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How Much Should We Trust the Dictator's GDP Estimates?

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Abstract

I study the manipulation of GDP statistics in weak and non-democracies. I show that the elasticity of official GDP figures to nighttime lights is systematically larger in more authoritarian regimes. This autocracy gradient in the night-lights elasticity of GDP cannot be explained by differences in a wide range of factors that may affect the mapping of night lights to GDP, such as economic structure, statistical capacity, rates of urbanization or electrification. The gradient is larger when there is a stronger incentive to exaggerate economic performance (years of low growth, before elections or after becoming ineligible for foreign aid) and is only present for GDP sub-components that rely on government information and have low third-party verification. The results indicate that yearly GDP growth rates are inflated by a factor of between 1.15 and 1.3 in the most authoritarian regimes. Correcting for manipulation substantially changes our understanding of comparative economic performance at the turn of the XXI century.

Keywords: GDP, nighttime lights, growth, autocracy, bias

JEL codes: C82, D73, E01, H11, O47

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1 Introduction

The importance of economic performance for political survival is well known. The economy is a frequent object of political debate -"It's the economy, stupid" - and a major determinant of turnover in both democracies and autocracies (Burke and Leigh, 2010; Brückner and Ciccone, 2011). However, agents lack perfect information about the state of the economy and must rely on imperfect estimates, such as Gross Domestic Product (GDP), to assess government performance (Leigh, 2009; Ashworth, 2012). Governments themselves usually produce these estimates, which gives rise to a moral hazard problem as they are constantly tempted to exaggerate how well the economy is doing. In this regard, GDP stands out as perhaps the most widely used measure of economic performance and, as such, one of the most profitable for governments to manipulate (Lepenies, 2016).

The manipulation of GDP statistics can lead to economic and political inefficiencies. From an economic perspective, a country's growth estimates affect the actions of other agents (trade partners, multilateral organizations, foreign investors) that may not be successful at teasing out the information content of official statistics.[1] From a political perspective, formal models of accountability show that incumbents have a strong incentive to manipulate the information available to citizens (Gehlbach et al., 2016). Thus, the inflation of GDP growth figures is likely to be hindering political accountability and improved governance. From an academic perspective, manipulation of GDP data can affect our understanding of the functioning of the economy and of the causes of development. It may also affect our assessment of specific policies, historical periods and country trajectories.[2] GDP is an essential part of the economist's toolkit.

Although the incentive to exaggerate economic performance is ever-present, we expect that a well-functioning democracy can rein in, to some extent, the impulse to manipulate official statistics. As Orwell once put it, "If liberty means anything at all it means the right to tell people what they do not want to hear." A strong democracy guarantees that political opponents and the media can freely scrutinize government figures and that an independent judiciary can investigate and prosecute those that fiddle with the numbers. Such checks and balances are largely absent in more autocratic regimes. The execution of the civil servants in charge of the 1937 population census of the USSR following its 'unsatisfactory' findings serves as an extreme example (Merridale, 1996). A more recent and less extreme example

[1] Although Cavallo et al. (2016) find evidence that Argentinian households interpret potentially biased inflation statistics in a sophisticated manner.

[2] Levy and Peart (2011) document the systematic overestimation of the Soviet Union's GDP growth rate in popular economics textbooks of the second half of the XX century and how it affected the comparative analysis of capitalist and socialist economies.

relates to the controversy that has surrounded China's growth figures for years, including Chinese premier Li Keqiang's alleged acceptance of the unreliability of the country's official GDP estimates (Clark et al., 2017).

In this paper, I look for evidence of increased manipulation of official GDP statistics in weak and non-democracies. For this purpose, I compare reported GDP figures to nighttime lights recorded by satellites from outer space. The former is a 'soft' measure of economic activity, which can be manipulated by national governments, while the latter is a 'hard' measure that is immune to manipulation (Henderson et al., 2012; Michalopoulos and Papaioannou, 2017). Using panel data for 179 countries between 1992 and 2008, I study whether the mapping of night lights to GDP differs systematically by regime type. That is to say, I examine whether the same amount of growth in nighttime light translates into more GDP growth in autocracies than in democracies.

In essence, the empirical strategy corresponds to a difference-in-difference research design. In the main specification, I regress ln(GDP) on ln(lights), a measure of autocracy and the interaction of the two (plus country and year fixed effects). Except for the autocracy terms, the specification, the data sources and the variable definitions are all identical to those employed by Henderson et al. (2012) in the seminal study on the use of nighttime lights as a measure of economic activity. The inclusion of the autocracy variable in the specification allows for the possibility that the nature of economic growth differs across regime types (e.g. sectoral or expenditure composition) in a way that is heterogeneously captured by the two measurements on economic activity. My object of interest is the interaction term, which captures the effect of autocracy on the mapping from night lights to GDP. The identifying assumption is that, in the absence of manipulation, this mapping should not be systematically affected by how democratic a country is.

The main finding of the paper is that the night-lights elasticity of GDP is significantly larger in more autocratic regimes. Said differently, the same amount of growth in nighttime lights translates into higher reported GDP growth in autocracies than in democracies, which I interpret as evidence of increased manipulation of official statistics in the former. This result is robust to the use of different regime classifications (Freedom House, Polity IV) and is mainly driven by countries at the bottom of the democracy spectrum. I find that the separation of powers and the development of independent political and economic institutions does indeed constrain the executive's ability to manipulate official statistics: the autocracy gradient is larger for countries without an elected legislature or executive, as well as for countries in which the central bank does not control monetary policy and for those lacking a national constitutional court. The gradient is also larger for countries with a civilian (rather than military or royal) dictatorship and for those that have had a communist regime.

The estimates indicate that yearly GDP growth is inflated in the most authoritarian regimes by a factor of 1.15 to 1.3. Adjustment for manipulation has important implications for our understanding of relative economic performance over the medium term. In the raw GDP data, only 4 of the 20 countries that experienced the highest aggregate growth over the sample period (1992-2008) were classified as 'free' by Freedom House, while 11 were classified as 'not free' and 5 as 'partially free.' After correcting for manipulation, the top-20 includes nine 'free' countries, with Cape Verde, Estonia, Latvia, South Korea and the Dominican Republic replacing Bhutan, Laos, UAE, Sudan and Ethiopia. At the very top of the ranking, adjusted aggregate GDP growth for China and Myanmar drops from above 1.2 log points to slightly less than 0.9.

There remain, of course, explanations other than manipulation that can account for the autocracy gradient in the night-lights elasticity of GDP. The most plausible ones relate to structural changes that correlate differentially with economic growth within regime types and that affect the mapping from night lights to GDP. I explore several such explanations and provide evidence against them. I show that the autocracy gradient cannot be explained by changes in the sectoral composition of the economy or in the composition of GDP. Heterogeneity in the elasticity resulting from differences in urbanization rates, spatial concentration or in access to electricity also fails to explain the main result. The findings are also robust to allowing for changes in various factors affecting nighttime lights, such as satellite changes over time, geographic location or top-coding. Another highly plausible alternative explanation relates to changes in the government's capacity to produce reliable official statistics (Jerven, 2013). However, I show that the results are not driven by differences in initial income or level of development (i.e. UN's 'least developed countries'). They are also not explained by cross-sectional differences in statistical capacity (World Bank, 2002).

I provide additional evidence in support of manipulation as the underlying mechanism by examining changes in the autocracy gradient as the incentive to exaggerate economic performance increases. I find that the gradient is larger in years of relatively low economic growth (as defined by country and year averages of lights), as well as in the year before elections. I also exploit fluctuations in Gross National Income (GNI) around the threshold used by the International Development Association (IDA) to determine access to grants and subsidized loans to study how the autocracy gradient changes as countries become ineligible for foreign aid. Among the set of low-income countries that were initially eligible for IDA grants and loans, I find that the autocracy gradient only arises after countries surpass the threshold value of GNI and become ineligible for further aid. Regarding the ability to exaggerate economic performance, I show that the autocracy gradient is only present for the GDP sub-components of investment and government expenditure, but not for private consumption, exports or imports. The former components rely on government estimates of public expenditure and investment, while the latter have some degree of third-party verification through micro-surveys or trade partners.

The increased manipulation of GDP figures that I uncover in weak and non-democracies is not easily anticipated or corrected. The autocracy gradient in the night-lights elasticity of GDP is not explained by variation in publicly-available measures of corruption or transparency. It does not disappear as GDP data gets revised over time. However, I do find that the autocracy gradient is not present in countries that subscribe to the International Monetary Fund's (IMF) Special Data Dissemination Standard (SDDS), a set of guidelines regarding the quality and availability of official statistics for countries wanting to access international financial markets.

This article contributes to several strands of the academic literature. Its most immediate contribution is to the literature on the manipulation of official statistics in authoritarian regimes.[3] In the seminal study on night lights as a source of information on economic activity, Henderson et al. (2012) interpreted the finding of much higher growth in GDP than in lights in Myanmar as potentially driven by "a governing regime that would not be averse to exaggerating GDP growth" (p.1021), but they did not pursue this point further. Three other studies have contributed towards filling this gap. Hollyer et al. (2011) show a positive correlation between democracy and the availability of economic data in the World Development Indicators. Magee and Doces (2015) and Wallace (2016) report a positive effect of autocracy on GDP growth after controlling for growth in nighttime lights or in electricity consumption.

As suggestive as these findings are, the previous studies are limited in their ability to identify intentional manipulation of the GDP figures. For instance, autocracy may affect GDP growth, even after controlling for growth in lights, due to differential rates of electrification conditional on income (Min, 2015).[4] As mentioned above, a positive correlation of autocracy and GDP, conditional on lights, may also be a result of differences in the nature of economic growth across regime types that are differentially captured by night lights and GDP. The present paper's difference-in-difference research design allows for these possibili-

[3]Other research has studied manipulation of government statistics without a focus on political institutions. Sandefur and Glassman (2015) study how governments in the developing world are themselves misled by public employees in charge of service provision. Kerner et al. (2017) provide evidence of manipulation of GNI around the IDA cut-off in countries that are highly dependent on foreign aid. Another strand of literature has studied the use of creative accounting by European countries trying to bypass EU budget rules (von Hagen and Wolff, 2006; Alt et al., 2014). Michalski and Stoltz (2013) find, more generally, that balance of payments data fails to satisfy Benford's law.

[4]For instance, electrification was a core component of early Soviet policy, with Lenin writing in 1920 that "Communism is Soviet Power plus the electrification of the whole country" (Coopersmith, 1992). I thank Georgy Egorov for providing me with this example.

ties and provides improved identification of the manipulation bias present in the GDP figures of weak and non-democracies. The additional findings regarding the factors that affect the autocracy gradient in the night-lights elasticity of GDP (institutions, low growth, elections, foreign aid) provide novel evidence in support of the hypothesis of increased manipulation of national accounts in autocracies.

This paper is also related to the more general literature on the manipulation of information in authoritarian regimes. Several theoretical papers have studied the incentives that autocrats have to manipulate information or to let the media operate freely (Egorov et al., 2009; Edmond, 2013; Gehlbach and Sonin, 2014; Lorentzen, 2014; Gehlbach et al., 2016). Empirically, King et al. (2013, 2017) have documented both censorship and fabrication of social media content by the Chinese government. Other empirical work has studied the effects of media bias and ideological indoctrination on electoral outcomes and political preferences in autocracies (Alesina and Fuchs-Schündeln, 2007; Enikolopov et al., 2011; Cantoni et al., 2017).[5] I contribute to this literature by providing evidence on the exaggeration of GDP figures as another mechanism through which the manipulation of information takes place in autocracies.

One country whose official statistics have received substantial attention is China. Some studies argue that Chinese GDP growth has been systematically exaggerated in the national accounts (Rawski, 2001; Young, 2003; Madisson, 2006). Others claim that there is no evidence of manipulation or that growth may actually be understated (Holz, 2006, 2014; Mehrotra and Pääkkönen, 2011; Nakamura et al., 2016; Clark et al., 2017). This paper provides several pieces of evidence that indicate substantial exaggeration of Chinese GDP figures. China is the country with the second-largest aggregate GDP growth rate over the sample period and is classified as highly authoritarian by all the sources I consult. Additionally, as a civil and communist dictatorship, China is one of the countries with the largest observed excess in the nightlights elasticity of GDP.

The findings in this paper shed light on a source of non-classical measurement error in reported GDP that could lead to bias in a wide array of empirical studies that make use of this data. A series of papers have started using micro-surveys or nighttime lights to assess and complement the information on living standards contained in national accounts (Deaton, 2005; Chen and Nordhaus, 2011; Henderson et al., 2012; Young, 2012; Pinkovskiy and Sala-i Martin, 2014, 2016a,b). I complement this literature by documenting the way in which political incentives and intentional manipulation lead to systematic discrepancies

[5] A separate literature has looked at the effects of exposure to uncensored media on residents of authoritarian regimes (Kern and Hainmueller, 2009; Bursztyn and Cantoni, 2016). On the other hand, Qian and Yanagizawa-Drott (2009, 2017) provide empirical evidence on the manipulation of information in democracies. Allcott and Gentzkow (2017) study the role of fake news in the 2016 US presidential election.

between GDP and other measures of economic activity.

Finally, this paper also belongs to the burgeoning literature in forensic economics (Zitzewitz, 2012). In particular, it is related to other studies that compare measurements from different sources (e.g. self-reported v.s. non-self-reported) to uncover hidden behavior (Fisman and Wei, 2004, 2009; Olken, 2007; Zinman and Zitzewitz, 2016). The most closely related paper in this vein is Cavallo (2013), which uses price data from online retailers to unmask manipulation of official inflation statistics in Argentina.

The rest of the paper is structured as follows. Section 2 provides some background information on national statistics and the political incentives and constraints that shape potential manipulation. Section 3 introduces the data and its sources. In section 4, I present the empirical strategy. Section 5 shows the results. Section 6 concludes.

2 Background: Production and Manipulation of GDP Estimates

Systematic measurement of national income only begun in the second quarter of the twentieth century and became increasingly sophisticated in response to the need for detailed economic information during the second world war (Coyle, 2014). Accordingly, the first estimate of Gross National Product (GNP) for the US dates back to 1942. The publication of the United Nation's System of National Accounts (SNA) in 1951 was a landmark event in the history of official statistics and reflected an increased interest in the homogeneous estimation of economic activity across countries. The cold war stood in the way of this goal for some time, with the Soviet Union and other communist countries employing the Material Product System (MPS) instead. However, many of these countries begun transitioning from the MPS to the SNA even before the fall of the Berlin wall. For example, China's transition started in 1985 and finished in 1992 (Xu, 2009). Nowadays, most countries follow the SNA or some variation of it (e.g. the European System of Accounts). The SNA was updated in 1968, 1993 and most recently in 2008.

GDP estimates are usually produced by statistical agencies ascribed to the national government. Preliminary estimates are produced on a quarterly basis and are revised when more information becomes available. As any student of introductory macroeconomics knows, GDP can be calculated in several ways: as the sum of expenditures, as the sum of incomes or as the sum of value-added across the economy. National statistical agencies collect information from multiple sources to produce such estimates. These sources include sectoral surveys, manufacturing and agricultural censuses and household surveys. They also include information reported by banks, public utilities, transportation companies and by various levels of government.

The starting point for the present inquiry is the idea that governments of all types have an incentive to exaggerate how well the economy is doing. This idea can be traced back to a large family of formal models of political accountability, according to which citizens decide whether to remove the incumbent from office based on some observable measure of performance (Ashworth, 2012). In this regard, GDP stands out as a highly salient and easily observable indicator on the state of the economy. In a democracy, low economic growth may lead voters to support the opposition party at the polls. In the case of autocracies, official statistics may act as coordination devices and trigger political action against the regime when economic performance is sufficiently unsatisfactory (Edmond, 2013; Hollyer et al., 2015). Low growth in an autocracy may also undermine the support that the incumbent receives from some key constituency, such as the military (Bueno de Mesquita et al., 2004). Available empirical evidence indicates that economic conditions are indeed an important determinant of political turnover in both democracies and autocracies (Burke and Leigh, 2010; Brückner and Ciccone, 2011).

Naturally, if the agency producing the GDP estimates on which the incumbent's political survival depends is under the control of the incumbent, there is a strong incentive to manipulate these estimates. Gehlbach et al. (2016, p.578) provide a sketch of a model of accountability with media control that can easily be adapted to the current setting. The main take-away of the model is that as long as manipulation is not permanent (i.e. positive probability of truth-telling), citizens will always update positively on the incumbent upon receiving good news. Thus, the incumbent has a strong incentive to engage in manipulation.[6]

The hypothesis that this paper seeks to test is whether democracy is able to rein in the impulse to manipulate official statistics. Underlying this hypothesis is the idea that a healthy democracy is characterized by a system of checks and balances that constrain the incumbent's ability to fiddle with the numbers. These checks and balances include formal political institutions, such as regular elections and the separation of powers. They also include the upholding of civil liberties that allow the public and the press to scrutinize the official figures and to hold the government accountable.

Such checks and balances are largely absent in authoritarian regimes. Many of them do not hold elections, although we observe a positive trend in recent years (Levitsky and Way, 2010). But elections in such hybrid regimes are not usually useful tools for political accountability, as they are easily manipulated through state-controlled media or outright

[6]The incumbent's optimal amount of manipulation is well-defined as increased manipulation reduces the magnitude of the change in beliefs.

fraud (Enikolopov et al., 2011, 2013). Perhaps more importantly, authoritarian regimes are characterized by a high concentration of power in the hands of the executive and by strong limitations on civil liberties. As a result, we expect less democratic regimes to have increased manipulation of official statistics.

Establishing how exactly the manipulation of GDP figures takes place is to some extent beyond the scope of this paper. However, the disaggregate analysis of GDP components below provides some clues as to whether the manipulation occurs in the production of the inputs that go into the estimation of GDP or in the reporting of the aggregate figure. Evidence from China indicates that provincial public officials exaggerate the amount of growth they report to the national government (Wallace, 2016), but this 'bottom-up' reporting system seems to be an example of Chinese exceptionalism.

3 Data

The data on GDP and nighttime lights that I use comes from the replication files of the Henderson et al. (2012) study on night lights as a measure of economic activity.[7] I intentionally use this replication data to ensure that the results are not driven by ad-hoc choices regarding data sources and definitions of variables.

Henderson et al. (2012) employ GDP data from the World Bank's World Development Indicators (WDI) from January 2010. The World Bank collects GDP data directly from national statistical offices and from the OECD for member countries. To study the effects of GDP data revisions, I complement the data in Henderson et al. (2012) with the publicly-available WDI vintages from 2005 to 2017. Data on other topics, such as GDP sub-components, sectoral composition, urbanization and electrification also comes from the World Bank.

Henderson et al. (2012) use raw data on nighttime luminosity from the National Oceanic and Atmospheric Administration (NOAA). Nighttime lights are available at the pixel-year level (roughly 0.86 square kilometers at the equator) since 1992. For each pixel, 30 different satellites provide a lights digital number (DN) ranging from 0 (unlit) to 63 (top-coded). Henderson et al. (2012) calculate simple averages for each pixel-year across satellites and construct an area-weighted average of DN among the pixels within each country. This is standard practice in the literature (Pinkovskiy and Sala-i Martin, 2016a).

Data on democracy is available from several sources. For most of the analysis in the paper, I use the Freedom in the World Index (FWI) that is published annually by Freedom House. The FWI uses as its input the answers to a questionnaire provided annually by

[7] Available at `https://www.aeaweb.org/articles?id=10.1257/aer.102.2.994`

a team of analysts and country specialists. It is the average of two sub-indices, one for 'civil liberties' and one for 'political rights.' Each of these sub-indices ranges from 0 to 6, with lower numbers corresponding to a greater enjoyment of rights or liberties.[8] The 'civil liberties' index is based on the answers to questions regarding freedom of expression and belief, associational and organizational rights, rule of law and personal autonomy. The 'political rights' index is based on answers to questions related to the electoral process, political pluralism and participation, and the functioning of government. Freedom House classifies countries as 'Free' if their FWI is below 2, 'Partially Free' if it is between 2 and 4, and 'Not Free' if it is greater than 4. Freedom House also provides a dummy for 'electoral democracies', which equals one for countries with a score of 2.5 or less in the 'Political Rights' index and particularly good scores in the area of electoral process.

Relative to other sources of information on democracy, Freedom House has data for a larger number of countries (15% increase over Polity IV). The FWI is also, by construction, more responsive to the *de facto* enjoyment of political rights and civil liberties than other measures focusing predominantly on *de jure* electoral rules and political institutions (Freedom House, 2017). This feature is desirable insofar as we expect democracy to constrain the incumbent's ability to manipulate information only to the extent that it provides a rich and comprehensive system of checks and balances. Furthermore, the period under study is characterized by an increasing number of hybrid regimes that combine electoral politics with features of authoritarianism (Levitsky and Way, 2010). The FWI is arguably the best-suited indicator to capture the complexity of such regimes.

After combining the Henderson et al. (2012) data on GDP and lights with the Freedom House data on democracy, I am left with 2,914 observations for 179 countries between 1992 and 2008. The map in panel (a) of Figure 1 shows the category corresponding to the average value of the FWI for each country between 1992 and 2008, while the map in panel (b) shows the change in FWI between these years. Cross-sectionally, the strongest democracies are concentrated in the Americas and western Europe, while most autocracies are in Africa and Asia. Panel (b) shows that there is much more within-region variation in the change of the FWI over time, especially in Africa and South America.

Of course, democracy is not an easily quantified concept and excessive reliance on particular events or characteristics can bias any indicator.[9] To address this problem, I consider three additional sources on democracy and verify the robustness of the results. These sources

[8]The original indices range from one to seven. I subtract one from both, so that the lowest scores (greatest enjoyment of rights and liberties) are normalized at zero. All references to FWI in the text correspond to this adjusted version.

[9]The Freedom House indicators have been charged in the past with being disproportionately favourable to countries with close ties to the United States (Giannone, 2010; Steiner, 2016; Bush, 2017).

are the Polity IV project, the Democracy-Dictatorship (DD) dataset updated by Cheibub et al. (2010) and the democratization data produced by Papaioannou and Siourounis (2008). Polity IV provides continuous measures of regime type, while the latter two provide binary indicators of democracy.

Table A1 in the Appendix provides summary statistics for the main variables employed in the paper, including the different measures of democracy. All sources suggest the world as a whole is relatively democratic over the sample period. The average country-year in the sample has an FWI value of 2.41, which corresponds to the 'partially free' category. The average polity2 score of 3.35 also indicates that the average country-year can be characterized as mildly democratic. 37% of country-years are classified as autocratic according to the definition of electoral democracy employed by Freedom House, while a slightly larger number (42%) is classified as autocratic by the measures provided by Papaioannou and Siourounis (2008) or Cheibub et al. (2010).

To further understand the FWI as a measure of democracy, I examine its correlation with a large set of observable political characteristics. For this purpose, I employ the IAEP dataset produced by Wig et al. (2015). This dataset documents both institutional arrangements (e.g. existence of a national constitutional court) and political outcomes (e.g. turnout at last legislative election) for a large number of countries and years.

Panel A in Table A2 in the Appendix shows results of bivariate cross-sectional regressions of countries' average FWI on various political characteristics. The results indicate that the index captures several features that are commonly associated with the distinction between autocracy and democracy. In particular, countries with higher FWI (less democratic) are more likely to have an official state party or to have banned parties. They are less likely to have an elected legislature, which is more likely to be unicameral if it exists. Countries with higher FWI also hold elections less frequently and are less likely to require voter registration. These countries are more likely to have one party in control of more than 90% of the legislature. They are less likely to have a constitutional court and more likely to have a new constitution enacted during the sample period.

Panel B of Table A2 shows results from panel regressions that seek to identify correlates of within-country changes in FWI. Two features stand out. First, having an elected legislature or executive is strongly and negatively correlated with the index (i.e. more democratic). Second, electoral protests or violence are positively associated with the index (i.e. less democratic).

4 Empirical Strategy

I assume that the true growth rate of economic activity (true income growth) in country i during year t is given by the unobserved variable $\tilde{y}_{i,t}$. I allow for the possibility that true income growth differs between democracies and autocracies by decomposing it into a baseline growth rate for democracies ($y^d_{i,t}$) and an adjustment factor α for autocracies ($a_{i,t} = 1$):

$$\tilde{y}_{i,t} = y^d_{i,t} + \alpha a_{i,t} \tag{1}$$

We can think of the reduced-form effect of autocracy on growth, α, as a composite of differences in growth from different sources. It is plausible that regime type correlates with differences in the spatial distribution of production (urban v.s. rural), in the sectoral composition of output (agriculture v.s. manufacturing) or in the way that output is allocated (private v.s. public).[10] Thus, even a small value of α may actually hide substantial differences in economic structure and in the nature of economic growth across countries with different political institutions.

Each country's government constructs an estimate of economic growth using the concept of Gross Domestic Product (GDP). I assume that the estimated GDP growth rate, $\text{gdp}_{i,t}$, is a linear function of true income growth and an error term with features corresponding to classical measurement error ($\epsilon_{i,t}$) as shown in equation (2). However, this estimate does not necessarily match the reported GDP growth rate, $\widehat{\text{gdp}}_{i,t}$, which is subject to manipulation in autocracies. To start, in equation (3) I consider the possibility that GDP growth is exaggerated by a constant value $\theta > 0$ in autocracies:

$$\text{gdp}_{i,t} = \beta\tilde{y}_{i,t} + \epsilon_{i,t} \tag{2}$$

$$\widehat{\text{gdp}}_{i,t} = \text{gdp}_{i,t} + \theta a_{i,t} \tag{3}$$

Following the seminal contributions of Chen and Nordhaus (2011) and Henderson et al. (2012), several papers have documented a positive and robust correlation between nighttime lights recorded by satellites from outer space and economic activity in various settings and at multiple levels of aggregation (Doll et al., 2006; Michalopoulos and Papaioannou, 2013, 2014, 2017; Donaldson and Storeygard, 2016; Pinkovskiy, 2017). Hence, I assume that the growth rate of night lights ($\text{lights}_{i,t}$) is also a linear function of true income growth and an error

[10] We can think of y^d as the share-weighted sum of growths in a partition of output in democracies (by sector, location, etc.): $y^d = \sum_{k=1}^{n} share^{dem}_k \times growth^{dem}_k$. The parameter α is then equal to the sum of adjustments for autocracies: $\alpha = \sum_{k=1}^{n} share^{aut}_k \times growth^{aut}_k - share^{dem}_k \times growth^{dem}_k$.

term corresponding to classical measurement error ($u_{i,t}$). But I posit two characteristics that difference night lights and GDP as measures of economic activity. First, growth in night lights may not capture equally well true income growth in democracies and autocracies ($\gamma^d \neq \gamma^a$ below).[11] This seems reasonable, given that night lights mostly capture increased consumption of electricity and that different economic structures and policies across political regimes can easily affect the mapping from income to electricity supply and consumption (Min, 2015; Burlig and Preonas, 2016). Second, night light data is collected, processed and published by an independent agency and cannot be manipulated:

$$\text{lights}_{i,t} = \gamma^d y^d_{i,t} + \gamma^a \alpha a_{i,t} + u_{i,t} \tag{4}$$

This set-up is similar to the empirical models in Henderson et al. (2012) and Pinkovskiy and Sala-i Martin (2016a). The two innovations are the distinction between economic growth in autocracies and democracies and the possibility of manipulation of GDP figures in the former. By combining equations (1)-(4), we can see what happens when we regress reported GDP growth on the growth of night lights and a measure of autocracy:

$$\widehat{\text{gdp}}_{i,t} = \frac{\beta}{\gamma^d}\text{lights}_{i,t} + (\lambda + \theta)a_{i,t} + \eta_{i,t} \tag{5}$$

In equation (5), λ is defined as $(1 - \frac{\gamma^a}{\gamma^d})\beta\alpha$ and η is a combination of the error terms ϵ and u. The main insight that equation (5) provides is that the autocracy coefficient from such a regression is a combination of the fixed reporting bias (θ) with the parameters that map regime type into true income growth and true income growth into growth in night lights and in GDP. If autocracies and democracies have different sources of true income growth and night lights (or GDP) cannot capture equally well growth from these sources, the autocracy coefficient in equation (5) fails to provide an unbiased estimate of the exaggeration in reported GDP taking place in autocracies.[12]

I now consider the possibility that autocracies exaggerate reported economic growth proportionally to the observed amount of growth, perhaps additionally to the fixed exaggeration captured by the parameter θ, although this is not necessary. Proportional inflation of growth figures reduces the likelihood of detection and allows for greater exaggeration in absolute terms at times of high growth. For instance, if growth is exaggerated by a factor of 1.2, the government reports a growth rate of 1.2% when the true rate is 1% and reports

[11] I make the simplifying assumption that the mapping from true income growth to GDP growth is independent of regime type, without loss of generality.

[12] We obtain a similar result if we allow night lights and GDP to capture economic growth equally well across regimes, but we assume that night lights are also affected by electrification policies that differ across regime types, conditional on income (Min, 2015).

a growth rate of 12% when the true rate is 10%. With proportional exaggeration of GDP figures in autocracies, the equation for reported GDP growth becomes

$$\widehat{\text{gdp}}_{i,t} = (1 + \sigma a_{i,t})\text{gdp}_{i,t} + \theta a_{i,t} \tag{3'}$$

If we substitute equations (1), (2) and (4) into (3'), we obtain the following:

$$\widehat{\text{gdp}}_{i,t} = \frac{\beta}{\gamma^d}\text{lights}_{i,t} + \frac{\beta\sigma}{\gamma^d}\left(\text{lights}_{i,t} \times a_{i,t}\right) + (\lambda + \theta + \sigma\epsilon)a_{i,t} + \sigma\lambda a_{i,t}^2 + \nu_{i,t} \tag{6}$$

Several things stand out from equation (6). First, the coefficient for the interaction of lights' growth and autocracy is increasing in σ, which is the proportional exaggeration of GDP that takes place in autocracies. If there is no exaggeration, the estimated coefficient on the interaction term should be zero. Second, we can actually back out the value of σ, the rate at which GDP growth is inflated in autocracies, by dividing the point estimate for the interaction term by the point estimate for lights. Third, we observe again that the autocracy coefficient is not easily interpreted, as it combines a potentially constant bias, differences in economic structure across regimes that are differentially captured by night lights and GDP, and the magnifying effect of relative manipulation on the measurement error in GDP. Fourth, the equation also indicates that the correct specification should include the square of autocracy.[13] This term captures the fact that the differential growth of autocracies, which is imperfectly captured by lights, is compounded by the proportional exaggeration of GDP under this type of regime.[14]

Following Henderson et al. (2012), I rewrite equation (6) in log-linear form in levels and disaggregate the error term $\nu_{i,t}$ into a country-specific component (μ_i), a year-specific component (δ_t) and an idiosyncratic error term ($\xi_{i,t}$). Using the Freedom in the World Index (FWI) to measure autocracy, I obtain the main equation that I take to the data:

$$\ln(\text{GDP})_{i,t} = \mu_i + \delta_t + \phi_0 \ln(\text{lights})_{i,t} + \phi_1\text{FWI}_{i,t} + \phi_2\text{FWI}_{i,t}^2 + \phi_3\left(\ln(\text{lights})_{i,t} \times \text{FWI}_{i,t}\right) + \xi_{i,t} \tag{7}$$

In this specification, μ_i is a country fixed effect, δ_t is a year fixed effect and $\epsilon_{i,t}$ is an error term clustered by country. $\ln(\text{lights})_{i,t}$ is the natural log of the area-weighted average of DN across all pixels within a country. This specification is identical to the main specification in Henderson et al. (2012) (i.e. Table 2, column 1), except for the terms involving the FWI. The main coefficient of interest is ϕ_3, which captures the autocracy gradient in the night-lights elasticity of GDP. $\phi_3 > 0$ implies that more authoritarian regimes have higher night lights

[13]I include the quadratic term in all regressions reported below for consistency, but all the main results are robust to its exclusion.

[14]If autocracy is measured in a binary way, its coefficient captures this effect as well.

elasticities of GDP and constitutes evidence of increased manipulation of the GDP figures in these countries. Based on the empirical model, I estimate $\sigma_{\hat{FWI}}$, the additional inflation of GDP figures resulting from a one unit increase in the FWI as $\frac{\phi_3}{\phi 0}$.

The identifying assumption is that, in the absence of proportional exaggeration of GDP figures in autocracies, the night-lights elasticity of GDP should not vary depending on how autocratic a country is. Importantly, the model above shows that differences in the economic structure or in the policies implemented by autocracies and democracies only matter to the extent that they are differentially captured by GDP and night lights. Furthermore, these differences are absorbed by the autocracy variables, FWI and FWI^2. Such differences do not affect the estimate of ϕ_3.

A more subtle form of bias could arise if economic fluctuations are related to differential changes across regime types in characteristics that affect the mapping from night lights to GDP. While above we were concerned with static differences across regimes (e.g. more government consumption or less electrification in autocracies, conditional on income), the current concern has to do with changing differences as income fluctuates (e.g. larger increase in government consumption in autocracies for the same amount of income growth). In what follows, I address concerns of this nature in two ways. First, I provide a large battery of robustness tests that indicate that differential changes in relevant characteristics are not behind the results. Second, I provide several pieces of evidence on the factors that affect the coefficient ϕ_3, all of which lend additional support to manipulation as the underlying mechanism.

5 Results

5.1 Summary statistics and non-parametric regressions

Before proceeding to the regression analysis, I examine some basic summary statistics and present results from non-parametric models. These exercises anticipate the findings from the following sections, without relying on the rich structure and the set of controls provided by the fixed-effects difference-in-difference model.

The top line in Table 1 shows the average yearly growth rates of nighttime lights and GDP in the sample. Averaging across countries and years, we observe that GDP grew 4% per year, while night lights had a higher growth rate of 5.2%. The remaining rows in the table disaggregate these growth rates for countries classified as 'free', 'partially free' and 'not free' by Freedom House. We observe that 'free' and 'not free' countries had essentially identical growth rates of nighttime lights at around 5%, but that the latter group had a substantially larger GDP growth rate (4.5% against 3.6%). A mean-comparison test confirms that the difference in the growth rate of GDP across these regimes is statistically significant at the 5% level (p=0.002), while the difference in the growth rate of night lights is not (p=0.897). A comparison of 'free' and 'partially free' countries provides very similar results, while the growth rates of 'partially free' and 'not free' countries are statistically indistinguishable for both variables. Thus, a simple comparison of means indicates that the same amount of growth in night lights translates onto a higher amount of GDP growth in more authoritarian regimes.

To further explore the relationship between regime type and the growth rates of GDP and lights, I estimate two non-parametric models. Panel (a) in Figure 2 shows the scatter plot of the growth rates of GDP and nighttime lights. Using this data, I estimate separate locally-weighted least-squares smoothers for each of the Freedom House categories, which are also shown in the graph. There does not appear to be any systematic ordering of the lines when there is negative growth in lights. However, the line for 'not free' countries is always above that of 'free' countries for all positive values of the growth rate of night lights. This again indicates that the same amount of growth in nighttime lights translates into systematically higher amounts of growth in GDP for more authoritarian regimes.

In panel (b), I use a local polynomial smoother instead and plot the 95% confidence interval of the non-parametric relationship between growth in GDP and lights for 'free' and 'non-free' countries. The results point in the same direction as above. The mapping from night lights to GDP differs across regimes when the change in night lights is positive, with less democratic countries reporting higher GDP growth for the same amount of growth in lights. The confidence intervals allow us to see that this difference is statistically significant for night-lights' growth rates in the interval between 0 and 10%.

5.2 Baseline estimates

Table 2 shows the main results of the paper. Column 1 replicates the main regression (Table 2, column 1) in Henderson et al. (2012) with the slightly reduced sample for which the FWI is available. The estimate for the night-lights elasticity of GDP is essentially identical, at 0.283, to the one of 0.277 found in the original study.

Column 2 shows estimates of equation (5), in which ln(GDP) is regressed on ln(lights) and the FWI as a measure of autocracy. Conditional on night lights, more autocratic regimes have lower reported GDP growth.[15] Assuming that autocracies would never understate

[15] This finding contradicts the main result in Magee and Doces (2015). The results differ because Magee and Doces (2015) use a first-differenced specification without country fixed effects, while I estimate the model in levels with country and year fixed effects, following Henderson et al. (2012). Table A8 in the Appendix

growth ($\theta \geq 0$), the negative point estimate indicates that $\lambda < 0$. This could happen if $\alpha < 0$ (i.e. autocracies grow less than democracies), or if $\gamma^a > \gamma^d$ (i.e. night lights pick up growth in autocracies better than in democracies).

Column 3 shows the results after introducing the interaction between ln(lights) and the FWI. I find that a one unit increase in the index is associated with a very precisely measured increase of 0.012 in the night-lights elasticity of GDP. The point estimate for the autocracy measure on its own now becomes very small and is not statistically significant at conventional levels. The results are almost identical after I introduce the square of the FWI, FWI^2, in column 4. Based on the econometric model developed in the previous section, I take the specification in column 4 to be my preferred specification for the rest of the paper.

The estimates in column 4 provide evidence of a large heterogeneity in the night-lights elasticity of GDP by regime type. The value of σ implied by these estimates is 0.05 (=0.012/0.238). Hence, a one unit increase in the FWI is associated with a 5% inflation of the GDP growth estimate. Relative to the baseline elasticity of 0.24 for the most democratic countries (FWI=0), the estimated elasticity for the most authoritarian ones (FWI=6) is 0.31. For this group, the regression results suggest that annual GDP growth is exaggerated by a factor of around 1.3.[16]

Next, I introduce greater flexibility in the autocracy gradient by replacing the FWI with dummies for 'partially free' and 'not free' countries, as defined by Freedom House ('free' is the omitted category). The estimates in column 5 indicate that the night-lights elasticity of GDP is on average 0.028 units higher among 'not free' countries than among 'free' ones. The implied σ indicates that 'not free' countries exaggerate GDP on average by 11%. 'Partially free' countries have an estimated elasticity that is larger than that of 'free countries' but smaller than that of 'not free' countries. The estimated elasticity for this group is statistically different from that of the 'not free' group (p=0.076), but not from the baseline elasticity for the 'free' group. This result indicates that the autocracy gradient in the night-lights elasticity of GDP is mostly driven by countries at the bottom of the democracy spectrum.

The estimate for the most authoritarian countries in column 5 is smaller than the one implied by the results with the continuous FWI in column 4. The attenuation comes from bundling countries into broader democracy categories. Figure 3 plots results from the regression with separate indicators for each value of the FWI (rounded to the nearest integer), with the lowest value (zero) as the omitted category. The estimates (dark round markers) show a clear increase in the night-lights elasticity of GDP as we move from lower to higher

further shows that the results are robust to first-differencing plus fixed effects.

[16]Disaggregate results (not reported) for the two sub-indices that underlie the FWI (political rights and civil liberties) are almost identical to those obtained with the FWI.

values of the FWI. The difference in the elasticity, relative to the most democratic countries, is statistically significant at the 5% level for countries with an FWI of 3 or more. The disaggregate results also point to a sharp increase in the elasticity for the largest value of the FWI, which corresponds to an excess elasticity of 0.09. Given the baseline elasticity of 0.23 for the most democratic regimes, the implied exaggeration rate in GDP growth estimates taking place in the least democratic countries is 1.39.

5.3 Within-country variation in regime type and transitions

The previous estimates of ϕ_3 exploit a mixture of cross-country and within-country variation in regime type. By allowing for a country-specific night-lights elasticity of GDP, we can ensure that only within-country variation in democracy informs the estimation. A specification of this nature is obviously quite stringent. It enhances the credibility of the findings, as we are now only exploiting changes in democracy within countries over time, but the country-specific elasticities absorb a lot of useful variation in regime type, especially if regimes vary more across countries than within them.

Results from such a specification for the fully disaggregate model are also shown in Figure 3 (light diamond markers). The results point to a weakly increasing elasticity as we move to higher values of the FWI. For most intermediate values, the elasticity is larger than the one for the most democratic countries, although the difference is not statistically significant. We still observe a jump in the elasticity for the most authoritarian regimes, but its magnitude is reduced by almost half relative to the previous estimates. Nevertheless, this increase is statistically significant at the 10% level (p=0.085) and indicates that countries that fall into the most autocratic category exaggerate their GDP estimates by a factor of 1.22 relative to the most democratic ones.

Another way of exploiting within-country variation in regime type involves tracking the night-lights elasticity of GDP as countries transition into and out of autocracy. For this purpose, I estimate modified versions of the flexible specification from column 5 of Table 2. I first disaggregate the interaction of ln(lights) and the dummy for 'not free' countries into separate ones for countries that experience a transition into this category lasting at least six years (to ensure the estimates are not driven by composition effects) and for all other 'not free' country-years. I then further disaggregate the interaction for the transition episodes by event year. Panel (a) of Figure 4 shows the point estimates and 95% confidence intervals for these interactions. I find that the night-lights elasticity of GDP increases as a country shifts towards autocracy and becomes statistically different from that of 'free' countries after five years. Panel (b) replicates the exercise for transitions out of autocracy, which take place when countries move from being classified as 'not free' to being labelled 'partially free.' In this case, we observe a steady decrease in the elasticity, which becomes statistically indistinguishable from that of 'free' countries after as few as three years.

The findings from these exercises on regime transitions tell us that statistical manipulation takes place as a country's political institutions deteriorate over time. They provide evidence against the possibility that the main result is driven by anomalies in the functioning of the economy very near to the time of a political transition (Brückner and Ciccone, 2011). They also indicate that the effect of regime type on the mapping from night lights to GDP is roughly symmetric as a country shifts towards democracy or as it moves away from it.

5.4 The autocracy gradient in long-run growth

The previous results are based on yearly fluctuations in GDP. A different question concerns the effect of autocracy on the mapping of night lights to GDP over longer periods of time. It may well be that the observed autocracy gradient at the yearly level is driven by occasional exaggerations that smooth out over time. However, if the previous results are correct and authoritarian regimes systematically exaggerate yearly GDP growth, we expect aggregate growth over a longer period to exhibit a more pronounced bias as a result of compounding: tomorrow's GDP is overstated relative to today's exaggerated estimate, etc.

Column 6 of Table 2 shows results from my preferred specification using averages of all variables for the years 1992/1993 and 2005/2006. Consistently with the previous findings, I observe that the autocracy gradient in the long-run night-lights elasticity of GDP is 1.5 times as large as the one observed for the yearly data. The results in column 6 imply a value of σ of 0.068, which means that aggregate GDP growth over the sample period is exaggerated in the most autocratic regimes by around 40%. The results from the flexible specification in column 7 paint a similar picture.

We can use these estimates to examine what happens to relative long-run economic performance when the raw GDP series is adjusted for the manipulation bias in autocracies. Panel (a) in Figure 5 shows the difference in ln(GDP) between 1992/3 and 2005/6 for the 20 economies with the largest growth during that period, according to the raw data reported in the World Bank's WDI. I classify countries in this ranking by regime type using the average value of the FWI and the Freedom House classification. Only four countries in this top-20 belong to the 'free' category, while five belong to the 'partially free' group. More than half of the countries in the top-20 of highest GDP growth between 1992 and 2006 have an authoritarian regime and are classified as 'not free' by Freedom House.

Panel (b) shows the top-20 after the GDP growth series has been deflated using the

σ estimate of 0.068 and the country's average value of the FWI. Once adjusted, the top-20 includes nine 'free' countries, with Cape Verde, Estonia, Latvia, South Korea and the Dominican Republic replacing Bhutan, Laos, United Arab Emirates, Sudan and Ethiopia. At the very top of the ranking, adjusted aggregate GDP growth for China and Myanmar drops from above 1.2 log points to slightly less than 0.9, making Ireland the country that grew the most over the sample period.[17]

5.5 Other measures of autocracy

In this section I replicate the main analysis using different sources and indicators on autocracy. The purpose of the exercise is two-fold. Mainly, I want to verify the robustness of the results to the use of different definitions or classifications of political regimes. Additionally, different indicators can provide rich information on the characteristics of the political environment that give rise to the observed autocracy gradient in the night-lights elasticity of GDP.

From the Polity IV dataset, I study the Polity2 score, as well as the separate indices for democracy and autocracy with which it is constructed. These indices range from zero to ten. The Polity 2 score, ranging from -10 to 10, results from subtracting the autocracy index from the democracy index. Thus, larger values of the Polity2 score correspond to higher levels of democracy. The results in column 1 of Table 3 are consistent with the previous findings, as they indicate that more democratic regimes have systematically lower elasticities. The estimates in column 1 point to an elasticity of 0.273 for the most democratic countries (Polity2=10). The implied value of σ in this case is 0.007, over a 20-point scale, which means that the most autocratic regimes exaggerate yearly GDP growth by a factor of 1.15.

The results in columns 2 and 3 show that the magnitude of the effect of a one unit increase in the autocracy score is more than twice as large as that of a similar increase in the democracy score. Only the former is statistically significant at the 5% level. These results point again to the lower end of the democracy spectrum as the main driver of the observed relation between regime type and the night-lights elasticity of GDP. Focusing on the autocracy score, the implied σ of 0.02 over a 10-point scale indicates that the most authoritarian regimes exaggerate yearly GDP estimates by a factor of 1.2.

Columns 4-7 show results using binary measures of autocracy. In all cases, the point

[17] A constant yearly GDP growth rate of 4.9% leads to an 87% aggregate growth over a 13-year period. A growth rate of 6.3% over the same period leads to an aggregate growth rate of 122%. Hence, the adjustment to aggregate GDP growth for China and Myanmar corresponds to a reduction of the yearly growth rate from 6.3% to 4.9%, which implies an exaggeration bias of 29%, in line with the yearly estimates of manipulation.

estimates indicate a larger night-lights elasticity of GDP in autocracies, which is statistically significant at the 1% level for all sources except the Democracy-Dictatorship (DD) classification. However, just as with the Freedom House categorical variables, the use of coarser groupings tends to attenuate the results. In column 4, I use the complement of the dummy for 'electoral democracy' produced by Freedom House. The results indicate a bias of 11% in autocracies. In column 5, I follow Acemoglu et al. (2016) and construct a hybrid measure of autocracy combining information from Freedom House and Polity IV. The results point to an exaggeration bias of around 7% in autocracies. Column 6 uses an autocracy dummy based on the classification of democratization episodes by Papaioannou and Siourounis (2008). The estimates indicate that autocracies exaggerate yearly GDP growth by a factor of 1.15.

Column 7 shows results using the dictatorship dummy from the DD dataset by Cheibub et al. (2010). This dataset, which updates earlier work by Przeworski et al. (2000), aims to capture a 'minimalist' definition of democracy based on four criteria: popularly-elected legislature, popularly-elected chief executive, multi-party elections, turnover across parties. When using this definition of autocracy, the point estimate for ϕ_3 has the expected sign, but a smaller magnitude than in the previous columns and it is not statistically significant (p=0.17). One interpretation of this result is that compliance with a minimal set of election-based criteria in order to be classified as a democracy is not sufficient to prevent the systematic manipulation of official statistics. A comprehensive set of checks and balances is required to restrain the incumbent's impulse to exaggerate economic growth. I return to this point and to the DD classification in section 5.8 below, in which I try to disentangle the contribution of several features of democracy to the prevention of statistical manipulation.

5.6 Robustness checks

In this section I provide a battery of robustness tests aimed at examining whether changes in other country characteristics can explain the autocracy gradient in the night-lights elasticity of GDP. I leave the tables for the appendix and provide a summary of the findings here. As discussed in section 3, the main concern for identification has to do with factors that change differentially across regimes as the economy grows and that could affect the mapping from night lights to GDP. Stable differences in economic structure or in policies that are differentially captured by night lights and GDP should be absorbed by the autocracy term (and its square) and should not affect the interaction term that is the object of interest.

A possible concern regarding the main result is that autocracies tend to have a larger public sector. The autocracy gradient may be arising because output growth is disproportionately allocated to the government in autocracies and because public spending is captured by night lights differently from private consumption. To address this concern, I run a series of robustness tests in which I allow the night-lights elasticity of GDP to vary depending on the share of GDP represented by each category. The results are shown in Table A3 in the appendix. Using my preferred specification, column 1 shows that the autocracy gradient is somewhat smaller and less precisely estimated for the sample for which data on GDP sub-components is available (p=0.079). Still, the implied σ of 0.035 points to a 21% exaggeration bias in the GDP figures of the most authoritarian regimes. The remaining columns show that this estimate is very robust to allowing for heterogeneity in the mapping of night lights to GDP arising from the share of GDP coming from any sub-component. The results are unchanged if I simultaneously allow for heterogeneity coming from all shares but one (estimates not reported).

Table A4 allows for the time-varying sectoral composition of the economy to affect the mapping of night lights to GDP. For instance, it could be the case that autocracies are more dependent on agriculture (or that the importance of agriculture changes differentially as the economy grows). If agricultural output translates to night lights at a lower rate than output from other sectors, this could explain the results. In columns 1 and 2, I allow for heterogeneity by the share of land devoted to agriculture and by the share of GDP represented by agriculture. Although I do find that the elasticity decreases in the agriculture share of GDP in column 2, the results on autocracy do not change. They are similarly unaffected if I allow for heterogeneity by the shares of industry, manufacturing or services. The results are also not explained by the share of GDP represented by natural resource rents, more generally, or by oil rents, more specifically.

Table A5 examines the heterogeneity in the mapping of night lights to GDP arising from different levels of development, patterns of urbanization, and access to electricity. Although it is plausible that economic activity translates into nighttime lights heterogeneously at different levels of income, the autocracy gradient cannot be explained by heterogeneity arising from differences across countries in the initial level of income (measured through lights or GDP, columns 1 and 2). Further tests including interactions of ln(lights) with dummies for countries classified as 'developing' and 'least developed' by the United Nations yield similar results (estimates not reported).

Another alternative explanation for the results could be that growth in lights is mainly capturing urban agglomeration and that authoritarian regimes are better at disincentivizing rural-urban migration (Wallace, 2014). A similar argument can be made regarding electrification, which affects night lights more than GDP and which results from policies that may differ across regime types (Min, 2015). However, I find that the results are robust to allowing for heterogeneity based on the share of the population living in urban areas (column 4) or the share of the population with access to electricity: total, urban or rural (columns 5-7).

Table A6 examines the role of various factors that affect the night lights measure and which may have incidence on the results. In column 1, I include a fourth-order polynomial in ln(lights) to allow for non-linearities in the mapping from night lights to GDP.[18] In column 2, I allow the baseline elasticity to vary on a yearly basis by including the interaction of ln(lights) with year fixed effects. These additional regressors flexibly allow for fluctuations in the night-lights elasticity of GDP over time, including those resulting from satellite changes and other common shocks. In column 3, I allow the baseline elasticity to change based on geographic location, which may affect luminosity through factors such as cloud cover or seasonal fluctuations in sunlight. For this purpose, I include second-order polynomials in the latitude and longitude of the capital city.[19] Column 4 implements a more stringent version of this test for the importance of location, by allowing the baseline elasticity to vary across 17 within-continent sub-regions. The results are fundamentally unchanged in all cases.

For the next set of tests, it is useful to bear in mind that the lights measure is an area-weighted average of the value of the lights digital number (DN) across all pixels within a country and that this number ranges from zero (unlit) to 63 (top-coded). It is plausible that economic growth in autocracies is concentrated around the centers of power or in areas privileged by the autocrat (Hodler and Raschky, 2014). If these areas become increasingly top-coded as the economy grows, the lights measure will fail to pick up growth in autocracies. In column 5 of Table A6, I allow the baseline elasticity to vary by country size (area), while in columns 6 and 7 I allow the elasticity to be affected by the number (log) of unlit or top-coded cells.[20] A complementary approach to the concern regarding spatial concentration is to allow the elasticity to vary depending on the Gini coefficient of the lights measure, which is what I do in column 8. The estimate of the autocracy gradient in the night-lights elasticity of GDP remains of roughly the same magnitude and precision in all cases.

Another plausible alternative explanation for the autocracy gradient revolves around variation in the state's capacity to produce statistical information. Jerven (2013) provides a detailed account of the limited data, funding and technical capacity that underlies the production of official statistics in sub-Saharan Africa. In this regard, it may well be the case that statistical offices in more authoritarian regimes are having to produce more speculative estimates of GDP growth. Some of the evidence I have already provided suggests this is not the case. For instance, the results in Table A5 show that the autocracy gradient in the

[18]The results are robust to the use of higher or lower-order polynomials

[19]I include the quadratic terms to take into account the fact that extreme values of latitude (i.e. the poles) may be subject to similar issues and that longitude +180 is the same as -180. Results are unchanged if I drop these terms.

[20]Results are unchanged if I use the fraction of cells that are top-coded or unlit instead.

mapping of night lights to GDP is not driven by differences in the initial level of income, which is a strong predictor of statistical capacity (Michalopoulos and Papaioannou, 2017). Similarly, the results allowing for sub-region-specific elasticities in Table A6 show that the gradient is not driven by differences in the elasticity across regions of the world. Furthermore, if the GDP estimates in autocracies involve relatively more guesswork, it is not obvious why the estimates should consistently overestimate economic growth.

Table A7 further examines the role of statistical capacity. For this purpose, I use information collected by the World Bank (2002) on various features of the official statistics of 117 developing countries, as well as the overall data quality score provided. These features include the periodic collection of population and agricultural census data; the periodic update of base years for national accounts and for the consumer price index (CPI); the adoption of international statistical guidelines such as the SDDS (more on this below) or the balance of payments manual version 5; the existence of a vital registration system, and the regular update of industrial production and export/import price indices. Column 1 shows that the estimate of ϕ_3 is somewhat smaller (0.008) and less precisely estimated for this smaller sample (p=0.073). Nevertheless, the implied σ of 0.029 means that the most autocratic regimes exaggerate yearly GDP growth by a factor of 1.18. The remaining columns show that the autocracy gradient in the night-lights elasticity of GDP remains relatively constant after allowing for the possible heterogeneity in the elasticity associated with any of the indicators of statistical capacity.

Finally, Table A8 verifies that the results are robust to potential misspecification of the relationship between night lights and GDP. Column 1 shows that the results are unaffected by the inclusion of country-specific time trends. In column 2, I include the lag of ln(lights) as an additional explanatory variable, while in column 3 I include the lag of ln(GDP). To alleviate concerns about Nickell bias in the dynamic panel model, column 4 replicates the analysis from the previous column using system-GMM, without observing any change to the results. In columns 5-8, I replace ln(GDP) and ln(lights) for their first difference. Column 5 shows that the first difference of ln(GDP) is positively correlated with the first difference of ln(lights). Column 6 shows that there is a positive autocracy gradient in the first-differenced model. Columns 7 and 8 show that the results are robust to the inclusion of the lagged value of ln(GDP), no matter whether the model is estimated through OLS or system-GMM.

5.7 GDP expenditure decomposition

In this section, I separately study the mapping from night lights to each of the sub-components of GDP according to the expenditure decomposition and I test for the presence of an autocracy gradient. Using the expenditure approach, GDP can be decomposed into private consumption, investment, government expenditure and net exports. The disaggregate analysis of each of these components may allow us to make progress in uncovering the way in which the fabrication of official statistics takes place.

The results in Table 4 show that within-country growth in nighttime lights is strongly correlated with growth in each of the GDP sub-components. More importantly, the results indicate that only in the cases of investment (column 2) and government expenditure (column 3) is the mapping from night lights to the GDP component heterogeneous by regime type. There is no evidence of an autocracy gradient for household final consumption, exports or imports.

These findings are illuminating on two aspects of the manipulation of official statistics. First, the fact that the autocracy gradient is not homogeneous across components suggests that the exaggeration does not take place at the time of reporting the final number. Instead, the results indicate that the manipulation occurs in the collection of some of the information that serves as input for the production of the GDP figure.

The specific components for which we observe an autocracy gradient are also highly informative about governments' ability to manipulate official statistics. The components of investment and government spending have the shared characteristic of being highly dependent on government-reported information. Naturally, the government itself is the primary source of information on government expenditure, while the estimate for investment incorporates sub-estimates for investment by various levels of government and by public enterprises (Lequiller and Blades, 2014). On the other hand, the estimates for private consumption rely to a large extent on sources such as household surveys, which are more difficult to manipulate. Similarly, the figures for exports and imports must roughly align with those reported by trade partners (but see Fisman and Wei (2004)). It seems likely that these different kinds of third-party verification constrain manipulation of the GDP sub-components for which we do not observe an autocracy gradient.

5.8 Unpacking democracy

In this section, I begin to study the factors that affect the manipulation of GDP statistics in weak and non-democracies. As illustrated by the null result above when using the 'minimalist' definition of democracy employed in the DD classification, an institutional arrangement providing a comprehensive set of checks and balances seems necessary to prevent systematic inflation of growth figures.

In Table 5, I show results from triple-difference regressions that examine how the autocracy gradient in the night-lights elasticity of GDP is affected by economic and political institutions. The results show that the autocracy gradient is smaller for countries with an elected legislature (column 1) or an elected executive (column 2), as coded in the IAEP dataset by Wig et al. (2015). Columns 3 and 4 examine the importance of judiciary and economic institutions. I find that the autocracy gradient is also smaller for the set of countries with a national constitutional court, as well as for those in which the central bank has authority over monetary policy.

All of the previous results indicate that independent political, economic and judicial institutions help to restrain the executive's impulse to exaggerate economic performance. Interestingly, it is the holding of national elections for the executive that leads to the largest reduction in the autocracy gradient of the night-lights elasticity of GDP. In fact, I fail to reject the null of no gradient at conventional levels of significance when the executive is popularly elected.

Finally, in column 5 I distinguish between countries that had a communist regime at some point in the past and those that did not. This is an interesting dimension to study because the countries with a communist history have had widely different patterns of political development after the collapse of the USSR. While most former members of the Soviet bloc in Eastern Europe experienced sharp democratization during the 1990s, several of the former members of the USSR have remained highly authoritarian. Studying the legacy of communism is also interesting because communist regimes have been known for the systematic manipulation of information. The censoring and fabrication of census data and photographs in the USSR under Stalin has been widely documented (Merridale, 1996; King, 1997). More recently, King et al. (2013, 2017) have provided evidence of censoring and fabrication of social media content in communist China. In line with these previous findings, the results in column 5 indicate that the autocracy gradient is more than twice as large among countries with a history of communism.

To further understand the role of political institutions, I make use of the sub-categories into which dictatorships and democracies are classified in the DD dataset (Cheibub et al., 2010). Democracies in this dataset are divided into three sub-categories: parliamentary, semi-parliamentary and presidential. Autocracies are also divided into three sub-categories: civilian, military and royal. Studying the nightlights elasticity of GDP across these regimes provides an opportunity for a more nuanced understanding of the relationship between autocracy and the manipulation of official statistics.

Figure 6 plots estimates for the interaction effects from an enlarged specification using the regime dummies. The omitted category is parliamentary democracy. The graph shows the existence of a clear gradient within democracies, with presidential democracies having a larger elasticity than semi-presidential democracies, which in turn have a larger elasticity than parliamentary democracies. Interestingly, this gradient aligns with the strength of democracy, as measured by the average FWI for each regime type (shown next to each marker in the figure). Civilian dictatorships, which have even higher average FWI than presidential democracies, have the largest elasticity, with an implied exaggeration bias of 23%.

Also worth noting is the fact that the elasticity is significantly lower for military and royal dictatorships, despite them having even higher average FWI values. One explanation for the observed difference among types of dictatorship is that royal and military dictatorships can deal with the threat of political turnover by means other than manipulation of information. In the case of royal dictatorships, these are mostly oil-rich 'rentier' states with low or no taxation and extensive patronage networks (Mahdavy, 1970; Ross, 2001).[21] Military dictatorships, on the other hand, have been found to engage in repression more than other forms of autocracy (Geddes et al., 2014).

5.9 Incentives for manipulation: Low growth and elections

In this section I continue with the analysis of the factors that shape the autocracy gradient in the night-lights elasticity of GDP. I begin by examining whether the autocracy gradient is larger at times of low economic growth. The hypothesis underlying this exercise is that the incentive to exaggerate economic performance is weaker when the economy is, in fact, performing relatively well. For this purpose, I first demean ln(lights) by country and year. I then code a country-year as having low growth if the demeaned value of ln(lights) is negative. In these cases, growth in lights is below the world average after adjusting for average differences in luminosity across countries. The final step involves estimating an enlarged version of equation (7) that allows for heterogeneity in the elasticity in years of low growth and, more importantly, for the autocracy gradient to vary in such years.

The results are shown in column 1 of Table 6.[22] The estimate for the triple-difference effect is positive and statistically significant (p=0.067). It corresponds to an 80% increase in the autocracy gradient relative to the one observed in years in which the economy is performing better than average, which remains positive but is smaller and imprecisely estimated (p=0.151). In other words, the same amount of growth in lights translates into more GDP growth in autocracies, especially in years in which the economy is growing less than the

[21] On average, oil rents represent 18% of GDP in royal dictatorships, 8% in other dictatorships and 1.4% in democracies.

[22] The specification I estimate includes the dummy for country-specific low-growth years and the complete set of interactions with ln(lights) and the FWI. Table A10 in the online appendix shows the complete set of estimates.

world average. The results using categorical variables in column 2 indicate that the excess elasticity at times of low growth more than doubles in the most authoritarian regimes.

These results lend support to the hypothesis of manipulation in more than one way. First, they indicate that the autocracy gradient is larger when the incentive to manipulate is stronger. Second, exaggerating at times of low growth means making up a smaller absolute amount of growth. A 20% overstatement means a 2 percentage point exaggeration when true growth is 10%, but a 0.2 percentage point exaggeration when true growth is 1%. Detection of the bias seems to be more difficult in the latter case. Similarly, the fact that manipulation does not seem to happen all the time, but only in certain years, also makes detection more difficult and would appear to be an optimal strategy from the perspective of an incumbent that wishes the manipulation to go undetected (Gehlbach et al., 2016).

I turn next to the effect of elections and the imminent possibility of political turnover. It seems plausible that, as a result of limited attention or memory, voters assign more weight to events occurring closer to election day in their assessment of the incumbent. Hence, the incentive to exaggerate economic performance is stronger right before elections take place. At this point, it is worth underlining that many of the undemocratic regimes in place during the sample period are actually hybrid regimes that regularly hold elections (Levitsky and Way, 2010). It is not the case that elections are equivalent to democracy.

To study the effect of elections, I use the data on election years in the IAEP dataset by Wig et al. (2015) and create a binary variable equal to one if the country has an election in the following year.[23] Replicating the previous analysis, the results in column 3 indicate a 20% increase in the autocracy gradient the year before elections, which is marginally insignificant (p=0.121). However, the estimates with the more flexible democracy categories in column 4 show a large and significant increase in the elasticity for the 'not free' group in the year before elections. The excess elasticity for this group increases by more than 50% in the year before elections, lending support to the hypothesis that highly authoritarian regimes exaggerate economic performance even more in the run-up to elections.

5.10 Incentives for manipulation: Eligibility for IDA aid

Since 1960, the World Bank has been providing grants and subsidized loans to the world's poorest countries through the International Development Association (IDA). In order to remain eligible for IDA assistance, countries must have a level of Gross National Income (GNI) per capita below a threshold value that is adjusted every year. Once countries surpass

[23] I focus on the year before elections as the lag in the publication of GDP figures makes this the more likely year for exaggeration. The IAEP data has the desirable feature that it only includes scheduled elections, assuaging concerns about endogenous timing.

the threshold, they start a graduation process that is completed once they are deemed to be creditworthy enough to apply for financing to the International Bank for Reconstruction and Development (IBRD).[24] Even if it does not automatically trigger graduation from the program, exceding the threshold does lead to a substantial reduction in the amount of foreign aid that countries receive. Galiani et al. (2017) estimate that aid flows as a share of GNI drop 59% after countries cross the threshold.

As a result of this set of incentives, we expect the willingness of governments to exaggerate economic performance to increase after crossing the GNI threshold. In Table 7, I test for this possibility. For this exercise, I use the universe of 82 low-income countries that were beneficiaries of IDA loans and grants at the start of the sample period. Column 1 in Table 7 verifies the strong correlation between night lights and GDP in this sample, while column 2 shows the overall autocracy gradient for these countries.

Starting in column 3, I introduce an indicator variable for years in which a country's GNI per capita is above the threshold value set by IDA for continued eligibility. 27 countries cross the threshold during the sample period. Consistent with the prediction of increased incentives for exaggeration of GDP growth, I observe an increase in the night-lights elasticity of GDP after countries cross the threshold (column 3). Of course, countries that cross have higher levels of GNI per capita and the variation in the elasticity could be a result of that. Column 4 shows that the jump in the elasticity is even larger and more precisely measured after allowing for heterogeneity in the night-lights elasticity of GDP as GNI per capita increases.

Column 5 allows for a change in the autocracy gradient after countries cross the GNI threshold. The results indicate that there is no autocracy gradient below the threshold and that the observed increase in the elasticity after crossing it is entirely driven by the emergence of the autocracy gradient. In other words, autocracies do not exaggerate economic growth when they are in peril of losing foreign aid, but they begin to do so once they become ineligible for further aid. Figure 7 shows results from the corresponding event study, looking at a 10-year window around the time of crossing. The graph shows a systematic increase in the autocracy gradient after countries cross the eligibility threshold.

Columns 6 to 8 provide several robustness tests of the finding in column 5. In column 6, I use the crossing countries and dates reported by Galiani et al. (2017), which differ in some cases from the ones I obtain by directly comparing the GNI data from the World Development Indicators to the IDA cut-offs. In column 7, I include in the sample the only three countries that satisfied the GNI criterion for eligibility (and also crossed the threshold

[24] Additional information on the types of loans and grants available through IDA can be found in Galiani et al. (2017) and Kerner et al. (2017).

during the sample period), but were excluded from the IDA program. These are Syria, Turkmenistan and Ukraine. Finally, in column 8, I drop Guyana and Indonesia, as they cross the threshold more than once. The results are quite robust to all these modifications.

5.11 Detection, correction and prevention of GDP manipulation

Unreliable official figures and weak statistical capacity have been a growing concern in the policy community. From this perspective, a better understanding of the potential of different tools to identify or prevent the manipulation of official statistics may provide valuable insights. In this section, I first examine whether the autocracy gradient in the night-lights elasticity of GDP is explained by existing measures of corruption or transparency. I then look at whether the autocracy gradient tends to disappear as GDP data gets revised over time. Finally, I study the International Monetary Fund's (IMF) Special Data Dissemination Standard (SDDS) as a potential tool for prevention or correction of statistical manipulation.

If the manipulation of GDP figures in authoritarian regimes is as systematic as the previous findings suggest, it may well be the case that this phenomenon is well-known by the people that regularly use these numbers. For instance, the countries that regularly exaggerate economic growth may have already been identified by existing indicators of transparency or corruption. I study this possibility in Table 8.

In columns 1-3, I use the Corruption Perceptions Index (CPI) produced by Transparency International. This index ranges from 0 to 10, with larger values corresponding to decreased perceptions of corruption. Column 1 shows results from the baseline specification using the reduced sample for which the CPI is available. In column 2, I replace the FWI with the CPI. I find that countries perceived to be more corrupt have larger night-lights elasticities of GDP, which lends support to the idea that more corrupt countries engage in more manipulation of official statistics. Column 3 includes both the FWI and the CPI. We observe that the coefficient for the interaction of lights and the CPI becomes slightly smaller and statistically insignificant, while the interaction of lights and FWI is unaffected. The results are very similar if I use the Control of Corruption Index from the World Bank (columns 4-6). In sum, existing measures of corruption fail to capture the variation in political institutions that underlies the manipulation of official statistics.

In columns 7-9 I use the HRV transparency index produced by Hollyer et al. (2014). This index is based on the availability of economic indicators in the World Bank's WDI, under the premise that more transparent regimes divulge more information. A larger value of the index indicates increased transparency. As before, column 7 shows the autocracy gradient for the smaller set of countries for which the HRV index is available. Column 8 shows the existence of a large and precisely estimated gradient using the HRV index. Countries classified as less transparent have larger night-lights elasticities of GDP. Column 9 includes both FWI and the HRV index. Both coefficients of interest are slightly reduced, but remain statistically significant at conventional levels. This indicates that the HRV transparency index indeed captures variation across countries in the manipulation of information, but that this variation only partially coincides with that captured by the FWI regime classification.

Taken together, the results in Table 8 indicate that the manipulation of statistics prevalent in authoritarian regimes is not captured by existing measures of corruption or transparency. A related question is whether the exaggeration of GDP figures washes out as the numbers get scrutinized and revised over time. To evaluate the effects of GDP revisions, I use data from the 2005-2017 vintages of the World Bank's WDI. All of these datasets contain GDP data since 1992. Later vintages contain additional years of information, but I limit the sample period to the years 1992-2003 to ensure that the changes in sample size do not contaminate the results. I then run separate regressions with GDP data from each vintage of the WDI. The idea is that earlier vintages have been subject to less revision. If revision is successful at limiting manipulation, we should observe a decrease in the autocracy gradient as we move to later vintages.

Figure 8 plots the estimate of ϕ_3 for each vintage of the WDI. I fail to find evidence of change in any direction as GDP data gets revised over time. The point estimate remains at roughly its baseline value of 0.012 and shows no evidence of correction or attenuation. These results can also be interpreted as a further robustness test, as they indicate that the findings are not sensitive to the vintage of the WDI datatset employed nor to a 30% reduction of the sample period.

I turn next to the ability of the IMF's SDDS to prevent or attenuate the bias in official statistics. The SDDS is a set of guidelines regarding the production, timeliness and availability of official economic and financial data. It was launched in 1996 in an attempt by the IMF to facilitate access to financial markets by member countries. Subscription is voluntary and involves the commitment to follow the prescribed guidelines and to provide the IMF with information on government statistical practices.

During the sample period, 48 countries subscribe to the SDDS. 33 of these have an average FWI value that ranks them as 'free', 9 are classified as 'partially free' and 6 are classified as 'not free'. The average value of the FWI among subscribers is 1.66, while among non-subscribers it is 2.67. Consistently with the previous evidence, these summary statistics already suggest that more authoritarian regimes are less willing to commit to policies favouring the transparency of official statistics.

To get a better sense of the magnitude of this selection effect, column 1 in Table 9 shows triple-difference estimates of the difference in the autocracy gradient of the nightlights elasticity of GDP for countries that subscribe to the SDDS. Although the triple-difference coefficient is somewhat imprecise (p=0.15), its magnitude indicates that the autocracy gradient is non-existent among countries that subscribe to the SDDS. The formal hypothesis test comparing the coefficients confirms that this is the case (p=0.29). In other words, only countries that have nothing to hide appear to select into the agreement.

The estimates for the categorical autocracy variables in column 2 paint a more nuanced picture, though. The triple-difference estimates suggest that 'partially free' countries that join the SDDS have a lower excess elasticity than those that do not, while the 'not free' ones that do join have an even higher excess elasticity than the ones that don't. The estimates of the elasticities in participating countries should be interpreted with caution, though, as the standard errors are quite large for both coefficients (p>0.5).

In columns 3 and 4, I use information on the year in which each country joined the SDDS and add additional interactions with an indicator variable from that year onward. These specifications correspond to a fourth-difference research design, as the indicator for the years after subscription only equals one if the indicator for subscribing countries equals one. The fourth-difference coefficient in column 3 points to a small and imprecisely-estimated decrease in the autocracy gradient. However, the corresponding estimates for the more flexible specification in column 4 show a large and statistically significant decrease in the excess elasticity for 'not free' countries after they subscribe to the SDDS. Formally, I fail to reject the hypothesis that the excess elasticity for 'not free' countries becomes zero following subscription (p=0.484).

Taken as a whole, these results suggest that the SDDS is effective at controlling the manipulation of GDP figures in weak and non-democracies. Most of the effect seems to be coming from countries with little or no manipulation self-selecting into the program, although we cannot rule out some treatment effect of subscription among highly autocratic nations.

6 Concluding Remarks

In this paper, I have shown that the elasticity of reported GDP estimates to nighttime lights measured by satellites from outer space is larger in more authoritarian regimes. This finding is robust to the use of different sources to classify regimes and cannot be explained by differences in a large set of characteristics that may affect the mapping from night lights to GDP. Further evidence on the factors that affect the autocracy gradient in the night-lights elasticity of GDP lends additional support to increased manipulation of GDP figures in weak and non-democracies as the underlying mechanism. I estimate that yearly growth figures may be inflated in the most authoritarian regimes by a factor of 1.15 to 1.3. Adjusting economic growth estimates for manipulation substantially changes our understanding of the economic success stories of the beginning of the XXI century.

The findings in this paper are a warning sign for academics, policy-makers and other agents that make regular use of official economic statistics from weak and non-democracies. These results provide additional justification for the use of innovative and 'harder' measures of economic performance, such as nighttime lights, in the study of economic development. They also point to several avenues for future research, including the application of the methodology employed in this paper to detect manipulation of information in other contexts.

The increased manipulation of GDP figures that I uncover in weak and non-democracies is not easily anticipated or corrected. The autocracy gradient in the night-lights elasticity of GDP is not explained by variation in publicly-available measures of corruption and does not disappear as GDP data gets revised over time. However, the findings on the IMF's Special Data Dissemination Standard provide preliminary evidence that transparency-promoting policies are effective at preventing manipulation of official statatistics.

References

Acemoglu, D., Naidu, S., Restrepo, P., and Robinson, J. A. (2016). Democracy Does Cause Growth. Forthcoming in Journal of Political Economy.

Alesina, A. and Fuchs-Schündeln, N. (2007). Goodbye Lenin (or Not?): The Effect of Communism on People's Preferences. *American Economic Review*, 97(4):1507–1528.

Allcott, H. and Gentzkow, M. (2017). Social Media and Fake News in the 2016 Election. *Journal of Economic Perspectives*, 31(2):211–236.

Alt, J., Lassen, D. D., and Wehner, J. (2014). It Isn't Just about Greece: Domestic Politics, Transparency and Fiscal Gimmickry in Europe. *British Journal of Political Science*, 44(4):707–716.

Ashworth, S. (2012). Electoral Accountability: Recent Theoretical and Empirical Work. *Annual Review of Political Science*, 15(1):183–201.

Brückner, M. and Ciccone, A. (2011). Rain and the Democratic Window of Opportunity. *Econometrica*, 79(3):923–947.

Bueno de Mesquita, B., Smith, A., Siverson, R. M., and Morrow, J. D. (2004). *The Logic of Political Survival*. MIT Press, Cambridge, MA.

Burke, P. J. and Leigh, A. (2010). Do Output Contractions Trigger Democratic Change? *American Economic Journal: Macroeconomics*, 2(4):124–57.

Burlig, F. and Preonas, L. (2016). Out of the Darkness and Into the Light? Development Effects of Rural Electrification. Energy Institute at Haas Working Paper 268.

Bursztyn, L. and Cantoni, D. (2016). A Tear in the Iron Curtain: The Impact of Western Television on Consumption Behavior. *Review of Economics and Statistics*, 98(1):25–41.

Bush, S. S. (2017). The Politics of Rating Freedom: Ideological Affinity, Private Authority, and the Freedom in the World Ratings. *Perspectives on Politics*, 15(3):711–731.

Cantoni, D., Chen, Y., Yang, D. Y., Yuchtman, N., and Zhang, Y. J. (2017). Curriculum and Ideology. *Journal of Political Economy*, 125(2):338–392.

Cavallo, A. (2013). Online and official price indexes: Measuring Argentina's inflatio. *Journal of Monetary Economics*, 60(2):152–165.

Cavallo, A., Cruces, G., and Perez-Truglia, R. (2016). Learning from Potentially Biased Statistics. *Brookings Papers on Economic Activity*, Spring:59–108.

Cheibub, J. A., Gandhi, J., and Vreeland, J. R. (2010). Democracy and Dictatorship Revisited. *Public Choice*, 143(1-2):67–101.

Chen, X. and Nordhaus, W. D. (2011). Using Luminosity Data as a Proxy for Economic Statistics. *Proceedings of the National Academy of Sciences*, 108(21):8589–8594.

Clark, H., Pinkovskiy, M., and Sala-i Martin, X. (2017). China's GDP Growth May be Understated. NBER Working Paper 23323.

Coopersmith, J. (1992). *The Electrification of Russia: 1880-1926*. Cornell University Press, Ithaca, NY.

Coyle, D. (2014). *GDP: A Brief but Affectionate History*. Princeton University Press, Princeton, NJ.

Deaton, A. (2005). Measuring Poverty in a Growing World (or Measuring Growth in a Poor World). *Review of Economics and Statistics*, 87(1):1–19.

Doll, C. N., Muller, J.-P., and Morley, J. G. (2006). Mapping Regional Economic Activity From Night-time Light Satellite Imagery. *Ecological Economics*, 57(1):75–92.

Donaldson, D. and Storeygard, A. (2016). The View from Above: Applications of Satellite Data in Economics. *Journal of Economic Perspectives*, 30(4):171–98.

Edmond, C. (2013). Information Manipulation, Coordination, and Regime Change. *Review of Economic Studies*, 80(4):1422–1458.

Egorov, G., Guriev, S., and Sonin, K. (2009). Why Resource-poor Dictators Allow Freer Media: A Theory and Evidence from Panel Data. *American Political Science Review*, 103(4):645–668.

Enikolopov, R., Korovkin, V., Petrova, M., Sonin, K., and Zakharov, A. (2013). Field Experiment Estimate of Electoral Fraud in Russian Parliamentary Elections. *Proceedings of the National Academy of Sciences*, 110(2):448–452.

Enikolopov, R., Petrova, M., and Zhuravskaya, E. (2011). Media and Political Persuasion: Evidence from Russia. *American Economic Review*, 101(7):3253–85.

Fisman, R. and Wei, S. (2004). Tax Rates and Tax Evasion: Evidence from "Missing Imports" in China. *Journal of Political Economy*, 112(2):471–496.

Fisman, R. and Wei, S.-J. (2009). The Smuggling of Art, and the Art of Smuggling: Uncovering the Illicit Trade in Cultural Property and Antiques. *American Economic Journal: Applied Economics*, 1(3):82–96.

Freedom House (2017). Populists and Autocrats: The Dual Threat to Global Democracy. Freedom in the World Report 2017.

Galiani, S., Knack, S., Xu, L. C., and Zou, B. (2017). The Effect of Aid on Growth: Evidence from a Quasi-experiment. *Journal of Economic Growth*, 22(1):1–33.

Geddes, B., Frantz, E., and Wright, J. G. (2014). Military Rule. *Annual Review of Political Science*, 17(1):147–162.

Gehlbach, S. and Sonin, K. (2014). Government Control of the Media. *Journal of Public Economics*, 118(Supplement C):163 – 171.

Gehlbach, S., Sonin, K., and Svolik, M. W. (2016). Formal Models of Nondemocratic Politics. *Annual Review of Political Science*, 19(1):565–584.

Giannone, D. (2010). Political and Ideological Aspects in the Measurement of Democracy: The Freedom House Case. *Democratization*, 17(1):68–97.

Henderson, J. V., Storeygard, A., and Weil, D. N. (2012). Measuring Economic Growth from Outer Space. *American Economic Review*, 102(2):994–1028.

Hodler, R. and Raschky, P. A. (2014). Regional Favoritism. *Quarterly Journal of Economics*, 129(2):995–1033.

Hollyer, J. R., Rosendorff, B. P., and Vreeland, J. R. (2011). Democracy and Transparency. *Journal of Politics*, 73(4):1191–1205.

Hollyer, J. R., Rosendorff, B. P., and Vreeland, J. R. (2014). Measuring Transparency. *Political Analysis*, 22(1):413–434.

Hollyer, J. R., Rosendorff, B. P., and Vreeland, J. R. (2015). Transparency, Protest, and Autocratic Instability. *American Political Science Review*, 109(4):764–784.

Holz, C. (2006). China's Reform Period Economic Growth: How Reliable Are Angus Maddison's Estimates? *Review of Income and Wealth*, 52(1):85–119.

Holz, C. A. (2014). The Quality of China's GDP Statistics. *China Economic Review*, 30(Supplement C):309 – 338.

Jerven, M. (2013). *Poor Numbers: How We Are Misled by African Development Statistics and What to Do About It.* Cornell University Press, Ithaca, NY.

Kern, H. L. and Hainmueller, J. (2009). Opium for the Masses: How Foreign Media Can Stabilize Authoritarian Regimes. *Political Analysis*, 17(4):377–399.

Kerner, A., Jerven, M., and Beatty, A. (2017). Does it Pay to be Poor? Testing for Systematically Underreported GNI Estimates. *Review of International Organizations*, 12(1):1–38.

King, D. (1997). *The Commissar Vanishes: The Falsification of Photographs and Art in Stalin's Russia.* Canongate Books, London,UK.

King, G., Pan, J., and Roberts, M. E. (2013). How Censorship in China Allows Government Criticism but Silences Collective Expression. *American Political Science Review*, 107(2):1–18.

King, G., Pan, J., and Roberts, M. E. (2017). How the Chinese Government Fabricates Social Media Posts for Strategic Distraction, Not Engaged Argument. *American Political Science Review*, 111(3):484–501.

Leigh, A. (2009). Does the World Economy Swing National Elections? *Oxford Bulletin of Economics and Statistics*, 71(2):163–181.

Lepenies, P. (2016). *The Power of a Single Number*. Columbia University Press, New York, NY.

Lequiller, F. and Blades, D. (2014). *Understanding National Accounts: Second Edition*. OECD Publishing.

Levitsky, S. and Way, L. A. (2010). *Competitive Authoritarianism: Hybrid Regimes Aster the Cold War*. Cambridge University Press, New York, NY.

Levy, D. M. and Peart, S. J. (2011). Soviet Growth and American Textbooks: An Endogenous Past. *Journal of Economic Behavior & Organization*, 78(1):110 – 125.

Lorentzen, P. (2014). China's Strategic Censorship. *American Journal of Political Science*, 58(2):402–414.

Madisson, A. (2006). Do Official Statistics Exaggerate China's GDP Growth? A Reply to Carsten Holz. *Review of Income and Wealth*, 52(1):121–126.

Magee, C. S. P. and Doces, J. A. (2015). Reconsidering Regime Type and Growth: Lies, Dictatorships, and Statistics. *International Studies Quarterly*, 59(2):223–237.

Mahdavy, H. (1970). The Patterns and Problems of Economic Development in Rentier States: The Case of Iran. In Cook, M., editor, *Studies in the Economic History of the Middle East from the Rise of Islam to the present day*. Oxford University Press, London.

Mehrotra, A. and Pääkkönen, J. (2011). Comparing China's GDP Statistics with Coincident Indicators. *Journal of Comparative Economics*, 39(3):406 – 411.

Merridale, C. (1996). The 1937 Census and the Limits of Stalinist Rule. *Historical Journal*, 39(1):225–240.

Michalopoulos, S. and Papaioannou, E. (2013). Pre-Colonial Ethnic Institutions and Contemporary African Development. *Econometrica*, 81(1):113–152.

Michalopoulos, S. and Papaioannou, E. (2014). National Institutions and Subnational Development in Africa. *Quarterly Journal of Economics*, 129(1):151–213.

Michalopoulos, S. and Papaioannou, E. (2017). Spatial Patterns of Development: A Meso Approach. NBER Working Paper 24088.

Michalski, T. and Stoltz, G. (2013). Do Countries Falsify Economic Data Strategically? Some Evidence That They Might. *Review of Economics and Statistics*, 95(2):591–616.

Min, B. (2015). *Power and the Vote: Elections and Electricity in the Developing World*. Cambridge University Press, New York, NY.

Nakamura, E., Steinsson, J., and Liu, M. (2016). Are Chinese Growth and Inflation Too Smooth? Evidence from Engel Curves. *American Economic Journal: Macroeconomics*, 8(3):113–44.

Olken, B. A. (2007). Monitoring Corruption: Evidence from a Field Experiment in Indonesia. *Journal of Political Economy*, 115(2):200–249.

Papaioannou, E. and Siourounis, G. (2008). Democratization and Growth. *Economic Journal*, 118(10):1520–1551.

Pinkovskiy, M. (2017). Growth discontinuities at borders. *Journal of Economic Growth*, 22(2):145–192.

Pinkovskiy, M. and Sala-i Martin, X. (2014). Africa is on Time. *Journal of Economic Growth*, 19(3):311–338.

Pinkovskiy, M. and Sala-i Martin, X. (2016a). Lights, Camera … Income! Illuminating the National Accounts-Household Surveys Debate. *Quarterly Journal of Economics*, 131(2):579–631.

Pinkovskiy, M. and Sala-i Martin, X. (2016b). Newer Need Not be Better: Evaluating the Penn World Tables and the World Development Indicators Using Nighttime Lights. NBER Working Paper 22216.

Przeworski, A., Alvarez, M., Cheibub, J. A., and Limongi, F. (2000). *Democracy and Development: Political Institutions and Well-Being in the World, 1950-1990*. Cambridge University Press, New York, NY.

Qian, N. and Yanagizawa-Drott, D. (2009). The Strategic Determinants of U.S. Human Rights Reporting: Evidence from the Cold War. *Journal of the European Economic Association*, 7(2-3):446–457.

Qian, N. and Yanagizawa-Drott, D. (2017). Government Distortion in Independently Owned Media: Evidence from U.S. News Coverage of Human Rights. *Journal of the European Economic Association*, 15(2):463–499.

Rawski, T. G. (2001). What is happening to China's GDP statistics? *China Economic Review*, 12(4):347 – 354.

Ross, M. (2001). Does Oil Hinder Democracy? *World Politics*, 53(3):325–361.

Sandefur, J. and Glassman, A. (2015). The Political Economy of Bad Data: Evidence from African Survey and Administrative Statistics. *Journal of Development Studies*, 51(2):116–132.

Steiner, N. D. (2016). Comparing Freedom House Democracy Scores to Alternative Indices and Testing for Political Bias: Are US Allies Rated as More Democratic by Freedom House? *Journal of Comparative Policy Analysis: Research and Practice*, 18(4):329–349.

von Hagen, J. and Wolff, G. B. (2006). What do deficits tell us about debt? Empirical evidence on creative accounting with fiscal rules in the EU. *Journal of Banking and Finance*, 30(12):3259–3279.

Wallace, J. (2014). *Cities and Stability: Urbanization, Redistribution, and Regime Survival in China*. Oxford University Press, New York, NY.

Wallace, J. (2016). Juking the Stats? Authoritarian Information Problems in China. *British Journal of Political Science*, 46(1):11–29.

Wig, T., Hegre, H., and Regan, P. M. (2015). Updated Data on Institutions and Elections 1960–2012: Presenting the IAEP Dataset Version 2.0. *Research & Politics*, 2(2):1–11.

World Bank (2002). *Building Statistical Capacity to Monitor Development Progress*. The World Bank, Washington DC.

Xu, X. (2009). The Establishment, Reform and Development of China's System of National Accounts. *Review of Income and Wealth*, 55(1):442–465.

Young, A. (2003). Gold into Base Metals: Productivity Growth in the People's Republic of China during the Reform Period. *Journal of Political Economy*, 111(6):1220–1261.

Young, A. (2012). The African Growth Miracle. *Journal of Political Economy*, 120(4):696–739.

Zinman, J. and Zitzewitz, E. (2016). Wintertime for Deceptive Advertising? *American Economic Journal: Applied Economics*, 8(1):177–92.

Zitzewitz, E. (2012). Forensic Economics. *Journal of Economic Literature*, 50(3):731–69.

Table 1: Average growth in GDP and nighttime lights across regime types

	Average growth rate	
	GDP	Night lights
Full sample (N=2,724)	0.0397	0.0522
	(0.057)	(0.234)
'Free' countries (N=1,182)	0.0357	0.0497
	(0.033)	(0.268)
'Partially free' countries (N=761)	0.0406	0.0572
	(0.0632)	(0.216)
'Not free' countries (N=781)	0.0446	0.051
	(0.0764)	(0.191)
p-value H_0: Free = Partially Free	0.049	0.498
p-value H_0: Free = Not Free	0.002	0.897
p-value H_0: Partially Free = Not Free	0.264	0.554

Notes: Table shows the average yearly growth rate of GDP and the nighttime lights Digital number (DN). The latter is the within-country area-weighted average of grid-level lights digital numbers (0-63). Countries are classified using the adjusted Freedom in the World Index (FWI), which ranges from 0 to 6, with lower values corresponding to greater enjoyment of civil liberties and political rights. Country is 'Free' if FWI< 2, 'Partially Free' if $2 \leq FWI < 4$ and 'Not Free' if $FWI \geq 4$. Standard deviation in parentheses.

Table 2: The autocracy gradient in the night-lights elasticity of GDP

	Dependent variable: $\ln(\text{GDP})_{i,t}$						
	Yearly fluctuations					Long-run growth	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$\ln(\text{lights})_{i,t}$	0.283***	0.279***	0.238***	0.238***	0.264***	0.264***	0.275***
	[0.031]	[0.031]	[0.034]	[0.035]	[0.032]	[0.042]	[0.040]
$\text{FWI}_{i,t}$		-0.017*	-0.005	-0.004		-0.054	
		[0.009]	[0.010]	[0.022]		[0.038]	
$\text{FWI}^2{}_{i,t}$				-0.000		0.010	
				[0.004]		[0.007]	
$\ln(\text{lights})_{i,t} \times \text{FWI}_{i,t}$			0.012***	0.012***		0.018**	
			[0.004]	[0.004]		[0.007]	
D(Partially Free)$_{i,t}$					-0.006		-0.021
					[0.017]		[0.039]
D(Not Free)$_{i,t}$					-0.012		-0.006
					[0.027]		[0.053]
$\ln(\text{lights})_{i,t} \times$ D(Partially Free)$_{i,t}$ [a]					0.015		0.037*
					[0.011]		[0.021]
$\ln(\text{lights})_{i,t} \times$ D(Not Free)$_{i,t}$ [b]					0.028**		0.065**
					[0.013]		[0.026]
Observations	2,914	2,914	2,914	2,914	2,914	334	334
Countries	179	179	179	179	179	167	167
(Within country) R^2	0.772	0.773	0.777	0.777	0.774	0.851	0.852
p-value H_0: a = b					0.076		0.160

Notes: Dependent variable is ln(GDP) in constant local currency units. ln(lights) is the natural logarithm of the area-weighted average of grid-level lights digital number (0-63). The adjusted Freedom in the World Index (FWI) ranges from 0 to 6, with lower values corresponding to greater enjoyment of civil liberties and political rights. Country is "Free" if $\text{FWI} < 2$, "Partially Free" if $2 \leq FWI < 4$ and "Not Free" if $FWI \geq 4$. D(Free) and its interaction with ln(lights) are the omitted categories in columns 5 and 7. All regressions include country and year fixed effects. In columns 1-5, the sample period is 1992-2008. In columns 6-7, the average of all variables for the years 1992/93 and 2005/06 is used instead. Robust standard errors clustered by country in brackets. *** p<0.01, ** p<0.05, * p<0.1

Table 3: Other measures of autocracy

	Dependent variable: $\ln(\text{GDP})_{i,t}$						
	Polity IV indices			Binary measures of autocracy			
	Polity2	Democracy	Autocracy	FH	ANRR	PS	DD
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$\ln(\text{lights})_{i,t}$	0.293***	0.267***	0.247***	0.261***	0.277***	0.272***	0.274***
	[0.029]	[0.032]	[0.030]	[0.031]	[0.029]	[0.045]	[0.032]
$\text{score}_{i,t}$	-0.004*	-0.005	-0.015	0.050**	0.023	0.053*	0.017
	[0.002]	[0.010]	[0.012]	[0.021]	[0.020]	[0.031]	[0.023]
$\text{score}^2{}_{i,t}$	0.000	0.000	0.003*				
	[0.000]	[0.001]	[0.002]				
$\ln(\text{lights})_{i,t} \times \text{score}_{i,t}$	-0.002**	-0.002	0.005**	0.031***	0.020***	0.040***	0.016
	[0.001]	[0.002]	[0.002]	[0.010]	[0.007]	[0.015]	[0.011]
Observations	2,531	2,458	2,458	2,881	2,531	1,936	2,911
Countries	156	155	155	177	156	167	179
(Within country) R^2	0.783	0.793	0.795	0.773	0.783	0.683	0.773

Notes: Dependent variable is ln(GDP) in constant local currency units. ln(lights) is the natural logarithm of the area-weighted average of grid-level lights digital number (0-63). The Polity2 score from the Polity IV project (column 1) is the difference between the democracy and autocracy scores and ranges from -10 to 10 (most democratic). The democracy (column 2) and autocracy (column 3) scores range from 0 to 10, with larger values corresponding to more democratic and autocratic regimes, respectively. The autocracy measure in column 4 is defined as one minus the 'electoral democracy' dummy produced by Freedom House. In column 5, the autocracy dummy equals one if the country is classified by Freedom House as 'not free' or the Polity score is less than or equal to zero, following Acemoglu et al. (2016). Column 6 uses the democracy indicator produced by Papaioannou and Siourounis (2008). Column 8 uses the dummy for autocracy from the Cheibub et al. (2010) DD dataset, which is an updated version of the Przeworski et al. (2000) dataset. All regressions include country and year fixed effects. Robust standard errors, clustered by country, are shown in brackets. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 4: The autocracy gradient in the night-lights elasticity of GDP sub-components

Dependent variable:	ln(Consumption)	ln (Investment)	ln(Government)	ln(Exports)	ln(Imports)
	(1)	(2)	(3)	(4)	(5)
$\ln(\text{lights})_{i,t}$	0.161***	0.355***	0.202***	0.340***	0.262***
	[0.033]	[0.121]	[0.051]	[0.082]	[0.059]
$\text{FWI}_{i,t}$	-0.016	-0.007	-0.048	-0.042	-0.056
	[0.031]	[0.057]	[0.039]	[0.058]	[0.038]
$\text{FWI}^2{}_{i,t}$	0.001	-0.004	0.008	0.001	0.002
	[0.005]	[0.011]	[0.007]	[0.010]	[0.006]
$\ln(\text{lights})_{i,t} \times \text{FWI}_{i,t}$	0.006	0.022**	0.027***	0.005	0.008
	[0.006]	[0.011]	[0.008]	[0.012]	[0.009]
Observations	2,624	2,622	2,624	2,624	2,624
Countries	167	167	167	167	167
(Within country) R^2	0.650	0.395	0.479	0.544	0.624

Notes: Dependent variable in the header (natural logarithm of value in constant local currency units). ln(lights) is the natural logarithm of the area-weighted average of grid-level lights digital number (0-63). The adjusted Freedom in the World Index (FWI) ranges from 0 to 6, with lower values corresponding to greater enjoyment of civil liberties and political rights. Dependent variable (log value in constant local currency units) in the header: household final consumption expenditure in column 1; gross capital formation in column 2; general government final consumption in column 3; exports of goods and services in column 4; imports of goods and services in column 5. Regressions include country and year fixed effects. Robust standard errors clustered by country are shown in brackets. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 5: The effect of political institutions on the autocracy gradient in the night-lights elasticity of GDP

	Dependent variable: $\ln(\text{GDP})_{i,t}$				
	Elected legislature (1)	Elected executive (2)	Central bank authority (3)	Constitutional court (4)	Communist history (5)
$\ln(\text{lights})_{i,t}$	0.098	0.220***	0.194***	0.225***	0.203***
	[0.102]	[0.040]	[0.046]	[0.032]	[0.032]
$\ln(\text{lights})_{i,t} \times \text{FWI}_{i,t}$ [a]	0.049**	0.019***	0.025***	0.024***	0.011**
	[0.021]	[0.006]	[0.008]	[0.007]	[0.004]
$\ln(\text{lights})_{i,t} \times x_{i,t}$	0.168*	0.041**	0.025	0.021	0.032
	[0.092]	[0.020]	[0.025]	[0.016]	[0.057]
$\ln(\text{lights})_{i,t} \times \text{FWI}_{i,t} \times x_{i,t}$ [b]	-0.040*	-0.012**	-0.011**	-0.013*	0.022**
	[0.022]	[0.006]	[0.005]	[0.007]	[0.010]
Observations	2,451	2,490	2,073	2,416	2,914
Countries	153	154	139	152	179
(Within country) R^2	0.793	0.788	0.798	0.792	0.783
p-value H_0: a + b = 0	0.074	0.124	0.010	0.003	0.001

Notes: Dependent variable is ln(GDP) in constant local currency units. ln(lights) is the natural logarithm of the area-weighted average of grid-level lights digital number (0-63). The adjusted Freedom in the World Index (FWI) ranges from 0 to 6, with lower values corresponding to greater enjoyment of civil liberties and political rights. Each column includes the binary variable in the header (x) and all its interactions with ln(lights) and FWI. In column 1, $x_{i,t}$ is a dummy indicating whether the country holds national elections for the legislature. In column 2, $x_{i,t}$ is a dummy indicating whether the country holds national elections for the executive. In column 3, $x_{i,t}$ is a dummy indicating whether the central bank has authority over monetary policy. In column 4, $x_{i,t}$ is a dummy indicating whether the country has a national constitutional court. In column 5, $x_{i,t}$ is a dummy indicating whether the country had had a communist regime at some point in time. All of these variables are time-varying with the exception of the dummy for communist history in column 5. All regressions include country and year fixed effects. Only the estimates for ln(lights) and its interactions are shown in the table. See the online appendix for full results. Robust standard errors, clustered by country, are shown in brackets. *** p<0.01, ** p<0.05, * p<0.1

Table 6: Incentives for manipulation I: Economic under-performance and elections

	Dependent variable: $\ln(\text{GDP})_{i,t}$			
	Low growth		Before election	
	(1)	(2)	(3)	(4)
$\ln(\text{lights})_{i,t}$	0.241***	0.258***	0.261***	0.287***
	[0.042]	[0.040]	[0.040]	[0.035]
$\ln(\text{lights})_{i,t} \times x_{i,t}$	-0.008	-0.001	-0.002	-0.001
	[0.007]	[0.005]	[0.003]	[0.002]
$\ln(\text{lights})_{i,t} \times \text{FWI}_{i,t}$	0.006		0.010**	
	[0.004]		[0.004]	
$\ln(\text{lights})_{i,t} \times \text{FWI}_{i,t} \times x_{i,t}$	0.005*		0.002	
	[0.003]		[0.001]	
$\ln(\text{lights})_{i,t} \times \text{D(Partially Free)}_{i,t}$		0.010		0.014
		[0.012]		[0.012]
$\ln(\text{lights})_{i,t} \times \text{D(Not Free)}_{i,t}$		0.010		0.023*
		[0.014]		[0.013]
$\ln(\text{lights})_{i,t} \times \text{D(Partially Free)}_{i,t} \times x_{i,t}$		0.002		-0.001
		[0.009]		[0.005]
$\ln(\text{lights})_{i,t} \times \text{D(Not Free)}_{i,t} \times x_{i,t}$		0.022*		0.013**
		[0.012]		[0.005]
Observations	2,914	2,914	2,500	2,500
Countries	179	179	154	154
(Within country) R^2	0.781	0.778	0.781	0.779

Notes: Dependent variable is ln(GDP) in constant local currency units. ln(lights) is the natural logarithm of the area-weighted average of grid-level lights digital number (0-63). Adjusted Freedom in the World Index (FWI) ranges from 0 to 6, with lower values corresponding to greater enjoyment of civil liberties and political rights. Country is "Free" if FWI< 2, "Partially Free" if $2 \leq FWI < 4$ and "Not Free" if $FWI \geq 4$. D(Free) and its interactions are the omitted categories in columns 2 and 4. In columns 1-2, $x_{i,t}$ is a dummy equal to one if the value of ln(lights) demeaned by country and year is negative. In columns 3-4, $x_{i,t}$ is a dummy equal to one if there is a national election in the following year. Only the estimates for ln(lights) and its interactions are shown in the table. See the online appendix for full results. All regressions include country and year fixed effects. Robust standard errors, clustered by country, are shown in brackets. *** p<0.01, ** p<0.05, * p<0.1

Table 7: Incentives for manipulation II: Eligibility for IDA loans and grants

	Dependent variable: $\ln(\mathrm{GDP})_{i,t}$							
	Baseline results (reduced sample)		Changing elasticity above GNI threshold			Galiani et al. (2017) crossings	Ineligible countries	Crossings ≤ 1
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\ln(\mathrm{lights})_{i,t}$	0.252***	0.210***	0.233***	0.244***	0.226***	0.225***	0.239***	0.236***
	[0.037]	[0.042]	[0.037]	[0.035]	[0.041]	[0.041]	[0.041]	[0.041]
$\ln(\mathrm{lights})_{i,t} \times \mathrm{FWI}_{i,t}$		0.012*			0.004	0.004	0.004	0.001
		[0.007]			[0.006]	[0.006]	[0.006]	[0.006]
$\ln(\mathrm{lights})_{i,t} \times \mathrm{D(GNI{>}threshold)}_{i,t}$			0.061*	0.081***	0.001	0.001	-0.000	-0.017
			[0.032]	[0.025]	[0.035]	[0.037]	[0.036]	[0.029]
$\ln(\mathrm{lights})_{i,t} \times \mathrm{GNI}_{i,t}$				-0.048***	-0.043***	-0.040***	-0.046***	-0.049***
				[0.010]	[0.010]	[0.010]	[0.011]	[0.009]
$\ln(\mathrm{lights})_{i,t} \times \mathrm{FWI}_{i,t} \times \mathrm{D(GNI{>}threshold)}_{i,t}$					0.023*	0.023*	0.024*	0.028**
					[0.013]	[0.014]	[0.013]	[0.012]
Observations	1,308	1,308	1,308	1,308	1,308	1,308	1,357	1,274
Countries	82	82	82	82	82	82	85	80
(Within country) R^2	0.760	0.766	0.774	0.794	0.806	0.807	0.799	0.811

Notes: Dependent variable is ln(GDP) in constant local currency units. ln(lights) is the natural logarithm of the area-weighted average of grid-level lights digital number (0-63). The adjusted Freedom in the World Index (FWI) ranges from 0 to 6, with lower values corresponding to greater enjoyment of civil liberties and political rights. GNI is Gross National Income per capita in thousands of current US dollars using Atlas method. $\mathrm{D(GNI{>}threshold)}_{i,t}$ equals one if GNI per capita is above the yearly value set by IDA for eligibility for loans and grants. All regressions include the relevant individual variables and second-order interaction terms (estimates not reported). All regressions include country and year fixed effects. Robust standard errors clustered by country in brackets. Baseline sample includes all countries that were eligible for IDA aid at some point in the sample period (current + graduates). In column 6, I use the crossing dates reported by Galiani et al. (2017). In column 7, I include Syria, Turkmenistan and Ukraine, which were not excluded from IDA aid. In column 8, I exclude Guyana and Indonesia, which cross the threshold more than once. *** p<0.01, ** p<0.05, * p<0.1

Table 8: Capturing manipulation: Existing measures of corruption and transparency

	Dependent variable: $\ln(\text{GDP})_{i,t}$								
	Corruption Perception Index (CPI)			Control of Corruption Index (CCI)			Transparency index (HRV)		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$\ln(\text{lights})_{i,t}$	0.130***	0.219***	0.167***	0.172***	0.201***	0.172***	0.270***	0.296***	0.269***
	[0.041]	[0.056]	[0.048]	[0.035]	[0.033]	[0.034]	[0.037]	[0.033]	[0.035]
$\text{FWI}_{i,t}$	-0.005		-0.005	0.002		0.009	0.016		0.018
	[0.022]		[0.021]	[0.024]		[0.024]	[0.027]		[0.027]
$\text{FWI}^2_{i,t}$	0.000		0.001	-0.001		-0.002	-0.003		-0.004
	[0.005]		[0.005]	[0.004]		[0.004]	[0.005]		[0.005]
$\ln(\text{lights})_{i,t} \times \text{FWI}_{i,t}$	0.020***		0.020***	0.009*		0.008*	0.009**		0.007*
	[0.007]		[0.007]	[0.005]		[0.004]	[0.004]		[0.004]
$x_{i,t}$		0.023*	0.024*		0.047*	0.044*		0.012	0.012
		[0.013]	[0.013]		[0.026]	[0.025]		[0.008]	[0.007]
$\ln(\text{lights})_{i,t} \times x_{i,t}$		-0.009*	-0.008		-0.010	-0.004		-0.009**	-0.007**
		[0.005]	[0.005]		[0.011]	[0.010]		[0.004]	[0.003]
Observations	1,310	1,310	1,310	1,705	1,705	1,705	2,015	2,015	2,015
Countries	169	169	169	178	178	178	122	122	122
(Within country) R^2	0.796	0.795	0.800	0.762	0.761	0.764	0.824	0.823	0.827

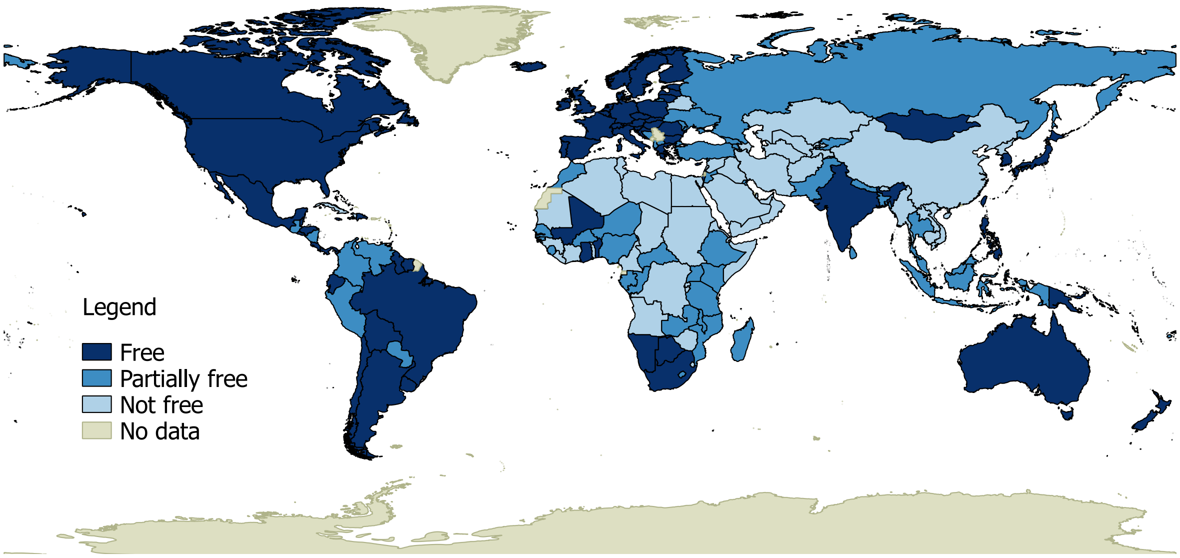
Notes: Dependent variable is ln(GDP) in constant local currency units. ln(lights) is the natural logarithm of the area-weighted average of grid-level lights digital number (0-63). The adjusted Freedom in the World Index (FWI) ranges from 0 to 6, with lower values corresponding to greater enjoyment of civil liberties and political rights. The Corruption Perceptions Index (CPI) used in columns 1-3 is produced by Transparency International and has been re-scaled from 0 to 10, with larger values corresponding to decreased perception of corruption. The Control of Corruption Index (CCI) used in columns 4-6 is produced by the World Bank and ranges from -2.5 to 2.5, with larger values corresponding to decreased perception of corruption. The source of the HRV transparency index used in columns 7-9 is Hollyer et al. (2014). The HRV transparency index is based on data availability in the World Bank's WDI, with larger values corresponding to increased availability of information and transparency. Observed values of the HRV index range from -3.04 to 9.98. All regressions include country and year fixed effects. Robust standard errors, clustered by country, are shown in brackets. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 9: Preventing manipulation: IMF's Special Data Dissemination Standard (SDDS)

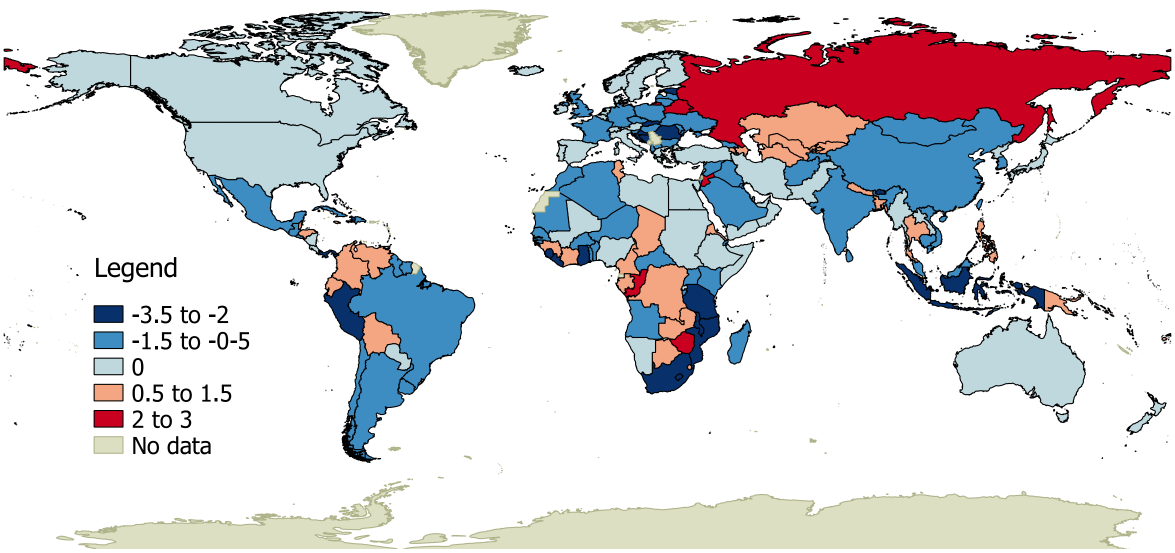
	Dependent variable: $\ln(\text{GDP})_{i,t}$			
	Selection		Treatment effect	
	(1)	(2)	(3)	(4)
$\ln(\text{lights})_{i,t}$	0.231***	0.262***	0.242***	0.272***
	[0.040]	[0.035]	[0.040]	[0.036]
$\ln(\text{lights})_{i,t} \times \text{D(SDDS country)}_i$	0.070	0.012	0.011	-0.038
	[0.055]	[0.051]	[0.053]	[0.048]
$\ln(\text{lights})_{i,t} \times \text{FWI}_{i,t}$ [a]	0.013**		0.012**	
	[0.005]		[0.005]	
$\ln(\text{lights})_{i,t} \times \text{FWI}_{i,t} \times \text{D(SDDS country)}_i$ [b]	-0.016		-0.013	
	[0.011]		[0.012]	
$\ln(\text{lights})_{i,t} \times \text{D(Partially Free)}_{i,t}$		0.017		0.016
		[0.014]		[0.014]
$\ln(\text{lights})_{i,t} \times \text{D(Not Free)}_{i,t}$		0.024		0.023
		[0.016]		[0.016]
$\ln(\text{lights})_{i,t} \times \text{D(Partially Free)}_{i,t} \times \text{D(SDDS country)}_i$		-0.013		-0.012
		[0.026]		[0.035]
$\ln(\text{lights})_{i,t} \times \text{D(Not Free)}_{i,t} \times \text{D(SDDS country)}_i$		0.023		0.037
		[0.040]		[0.049]
$\ln(\text{lights})_{i,t} \times \text{D(SDDS)}_{i,t}$			0.010	0.009
			[0.015]	[0.013]
$\ln(\text{lights})_{i,t} \times \text{FWI}_{i,t} \times \text{D(SDDS)}_{i,t}$ [c]			-0.007	
			[0.009]	
$\ln(\text{lights})_{i,t} \times \text{D(Partially Free)}_{i,t} \times \text{D(SDDS)}_{i,t}$				0.013
				[0.025]
$\ln(\text{lights})_{i,t} \times \text{D(Not Free)}_{i,t} \times \text{D(SDDS)}_{i,t}$				-0.086**
				[0.035]
Observations	2,914	2,914	2,914	2,914
Countries	179	179	179	179
(Within country) R^2	0.778	0.775	0.781	0.778
p-value H_0: a + b = 0	0.289		0.980	
p-value H_0: a + b + c = 0			0.869	

Notes: Dependent variable is ln(GDP) in constant local currency units. ln(lights) is the natural logarithm of the area-weighted average of grid-level lights digital number (0-63). Adjusted Freedom in the World Index (FWI) ranges from 0 to 6, with lower values corresponding to greater enjoyment of civil liberties and political rights. Country is "Free" if FWI$<$ 2, "Partially Free" if $2 \leq FWI < 4$ and "Not Free" if $FWI \geq 4$. D(Free) and its interactions is omitted in even-numbered columns. D(SDDS country)_i is a dummy equal to one for countries that joined the SDDS during the sample period. $\text{D(SDDS)}_{i,t}$ is a dummy equal to one following subscription to the SDDS. All regressions include country and year fixed effects. They also include all lower order interactions (see Appendix for the full table). Robust standard errors, clustered by country, are shown in brackets. *** p<0.01, ** p<0.05, * p<0.1

Figure 1: The Freedom in the World Index (FWI)



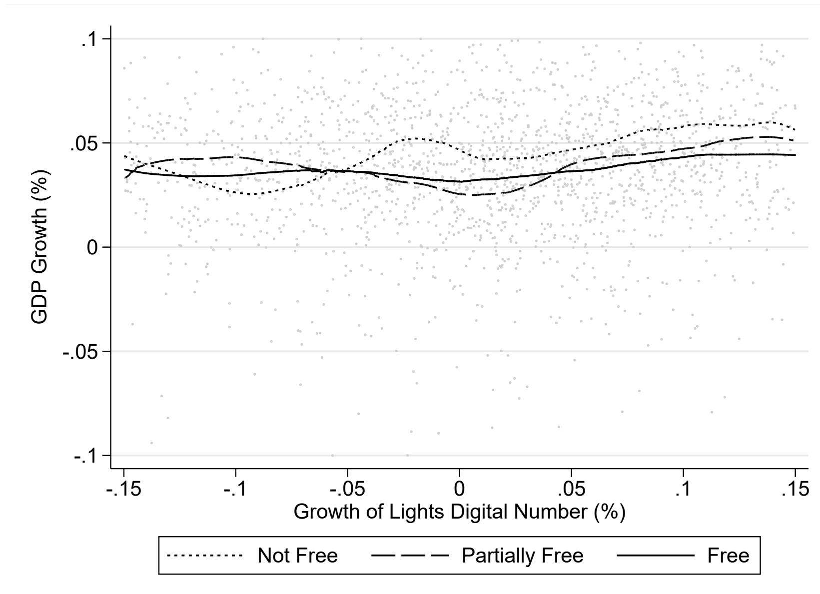
(a) Average 1992-2008



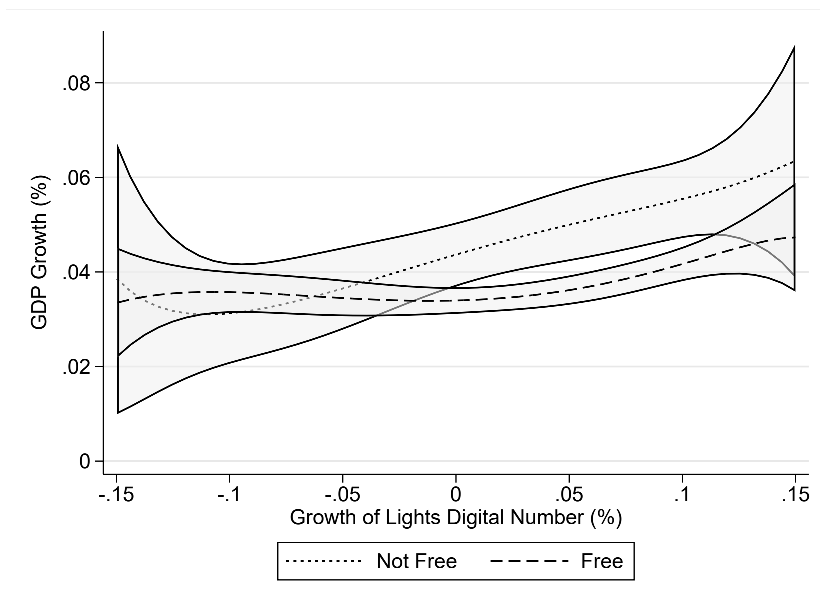
(b) Change between 1992 and 2008

Note: Panel (a) shows the average Freedom in the World Index (FWI) per country for the period 1992-2008. The adjusted FWI ranges from 0 to 6, with lower values corresponding to greater enjoyment of civil liberties and political rights. Countries are classified as "Free" if the FWI is less than two, "Partially Free" if greater than or equal to two but less than four, "Not Free" if greater than or equal to four. Panel (b) shows the difference in the FWI between the years 1992 and 2008. Some countries lacked data for 1992, so the earliest year with available information was used: 1993 for Andorra, Czech Republic, Eritrea and Monaco; 1994 for Palau; 1999 for Timor-Leste and Slovakia.

Figure 2: Non-parametric estimation



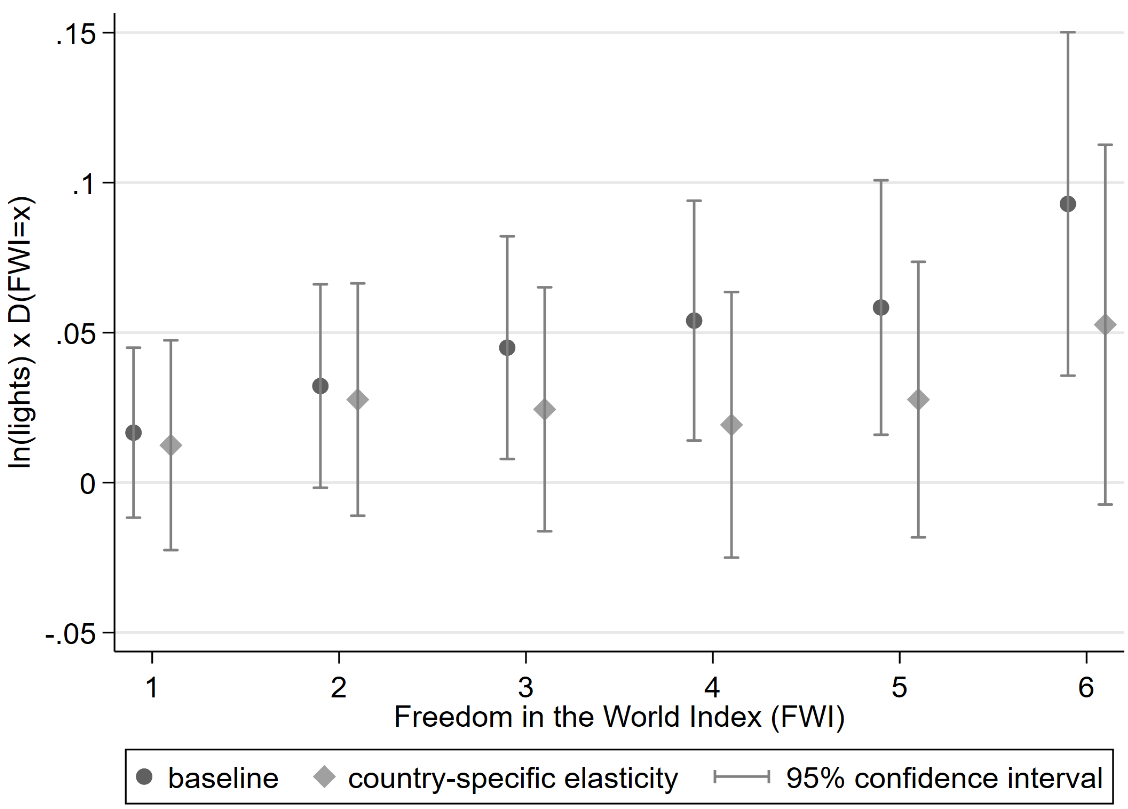
(a) Locally-weighted smoothing



(b) Local polynomial smoothing

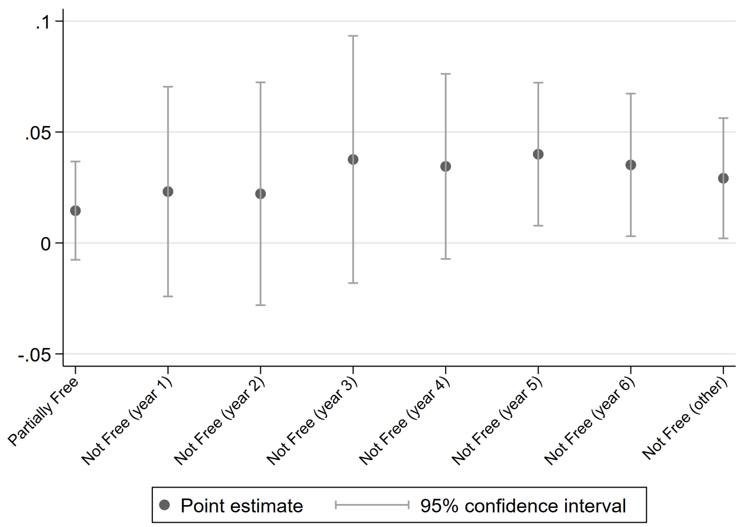
Note: Panel (a) shows the scatter of yearly growth in GDP and nighttime lights (DN). Also shown are separate Lowess locally-weighted regression estimates for 'free', 'partially free' and 'not free' countries. Countries are classified using the adjusted Freedom in the World Index (FWI), which ranges from 0 to 6, with lower values corresponding to greater enjoyment of civil liberties and political rights. Country is 'Free' if FWI<2, 'Partially Free' if $2 \leq FWI < 4$ and 'Not Free' if $FWI \geq 4$. Panel (b) shows estimates and 95% confidence intervals of kernel-weighted local polynomial regressions for 'free' and 'not free countries' over the same sample. For this exercise, I use a quartic kernel and a third-order polynomial. The bandwidth for all regressions is 0.3. For these figures, observations with growth of lights DN below -0.15 or above 0.15 are excluded. See online appendix for corresponding figures with the full sample.

Figure 3: The night-lights elasticity of GDP at each value of FWI

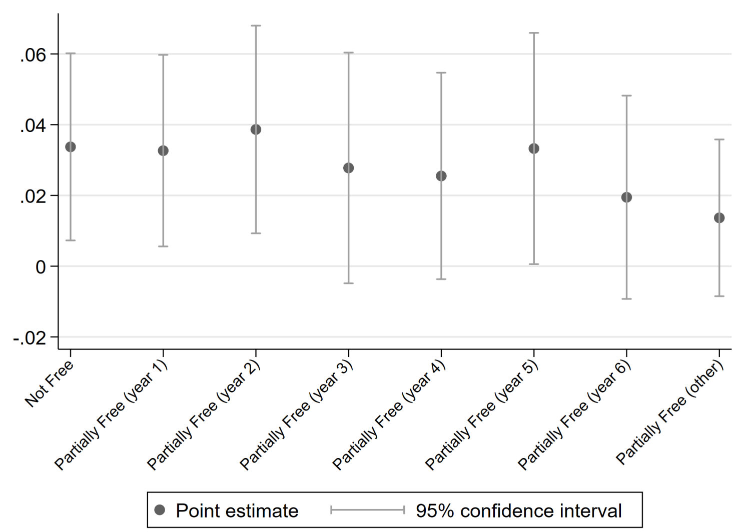


Note: The graph shows point estimates and 95% confidence intervals of a regression of ln(GDP) on the interaction of ln(lights) with each value of FWI (rounded to the nearest integer). Other regressors are ln(lights) [not reported] and separate indicators for each value of FWI [also not reported, omitted category is FWI=0]. The round markers correspond to the baseline specification with country and year fixed effects (i.e. a fully disaggregated version of column 5 of Table 2). The diamond markers show results from an enlarged specification with a full set of interactions of ln(lights) with country dummies [not reported]. Sample for both regressions includes 2,914 observations from 179 countries. Standard errors clustered by country.

Figure 4: Political Transitions



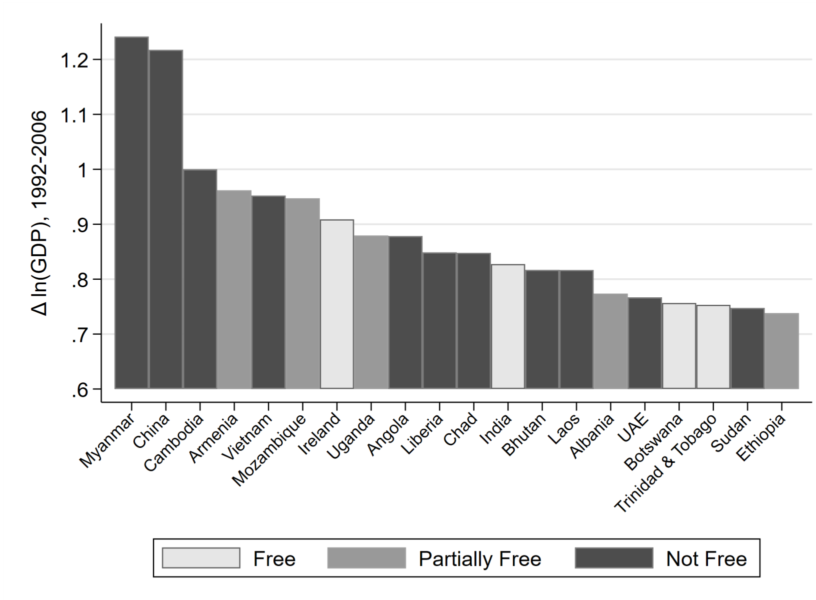
(a) Into Autocracy



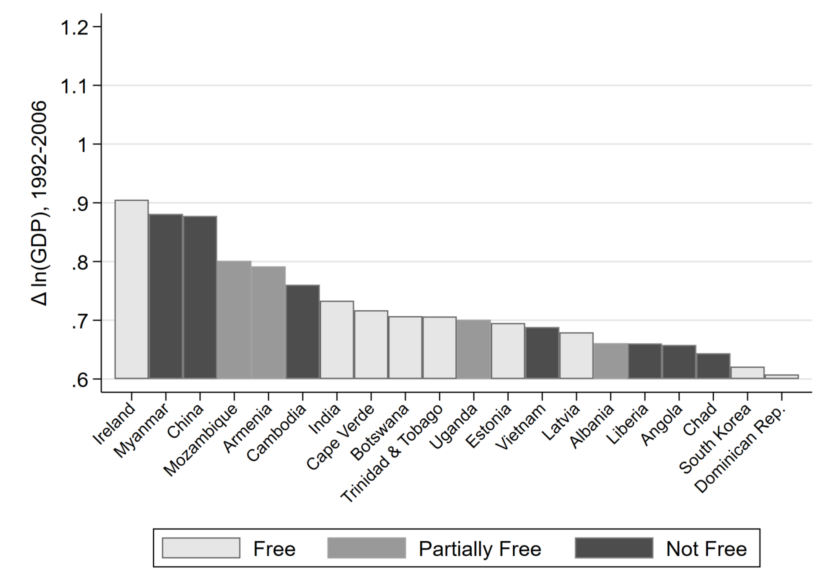
(b) Out of Autocracy

Note: Each panel shows point estimates and 95% confidence intervals of a fixed-effects regression (country and year) of ln(GDP) on ln(lights) [not reported] and its interaction with dummies for 'partially free,' and 'not free' countries, as defined by the Freedom in the World Index (FWI) (the interaction with 'free' is the omitted category). In panel (a), the interaction with 'not free' countries is disaggregated into individual ones for the first six years after a transition (i.e. becoming 'Not Free') and a separate interaction for all other 'not Free' country-years. Only countries with six consecutive years of 'not Free' status after a transition contribute to the transition estimates. Panel (b) includes equivalent disaggregate interactions for the first six years after a transition out of 'not Free' status. Both regressions also include dummies for the relevant 'partially free' and 'not free' categories [not reported]. Sample for both regressions includes 2,914 observations from 179 countries. Standard errors clustered by country.

Figure 5: Top 20 Fastest-Growing Economies: 1992/3 - 2005/6



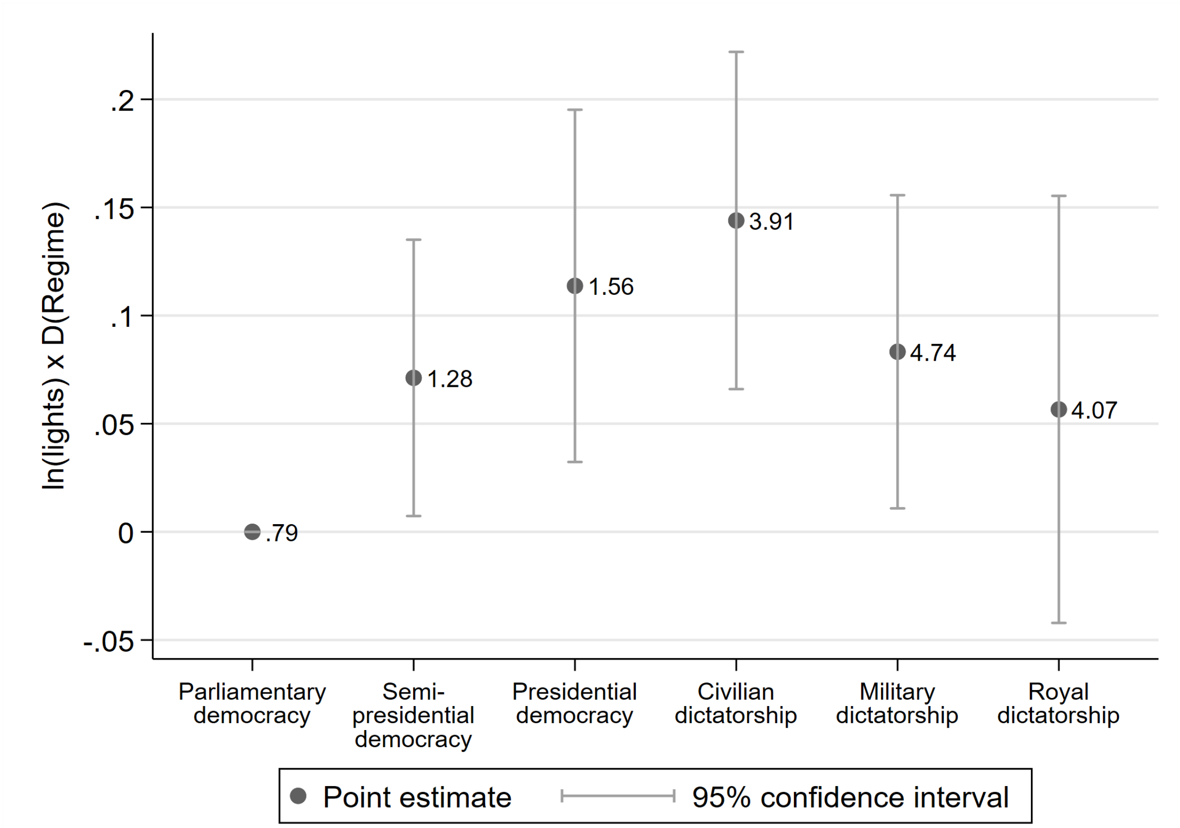
(a) Raw data



(b) Adjusted for Manipulation

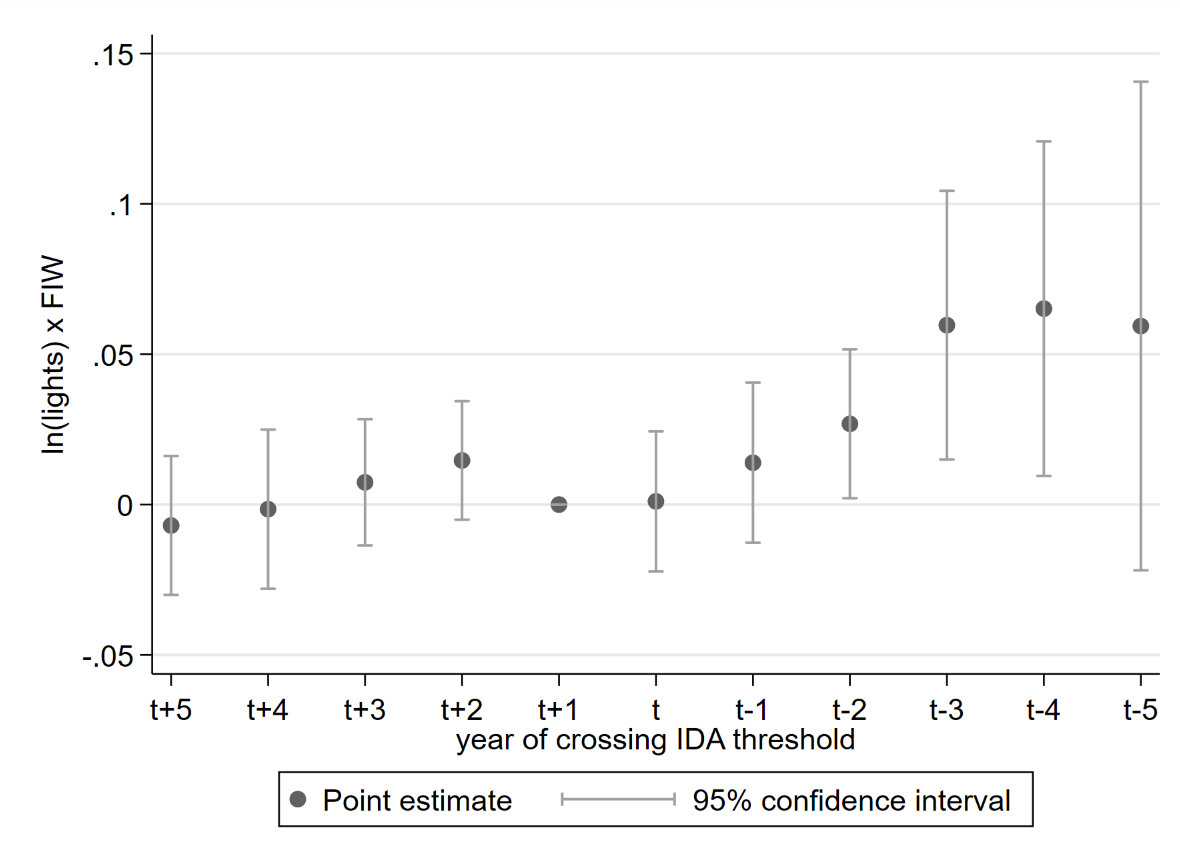
Note: Panel (a) shows the 20 countries with the largest change in ln(GDP) between 1992/3 and 2005/6 (two-year average in both cases), as reported in the World Bank's World Development Indicators. Countries are classified according to their average value of the Freedom in the World Index (FWI). The adjusted FWI ranges from 0 to 6, with lower values corresponding to greater enjoyment of civil liberties and political rights. Country is "Free" if FWI$<$ 2, "Partially Free" if $2 \leq FWI < 4$ and "Not Free" if $FWI \geq 4$. Panel (b) shows the same information after the ln GDP series has been adjusted for manipulation. The adjustment is based on the estimate of the bias parameter σ implied by the results in column 8 of Table 2. See Section 4 for the underlying empirical model.

Figure 6: The night-lights elasticity of GDP across regime types (DD classification)



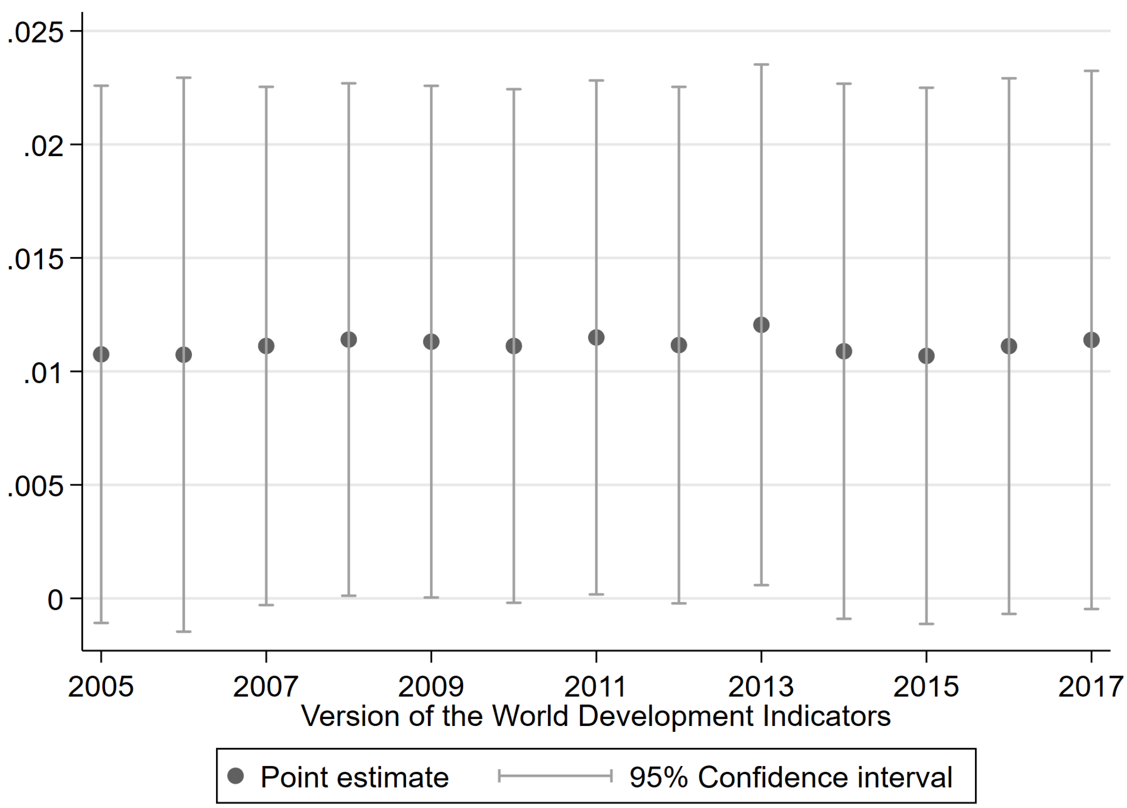
Note: The graph shows point estimates and 95% confidence intervals of a regression of ln(GDP) on the interaction of ln(lights) and five regime-type dummies. Other regressors include ln(lights) and the five regime-type dummies (estimates not reported). These regime types correspond to the classification in the DD dataset produced by Cheibub et al. (2010). The omitted category is 'parliamentary democracy'. Reported next to each marker is the average value of FWI for that regime type. The regression also includes country and year fixed effects. Sample includes 2,911 observations from 179 countries. Standard errors are clustered by country.

Figure 7: The autocracy gradient in the night-lights elasticity of GDP around the time of crossing the GNI threshold for IDA eligibility



Note: The graph shows point estimates and 95% confidence intervals of a regression of ln(GDP) on the triple interaction of ln(lights) with FWI and with separate yearly dummies in a 10-year window around the crossing of the GNI threshold for IDA eligibility [Omitted category is the year before crossing]. Other regressors not reported include ln(lights), FWI, FWI squared, a full set of dummies for all years before and after crossing (-11 to +11), as well as all second-order interactions between ln(lights), FWI and the full set of event-year dummies. Regression also includes country and year fixed effects. Sample includes all IDA eligible countries that cross the threshold once at the most and that are observed for the entire 10-year window if crossing: 1,063 observations from 66 countries. Standard errors are clustered by country.

Figure 8: Yearly Revisions of the World Development Indicators



Note: The figure shows point estimates and 95% confidence intervals for a set of fixed-effects (country and year) regressions of ln(GDP) on ln(lights) [not reported], FWI [not reported], and its interaction. The estimates shown correspond to separate regressions, each one using GDP figures from a different version of the World Development Indicators (2005-2017). All regressions were estimated with a fixed sample of 1,970 observations from 173 countries between 1992 and 2003. Standard errors clustered by country.

APPENDIX (for online publication)

Appendix A Additional Results

Table A1: Summary Statistics

Variable	Mean	Std. Dev.	Min	Max	N	Countries	Source
ln(lights)	-0.15	2.00	-5.95	3.89	2,914	179	Henderson et al. (2012)
ln(GDP)	25.37	4.06	0.38	35.27	2,914	179	Henderson et al. (2012)
FWI	2.41	1.92	0	6	2,914	179	Freedom House
Political Rights score	2.39	2.14	0	6	2,914	179	Freedom House
Civil Liberties score	2.43	1.77	0	6	2,914	179	Freedom House
Polity 2 score	3.35	6.47	-10	10	2,531	155	Polity IV
Democracy score	5.42	3.88	0	10	2,458	155	Polity IV
Autocracy score	1.99	2.89	0	10	2,458	155	Polity IV
D(Autocracy)	0.37	0.48	0	1	2,881	177	Freedom House
D(Autocracy)	0.37	0.48	0	1	2,531	156	Freedom House / Polity IV
D(Autocracy)	0.43	0.49	0	1	1,936	167	Papaioannou and Siourounis (2008)
D(Autocracy)	0.42	0.49	0	1	2,911	179	Cheibub et al. (2010)

Notes: ln(GDP) in constant local currency units. ln(lights) is the natural logarithm of the area-weighted average of grid-level lights digital number (0-63). The adjusted Freedom in the World Index (FWI) ranges from 0 to 6, with lower values corresponding to greater enjoyment of civil liberties and political rights. The adjusted Political Rights and Civil Liberties scores range from 0 to 6, with lower values representing greater enjoyment of rights and liberties. The Polity2 score from the Polity IV project is the difference between the democracy and autocracy scores and ranges from -10 to 10 (most democratic). The democracy and autocracy scores range from 0 to 10, with larger values corresponding to more democratic and autocratic regimes, respectively. Sample includes all country-years between 1992 and 2008 with non-missing data for ln(lights), ln(GDP) and FWI.

Table A2: Correlates of the Freedom in the World Index (FWI)

	Point estimate (1)	Standard error (2)	N (3)
A: Dependent variable: FWI_i (average)			
D(Official state party)$_i$[1]	0.858**	[0.367]	157
D(Banned parties)$_i$[1]	0.490*	[0.256]	157
D(Registration required to vote)$_i$[1]	-1.183***	[0.369]	155
D(Legislature elected through national elections)$_i$[2]	-1.326***	[0.273]	156
D(Executive elected through national elections)$_i$[2]	0.114	[0.299]	157
Share of years with national elections$_i$	-3.080***	[0.954]	157
Average turnout for legislative elections (% eligible pop.)$_i$	0.005	[0.009]	145
D(No party with seats $\geq$ 90% of lower house of legislature)$_i$[2]	-1.166***	[0.309]	146
D(National elections boycotted by major party)$_i$[1]	0.455	[0.284]	148
D(Election outcome provokes protest or violence)$_i$[1]	0.443	[0.273]	149
D(Scheduled elections postponed or cancelled)$_i$[1]	0.339	[0.272]	149
D(New Constitution)$_i$[1]	0.748***	[0.249]	153
D(Unicameral legislature)$_i$[1]	0.631**	[0.251]	156
D(Executive can propose constitutional amendments)$_i$[1]	0.124	[0.275]	155
D(Executive can veto legislation)$_i$[1]	-0.440	[0.279]	155
D(Executive can dissolve the legislature)$_i$[1]	-0.497*	[0.282]	155
D(Executive has power to call elections)$_i$[1]	-0.307	[0.250]	155
D(National constitutional court)$_i$[1]	-0.965***	[0.244]	155
D(Central bank has authority over monetary policy)$_i$[1]	0.053	[0.275]	140
B: Dependent variable: $FWI_{i,t}$ (yearly)			
D(Official state party)$_{i,t}$	0.204	[0.288]	2,442
D(Banned parties)$_{i,t}$	0.180*	[0.103]	2,447
D(Registration required to vote)$_{i,t}$	-0.075	[0.081]	2,394
D(Legislature elected through national elections)$_{i,t}$	-0.316**	[0.143]	2,451
D(Executive elected through national elections)$_{i,t}$	-0.536***	[0.196]	2,490
D(Election year)$_{i,t}$	-0.041*	[0.021]	2,499
Turnout in last legislative election$_{i,t}$	0.001	[0.003]	2,028
D(No party with seats $\geq$ 90% of lower house of legislature)$_{i,t}$	-0.050	[0.160]	2,051
D(Last election boycotted by major party)$_{i,t}$	0.109	[0.095]	2,142
D(Last election outcome provoked protest or violence)$_{i,t}$	0.262***	[0.091]	2,146
D(Last election postponed or cancelled)$_{i,t}$	-0.057	[0.071]	2,148
D(New Constitution)$_{i,t}$	0.031	[0.080]	2,372
D(Unicameral legislature)$_{i,t}$	-0.069	[0.153]	2,453
D(Executive can propose constitutional amendments)$_{i,t}$	0.084	[0.110]	2,439
D(Executive can veto legislation)$_{i,t}$	0.088	[0.138]	2,337
D(Executive can dissolve the legislature)$_{i,t}$	0.058	[0.151]	2,354
D(Executive has power to call elections)$_{i,t}$	-0.105	[0.097]	2,394
D(National constitutional court)$_{i,t}$	-0.099	[0.211]	2,416
D(Central bank has authority over monetary policy)$_{i,t}$	-0.048	[0.091]	2,073

Notes: Panel A shows results of bivariate cross-sectional regressions of the average FWI (1992 -2008) on the variable in the leftmost column. Regressions include 14 subregion fixed effects. Panel B shows similar results in a panel setting with the yearly value of FWI as the dependent variable and country and year fixed effects on the right-hand side. Robust standard errors in brackets in column 2 (clustered by country in panel B). [1] At any point in sample period. [2] Throughout the sample period. *** p<0.01, ** p<0.05, * p<0.1

Table A3: Robustness Checks I: GDP Composition

	Dependent variable: $\ln(\text{GDP})_{i,t}$					
	Baseline (1)	Consumption (2)	Investment (3)	Government (4)	Exports (5)	Imports (6)
$\ln(\text{lights})_{i,t}$	0.215***	0.199***	0.194***	0.241***	0.216***	0.208***
	[0.030]	[0.038]	[0.028]	[0.033]	[0.031]	[0.033]
$\text{FWI}_{i,t}$	0.003	0.001	0.003	-0.000	0.005	0.003
	[0.023]	[0.023]	[0.023]	[0.022]	[0.022]	[0.022]
$\text{FWI}_{i,t}{}^2$	-0.001	-0.001	-0.001	-0.000	-0.001	-0.001
	[0.004]	[0.004]	[0.004]	[0.004]	[0.004]	[0.004]
$x_{i,t}$		-0.004***	0.004***	-0.004**	0.002	-0.001
		[0.001]	[0.001]	[0.002]	[0.001]	[0.001]
$\ln(\text{lights})_{i,t} \times \text{FWI}_{i,t}$	0.008*	0.008**	0.008*	0.008*	0.007*	0.009**
	[0.004]	[0.004]	[0.004]	[0.004]	[0.004]	[0.004]
$\ln(\text{lights})_{i,t} \times x_{i,t}$		-0.000	0.001*	-0.002	-0.000	0.000
		[0.000]	[0.000]	[0.001]	[0.000]	[0.000]
Observations	2,624	2,624	2,624	2,624	2,624	2,624
Countries	167	167	167	167	167	167
(Within country) R^2	0.785	0.812	0.794	0.788	0.789	0.789

Notes: Dependent variable is ln(GDP) in constant local currency units. ln(lights) is the natural logarithm of the area-weighted average of grid-level lights digital number (0-63). The adjusted Freedom in the World Index (FWI) ranges from 0 to 6, with lower values corresponding to greater enjoyment of civil liberties and political rights. Column 1 replicates the baseline specification for the reduced sample for which GDP composition data is available. Regressions in columns 2-6 include the percentage of GDP corresponding to the category in the header and its interaction with ln(lights) as additional controls: household final consumption expenditure in column 2; gross capital formation in column 3; general government final consumption in column 4; exports in column 5; imports in column 6. All regressions include country and year fixed effects. Robust standard errors clustered by country are shown in brackets. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table A4: Robustness Checks II: Sectoral Composition of the Economy

	Dependent variable: $\ln(\text{GDP})_{i,t}$						
	Agriculture		Nat. resources	Oil	Industry	Manufacturing	Services
	(% land)	(% GDP)	(% GDP)	(% GDP)	(% GDP)	(% GDP)	(% GDP)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$\ln(\text{lights})_{i,t}$	0.240***	0.265***	0.230***	0.220***	0.223***	0.199***	0.254***
	[0.043]	[0.044]	[0.037]	[0.052]	[0.043]	[0.045]	[0.039]
$\text{FWI}_{i,t}$	-0.005	0.004	-0.003	0.016	0.001	0.003	0.001
	[0.023]	[0.022]	[0.022]	[0.026]	[0.023]	[0.025]	[0.023]
$\text{FWI}^2{}_{i,t}$	0.000	-0.001	-0.001	-0.005	-0.001	-0.001	-0.000
	[0.004]	[0.004]	[0.004]	[0.005]	[0.004]	[0.005]	[0.004]
$x_{i,t}$	0.000	-0.009***	0.003	0.002	0.003	0.002	-0.000
	[0.002]	[0.002]	[0.002]	[0.003]	[0.002]	[0.002]	[0.001]
$\ln(\text{lights})_{i,t} \times \text{FWI}_{i,t}$	0.012***	0.013***	0.009**	0.015**	0.012***	0.011**	0.012***
	[0.004]	[0.004]	[0.004]	[0.006]	[0.004]	[0.005]	[0.004]
$\ln(\text{lights})_{i,t} \times x_{i,t}$	-0.000	-0.002**	0.001**	-0.000	0.000	0.002**	-0.000
	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]
Observations	2,898	2,650	2,877	2,101	2,562	2,456	2,562
Countries	179	170	178	133	167	164	167
(Within country) R^2	0.776	0.802	0.785	0.794	0.787	0.786	0.783

Notes: Dependent variable is ln(GDP) in constant local currency units. ln(lights) is the natural logarithm of the area-weighted average of grid-level lights digital number (0-63). The adjusted Freedom in the World Index (FWI) ranges from 0 to 6, with lower values corresponding to greater enjoyment of civil liberties and political rights. Each column includes the variable in the header (x) and its interaction with ln(lights) as additional controls. All these variables correspond to sectoral shares of GDP (expressed as a percentage) except for column 1, which is the percentage of land devoted to agriculture. All regressions include country and year fixed effects. Robust standard errors, clustered by country, are shown in brackets. *** p<0.01, ** p<0.05, * p<0.1

Table A5: Robustness Checks III: Development, Urbanization, Electrification

	Dependent variable: $\ln(\text{GDP})_{i,t}$						
	Initial values		Population		Access to electricity		
	ln(GDP)	ln(lights)	ln(Total)	Urban share	Total	Urban	Rural
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$\ln(\text{lights})_{i,t}$	0.325***	0.232***	-0.144	0.287***	0.217***	0.241***	0.223***
	[0.095]	[0.036]	[0.146]	[0.043]	[0.045]	[0.047]	[0.042]
$\text{FWI}_{i,t}$	-0.004	-0.004	-0.004	-0.011	-0.002	-0.014	0.002
	[0.023]	[0.023]	[0.024]	[0.023]	[0.023]	[0.025]	[0.023]
$\text{FWI}^2{}_{i,t}$	-0.000	-0.000	-0.000	0.001	-0.001	0.000	-0.001
	[0.004]	[0.004]	[0.004]	[0.004]	[0.004]	[0.005]	[0.004]
$x_{i,t}$			0.079	0.004	-0.001	0.001	-0.000
			[0.114]	[0.004]	[0.001]	[0.001]	[0.001]
$\ln(\text{lights})_{i,t} \times \text{FWI}_{i,t}$	0.012***	0.011**	0.011***	0.010**	0.012***	0.011**	0.008*
	[0.004]	[0.004]	[0.004]	[0.004]	[0.004]	[0.005]	[0.005]
$\ln(\text{lights})_{i,t} \times x_{i,t}$	-0.009	-0.005	0.026	-0.001*	0.000	-0.000	0.000
	[0.008]	[0.010]	[0.010]	[0.001]	[0.000]	[0.000]	[0.000]
Observations	2,914	2,914	2,914	2,914	2,847	2,220	2,776
Countries	179	179	179	179	178	170	175
(Within country) R^2	0.778	0.777	0.780	0.779	0.782	0.808	0.775

Notes: Dependent variable is ln(GDP) in constant local currency units. ln(lights) is the natural logarithm of the area-weighted average of grid-level lights digital number (0-63). The adjusted Freedom in the World Index (FWI) ranges from 0 to 6, with lower values corresponding to greater enjoyment of civil liberties and political rights. Each column includes the variable in the header (x) [if time-varying] and its interaction with ln(lights) as additional controls. In column 1, the natural log of GDP in 1992, or the first available year; In column 2, the 1992-1994 average of ln(lights); The specification in column 3 includes log population while the one in column 4 uses the percentage of population living in urban areas; The percentage with access to electricity in column 5; the percentages of urban and rural population with access to electricity, respectively, in columns 6 and 7. All regressions include country and year fixed effects. Robust standard errors, clustered by country, are shown in brackets. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table A6: Robustness Checks IV: Characteristics of Nighttime Lights

	Dependent variable: $\ln(\text{GDP})_{i,t}$							
	Lights quartic	Year FE x lights	Latitude, longitude	Region FE x lights	Area	Top-coding	Unlit cells	Lights Gini
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\ln(\text{lights})_{it}$	0.233***	0.231***	0.232***	0.349***	0.054	0.225***	0.050	0.438***
	[0.043]	[0.034]	[0.047]	[0.103]	[0.100]	[0.036]	[0.097]	[0.114]
$\text{FWI}_{i,t}$	-0.003	-0.003	-0.003	-0.008	-0.001	-0.001	-0.001	-0.005
	[0.023]	[0.022]	[0.023]	[0.023]	[0.023]	[0.022]	[0.023]	[0.023]
$\text{FWI}^2{}_{i,t}$	-0.000	-0.000	-0.000	0.000	-0.001	-0.001	-0.001	0.000
	[0.004]	[0.004]	[0.004]	[0.004]	[0.004]	[0.004]	[0.004]	[0.004]
$x_{i,t}$						0.013**	-0.067**	0.506*
						[0.006]	[0.028]	[0.278]
$\ln(\text{lights})_{it} \times \text{FWI}_{i,t}$	0.011***	0.013***	0.011***	0.009**	0.010**	0.012***	0.011***	0.012***
	[0.004]	[0.004]	[0.004]	[0.004]	[0.004]	[0.004]	[0.004]	[0.004]
$\ln(\text{lights})_{it} \times x_{i,t}$					0.017*	0.001	0.017*	-0.195*
					[0.009]	[0.002]	[0.009]	[0.108]
Observations	2,914	2,914	2,914	2,914	2,914	2,914	2,914	2,914
Countries	179	179	179	179	179	179	179	179
(Within country) R^2	0.780	0.778	0.780	0.790	0.779	0.779	0.779	0.778

Notes: Dependent variable is ln(GDP) in constant local currency units. ln(lights) is the natural logarithm of the area-weighted average of grid-level lights digital number (0-63). The adjusted Freedom in the World Index (FWI) ranges from 0 to 6, with lower values corresponding to greater enjoyment of civil liberties and political rights. Each column includes the variable x in the header (if time-varying) and its interaction with ln(lights). The model in column 1 includes a quartic polynomial in ln(lights) [coefficients on the higher powers not reported]. In column 2, ln(lights) is interacted with a full set of year fixed effects (estimates not shown); In column 3, quadratics for both the longitude and latitude of the country's capital (estimates not shown). In column 4, ln(lights) is interacted with 17 subregional fixed effects (estimates not shown); In column 5, the natural log of permanent ice-free land area in square km; In columns 6 and 7, the natural log of the number of top-coded (DN=63) and unlit (DN=0) cells, respectively; In column 8, the natural log of the Gini coefficient of night lights. All regressions include country and year fixed effects. Robust standard errors, clustered by country, are shown in brackets. *** p<0.01, ** p<0.05, * p<0.1

Table A7: Robustness Checks V: Data Quality and Statistical Capacity

	Dependent variable: $\ln(\mathrm{GDP})_{i,t}$											
		Time-invariant binary measure of statistical capacity										
	Baseline (reduced sample)	Nat. acc. base year ≥ 1991	CPI base year ≥ 1991	Pop. census ≥ 1991	Agr. census ≥ 1991	BOP manual v5	SDDS	Vital registr. system	External debt is actual	Industrial production index	Imp/Exp price index	Data quality score
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
$\ln(\text{lights})_{i,t}$	0.273***	0.248***	0.274***	0.276***	0.279***	0.242***	0.280***	0.253***	0.265***	0.283***	0.279***	0.267***
	[0.045]	[0.046]	[0.059]	[0.045]	[0.052]	[0.072]	[0.048]	[0.047]	[0.071]	[0.048]	[0.047]	[0.069]
$\mathrm{FWI}_{i,t}$	0.010	0.012	0.010	0.010	0.011	0.011	0.008	0.011	0.010	0.007	0.009	0.010
	[0.028]	[0.028]	[0.028]	[0.028]	[0.028]	[0.028]	[0.027]	[0.028]	[0.028]	[0.028]	[0.028]	[0.028]
$\mathrm{FWI}^2{}_{i,t}$	-0.002	-0.002	-0.002	-0.002	-0.002	-0.002	-0.002	-0.002	-0.002	-0.002	-0.002	-0.002
	[0.005]	[0.005]	[0.005]	[0.005]	[0.005]	[0.005]	[0.005]	[0.005]	[0.005]	[0.005]	[0.005]	[0.005]
$\ln(\text{lights})_{i,t} \times \mathrm{FWI}_{i,t}$	0.008*	0.009**	0.008*	0.008*	0.008*	0.009*	0.007	0.009**	0.008*	0.008	0.008*	0.008*
	[0.005]	[0.004]	[0.005]	[0.004]	[0.005]	[0.005]	[0.005]	[0.004]	[0.005]	[0.005]	[0.005]	[0.005]
$\ln(\text{lights})_{i,t} \times x_i$		0.056	-0.003	-0.004	-0.020	0.038	-0.051	0.044	0.010	-0.051	-0.044	0.001
		[0.060]	[0.054]	[0.055]	[0.051]	[0.070]	[0.048]	[0.066]	[0.069]	[0.071]	[0.060]	[0.012]
Observations	1,938	1,938	1,938	1,938	1,938	1,938	1,938	1,938	1,938	1,938	1,938	1,938
Countries	117	117	117	117	117	117	117	117	117	117	117	117
(Within country) R^2	0.785	0.786	0.785	0.785	0.785	0.785	0.785	0.785	0.785	0.785	0.785	0.785

Notes: Dependent variable is ln(GDP) in constant local currency units. ln(lights) is the natural logarithm of the area-weighted average of grid-level lights digital number (0-63). The adjusted Freedom in the World Index (FWI) ranges from 0 to 6, with lower values corresponding to greater enjoyment of civil liberties and political rights. Column 1 shows the baseline specification for the reduced sample for which cross-sectional data on statistical capacity is available from the World Bank (2002). Starting in column 2, each column includes the interaction of the variable in the header (x_i) with ln(lights): in columns 2 and 3, respective dummies if the base year of the national accounts or the consumer price index is more recent than 1991. In columns 4 and 5, respective dummies if there was a population or agricultural census after 1991. In columns 6 and 7, dummies for the adoption of the Balance of Payments manual v. 5 or the Special Data Dissemination Standard. In column 8, a dummy for the existence of a vital registration system. In column 9, a dummy if information on external debt is actual or preliminary (rather than estimated). In columns 10 and 11, dummies for the availability of a industrial production index or an import/export price index. In column 12, the data quality score, which ranges from 0 to 10 with higher values corresponding to better data quality. All regressions include country and year fixed effects. Robust standard errors, clustered by country, are shown in brackets. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table A8: Robustness Checks VI: Specification checks

	Dependent variable: $\ln(\text{GDP})_{i,t}$				Dependent variable: $\Delta\ln(\text{GDP})_{i,t}$			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\ln(\text{lights})_{i,t}$	0.156***	0.167***	-0.013	0.002				
	[0.036]	[0.029]	[0.014]	[0.027]				
$\Delta\ln(\text{lights})_{i,t}$					0.060**	0.001	0.006	0.002
					[0.024]	[0.013]	[0.013]	[0.014]
$\text{FWI}_{i,t}$	0.016	-0.001	0.008	-0.001		0.018**	0.017**	0.026
	[0.018]	[0.024]	[0.009]	[0.018]		[0.008]	[0.008]	[0.019]
$\text{FWI}^2_{i,t}$	-0.002	-0.001	-0.001	-0.001		-0.004***	-0.004***	-0.008***
	[0.003]	[0.004]	[0.002]	[0.003]		[0.001]	[0.002]	[0.003]
$\ln(\text{lights})_{i,t} \times \text{FWI}_{i,t}$	0.009**	0.011**	0.009***	0.013***				
	[0.004]	[0.004]	[0.003]	[0.005]				
$\Delta\ln(\text{lights})_{i,t} \times \text{FWI}_{i,t}$						0.027***	0.024***	0.029***
						[0.009]	[0.009]	[0.009]
$\ln(\text{lights})_{i,t-1}$		0.098***						
		[0.025]						
$\ln(\text{GDP})_{i,t-1}$			0.870***	1.000***			-0.104***	0.048
			[0.030]	[0.078]			[0.020]	[0.049]
Observations	2,914	2,736	2,724	2,724	2,811	2,724	2,724	2,724
Countries	179	179	179	179	188	179	179	179
(Within country) R^2	0.906	0.782	0.952		0.097	0.150	0.204	
Country-specific time trend	Yes	No	No	No	No	No	No	No
Estimation	OLS	OLS	OLS	GMM	OLS	OLS	OLS	GMM

Notes: The dependent variable in columns 1-4 is ln(GDP) in constant local currency units. The dependent variable in columns 5-8 is the yearly change in ln(GDP). ln(lights) is the natural logarithm of the area-weighted average of grid-level lights digital number (0-63). The adjusted Freedom in the World Index (FWI) ranges from 0 to 6, with lower values corresponding to greater enjoyment of civil liberties and political rights. All regressions include country and year fixed effects. Column 1 includes a country-specific time trend. The method of estimation in columns 4 and 8 is system-GMM (Blundell-Bond). Robust standard errors, clustered by country, are shown in brackets. *** p<0.01, ** p<0.05, * p<0.1

Table A9: The effect of political institutions on the autocracy gradient in the night-lights elasticity of GDP (Full Table)

	Dependent variable: $\ln(\text{GDP})_{i,t}$				
	Elected legislature (1)	Elected executive (2)	Central bank independence (3)	Constitutional court (4)	Communist history (5)
$\ln(\text{lights})_{i,t}$	0.098	0.220***	0.194***	0.225***	0.203***
	[0.102]	[0.040]	[0.046]	[0.032]	[0.032]
$\text{FWI}_{i,t}$	0.008	-0.019	-0.036	-0.007	-0.007
	[0.059]	[0.025]	[0.039]	[0.029]	[0.023]
$\text{FWI}^2{}_{i,t}$	0.003	0.001	0.005	0.002	0.001
	[0.005]	[0.004]	[0.005]	[0.004]	[0.004]
$x_{i,t}$	0.129	0.001	-0.034	-0.012	
	[0.177]	[0.046]	[0.059]	[0.053]	
$\text{FWI}_{i,t} \times x_{i,t}$	-0.026	0.012	0.009	-0.007	-0.033
	[0.047]	[0.015]	[0.030]	[0.016]	[0.023]
$\ln(\text{lights})_{i,t} \times \text{FWI}_{i,t}$ [a]	0.049**	0.019***	0.025***	0.024***	0.011**
	[0.021]	[0.006]	[0.008]	[0.007]	[0.004]
$\ln(\text{lights})_{i,t} \times x_{i,t}$	0.168*	0.041**	0.025	0.021	0.032
	[0.092]	[0.020]	[0.025]	[0.016]	[0.057]
$\ln(\text{lights})_{i,t} \times \text{FWI}_{i,t} \times x_{i,t}$ [b]	-0.040*	-0.012**	-0.011**	-0.013*	0.022**
	[0.022]	[0.006]	[0.005]	[0.007]	[0.010]
Observations	2,451	2,490	2,073	2,416	2,914
Countries	153	154	139	152	179
(Within country) R^2	0.793	0.788	0.798	0.792	0.783
p-value H_0: a + b = 0	0.074	0.124	0.010	0.003	0.001

Notes: Dependent variable is ln(GDP) in constant local currency units. ln(lights) is the natural logarithm of the area-weighted average of grid-level lights digital number (0-63). The adjusted Freedom in the World Index (FWI) ranges from 0 to 6, with lower values corresponding to greater enjoyment of civil liberties and political rights. Each column includes the binary variable in the header (x) and all its interactions with ln(lights) and the FIW index. In column 1, $x_{i,t}$ is a dummy indicating whether the country has an elected legislature. In column 2, $x_{i,t}$ is a dummy indicating whether the country has an elected executive. In column 3, $x_{i,t}$ is a dummy indicating whether the central bank has authority over monetary policy. In column 4, $x_{i,t}$ is a dummy indicating whether the country has a national constitutional court. In column 5, $x_{i,t}$ is a dummy indicating whether the country had had a communist regime at some point in time. All of these variables are time-varying with the exception of the dummy for communist history in column 5. All regressions include country and year fixed effects. Robust standard errors, clustered by country, are shown in brackets. *** p<0.01, ** p<0.05, * p<0.1

Table A10: Incentives for manipulation (full table)

	Dependent variable: ln(GDP)$_{i,t}$			
	Low growth		Before election	
	(1)	(2)	(3)	(4)
ln(lights)$_{i,t}$	0.241***	0.258***	0.261***	0.287***
	[0.042]	[0.040]	[0.040]	[0.035]
$x_{i,t}$	0.029*	0.021*	-0.000	0.009**
	[0.015]	[0.012]	[0.007]	[0.004]
ln(lights)$_{i,t}$ × $x_{i,t}$	-0.008	-0.001	-0.002	-0.001
	[0.007]	[0.005]	[0.003]	[0.002]
FWI$_{i,t}$	0.001		-0.010	
	[0.023]		[0.024]	
FWI$^2{}_{i,t}$	-0.001		0.001	
	[0.004]		[0.004]	
$x_{i,t}$ × FWI$_{i,t}$	-0.009		0.004	
	[0.006]		[0.003]	
ln(lights)$_{i,t}$ × FWI$_{i,t}$	0.006		0.010**	
	[0.004]		[0.004]	
ln(lights)$_{i,t}$ × FWI$_{i,t}$ × $x_{i,t}$	0.005*		0.002	
	[0.003]		[0.001]	
D(Partially Free)$_{i,t}$		0.001		-0.000
		[0.018]		[0.019]
D(Not Free)$_{i,t}$		-0.002		-0.012
		[0.028]		[0.027]
$x_{i,t}$ × D(Partially Free)$_{i,t}$		-0.021		-0.017**
		[0.016]		[0.007]
$x_{i,t}$ × D(Not Free)$_{i,t}$		-0.031		0.017*
		[0.025]		[0.010]
ln(lights)$_{i,t}$ × D(Partially Free)$_{i,t}$		0.010		0.014
		[0.012]		[0.012]
ln(lights)$_{i,t}$ × D(Not Free)$_{i,t}$		0.010		0.023*
		[0.014]		[0.013]
ln(lights)$_{i,t}$ × D(Partially Free)$_{i,t}$ × $x_{i,t}$		0.002		-0.001
		[0.009]		[0.005]
ln(lights)$_{i,t}$ × D(Not Free)$_{i,t}$ × $x_{i,t}$		0.022*		0.013**
		[0.012]		[0.005]
Observations	2,914	2,914	2,500	2,500
Countries	179	179	154	154
(Within country) R^2	0.781	0.778	0.781	0.779

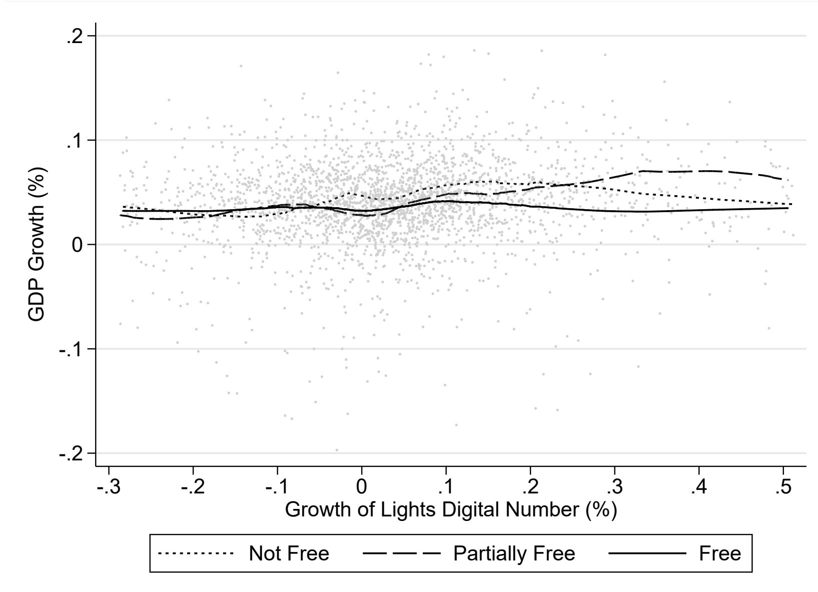
Notes: Dependent variable is ln(GDP) in constant local currency units. ln(lights) is the natural logarithm of the area-weighted average of grid-level lights digital number (0-63). Adjusted Freedom in the World Index (FWI) ranges from 0 to 6, with lower values corresponding to greater enjoyment of civil liberties and political rights. Country is "Free" if FWI$<$ 2, "Partially Free" if $2 \leq FWI < 4$ and "Not Free" if $FWI \geq 4$. D(Free) and its interactions is omitted in columns 2,4,6,8,10. In columns 1-2, $x_{i,t}$ is a dummy equal to one if the value of ln(lights) demeaned by country and year is negative. In columns 3-4, $x_{i,t}$ is a dummy equal to one if there is a national election in the following year. All regressions include country and year fixed effects. Robust standard errors, clustered by country, are shown in brackets. *** p$<$0.01, ** p$<$0.05, * p$<$0.1

Table A11: Impact of the Special Data Dissemination Standard (SDDS) (full table)

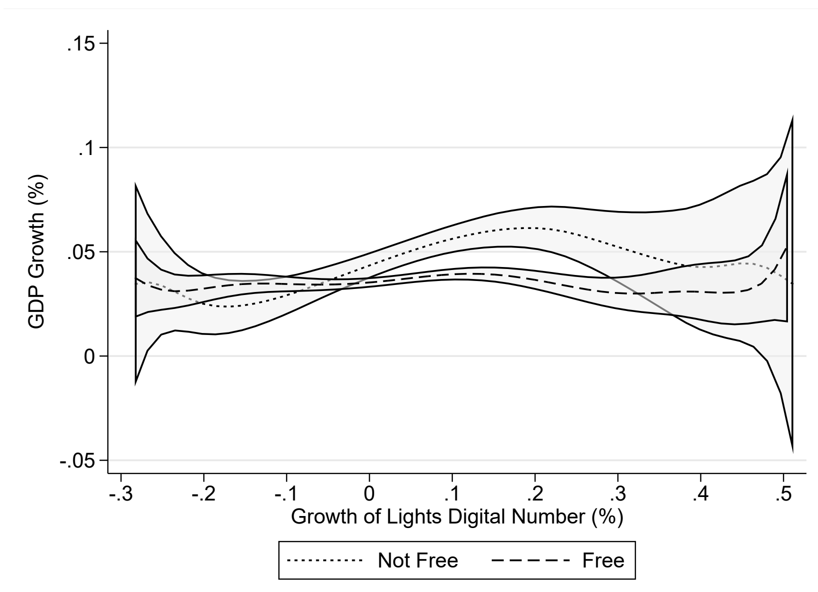
	Dependent variable: $\ln(\text{GDP})_{i,t}$			
	Selection		Treatment effect	
	(1)	(2)	(3)	(4)
$\ln(\text{lights})_{i,t}$	0.231***	0.262***	0.242***	0.272***
	[0.040]	[0.035]	[0.040]	[0.036]
$\text{FWI}_{i,t}$	-0.005		-0.003	
	[0.024]		[0.023]	
$\text{FWI}^2{}_{i,t}$	-0.000		-0.001	
	[0.004]		[0.004]	
D(Partially Free)$_{i,t}$		-0.002		-0.003
		[0.025]		[0.026]
D(Not Free)$_{i,t}$		-0.034		-0.037
		[0.037]		[0.038]
D(SDDS country)$_i$ × FWI$_{i,t}$	0.016		0.018	
	[0.017]		[0.018]	
D(SDDS country)$_i$ × D(Partially Free)$_{i,t}$		-0.003		0.007
		[0.034]		[0.045]
D(SDDS country)$_i$ × D(Not Free)$_{i,t}$		0.071		0.070
		[0.046]		[0.057]
D(SDDS)$_{i,t}$			0.036	0.040
			[0.029]	[0.027]
D(SDDS)$_{i,t}$ × FWI$_{i,t}$			0.012	
			[0.011]	
D(SDDS)$_{i,t}$ × D(Partially Free)$_{i,t}$				-0.003
				[0.037]
D(SDDS)$_{i,t}$ × D(Not Free)$_{i,t}$				0.072
				[0.044]
ln(lights)$_{i,t}$ × D(SDDS country)$_i$	0.070	0.012	0.011	-0.038
	[0.055]	[0.051]	[0.053]	[0.048]
ln(lights)$_{i,t}$ × FWI$_{i,t}$	0.013**		0.012**	
	[0.005]		[0.005]	
ln(lights)$_{i,t}$ × FWI$_{i,t}$ × D(SDDS country)$_i$	-0.016		-0.013	
	[0.011]		[0.012]	
ln(lights)$_{i,t}$ × D(Partially Free)$_{i,t}$		0.017		0.016
		[0.014]		[0.014]
ln(lights)$_{i,t}$ × D(Not Free)$_{i,t}$		0.024		0.023
		[0.016]		[0.016]
ln(lights)$_{i,t}$ × D(Partially Free)$_{i,t}$ × D(SDDS country)$_i$		-0.013		-0.012
		[0.026]		[0.035]
ln(lights)$_{i,t}$ × D(Not Free)$_{i,t}$ × D(SDDS country)$_i$		0.023		0.037
		[0.040]		[0.049]
ln(lights)$_{i,t}$ × D(SDDS)$_{i,t}$			0.010	0.009
			[0.015]	[0.013]
ln(lights)$_{i,t}$ × FWI$_{i,t}$ × D(SDDS)$_{i,t}$			-0.007	
			[0.009]	
ln(lights)$_{i,t}$ × D(Partially Free)$_{i,t}$ × D(SDDS)$_{i,t}$				0.013
				[0.025]
ln(lights)$_{i,t}$ × D(Not Free)$_{i,t}$ × D(SDDS)$_{i,t}$				-0.086**
				[0.035]
Observations	2,914	2,914	2,914	2,914
Countries	179	179	179	179
(Within country) R^2	0.778	0.775	0.781	0.778

Notes: Dependent variable is ln(GDP) in constant local currency units. ln(lights) is the natural logarithm of the area-weighted average of grid-level lights digital number (0-63). Adjusted Freedom in the World Index (FWI) ranges from 0 to 6, with lower values corresponding to greater enjoyment of civil liberties and political rights. Country is "Free" if FWI< 2, "Partially Free" if $2 \leq FWI < 4$ and "Not Free" if $FWI \geq 4$. D(Free) and its interactions is omitted in even-numbered columns. D(SDDS country)$_i$ is a dummy equal to one for countries that joined the SDDS during the sample period. D(SDDS)$_{i,t}$ is a dummy equal to one following subscription to the SDDS. All regressions include country and year fixed effects. Robust standard errors, clustered by country, are shown in brackets. *** p<0.01, ** p<0.05, * p<0.1

Figure A1: Non-parametric estimation (full sample)



(a) Locally-weighted smoothing



(b) Local polynomial smoothing

Note: Panel (a) shows the scatter of yearly growth in GDP and nighttime lights (DN). Also shown are separate Lowess locally-weighted regression estimates for 'free', 'partially free' and 'not free' countries. Countries are classified using the adjusted Freedom in the World Index (FWI), which ranges from 0 to 6, with lower values corresponding to greater enjoyment of civil liberties and political rights. Country is 'Free' if FWI<2, 'Partially Free' if $2 \leq FWI < 4$ and 'Not Free' if $FWI \geq 4$. Panel (b) shows estimates of quartic-kernel-weighted local third-order polynomial regressions for 'free' and 'not free countries' over the same sample. The bandwidth for all regressions is 0.3. For these figures, growth of lights DN has been truncated at the 2.5 and 97.5 percentiles.