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Tracking Economic Activity in Response to the COVID-19 Crisis Using Nighttime Lights

The Case of Morocco

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Abstract

Over the past decade, nighttime lights have become a widely used proxy for measuring economic activity. This paper examines the potential for high frequency nighttime lights data to provide "near real-time" tracking of the economic impacts of the COVID-19 crisis in Morocco. At the national level, there exists a strong correlation between quarterly movements in Morocco's overall nighttime light intensity and movements in its real GDP. This finding supports the use of lights data to track the economic impacts of the COVID-19 crisis at higher temporal frequencies and at the subnational level, for which GDP data are unavailable. Consistent with large economic impacts of the crisis, Morocco experienced a large drop in the overall intensity of its lights in March 2020, from which it has subsequently struggled to recover, following the country's first COVID-19 case and the introduction of strict lockdown measures. At the subnational level, while all regions shared in March's national decline in nighttime light intensity, Rabat – Salé – Kénitra, Tanger – Tetouan – Al Hoceima, and Fès – Meknès suffered much larger declines than others. Since then, the relative effects of the COVID-19 shock across regions have largely persisted. Overall, the results suggest that, at least for Morocco, changes in nighttime lights can help to detect the timing of changes in the direction of real GDP, but caution is needed in using lights data to derive precise quantitative estimates of changes in real GDP.

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Tracking Economic Activity in Response to the COVID-19 Crisis Using Nighttime Lights – The Case of Morocco

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1. Introduction

Since it was first identified in Wuhan, China, in December 2019, the COVID-19 virus has swept the globe, resulting in not only a devastating loss of life,[2] but also widespread economic crisis. In its October 2020 World Economic Outlook, the IMF projected that global real GDP in 2020 was on track to fall by 4.4 percent (IMF, 2020a). This compares to its projection of a 3.4 percent increase in global real GDP made just prior to the global spread of COVID-19 (IMF, 2020b). Among other things, the devastating loss of incomes and livelihoods has resulted in a major setback in the global fight against extreme poverty, with World Bank forecasts indicating a rise of 88 million in the number of people living on less than $1.90 per day in 2020 as a result of the pandemic (World Bank, 2020).

Crucial to the formulation of effective policy responses to the crisis is not just up-to-date information on the progression of the disease itself, but also data that are as near as real-time as possible on the associated economic impacts. Such data are important for both the design of economic relief packages and in assessing the possible economic trade-offs associated with lockdowns and other non-pharmaceutical interventions (NPIs) that aim to control the spread of the disease. Not only is the availability of near real-time data on economic activity important at the national level, but also at the more local, subnational, level, especially as many countries have moved away from national lockdowns to more geographically differentiated strategies of combatting the disease.

Unfortunately, however, conventional measures of economic activity produced by national statistics offices are ill-suited to providing such (near) real-time monitoring of economic activity. This is because official data on economic activity, even at the national level, are often only available after a long lag and at a relatively low temporal frequency. For example, at best, GDP data tend to be reported at a quarterly frequency at the national level, and an annual frequency at the subnational level. For many countries, especially developing countries, there are no subnational GDP data available at all, and, where they are available, they only tend to be so for very broadly defined geographic regions (Roberts, forthcoming). In light of this, there has been growing research interest in the development of alternative indicators or proxy measures of economic activity that can be produced at a high temporal frequency on a (near) real-time basis, including for subnational areas.[3] Among the alternative indicators that have been investigated are data derived from credit card transactions and private sector payroll firms (Chetty *et al.*, 2020), Google Trends search data (Woloszko, 2020), and data on outdoor air pollution levels (Masaki *et al.*, 2020). In this paper, we investigate the potential of a further unconventional measure of economic activity – outdoor artificial lighting as detected by satellite sensors, commonly referred to as "nighttime lights" – to facilitate (near) real-time tracking of economic activity in response to the evolving COVID-19 crisis, focusing on the specific case of Morocco.

In particular, we use monthly and quarterly measures of nighttime light intensity derived from data collected by the Visible Infrared Imaging Radiometer Suite (VIIRS) sensor onboard the Suomi National Polar-Orbiting Partnership (NPP) satellite, which is jointly operated by NASA and the

[2] At the time of writing, the worldwide death toll from COVID-19 is fast approaching two million.

[3] Some of this research interest pre-dates the COVID-19 crisis. The crisis, however, has given an extra impetus to research in this area.

US government's National Oceanic and Atmospheric Administration (NOAA). We first investigate whether, at the national level, movements in nighttime light intensity are correlated with movements in real GDP using quarterly data for a period covering the third quarter (Q3) of 2012 to the first quarter (Q1) of 2020.[4] Having established the existence of a statistically significant correlation subject to suitable cleaning of the lights data to remove background noise, we progress to examine the evolution of Morocco's monthly nighttime lights following the announcement of the country's first confirmed case of COVID-19 on March 2, 2020 at both the national and subnational (regional) levels. In doing so, we focus on measures of nighttime lights that have been adjusted to control for "normal" seasonal variation. We also examine the evolution of nighttime lights following the onset of COVID-19 relative to estimated pre-COVID-19 trends, where these trends help to define the potential counterfactual evolution of lights in the absence of COVID-19.

Our paper builds on a well-established literature in economics that uses nighttime lights data to proxy the measurement of economic activity.[5] This literature dates back to Henderson *et al.* (2012), who, using a global panel of countries, found that the growth of a country's nighttime light intensity provides a good proxy for its GDP growth over the long-term. They also found that fluctuations in light intensity at the national level are able to track annual fluctuations in economic growth.[6] Since Henderson *et al.*, the use of nighttime lights to proxy economic activity has become commonplace within the economics literature, especially in the urban and spatial economics literatures where analysis is constrained by the lack of official GDP data (see, for example, Bleakley and Lin, 2012; Storeygard, 2016; Jedwab *et al*., 2021).[7] More generally, a recent review uncovers more than 150 studies in economics that have used nighttime lights (Gibson *et al.*, 2020). However, the use of nighttime lights to proxy for economic activity has not been without some controversy. Chen and Nordhaus (2011) are more downbeat in their findings than Henderson *et al.* (2012) on the ability of lights data to reliably proxy economic activity, especially for low-output-density, typically more agricultural, regions. Meanwhile, there is evidence that, while lights are able to predict longer-run variation in economic activity over space (i.e. across countries or subnational regions), they perform much more poorly in predicting changes in economic activity over time (Goldblatt *et al.*, 2020).

With only a very few exceptions, however, the economics literature that uses nighttime lights measures to proxy levels and changes in economic activity relies on data from satellite sensors that were part of the now defunct US government Defense Meteorological Satellite Program -

[4] The third quarter of 2012 is the first full quarter for which it is possible to construct measures of nighttime light intensity using VIIRS data, while 2020 Q1 was the last full quarter for which national real GDP data were available for Morocco at the time of this work. Quarterly is the highest frequency at which national GDP data are available for Morocco.

[5] The economics literature using nighttime lights to proxy for economic activity is pre-dated by a small number of studies from the remote sensing literature which investigate the potential of lights data to be used in this way (see, for example, Sutton *et al.*, 2007).

[6] Henderson *et al.* (2012) also estimate optimal weights for the combination of nighttime lights data with official GDP data to provide a superior measure of economic activity than each alone is able to provide.

[7] A further attraction of nighttime lights data to urban and spatial economists is that, by virtue of the data's spatial granularity, they allow for the construction of proxy measures of economic activity that need not conform to the administrative boundaries of cities, which may or may not capture their true extents. In this regard, a further use of lights data has been to help identify the actual extents of cities (see, *inter alia*, Zhou *et al.*, 2015; Ellis and Roberts, 2016; Baragwanath *et al.*, 2019; Dingel *et al.*, 2019).

Operational Linescan System (DMSP-OLS).[8] While in addition to global coverage, these data have the advantage of having a relatively long historical annual time series spanning the period 1992 – 2013, they suffer from several drawbacks that undermine their ability to accurately proxy economic activity (Gibson *et al.*, 2021). Most notable among these drawbacks are those of top coding, the so-called "overglow" or "blooming" phenomenon, and the absence of onboard satellite intertemporal calibration of the data. Top coding refers to the fact that the DMSP-OLS sensors were unable to detect levels of nighttime luminosity above a certain threshold due to sensor saturation. This leads to the cores of many cities, where much economic activity is concentrated, being top coded with the result that increases in their brightness over time cannot be detected.[9] Meanwhile, "overglow" or "blooming" refers to the fact that the light emitted from a given point on the earth is recorded in the DMSP-OLS data as covering an area that extends, often very far, beyond that point. This means that the light, and the economic activity that it potentially measures, is spatially misattributed across locations, which is a particular problem for subnational analysis. According to Gibson (2020), both top-coding and overglow result in mean-reverting errors in the DMSP-OLS lights data, implying that it understates the true luminosity of brightly lit areas relative to less brightly lit areas. Finally, the absence of onboard intertemporal calibration of the DMSP-OLS lights data undermines their comparability over time, which may help to explain Goldblatt *et al.*'s (2020) finding that they perform poorly in predicting changes in economic activity over time.

By contrast, as stated earlier, we make use, in this paper, of nighttime lights data from the VIIRS satellite sensor. These data are not subject to the top-coding problem, while the "overglow" problem, while not completed eradicated, is also much less severe (Small, 2019). Because the data undergo onboard calibration, they are also more comparable over time (Gibson *et al.*, 2021). As such, the data appear, *prima facie*, better suited to detecting changes in economic activity over time than the old DMSP-OLS data. Unlike the DMSP-OLS data, which are only available at an annual frequency, the VIIRS data are also publicly available at a monthly frequency with a short time lag, which is crucial from the perspective of providing potential near real-time monitoring of the economic impacts of the COVID-19 crisis. In seeking to examine the potential of VIIRS lights to track the economic impacts of the crisis, our paper is related to those of Elvidge *et al.* (2020), who demonstrate a dimming and subsequent recovery of VIIRS lights across China associated with the COVID-19 pandemic, and Beyer *et al.* (2020), who look at the evolution of VIIRS lights for India in response to the pandemic. By focusing on Morocco, the evidence provided in this paper complements Elvidge *et al.*'s and Beyer *et al.*'s evidence for China and India respectively.[10]

From a remote sensing perspective, Morocco is ideally suited to the exploration of the potential of nighttime lights to provide high frequency tracking of the economic impacts of the COVID-19 crisis. This is because, by virtue of its latitude, Morocco has extremely low cloud-coverage, which, for any given month, results in more high-quality observations of nighttime lights. The study of

[8] The exceptions include Roberts (2018), Beyer *et al.* (2020), and Gibson *et al.* (2021).

[9] In the DMSP-OLS data, nighttime light intensity is measured on a digital number (DN) scale that has a range of 0-63. Top-coding, therefore, occurs at DN = 63. In addition to the standard DMSP-OLS lights data, there is a radiance-calibrated version of the data that was derived based on experiments with adjusting the gain settings of the satellite sensors. This version of the data, which is available for seven years between 1996 and 2011, is not subject to the top-coding problem.

[10] Although not focused on the COVID-19 pandemic, a further related paper is Chodorow-Reich *et al.* (2020), who study the impacts of India's demonetization on real economic activity across districts using, *inter alia*, VIIRS nighttime lights data.

the economic impacts of COVID-19 in Morocco and its subnational regions is also, of course, interesting in its own right, especially given the lack of knowledge surrounding these impacts. Since its onset, and at the time of writing, there have been nearly 454,000 COVID-19 cases in Morocco and almost 7,800 COVID related deaths. Little, however, is known about the exact evolution of the economic impacts of the crisis on Morocco and how these have played-out across its different regions.

The structure of the remainder of this paper is as follows. Section 2 describes the VIIRS nighttime lights data and our procedures for cleaning and processing the data, in addition to the national real GDP data for Morocco. Section 3 describes our analysis of the correlation between changes in nighttime light intensity and real GDP at the national level using quarterly data, which acts as a test of whether the lights data provide a viable proxy for tracking changes in economic activity, both at a higher temporal frequency and at the subnational level, in the absence of GDP data. Section 4 presents our analysis of the evolution of nighttime lights at the monthly frequency in response to the COVID-19 crisis at both the national and subnational regional levels. Section 5 concludes by discussing caveats and possible future extensions to the analysis.

2. Data

2.1. Nighttime lights data

As discussed above, the nighttime lights data that we use are derived from observations collected by the VIIRS satellite sensor onboard the Soumi-NPP satellite. In particular, we use the monthly composites of VIIRS lights produced by the Earth Observation Group (EOG) at the Colorado School of Mines.[11] These composites cover virtually the entire globe at a resolution of 15 arc seconds, which is equal to 460 m^2 at the equator.[12] This is much higher than the 30 arc second resolution (approximately 1 km^2 at the equator) of the old DMSP-OLS lights data. For each pixel, the composites report luminosity in nanowatts/cm^2/sr as an average calculated over all cloud-free nights in a given month. We make use of the monthly composites for April 2012 – September 2020, where the April 2012 composite is the first composite that was produced following the launch of the Suomi-NPP satellite in 2011.[13]

In creating the monthly composites, EOG filter-out both lightning and lunar illumination prior to averaging. However, unlike the annual composites, which are only currently available for 2015 and 2016, which EOG also produce, they do not filter out lights from aurora, fires, boats, and other ephemeral lights. As such, the data are still subject to, potentially considerable, background noise. In an effort to screen out this background noise, we undertake further cleaning of the monthly composites by applying various masks to the data. In particular, we experiment with four different background masks, which we refer to as: (i) the "EOG mask"; (ii) the "cluster mask"; (iii) the "population mask"; and (iv) the "built-up area" mask. The ***EOG mask*** zeroes out nighttime lights

[11] This group was formerly based at NOAA. The group is the same as that which produced the DMSP-OLS annual composite nighttime lights data sets on which the overwhelming majority of research that has used nighttime lights has relied.
[12] The composites cover the globe from 75 N latitude to 65 S.
[13] Monthly VIIRS composites are made freely available by EOG with a lag of three months on their website (https://payneinstitute.mines.edu/eog-2/viirs/). We obtained access to the composites through EOG's paid subscription service which provides access with a maximum lag of around two weeks.

values for pixels that EOG mask out in the creation of their annual lights products for 2015 and 2016, which, as noted above, have been subjected to further cleaning over and above their monthly composites.[14] Meanwhile, the ***cluster mask*** excludes both outlier nighttime lights values and pixels that are identified as belonging to background noise clusters following the procedure of Beyer *et al.* (2020). The ***population mask***, by contrast, uses the European Commission's GHS-POP gridded population data set to remove lights values that are associated with areas in which no population is estimated to have been present in 2015.[15] Finally, the ***built-up area*** mask removes lights values that are associated with areas in which there was no detected built-up area in 2018. To derive this mask, we use the built-up area layer from the 2018 MODIS land use – land cover product with a 1 km buffer to account for potential under-detection of built-up area.[16] It should be noted that none of these masks is perfect – all are imperfect substitutes for the full, computationally highly intensive, cleaning procedure that EOG has yet to apply to its series of monthly composites. The cluster mask is the least spatially extensive mask, in terms of pixels zeroed-out, followed by the EOG mask, population mask and built-up area mask. Given that it is *a priori* unclear which of the masks is best – in terms of allowing changes in the lights data to proxy changes in economic activity – we treat this as an empirical question. We settle this empirical question by examining the strength of the estimated correlations between the four different cleaned lights data series that result from the application of the masks and GDP (see Section 4 below).[17]

Even after the application of the above described masks, however, distortions in the nighttime lights data for Morocco remain for June in each year. This is due to the summer solstice, which results in "stray-light" contamination of the data. Such contamination arises from the satellite carrying the VIIRS instrument being illuminated by sunlight while observing areas of the Earth's surface where the sun is under the horizon (Elvidge *et al.*, 2017). Given the severity of this contamination for Morocco, we drop the June data for each year in our analysis that follows.[18]

As our measure of aggregate nighttime light intensity, we use the "sum of lights" (SOL), which, for any given area, is derived by adding up values of the intensity of lights for all pixels in the cleaned data that fall within that area. Hence, we calculate SOL values for all months (bar June for each year) between April 2012 and September 2020 for both Morocco overall and its Admin-1 level subnational regions. In addition to the monthly SOL values, we also calculate quarterly SOL values for Morocco overall by averaging SOL values over the months in each quarter. The quarterly SOL values are used to examine the correlation between changes in the nighttime lights data and changes in real GDP.

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[14] The EOG cleaning procedure is described in Elvidge *et al.* (2017). Both Beyer *et al.* (2020) and Gibson *et al.* (2021) apply similar EOG masks to clean VIIRS monthly composites of background noise for India (Beyer *et al.*) and Indonesia, China and South Africa (Gibson *et al.*).

[15] GHS-POP can be downloaded from https://ghsl.jrc.ec.europa.eu/download.php?ds=pop.

[16] The MODIS product is available from https://modis.gsfc.nasa.gov/data/dataprod/mod12.php. MODIS is an acronym for Moderate Resolution Imaging Spectroradiometer and is an instrument aboard NASA's Terra and Aqua satellites.

[17] Given that GHS-POP grids population based on distributing population counts for administrative units across the built-up area within those units, the population mask may also be considered to be a built-up area mask. However, the built-up area layer according to which GHS-POP grids population differs from the 2018 MODIS land use – land cover product. The differences in detection of built-up area explain the differences between the two masks.

[18] EOG do provide a "stray-light corrected" configuration of their monthly VIIRS composites in addition to the versions of the composites that we use. However, the correction procedure is considered imperfect and affects the more general quality of the data. The decision to use the non-corrected data and drop June for each year was based on advice received from EOG.

2.2. Real GDP data

Quarterly real GDP data, which is the highest frequency that is available, covering the period 2012 Q3 – 2020 Q1, come from Morocco's Directorate of Statistics. These are national level data that are measured in chained prices with a base year of 2007. The data are available only as a seasonally adjusted series, where seasonal adjustment has been performed by the Directorate of Statistics using the US Census Bureau's X-12-ARIMA procedure (Findley *et al.*, 1998).

3. Ability of nighttime lights to track economic activity

To test whether or not changes in nighttime light intensity can reasonably be used to proxy changes in economic activity at a high temporal frequency and/or at spatial scales at which official data on such activity are unavailable, we run several regressions to examine the correlation between changes in light intensity and changes in real GDP at the national level for Morocco using quarterly data for the period 2012 Q3 – 2020 Q1.[19] These regressions are as follows:

$$\ln(GDP_t) = \alpha + \beta t + \gamma Q + \delta \ln(SOL_t) + \varepsilon_t \qquad [1]$$
$$\ln(GDP_t) = \alpha + \beta Y + \gamma Q + \delta \ln(SOL_t) + \varepsilon_t \qquad [2]$$
$$\ln(GDP)_{D,t} = \alpha + \beta \ln(SOL)_{D,t} + \varepsilon_t \qquad [3]$$

In equation [1], the natural log of Morocco's real GDP in quarter t is regressed on its SOL for the same quarter while controlling for both a linear time trend and quarter effects as captured by the set of quarterly dummies, Q. We also estimate equation [1] without the quarterly dummies. In this case, the regression tests whether quarterly changes in SOL can explain quarterly deviations of GDP from its growth path. When the quarterly dummies are included, the regression tests whether changes in SOL can predict deviations in GDP around its growth path over and above regular quarterly fluctuations. Meanwhile, in equation [2], the linear time trend from equation [1] is replaced by a full set of year effects.[20] As with equation [1], we estimate [2] both excluding and including the quarter effects, Q. Finally, in equation [3], we regress de-trended (ln) GDP on de-trended (ln) SOL where de-trending is performed separately for both the ln(GDP) and ln(SOL) series. This is done by first separately regressing each of ln(GDP) and ln(SOL) on either a linear time trend or a full-set of year effects. The residuals from these separate regressions then act as the de-trended ln(GDP) and ln(SOL) time series.[21] In total, therefore, we estimate six regression specifications – both equations [1] and [2] each with and without the quarter effects, and equation [3] based on de-trending using a linear time trend and year effects. These six specifications are estimated for SOL calculated both on the basis of the "raw" light data provided by EOG and for each of the four SOL series that have been cleaned using the EOG, cluster, population and built-up area masks. In all cases, regression is by least squares with Newey-West standard errors, assuming a first-order serial correlation process for the error term (Newey and West, 1987).[22]

[19] We exclude the Q2 data for each year due to the straylight corruption of the June nighttime lights data (see Section 2.1).

[20] The control for a time trend / year effects helps avoid spurious correlation between nighttime lights and GDP.

[21] It will be noted from Table [1] that estimation of equation [3] produces identical point estimates of the coefficient on ln (SOL_t) as estimation of equation [1] when excluding the quarter effects. The difference lies in the associated standard errors (t-values), which are smaller (larger) when we estimate equation [3].

[22] This is based on the rejection of the hypothesis that the error terms in the regressions are serially uncorrelated using both Durbin's alternative test for serial correlation and the Breusch-Godfrey test for serial correlation. In general,

Table 1. Relationship between nighttime lights and GDP, quarterly data

	Time trend	Time trend + quarter effects	Year effects	Year + quarter effects	De-trended (time trend)	De-trended (year effects)
"Raw" nighttime lights data						
	[1a]	[1b]	[2a]	[2b]	[3a]	[3b]
ln(SOL)	0.025 (0.89)	0.020 (1.39)	0.083 (1.19)	0.006 (0.68)	0.025 (0.91)	0.083 (1.50)
R^2	0.95	0.99	0.93	0.99	0.03	0.11
EOG mask						
ln(SOL)	0.129** (2.26)	0.088*** (3.86)	0.295*** (4.43)	0.051** (2.25)	0.129** (2.31)	0.295*** (5.56)
R^2	0.96	0.99	0.95	0.99	0.13	0.37
Cluster mask						
ln(SOL)	0.100** (2.11)	0.06*** (3.11)	0.262*** (4.23)	0.035 (1.54)	0.100** (2.16)	0.262*** (5.30)
R^2	0.96	0.99	0.95	0.99	0.11	0.35
Population mask						
ln(SOL)	0.109* (1.91)	0.089*** (3.96)	0.250*** (3.26)	0.051** (2.52)	0.109* (1.96)	0.250*** (4.09)
R^2	0.96	0.99	0.94	0.99	0.10	0.29
Built-up area mask						
ln(SOL)	0.082 (1.17)	0.087*** (3.65)	0.197 (1.55)	0.052*** (3.81)	0.082 (1.20)	0.197* (1.94)
R^2	0.95	0.99	0.93	0.99	0.06	0.18

Notes: ***, ** and * indicate significance at the 1, 5 and 10 percent levels respectively. t-values are reported in parentheses and are based on Newey-West standard errors, assuming a first-order serial correlation process. Estimated constant terms in the regressions not reported.

Table 1 reports the regression results. As can be seen, there is no statistically significant relationship between lights and GDP for any of the six regression specifications when using the "raw" lights data to calculate SOL. The fit of the de-trended regressions in columns [3a] and [3b], as indicated by their R^2 values, is furthermore very low. However, once we filter-out background noise from the lights data, we do obtain statistically significant relationships for most of the specifications, along with better fits for the de-trended regressions. While this is the case for the results based on all four masks, it is the EOG mask followed by the cluster mask which generates the strongest predictive relationships, judged based both on statistical significance and the fits of the de-trended regressions. If we focus, in particular, on the column [3b] results then the estimated elasticity of GDP with respect to SOL is 0.295 when using the EOG mask, which is significant at the 1 percent level, with an R^2 of 0.37. This implies that changes in the intensity of Morocco's nighttime lights around their trend can explain just over one-third of the variation in GDP around

results are very similar when we instead estimate using standard OLS or instead assume a second-order serial correlation process. Note that Newey-West standard errors are also robust to heteroskedasticity.

its trend. The estimated elasticity of GDP with respect to SOL when using the cluster mask is slightly lower at 0.262.[23] Nevertheless, it remains highly statistically significant. At 0.35, the R^2 is likewise very slightly lower.[24]

Figure 1a. Relationship between nighttime lights and GDP, EOG mask

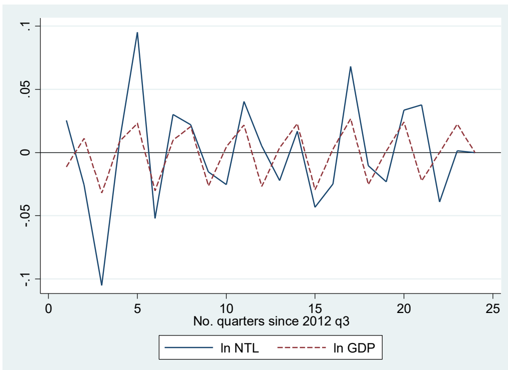
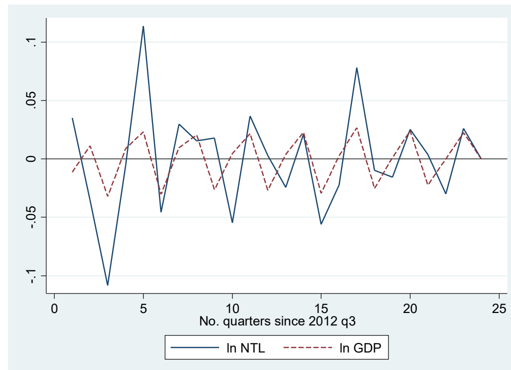


Figure 1b. Relationship between nighttime lights and GDP, cluster mask



Notes: Based on column [3b] regression results in Table 1 for the sample-period 2012 Q3 – 2020 Q1. Estimation results exclude Q2 data due to corruption of the June nighttime lights data associated with the "stray light" phenomenon.

Nevertheless, an R^2 of 0.35 - 0.37 still implies that fluctuations in nighttime light intensity are unable to explain almost two-thirds of the quarterly variation in real GDP, meaning that the relationship is noisy. This is evident from Figure 1, which provides a visualization of the column [3b] results based on the EOG and cluster masks from Table 1. Hence, for both masks, it can be seen that the magnitude of the change in lights is much closer to the magnitude of the change in real GDP for some fluctuations than for others. Consistent with this, if we focus on the data for the period 2014 Q1 – 2020 Q1 rather than for 2012 Q3 – 2020 Q1 then the estimated elasticity of GDP with respect to SOL increases to 0.35 – 0.36, depending on the mask used. For the most recent fluctuations, visual inspection of Figure 1 suggests that the elasticity may even be close to unity, especially for results based on the cluster mask. Despite this, it is also apparent from Figure 1 that, throughout the sample-period, the timing of changes in nighttime light intensity line-up well with the timing of changes in real GDP. This implies that the cleaned lights data are better used to capture changes in the direction of real economic activity than to provide precise quantitative estimates, based on the overall estimated elasticity, of the change in real GDP for any given fluctuation.[25]

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[23] Our estimated elasticity of 0.262 – 0.295 is remarkably close to that obtained by Henderson *et al.* (2012), which they obtain using annual GDP and lights data for a global panel of countries. This is despite the fact that Henderson *et al.*'s analysis is based on the old DMSP-OLS data as opposed to the newer VIIRS data.

[24] Annex 1 presents results based on the EOG and cluster masks, from the estimation of equations [1] – [3] for the industry, services and agriculture sectors. These regressions suggest that fluctuations in light intensity are most predictive of fluctuations in industry GDP. This is notably the case in the estimation of equation [2] and of equation [3] when de-trending is based on year effects. Interestingly, fluctuations in light intensity also hold some predictive ability for fluctuations in agricultural GDP when estimating equation [1] and also equation [3] when de-trending is based on a linear time trend.

[25] One might suspect the relationship between fluctuations in real GDP and SOL of being asymmetric between expansions and contractions in economic activity. For example, Henderson *et al.* (2012) hypothesize "the possibility that because some lights growth reflects the installation of new capacity, lights are nondecreasing, so that economic downturns will not be reflected in lights." However, they find no evidence in support of such an asymmetric

4. COVID-19 and the evolution of Morocco's nighttime lights

Having established that the lights data can reasonably be used to monitor changes, and especially the timing of changes, in real economic activity, we now turn to examine the evolution of Morocco's lights in response to the COVID-19 crisis. In doing so, we first focus on the monthly evolution at the national level before turning to examine the monthly evolution at the subnational regional level. In both cases, our methodology involves estimating a multivariate regression that models the evolution of SOL as following an exponential time trend while controlling for systematic differences in light intensity between months that are allowed to differ between the pre- and post-COVID-19 onset periods. From this model, SOL values adjusted for both seasonal effects and the pre-crisis trend are derived, and changes in these values calculated.

More formally, using monthly SOL data for the period April 2012 – September 2020 (excluding June data for each year), we estimate the following regression:

$$\ln(SOL_{i,m}) = \alpha + \beta m + \gamma Month + \delta(COVID.Month) + \varepsilon_{i,m} \qquad [4]$$

where $SOL_{i,m}$ is a geographic area *i*'s SOL in month m, m is a time-trend variable, *Month* are a full set of monthly dummies and *COVID* is a dummy variable which equals one if a month falls in the post-COVID-19 onset period. Given that Morocco's first case of COVID-19 was announced on March 2, 2020, we define the post-COVID-19 onset period as consisting of all months from March 2020 onwards. For pre-COVID-19 months, the estimated residuals from this regression, $\hat{\varepsilon}_{i,m}$, give the seasonally adjusted SOL values relative to the pre-COVID-19 SOL trend growth path, the estimated slope of which is itself given by $\hat{\beta}$.[26] Meanwhile, $\hat{\delta}$ provides estimates of seasonally adjusted SOL values relative to the pre-crisis trend for post-COVID-19 onset months. As with the regressions in Section 3, we estimate equation [4] using least squares with Newey-West standard errors to control for both first-order serial correlation and heteroskedasticity.[27]

A corollary of our approach to examining the evolution of lights following the onset of COVID-19 is that we effectively use the pre-COVID-19 trend growth path of an area's nighttime lights – be the area Morocco overall or one of its subnational regions – as defining the counterfactual relative to which changes in seasonally-adjusted light intensity are measured. A conceptual illustration of this is provided by Figure 2. In this figure, $\hat{\varepsilon}_{Feb.}$ is the (hypothetical) residual from estimating equation [4] for February 2020 – the last pre-COVID-19 onset month – and corresponds to the (ln) percentage points by which area *i*'s seasonally adjusted SOL deviated from its pre-COVID-19 growth trend in that month. Meanwhile, $\hat{\delta}_{March}$ corresponds to the estimated coefficient on the interaction dummy variable ($COVID.Month$) for March 2020. This is an estimate of the (ln) percentage points by which area i's seasonally adjusted SOL deviated from the

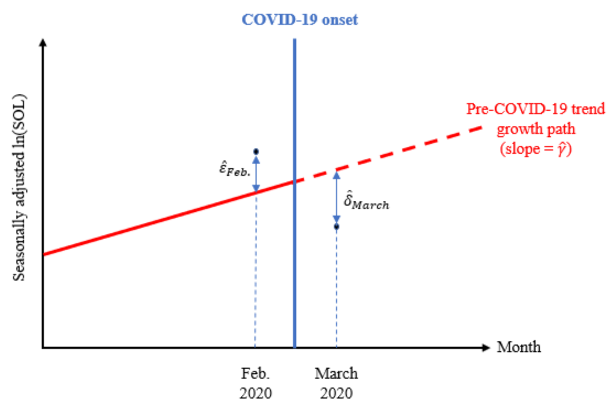
relationship in their own work, and, from Figure 1, there likewise seems no evidence to support the existence of an asymmetric relationship in quarterly data for Morocco.

[26] Seasonal adjustment is provided by the inclusion of the month dummies.

[27] The use of Newey-West standard errors only matters for the testing of the statistical significance of δ and other model parameters, and not for the point estimates of those parameters. As with the regressions in Section 3, the use of Newey-West standard errors is justified by the rejection of the hypothesis that the error terms are serially uncorrelated using both Durbin's alternative test for serial correlation and the Breusch-Godfrey test for serial correlation.

pre-COVID-19 growth trend in the month in which Morocco's first COVID-19 case was announced. Given this, $\hat{\delta}_{March} - \hat{\varepsilon}_{Feb.}$ then provides a measure of the "impact" of COVID-19 on area i's (seasonally adjusted) light intensity, which is equal to the (ln) percentage point change in SOL between the two months relate to the estimated pre-COVID-19 trend growth path of nighttime light intensity.

Figure 2. Conceptual illustration of estimation of effects of COVID-19 on nighttime light intensity



In addition to presenting estimates of changes in seasonally adjusted SOL relative to the pre-COVID-19 estimated trend growth path, we also present estimates of year-on-year (y-o-y) changes in seasonally adjusted SOL relative to this same growth path. For March 2020, such an estimate corresponds to $\hat{\delta}_{March} - \hat{\varepsilon}_{March,2019}$ where $\hat{\varepsilon}_{March,2019}$ is the residual for March 2019 from estimating equation [4].

4.1. National-level results

The monthly national level results based on the EOG and cluster masks which generate the strongest predictive relationships between lights and real GDP in quarterly data (see Section 3) are presented in Table 2 and Figure 3.[28] Three key findings are worth highlighting. The first is that, following the detection of the first COVID-19 case and the imposition of strict non-pharmaceutical interventions (NPIs) to control the disease's spread, Morocco witnessed a sharp fall in the intensity of its nighttime lights. Figure 4 shows the sharp increase in the numbers of confirmed COVID-19 cases and deaths that occurred in Morocco in March 2020 following the detection of the first case, while Figure 5 shows the sharp increase in the stringency of Morocco's NPIs, as captured by Hale *et al.*'s (2020) NPI stringency index, that was implemented in reaction to this. Accompanying this, Morocco witnessed a steep month-on-month decline in its overall light intensity (i.e. seasonally adjusted SOL) relative to the pre-crisis trend. Depending on the background noise mask used, this decline was between 8.0 and 10.9 percentage points (Table 2; Figure 3).[29] As a result, whereas in

[28] Results based on the application of the population and built-up area masks are available on request. The full results from the estimation of equation [4] based on the EOG and cluster masks are reported in Annex 2.
[29] Assuming an elasticity of 0.30, this corresponds to a fall in real GDP of 2.4 – 3.3 percentage points, although, as discussed in Section 3, any precise estimate of the change in real GDP derived from the lights data needs to be treated with caution.

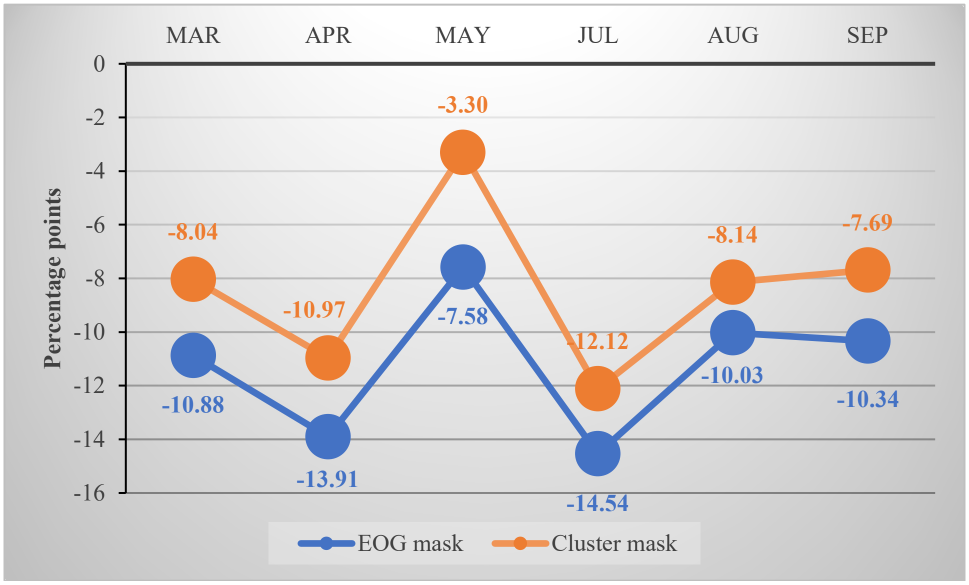
February 2020, prior to the first case, the intensity of Morocco's lights had been 2.5 – 3.0 percentage points *above* its pre-COVID-19 trend, by March, the intensity was 5.6 – 7.9 percentage points *below* its pre-COVID-19 trend (Table 2). Based on the EOG mask that produces the strongest results in terms of the correlation with real GDP, this month-on-month decline in lights was the largest that Morocco had experienced since December 2013.[30] An even larger decline in light intensity, relative to the pre-crisis trend, is evident on a year-on-year basis – between March 2019 and March 2020, seasonally adjusted SOL fell by 8.8 – 13.4 percentage points relative to this trend.

Table 2. Nighttime lights statistics

Difference from trend (%)							
Mask	**Feb. 2020**	**Mar. 2020**	**Apr. 2020**	**May 2020**	**Jul. 2020**	**Aug. 2020**	**Sep. 2020**
EOG	3.00	-7.88**	-10.92***	-4.58**	-11.55***	-7.03**	-7.34***
Cluster	2.48	-5.57**	-8.49***	-0.83	-9.64***	-5.66*	-5.22*
Change relative to trend (percentage points)							
Mask		**Feb. → Mar.**	**Mar. → Apr.**	**Apr. → May**	**May → Jul.**	**Jul. → Aug.**	**Aug. → Sep.**
EOG		-10.88	-3.03	6.34	-6.97	4.52	-0.32
Cluster		-8.04	-2.92	7.66	-8.81	3.98	0.44
y-o-y change relative to trend (percentage points)							
Mask	**Feb. 2020**	**Mar. 2020**	**Apr. 2020**	**May 2020**	**Jul. 2020**	**Aug. 2020**	**Sep. 2020**
EOG	1.47	-13.44	-12.00	-7.05	-6.49	2.94	-6.25
Cluster	5.94	-8.79	-11.54	-3.41	-4.36	3.79	-4.81
Notes: ***, ** and * indicate significance at the 1, 5 and 10 percent levels respectively. EOG = excludes areas excluded in 2015 and 2016 annual VIIRS composites; Cluster = Bayer *et al.* (2020) mask; trend refers to the pre-COVID-19 trend of seasonally adjusted SOL, as estimated using monthly data for Apr. 2012 – Feb. 2020. No results reported for June 2020 due to stray-light contamination of lights data.							

[30] The fall was also the fourth largest since data records began, based on the EOG mask results. The three largest month-on-month declines in seasonally adjusted light intensity relative to the pre-COVID-19 trend were in December 2013 (-14.70 percentage points), March 2013 (-14.28 percentage points), and November 2012 (-14.07 percentage points).

Figure 3. Changes in seasonally adjusted NTL intensity from Feb. 2020, relative to pre-COVID-19 trend



Notes: EOG mask omits areas excluded in 2015 and 2016 annual VIIRS composites; Cluster mask is based on the methodology of Bayer *et al.* (2020).

Figure 4. Confirmed COVID-19 cases and deaths

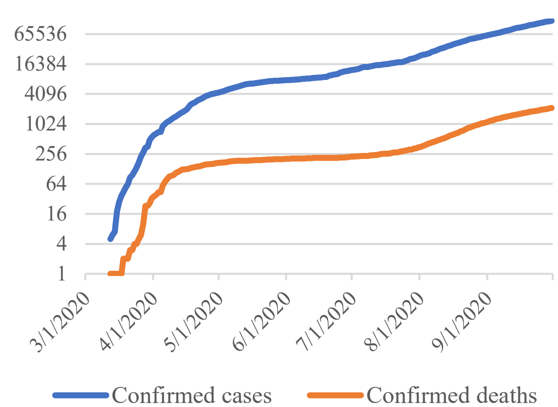
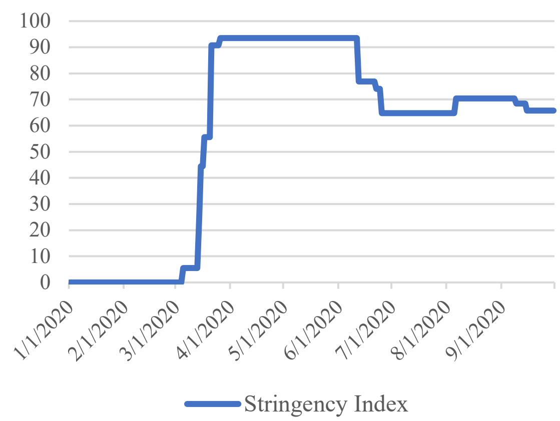


Figure 5. NPI stringency index



Note: Derived from Oxford University COVID-19 Government Response Tracker data (Hale *et al*., 2020).

The second finding to highlight is that Morocco's nighttime lights showed some signs of recovery in May 2020 as COVID-19 cases and deaths both leveled-off. Hence, following March's large drop, Morocco experienced a further, much smaller, drop in its overall (seasonally adjusted) light intensity in April 2020 of between –2.9 and –3.0 percentage points, relative to the pre-COVID-19 trend (Table 2). This left Morocco's lights between 11.0 and 13.9 percentage points dimmer in April 2020 than they were in February 2020, the final pre-crisis month (Figure 3). May, however, then saw a partial recovery in the intensity of Morocco's seasonally adjusted lights as the numbers of confirmed COVID-19 cases and deaths stabilized (Figure 4). Relative to the pre-crisis trend, seasonally adjusted light intensity increased by 6.3 – 7.7 percentage points between April and May 2020 (Table 2). On a year-on-year basis, however, May's change in nighttime light intensity remained negative.

In our final finding to highlight, however, the partial May recovery was short-lived, and, by September 2020, Morocco's lights were as dim as they were in April following the initial impact of the COVID-19 shock. In particular, although we lack usable June lights data due to the stray-light problem, Figure 3 shows that, by July, the May uptick in seasonally adjusted light intensity had been more than wiped-out. Relative to the pre-crisis trend, light intensity had thus reverted to just below its April level. This coincided with an upturn in the growth in the number of confirmed COVID-19 cases (Figure 4). In August, seasonally adjusted light intensity increased, but, by September, Morocco's seasonally adjusted light intensity remained, relative to the pre-crisis trend, 7.7 – 10.3 percentage points below its level in the final pre-COVID-19 month of February 2020. This is where it stood in April 2020 following the initial impact of the shock, implying the absence of any overall recovery with light intensity standing a statistically significant 5.2 - 7.3 percentage points below the pre-crisis trend (Table 2).

4.2. Subnational results[31]

Table 3 and Figure 6 present our subnational results which cover nine of Morocco's Admin-1 level regions, as defined by their current boundaries, which date back to 2015.[32] The first finding worth emphasizing is that while all regions shared in March 2020's national decline in nighttime lights, some suffered more than others. Thus, out of the nine regions analyzed, Fès – Meknès experienced the largest month-on-month decline – 16.5 percentage points – in the intensity of its seasonally adjusted lights in March relative to its pre-COVID-19 trend growth path. Tanger – Tetouan - Al Hoceima and Oriental - RIF also experienced declines in excess of 15 percentage points, while a further three (Rabat – Salé – Kénitra, Drâa- Tafilalet, and Marrakech – Safi) experienced declines in excess of 10 percentage points. The only region to escape a large fall in the intensity of its lights in March was Souss – Massa (- 0.5 percentage points). Given an assumed elasticity of 0.30, a 15 (10) percentage point decline in light intensity is equivalent to a 4.5 (3.0) percentage point drop in real GDP, although, as noted above, any attempt to derive precise quantitative estimates of changes in real GDP needs to be treated with caution.

In addition to the heterogeneous reaction of nighttime lights to the onset of Morocco's COVID-19 crisis in March 2020, Table 3 and Figure 6 also reveal that the effects of the shock have been highly persistent across regions. Thus, while light intensity levels relative to pre-crisis trends have fluctuated at the regional level since March, there is a strong correlation between the initial impact of the shock in March and the overall impact as observed in September 2020. This is reflected in an estimated correlation coefficient of 0.69 and an estimated Spearman's rank correlation coefficient of 0.75 between the change in a region's seasonally adjusted light intensity between

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[31] The reported subnational results are based on the cleaning of the lights data using the EOG mask, which produces the strongest results in terms of the correlation of nighttime lights with national economic activity. Results are, however, qualitatively similar regardless of the choice of mask.

[32] Our analysis excludes three relatively sparsely populated regions that were not fully covered by the nighttime lights data provided by EOG under their subscription service. However, an analysis of December 2019 lights data, where we have complete coverage of all regions including these, shows that they accounted for only 4.6 percent of total SOL for that month (calculated using pixel values equal to or greater than one), which is consistent with their low overall density of economic activity. Furthermore, results from Gibson *et al.* (2021), based on data for Indonesia, China and South Africa, suggest that VIIRS lights data are less of a reliable proxy for economic activity for low-density regions.

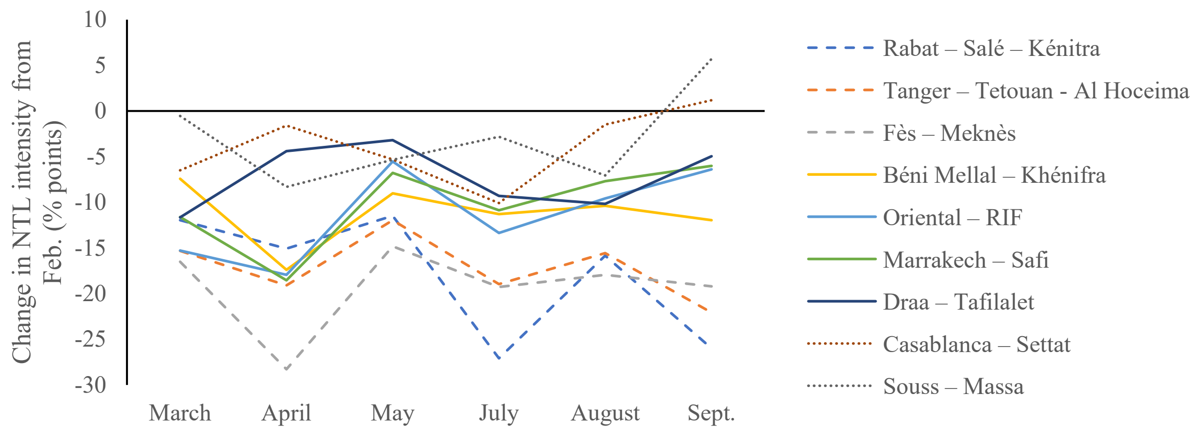
February and September and the change in its seasonally adjusted light intensity between February and March. Consistent with this, the two regions, Rabat – Salé – Kénitra and Tanger – Tetouan - Al Hoceima, that were initially hardest hit by the crisis remained the hardest hit in September. Conversely, Souss – Massa and Casablanca – Settat, which were the two regions initially least hard hit, were also the only two to have recovered to levels of nighttime light intensity, relative to the pre-COVID-19 trend, that were above their pre-crisis levels in February (Figure 6).

Table 3. Changes in light intensity relative to pre-COVID-19 trend (percentage points), Admin-1 regions

Admin-1 unit	**Change from previous month, percentage points (*Change from February 2020, percentage points*)**					
	March 2020	**April 2020**	**May 2020**	**July 2020**	**August 2020**	**Sept. 2020**
Rabat – Salé – Kénitra	-11.95 (*-11.95*)	-3.11 (*-15.06*)	3.58 (*-11.48*)	-15.60 (*-27.08*)	11.23 (*-15.85*)	-10.14 (*-25.99*)
Tanger – Tetouan - Al Hoceima	-15.33 (*-15.33*)	-3.76 (*-19.10*)	7.13 (*-11.96*)	-6.98 (*-18.95*)	3.40 (*-15.55*)	-6.52 (*-22.07*)
Fès – Meknès	-16.49 (*-16.49*)	-11.79 (*-28.28*)	13.47 (*-14.82*)	-4.47 (*-19.28*)	1.36 (*-17.93*)	-1.27 (*-19.20*)
Béni Mellal – Khénifra	-7.42 (*-7.42*)	-9.97 (*-17.39*)	8.37 (*-9.02*)	-2.28 (*-11.29*)	0.90 (*-10.39*)	-1.57 (*-11.96*)
Oriental – RIF	-15.28 (*-15.28*)	-2.65 (*-17.94*)	12.41 (*-5.53*)	-7.82 (*-13.35*)	3.78 (*-9.57*)	3.18 (*-6.39*)
Marrakech – Safi	-11.62 (*-11.62*)	-6.92 (*-18.54*)	11.76 (*-6.78*)	-4.08 (*-10.86*)	3.16 (*-7.70*)	1.69 (*-6.01*)
Drâa – Tafilalet	-11.65 (*-11.65*)	7.26 (*-4.40*)	1.20 (*-3.19*)	-6.10 (*-9.29*)	-0.87 (*-10.16*)	5.21 (*-4.95*)
Casablanca – Settat	-6.49 (*-6.49*)	4.90 (*-1.58*)	-3.72 (*-5.30*)	-4.78 (*-10.08*)	8.59 (*-1.49*)	2.67 (*1.18*)
Souss – Massa	-0.53 (*-0.53*)	-7.88 (*-8.31*)	13.66 (*5.35*)	-8.18 (*-2.83*)	-4.23 (*-7.06*)	12.75 (*5.70*)

Notes: Admin-1 area boundaries conform to current regional boundaries based on the shapefile downloaded from: https://www.arcgis.com/home/item.html?id=21bcbcaa915c433ba7c7850bafeede7b. No results reported for June due to stray-light contamination of the nighttime lights data.

Figure 6. Changes in light intensity relative to pre-COVID-19 trend (percentage points), Admin-1 areas



Notes: Admin-1 area boundaries conform to current regional boundaries based on the shapefile downloaded from: https://www.arcgis.com/home/item.html?id=21bcbcaa915c433ba7c7850bafeede7b. No results reported for June 2020 due to stray-light contamination of the nighttime lights data.

More generally, our results allow us to distinguish between three groups of regions in Morocco – the hardest hit, the hard-hit and the recovered. In addition to Rabat – Salé – Kénitra and Tanger – Tetouan - Al Hoceima, the ***hardest hit*** group also includes Fès – Meknès. Compared to their pre-crisis trends, these areas had September 2020 levels of light intensity between 19.2 and 26.0 percentage points lower than they were in February 2020. This corresponds to a 5.8 – 7.8 percentage points drop in real GDP given an elasticity of 0.30 with the caveat, again, that estimated real GDP changes need to be treated with caution. The ***hard-hit*** group meanwhile comprises Drâa – Tafilalet, Marrakech – Safi, Oriental – RIF and Béni Mellal – Khénifra. This group suffered light intensity (estimated real GDP) declines between February and September 2020 in the range of 5.0 – 12.0 (1.5 – 3.6) percentage points. Finally, Souss – Massa and Casablanca – Settat are the ***recovered*** group, with September 2020 light intensity (estimated real GDP) levels that were 1.2 (0.4) and 5.7 (1.7) percentage points respectively above their February 2020 levels, relative to pre-crisis trends (Table 3, Figure 6). However, whether or not Souss – Massa and Casablanca – Settat have retained their recovered status as Morocco's COVID-19 crisis has further evolved is an open question.

5. Conclusion

This paper has explored the potential for high frequency nighttime lights data to provide "near real-time" tracking of the economic impacts of the COVID-19 crisis for the specific case of Morocco. At the national level, we have seen that there exists a strong correlation between quarterly movements in Morocco's overall nighttime light intensity and movements in its real GDP, which supports the use of lights data to track the economic impacts of the COVID-19 crisis at both higher temporal frequencies and at the subnational level, for which GDP data are unavailable. Consistent with large economic impacts of the crisis, Morocco experienced a large drop in the overall intensity of its lights in March 2020, from which it has subsequently struggled to recover. At the subnational level, while all regions shared in March's national decline in nighttime light intensity, Rabat – Salé – Kénitra, Tanger – Tetouan – Al Hoceima, and Fès – Meknès suffered much larger declines than others. Since then, the relative effects of the COVID-19 shock across regions have largely persisted.

Our analysis can potentially be extended in several directions. Thus, while we have analyzed the evolution of nighttime lights, as a proxy measure of economic activity for both Morocco overall and for its Admin-1 regions, the methods showcased in this paper can equally be applied to more finely defined geographic areas, including both Admin-2 units and cities as defined based on, for example, their functional areas.[33] Similar analysis can likewise be applied to other Middle East and North African (MENA) countries, taking advantage of the region's low cloud-cover which facilitates frequent high-quality observation of nighttime lights. Another natural extension of our analysis would be to investigate the underlying determinants of the heterogenous nighttime lights reactions of Morocco's different regions to the COVID-19 crisis, which might include, for example, differences in their economic and demographic structures, as well as differences in the spread of the disease itself and the associated policy reactions.

[33] Some caution will, however, be required with such an extension given Gibson *et al.*'s (2021) finding that VIIRS lights provide a less reliable proxy for economic activity for lower level spatial units than they do for higher level ones.

Finally, a few caveats should be kept in mind when considering the results in both this paper and other nighttime lights-based analysis of the economic impacts of COVID-19. Perhaps most importantly, while we have shown the use of nighttime lights to track high frequency changes in economic activity to be reasonable for Morocco, we have also demonstrated that the relationship between lights and real GDP contains quite significant noise. This means that the results presented should be taken as suggestive of the evolution of economic activity following the onset of the COVID-19 crisis rather than as providing the final word on the magnitude of this evolution, where much more caution is needed. Ideally, one would like to triangulate the results presented in this paper with those obtained from other high frequency, potentially near real-time, proxy measures of economic activity. A further issue which we have seen to particularly affect Morocco is the distortion of its June lights data due to the "stray light" phenomenon.

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Annex 1. Relationship between nighttime light intensity and sectoral GDP

Table A1. Relationship between nighttime lights and GDP generated by different sectors, quarterly data (2012 Q3 – 2020 Q1)

	Time trend	**Time trend + quarter effects**	**Year effects**	**Year + quarter effects**	**De-trended (time trend)**	**De-trended (year effects)**
	[1a]	[1b]	[2a]	[2b]	[3a]	[3b]
EOG mask						
Industry						
ln(SOL)	0.143 (1.49)	0.051 (0.90)	0.453*** (3.91)	0.173** (2.58)	0.143 (1.52)	0.453*** (4.28)
R^2	0.86	0.95	0.90	0.98	0.07	0.49
Services						
ln(SOL)	-0.057 (-1.07)	-0.078* (-2.05)	0.141*** (3.02)	-0.015 (-0.52)	-0.057 (-1.11)	0.141*** (3.78)
R^2	0.97	0.98	0.97	0.99	0.05	0.23
Agriculture						
ln(SOL)	0.460** (2.11)	0.533** (2.81)	0.026 (0.21)	0.159 (0.96)	0.460*** (2.15)	0.026 (0.26)
R^2	0.43	0.48	0.92	0.93	0.12	0.00
Cluster mask						
Industry						
ln(SOL)	0.143* (1.77)	0.063 (1.11)	0.413*** (3.58)	0.149* (2.00)	0.143* (1.82)	0.413*** (4.48)
R^2	0.86	0.95	0.90	0.97	0.10	0.48
Services						
ln(SOL)	-0.013 (-0.39)	-0.03 (-1.04)	0.137*** (3.63)	-0.002 (-0.06)	-0.013 (-0.40)	0.137*** (4.55)
R^2	0.97	0.98	0.97	0.99	0.00	0.252
Agriculture						
ln(SOL)	0.335* (1.72)	0.398** (2.18)	-0.052 (-0.40)	0.032 (0.19)	0.335* (1.77)	-0.05 (-0.50)
R^2	0.40	0.46	0.92	0.93	0.09	0.01

Notes: ***, ** and * indicate significance at the 1, 5 and 10 percent levels respectively. t-values are reported in parentheses and are based on Newey-West standard errors, assuming a first-order serial correlation process. Estimated constant terms in the regressions not reported.

Annex 2. Full results from estimation of equation [4] – EOG and cluster masks

Table A2. Full results from estimation of equation [4]

Dependent variable: $\ln(SOL_{i,m})$		
	EOG mask	**Cluster mask**
Time trend	0.005***	0.006***
	(16.02)	(16.98)
COVID ×		
March	-0.079**	-0.056**
	(-2.52)	(-2.07)
April	-0.109***	-0.085***
	(-4.75)	(-3.78)
May	-0.046**	-0.008
	(-2.48)	(-0.35)
July	-0.115***	-0.0964***
	(-4.10)	(-3.23)
August	-0.070**	-0.0566*
	(-2.49)	(-1.74)
Sept.	-0.073***	-0.0522*
	(-3.06)	(-1.92)
Constant	13.411***	13.499***
	(578.63)	(593.31)
R^2	0.868	0.873
F	7.73***	12.54***
n	93	93

Notes: ***, ** and * indicate significance at the 1, 5 and 10 percent levels respectively. t-values are reported in parentheses and are based on Newey-West standard errors, assuming a first-order serial correlation process. F(12, 75) refers to an F-test of the joint significance of all explanatory variables with 12 and 75 degrees of freedom. Regressions also include month dummies (estimated co-efficients not reported) but exclude June data due to stray-light contamination of the data. EOG mask excludes areas excluded in 2015 and 2016 annual VIIRS composites; Cluster mask refers to Bayer *et al.* (2020) mask.