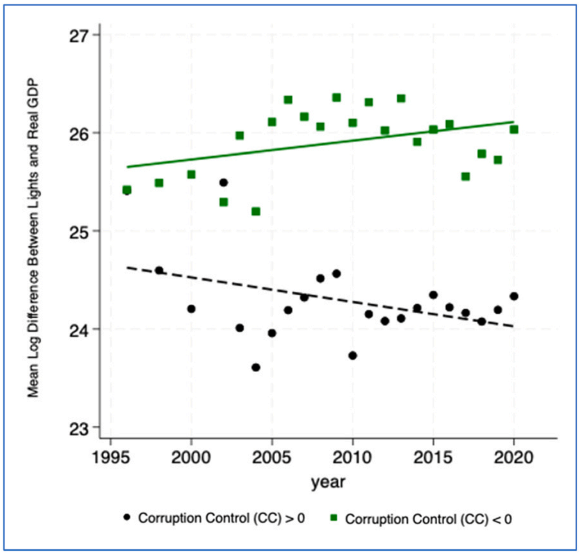

Fig. 1. Mean Annual divergence between GDP and nightlights: by level of corruption control. *Compiled by authors.*

those country-year observations with positive corruption control, the mean divergence is lower at the start of the sample and continues to decline overtime, while the opposite is true for those with negative corruption control, i.e. the more corrupt countries in the sample. This descriptive evidence, which supports our theory that corruption can affect GDP-data manipulation, warrants a closer examination, and so in the next section, we formalize our estimation strategy.

3.3. Estimation strategy

To identify the effect of corruption on data manipulation, we use fixed-effects estimation at the country level and year level to account for unobserved heterogeneity at the country level, as well as time-specific shocks. For country *i* in year *t*, we define our dependent variable $differential_{it}$ as the difference between $\ln(real\_GDP)_{it}$, which is the natural logarithm of the local currency GDP at constant 2005 prices, and $\ln(lights)_{it}$, the natural logarithm of the area-weighted average nightlights digital number, i.e. $differential_{it} = \ln(real\_GDP)_{it} - \ln(lights)_{it}$.

Our base-line specification can be formalized as follows:

$$differential_{it} = \alpha + \beta_1 CC_{it} + \mu_i + \tau_t + \varepsilon_{it} \tag{1}$$

where CC_{it} is the explanatory variable of interest "Control of Corruption," which is a continuous standardized variable, where most values lie between −2.5 and 2.5 standard deviations away from mean 0; observations with values −2.5 (and beyond) indicate no control of corruption, while those which are 2.5 (and greater) indicate full control of corruption. We include μ_i to control for time-invariant country-level unobserved heterogeneity and τ_t to account for year-specific shocks. We do not include any controls in our baseline regression, but add them for subsequent specifications. Finally, we further cluster the standard errors at the country level to account for heteroskedasticity in our panel data, as suggested by Abadie et al. (2023).

Recent empirical evidence from Martinez (2022) suggests economic activity is lower than indicated by official statistics in highly autocratic countries. We examine this in model specification (2) given below:

$$differential_{it} = \alpha + \beta_1 CC_{it} + \beta_2 Free\_Index_{it} + \mu_i + \tau_t + \varepsilon_{it}. \tag{2}$$

Here, $Free\_Index_{it}$ is the average score of the two categories—political rights and civil liberties—in Freedom House's *Freedom in the World* database; values range between 0 and 7. Country and year fixed effects are included as in Eq. (1), and errors are clustered at the country level.

The final model specification includes sectoral-level GDP, as well as a measure for capturing informal economic activity, along the lines of Briviba et al. (2024). Empirical evidence shows that informal economic activity is captured by lights (e.g. Ghosh et. al., 2009), which might not exist in official GDP data, and so it can also affect the differential. Similarly, different sectors affect lights differently, and so including sectoral level GDP can help identify the channel through which such manipulations might occur. Eq. (3) below captures the final specification:

$$differential_{it} = \alpha + \beta_1 CC_{it} + \beta_2 Free\_Index_{it} + \beta_3 Inf_{DGE\,it} + \beta_4 Man_{NVA\,it} + \beta_5 AgF_{NVA\,it} + \beta_6 Ind_{NVA\,it} + \beta_7 Srv_{NVA\,it} + \mu_i + \tau_t + \varepsilon_{it}. \tag{3}$$

Inf_DGE_{it} is the Dynamic General Equilibrium (DGE) model estimates of the share of informal output with respect to total GDP for country *i* in year *t*, and is obtained from the *World Bank Informal Economy* database (World Bank, 1990–2018). Man_NVA_{it}, AgF_NVA_{it},

Ind_NVA_{it}, and Srv_NVA_{it} are the share of net-value added (as a percentage of GDP) in country *i* at year *t* in each of these industries: Manufacturing *(Man_NVA)*; Agriculture and Forestry (*AgF_NVA*); Industry (*Ind_NVA*); and Services (*Srv_NVA*). As with the previous two specifications, we continue to include country and year fixed effects and cluster the errors at the country level.

A potential concern with our identification strategy is that institutional variables such as Control of Corruption evolve slowly over time, limiting within-country variation and raising the possibility that fixed-effects estimates are identified from relatively small changes. This concern is particularly relevant in short panels. However, our dataset spans 25 years (1996–2020), providing sufficient temporal depth to capture medium-run shifts in governance quality. We are able to extend our panel to more recent years by leveraging the harmonized DMSP–VIIRS nightlights dataset developed by Li et al. (2020), which places both satellite series on a consistent scale and improves cross-time comparability. Country fixed effects are essential in this setting, as they absorb time-invariant characteristics—such as historical legacies of central planning, geography, and administrative capacity—that could otherwise confound the relationship between corruption and economic reporting. Year fixed effects similarly account for global shocks and common trends. While this specification reduces reliance on cross-sectional comparisons, it strengthens internal validity by isolating within-country associations that are less susceptible to structural bias.

A second concern relates to potential cyclical dynamics in the dependent variable. Although both GDP and nightlight intensity respond to macroeconomic fluctuations, our outcome variable is defined as the differential between the two—thereby capturing deviations across two co-moving indicators of economic activity rather than changes in output itself. This structure, combined with the inclusion of year fixed effects, helps dampen the influence of transitory global shocks and business-cycle effects. What remains is variation in the GDP–NTL gap that is less likely to reflect short-term macroeconomic noise and more plausibly associated with institutional conditions. We do not claim to establish causal effects; rather, we interpret our findings as evidence of a robust association between corruption control and the credibility of reported economic activity.[9]

4. Results

We now turn to the core empirical results on how corruption affects the discrepancy between reported GDP and satellite-based measures of economic activity. We begin with the full sample of post-communist countries, then compare those that have joined the European Union to those that have not. The results are organized around two specifications: one using the standardized Control of Corruption estimate, and another using corruption-level dummies to test for nonlinear effects.

Table 2 presents the results of corruption effects on GDP distortion. Columns (1), (2), and (3) use the standardized variable “Control of Corruption” as the main regressor, while columns (4) through (6) include two indicator variables: “Low Corruption Control” (equal to 1 if the estimate is below −0.5) and “Medium Corruption Control” (equal to 1 if between −0.5 and 0.5). The omitted category is countries with high corruption control (above 0.5). Baseline results from Eq. (1) are in columns (1) and (4); Eq. (2) adds the “Freedom Index” in columns (2) and (5); the final model, shown in columns (3) and (6), includes informal economic activity and sectoral net value added.

Across all three specifications, control of corruption is associated with a reduction in the GDP/lights differential: as corruption is brought under control, the discrepancy between reported GDP and observed nightlights narrows. The effect size ranges from −0.344 to −0.284, with the final model (column 3) indicating a 24.7% decrease in the gap for a one standard deviation increase in control of corruption.[10] These estimates are statistically significant at the 10% level. This pattern is consistent with the interpretation that more corrupt environments exhibit larger discrepancies between reported GDP and independently observed economic activity, as captured by satellite imagery.

When examining nonlinear effects in columns (4) to (6), the results are less conclusive. The coefficient on “Low Corruption Control” is positive, suggesting greater distortion in highly corrupt countries, but is not statistically significant. “Medium Corruption Control” also yields small and insignificant estimates.

Interestingly, the Freedom Index has no discernible effect on the GDP/lights differential in our sample, even though previous research, such as Martinez (2022), has established a broader link between political freedom and GDP manipulation in this sample of post-communist countries. In our case, the lack of a significant effect may reflect the narrower institutional context of post-communist countries, where variation in the Freedom Index is limited. Alternatively, it is possible that corruption plays a more dominant and direct role in shaping reporting behavior in these settings, crowding out the marginal influence of political freedoms.

Among the control variables, only one stands out: the share of agriculture. A 1% increase in the share that agriculture contributes to GDP is associated with a 4.6% increase in the GDP-NTL elasticity. This is consistent with the fact that agricultural activity tends to generate little night-time light and is therefore poorly captured by satellite imagery.

The post-communist countries in this study offer a unique opportunity to explore the institutional dimensions of corruption: while some have decisively broken with their communist past, others remain deeply shaped by its legacy. Among these, the post-communist countries that have joined the European Union stand apart. EU accession requires compliance with the Copenhagen criteria—among them, the establishment of stable institutions that uphold the rule of law and democratic governance.[11] Beyond formal membership, the EU imposes an extensive framework of procedures, oversight mechanisms, and standards for national statistical systems, making

9 This interpretation is supported by the consistency of our results across nonlinear specifications, alternative corruption indicators (CPI), and leave-one-out analyses, which mitigate concerns that the findings are driven by random fluctuations or isolated outliers.

10 We derive this number from the following formula given our log-level regression: $(e^{\beta} - 1)$*100

11 https://european-union.europa.eu/principles-countries-history/eu-enlargement_en

Table 2
The effect of control of corruption on GDP data manipulation.

	ln(real GDP) – ln(lights)					
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
Control of Corruption	-0.344*	-0.333*	-0.284*			
	(0.189)	(0.195)	(0.147)			
Freedom Index		0.023	0.038		0.056	0.071
		(0.067)	(0.080)		(0.070)	(0.080)
Informal Economy			0.015			0.020
			(0.020)			(0.020)
Agriculture (NVA)			0.035			0.045*
			(0.021)			(0.022)
Manufacturing (NVA)			-0.026			-0.019
			(0.024)			(0.025)
Industry (NVA)			0.011			0.018
			(0.024)			(0.026)
Services (NVA)			0.004			0.012
			(0.021)			(0.023)
Low Corruption Control				0.132	0.101	0.088
				(0.308)	(0.303)	(0.230)
Medium Corruption Control				-0.057	-0.074	-0.079
				(0.224)	(0.217)	(0.182)
Observations	594	594	502	594	594	502
R-squared	0.844	0.845	0.854	0.841	0.842	0.853
Number of countries	27	27	24	27	27	24
Country FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.
Standard errors clustered at the country level in parentheses.
Notes: Sample spans the years 1996–2020. 'Control of Corruption' is standardized, with values −2.5 and below indicating no control of corruption, while those with 2.5 (and above) have complete control of corruption. 'GDP' is the real output in constant local currency units. 'Lights' is the area-weighted average of nightlights captured by satellites. Our dependent variable is the differential 'ln(GDP) – ln(lights)' which captures the data discrepancy between the two measures of economic activity. 'Freedom Index' comes from the *Freedom in the World* database, ranges between 0 and 7 (with greater values indicating less freedom); it is the average of the two scores: Political Rights and Civil Liberty. 'Informal Economy' is the DGE model estimates of informal output from the *World Bank Informal Economy* database. 'Industry,' 'Manufacturing,' 'Services' and 'Agriculture' capture sectoral level economic activity; each is the net value added in their respective sector as a percentage of GDP. In columns (4)-(6) we decompose Control of Corruption into two dummies: 'Low CC' takes the value of 1 if the country has control of corruption below −0.5 and 0 otherwise, and 'Medium CC' is an indicator that is 1 if corruption control is between −0.5 and 0.5, while those countries with high level of corruption control serve as the reference category. Serbia, Montenegro and Kosovo are excluded from the sample due to changing borders during the sample period.

systematic manipulation of official economic data both institutionally difficult and politically costly.

In contrast, post-communist countries outside the EU have neither undergone this convergence process nor are subject to the same constraints. As such, we expect corruption to play a more distortive role in these settings, with clearer discrepancies between reported GDP and observed night-time lights. This institutional divergence motivates our decision to analyze EU and non-EU countries separately, rather than rely on a single EU dummy, which would risk masking the structural and behavioral differences that underpin our hypothesis.

Table 3 reports the regression results for the 16 non-EU post-communist countries in our sub-sample: Albania, Armenia, Azerbaijan, Bosnia and Herzegovina, Belarus, North Macedonia, Georgia, Kazakhstan, Kyrgyzstan, Moldova, Mongolia, Russia, Tajikistan, Turkmenistan, Ukraine and Uzbekistan. Kosovo, Serbia and Montenegro are excluded due to changing borders which would compromise their lights data. As before, columns (1), (2) and (3) include the control of corruption standardized estimate, while columns (4), (5), and (6) include the indicator variables.

The results indicate a statistically significant association between corruption and the divergence between reported GDP and nightlights in the non-EU post-communist countries. The effect of the control of corruption variable is larger than in the full sample: −0.383 versus −0.284. A one standard deviation increase in corruption control is associated with a 31.8% reduction in the GDP-NTL gap, statistically significant at the 10% level.

When switching from high to medium control of corruption, the differential increases by 120.1–124.1%, and further increases by 143.7–148.3% when shifting to low control of corruption. These estimates are statistically significant at the 1% level and are consistent with the interpretation that weaker institutional quality is associated with a larger gap between official GDP figures and independently measured economic activity.

We therefore reject the null hypothesis at conventional significance levels and find statistically robust evidence of a positive association between corruption and the discrepancy between reported GDP and light-based proxies. Higher levels of corruption are associated with a larger divergence between reported and satellite-based measures of economic activity.

Again, the Freedom Index has no significant effect in the non-EU group. The only other significant variable is manufacturing: a 1% increase in its share leads to a 5.3% reduction in the GDP-NTL gap. This is intuitive, as manufacturing tends to occur in electrified, formal environments more likely to be visible via night-time satellite imagery.

Table 3
The effect of control of corruption on GDP data manipulation – non-EU only.

	ln(real GDP) – ln(lights)					
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
Control of Corruption	-0.376	-0.364	-0.383*			
	(0.225)	(0.227)	(0.199)			
Freedom Index		0.036	0.033		0.020	0.001
		(0.082)	(0.092)		(0.080)	(0.102)
Informal Economy			-0.007			-0.002
			(0.017)			(0.018)
Agriculture (NVA)			0.027			0.026
			(0.019)			(0.022)
Manufacturing (NVA)			-0.053*			-0.054*
			(0.029)			(0.030)
Industry (NVA)			0.008			0.011
			(0.017)			(0.019)
Services (NVA)			0.001			0.001
			(0.018)			(0.020)
Low Corruption Control				0.907***	0.891***	0.897***
				(0.172)	(0.213)	(0.271)
Medium Corruption Control				0.807***	0.793***	0.789***
				(0.134)	(0.165)	(0.249)
Observations	352	352	282	352	352	282
R-squared	0.852	0.852	0.867	0.855	0.855	0.872
Number of countries	16	16	14	16	16	14
Country FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES
Non-EU	YES	YES	YES	YES	YES	YES

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.
Standard errors clustered at the country level in parentheses.
Notes: Sample spans the years 1996–2020 and is limited to non-EU post-communist countries only. ‘Control of Corruption’ is standardized, with values −2.5 and below indicating no control of corruption, while those with 2.5 (and above) have complete control of corruption. ‘GDP’ is the real output in constant local currency units. ‘Lights’ is the area-weighted average of nightlights captured by satellites. Our dependent variable is the differential ‘ln(GDP) – ln(lights)’ which captures the data discrepancy between the two measures of economic activity. ‘Freedom Index’ comes from the *Freedom in the World* database, ranges between 0 and 7 (with greater values indicating less freedom); it is the average of the two scores: Political Rights and Civil Liberty. ‘Informal Economy’ is the DGE model estimates of informal output from the *World Bank Informal Economy* database. ‘Industry,’ ‘Manufacturing,’ ‘Services’ and ‘Agriculture’ capture sectoral level economic activity; each is the net value added in their respective sector as a percentage of GDP. In columns (4)-(6) we decompose Control of Corruption into two dummies: ‘Low CC’ takes the value of 1 if the country has control of corruption below −0.5 and 0 otherwise, and ‘Medium CC’ is an indicator that is 1 if corruption control is between −0.5 and 0.5, while those countries with high level of corruption control serve as the reference category. Serbia, Montenegro and Kosovo are excluded from the sample due to changing borders during the sample period.

Table 4 presents the same analysis for the 11 EU countries: Croatia, Czechia, Slovakia, Slovenia, Hungary, Poland, Estonia, Latvia, Lithuania, Bulgaria, and Romania. The results here are markedly different. We fail to reject the null that corruption control has an effect on the GDP-NTL elasticity in any specification, and the magnitude of the coefficient in the final model is near zero. In columns (4) to (6), the "Low Corruption Control" dummy dropped due to lack of variation. For "Medium Corruption Control," the coefficient is unexpectedly negative and weakly significant in columns (4) and (5), but becomes insignificant once all controls are added in column (6). Thus, we again fail to reject the null.

This should not be interpreted as conclusive evidence that GDP manipulation does not occur within the EU. There is precedent to the contrary: for instance, Greece's misreporting during the 2010 Euro crisis.[12] However, it is plausible that prospective EU member states refrained from manipulation during the accession period due to expected scrutiny, and that post-accession institutional constraints now limit their ability to do so.

The only significant variables in the EU sample are manufacturing and industry shares. As with the non-EU sample, manufacturing share reduces the GDP-NTL gap, though the effect is slightly smaller. However, industry share increases the gap: a 1% increase is associated with a 10.5% rise in the differential. This likely reflects that some forms of industrial activity—such as utilities, construction, and high-tech production—contribute to GDP but are not visible from space.

Taken together, these findings reinforce the role of institutions in shaping the reliability of official statistics. In countries with weaker governance, the gap between reported GDP and night-time lights is larger, a pattern consistent with reduced statistical

[12] https://www.ft.com/content/33b0a48c-ff7e-11de-8f53-00144feabdc0

Table 4
The effect of control of corruption on GDP data manipulation – EU only.

	ln(real GDP) – ln(lights)					
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
Control of Corruption	0.102	0.124	0.036			
	(0.134)	(0.204)	(0.081)			
Freedom Index		0.026	-0.047		0.051	-0.025
		(0.107)	(0.060)		(0.081)	(0.064)
Informal Economy			0.045			0.050
			(0.048)			(0.045)
Agriculture (NVA)			0.036			0.021
			(0.053)			(0.052)
Manufacturing (NVA)			-0.045*			-0.041*
			(0.022)			(0.020)
Industry (NVA)			0.105**			0.093**
			(0.035)			(0.036)
Services (NVA)			0.048			0.042
			(0.030)			(0.031)
Medium Corruption Control				-0.168*	-0.182*	-0.083
				(0.076)	(0.084)	(0.063)
Observations	172	172	158	172	172	158
R-squared	0.970	0.970	0.983	0.972	0.972	0.984
Number of countries	11	11	10	11	11	10
Country FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES
Non-EU	YES	YES	YES	YES	YES	YES

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.
Standard errors clustered at the country level in parentheses.
Notes: Sample spans the years 1996–2020 and is limited to EU post-communist countries only. 'Control of Corruption' is standardized, with values −2.5 and below indicating no control of corruption, while those with 2.5 (and above) have complete control of corruption. 'GDP' is the real output in constant local currency units. 'Lights' is the area-weighted average of nightlights captured by satellites. Our dependent variable is the differential 'ln (GDP) – ln(lights)' which captures the data discrepancy between the two measures of economic activity. 'Freedom Index' comes from the *Freedom in the World* database, ranges between 0 and 7 (with greater values indicating less freedom); it is the average of the two scores: Political Rights and Civil Liberty. 'Informal Economy' is the DGE model estimates of informal output from the *World Bank Informal Economy* database. 'Industry,' 'Manufacturing,' 'Services' and 'Agriculture' capture sectoral level economic activity; each is the net value added in their respective sector as a percentage of GDP. In columns (4)-(6) we decompose Control of Corruption into two dummies: 'Low CC' takes the value of 1 if the country has control of corruption below −0.5 and 0 otherwise (and is dropped in this sample due to lack of observations), and 'Medium CC' is an indicator that is 1 if corruption control is between −0.5 and 0.5, while those countries with high level of corruption control serve as the reference category. Serbia, Montenegro and Kosovo are excluded from the sample due to changing borders during the sample period.

credibility. While satellite data are imperfect proxies, the cross-country contrasts observed here reveal meaningful differences in transparency and statistical credibility across regimes.

5. Robustness checks

We conduct several robustness checks to ensure the reliability of our findings, most of which are reported in the supplementary Appendix. Two of the most important are discussed below.

5.1. Wild bootstrap robust standard errors

First, we address the small cluster problem as described in Cameron and Miller (2015). When the number of clusters is small, cluster-robust standard errors can be biased downward—potentially leading to overrejection of the null. On the other hand, not clustering would ignore heteroskedasticity in the error structure. While there is no strict threshold for what constitutes "too few" clusters, Cameron and Miller (2015) suggest fewer than 20 for strongly balanced panels and fewer than 50 for unbalanced ones. In our case, the panel is strongly balanced, but the number of clusters ranges from 24 to 27 in the full sample, and drops to 10–11 (EU) and 14–16 (non-EU) in the split samples, raising potential concerns.

To address this, we implement the wild bootstrap method with 5000 repetitions, following the procedure outlined in Cameron et al. (2008), which yields cluster-robust confidence intervals and p-values. Fig. 2 presents the results across all three samples. The corruption control estimate remains significant at the 10% level in the full sample across all specifications. In the non-EU subsample, both "Low Corruption Control" and "Medium Corruption Control" remain significant at the 1% level. As before, we find no significant effect of corruption in the EU subsample, regardless of the corruption measure used.

5.2. Leave-one-out analysis

To confirm that our results are not driven by any single country, we perform a leave-one-out analysis for both the full post-

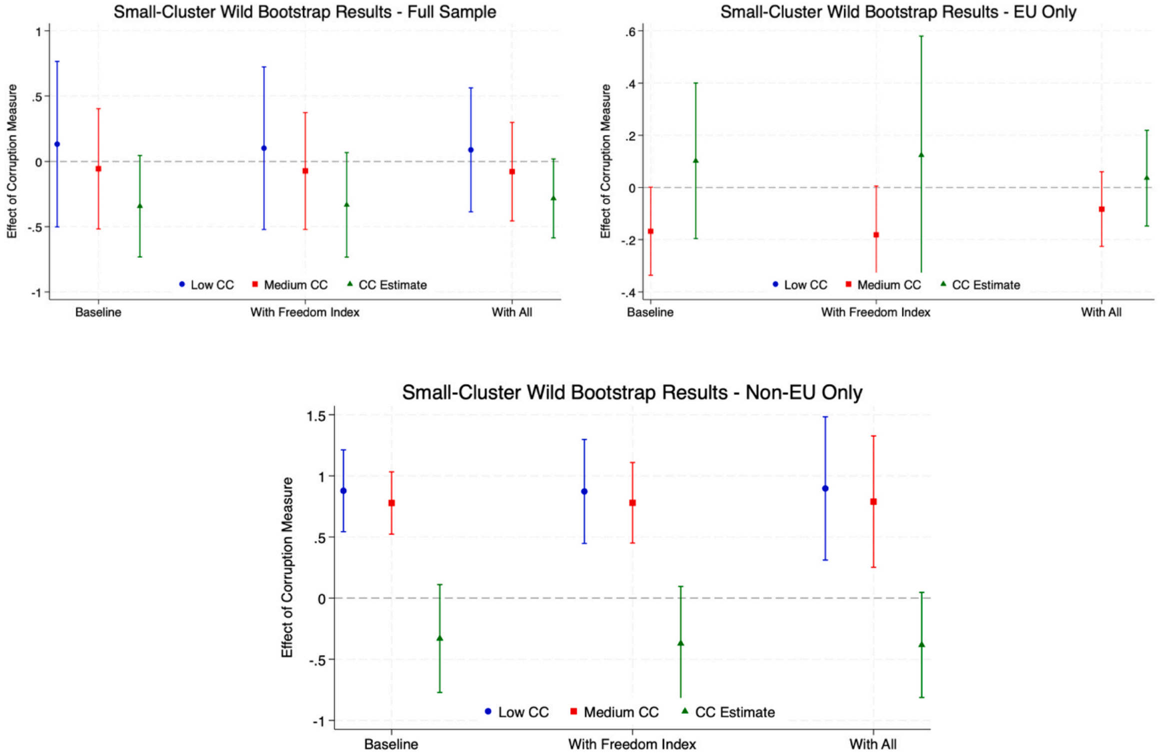

Fig. 2. Small cluster size correction with wild bootstrap – corruption control estimates with 95% CI. Notes: This shows the results of wild cluster bootstrap with 5000 repetitions to correct for the small cluster size when clustering at the country level. The point estimates with corresponding 95% Confidence Intervals are displayed for the entire sample, EU countries and Non-EU countries respectively. All estimates account for country and year fixed effects. Baseline estimates include only a measure of corruption control: the standardised CC estimate or the two indicators—Low CC and Medium CC. The second specification includes Freedom Index as a control in addition to each of the two measures of corruption control, while the last specification includes all controls: Informal DGE and Sectoral Net-Value Added as share of GDP for Agriculture, Manufacturing, Industry and Services. Corresponding tables are available in the supplementary Appendix.

communist sample and the non-EU subsample.[13] Each country is sequentially excluded, and the full model that includes all control variables (Eq. 3) is re-estimated. Fig. 3 presents the results: the upper panel shows the standardized corruption estimate for the full sample, while the lower panel shows the two indicator variables (Low and Medium Corruption Control) for the non-EU countries. Each point denotes the coefficient when one country is left out, with 95% confidence intervals shown as vertical lines. The dashed reference lines represent the original full-sample estimates.

The estimates are tightly clustered and largely consistent across iterations, suggesting that our results are not overly influenced by any individual country. In the full sample, 11 of 27 iterations yield statistically significant results at the 5% level, even though the original coefficient was significant only at the 10% level. This reinforces the robustness of our main finding: corruption is systematically associated with a larger divergence between reported GDP and satellite-based measures of economic activity.

The non-EU panel offers additional insight, especially for the nonlinear effects. The estimates for both Low and Medium Corruption Control remain stable when most countries are excluded. In nearly all cases, the coefficients hover close to the original values (Low CC = 0.893; Medium CC = 0.789), with confidence intervals that do not wildly fluctuate. This suggests a consistent institutional pattern in which lower corruption control is associated with higher GDP–NTL differentials.

There are, however, meaningful exceptions that deserve discussion. Georgia plays an outsized role in the estimation. When Georgia is excluded, the coefficient on Low Corruption Control drops sharply and loses statistical significance; Medium Corruption Control drops out of the regression altogether due to insufficient variation. This reflects Georgia's unique status as a relatively clean, reform-oriented country in the non-EU post-communist group. Its exclusion weakens the clarity of the corruption effect—not because Georgia distorts the results, but because it helps to anchor the contrast. In fact, the presence of a "clean" country like Georgia in the sample makes the broader pattern more visible: countries with entrenched corruption tend to exhibit larger discrepancies between reported and satellite-based measures of activity. Moldova also has a non-trivial influence, likely due to institutional volatility that affects its position in the corruption spectrum.

[13] We also perform the analysis for the EU subsample and find the estimates cluster around our original estimate and largely remain statistically insignificant with the exception of the exclusion of Hungary. It can be found in our supplementary appendix.

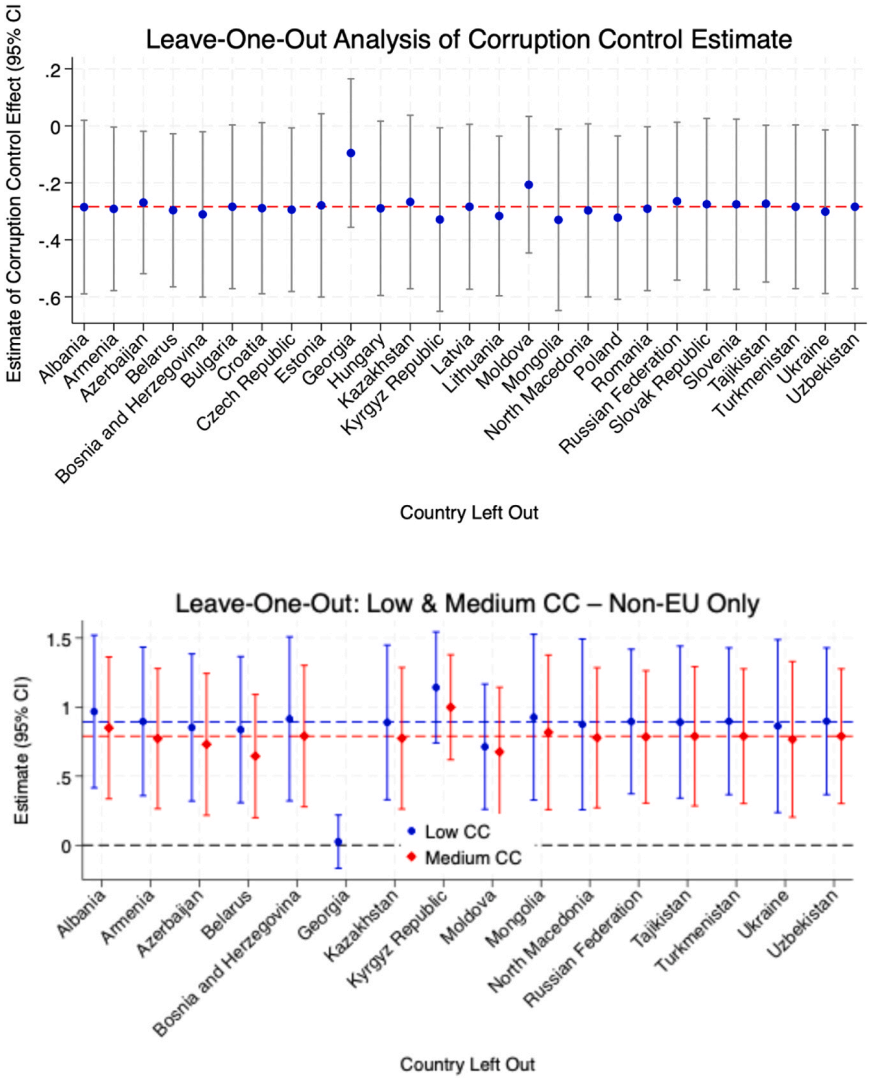

Fig. 3. Leave-one-out analysis: full sample and non-EU. Notes: Estimates of corruption control come from the fully specified model that includes all controls and country and time fixed effects, with standard errors clustered at the country-level. Each regression leaves out the country listed in the figure. The top reports the analysis from the full sample using standardized control of corruption measure as the regressor of interest, while the bottom shows the results of the exercise in the non-EU subsample only using the dummies "Low Corruption Control" and "Medium Corruption Control.".

More broadly, the stability of the coefficients in both panels—and across both corruption specifications—strengthens confidence in our findings. The results are not an artifact of a few extreme cases, but rather reflect a persistent relationship between institutional quality and data reliability in the post-communist world.

5.3. *Additional robustness tests*

We also verify that our results are robust to alternative specifications and data sources, available in the supplementary appendix. Using only nightlights from the original NOAA DMSP dataset (as opposed to the harmonized DMSP-VIIRS data), our estimates remain consistent. Similarly, substituting alternate measures of freedom from the *Freedom in the World* database—Free, Not Free, Politically—for our continuous Freedom Index does not alter the results. Finally, using the Corruption Perceptions Index (CPI) instead of the World Bank's Control of Corruption measure yields consistent findings as well.

6. Conclusion

This paper examines whether corruption influences the reliability of reported economic data, by analyzing discrepancies between official GDP figures and satellite-based measures of economic activity. Using harmonized nightlight data from 1996 to 2020, we assess whether countries with weaker corruption control exhibit larger gaps between official GDP figures and independently observed night-time light emissions.

Focusing on post-communist countries, where many governments inherited centralized statistical systems but diverged institutionally over time, we find that corruption is strongly associated with a widening gap between reported and observed activity. The results are especially pronounced in non-EU countries, where weaker governance appears to enable or incentivize manipulation. Among EU members, where institutional checks are stronger, this relationship disappears.

Our findings are robust to alternate specifications and control variables, including sectoral composition, informal economic activity, and political freedom. The use of country and year fixed effects helps isolate within-country variation and address time-invariant confounders. We also show that the results hold across two distinct measures of corruption, reinforcing the consistency of the pattern observed, and are not driven by any one country.

That said, several limitations remain. Night-time light intensity, while objective, may not fully capture all dimensions of economic activity—particularly in rural, service-based, or energy-efficient economies. These structural characteristics are largely time-invariant and are absorbed by our fixed effects framework, but some sectoral heterogeneity may remain. Moreover, while we interpret the widening gap between GDP and lights as suggestive of strategic misreporting, we cannot directly observe manipulation or intent. The divergence could partly reflect measurement error. However, its consistent and statistically significant association with corruption control makes pure error an unlikely sole explanation.

Finally, as with any observational study, our analysis does not establish causality. Although our empirical strategy controls for time-invariant country characteristics and time-varying observables, the possibility of endogeneity cannot be fully ruled out. For instance, governments facing economic pressure may both relax anti-corruption efforts and manipulate data, generating a spurious correlation. Future research employing instrumental variables or natural experiments could help address this limitation more directly.

Taken together, these findings suggest that corruption shapes not only economic governance, but the credibility of the statistics that underpin it. In settings with weak institutions, official GDP figures may diverge substantially from independent measures of real activity—raising concerns about the reliability of economic data. For policymakers and international partners, this highlights the value of external validation tools—such as satellite imagery and statistical audits—and the importance of safeguarding the independence of national statistical systems.

CRediT authorship contribution statement

Niveditha Prabakaran: Writing – original draft, Visualization, Software, Methodology, Formal analysis, Data curation, Conceptualization. **Gaygysyz Ashyrov:** Writing – original draft, Resources, Methodology, Formal analysis, Conceptualization.

Conflict of Interest

None.

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Appendix A. Supporting information

Supplementary data associated with this article can be found in the online version at doi:10.1016/j.ecosys.2026.101392.

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