Growth out of the blue

Measuring GDP is especially challenging in developing countries, where the informal sector is large and institutional constraints can be severe. As a result, GDP growth estimates are often met with skepticism. But new technologies offer an opportunity to improve matters. Luminosity observed from satellites has been shown to be a good proxy for economic activity, and methodologies have been developed in recent years to predict GDP over time and across space based on nightlight intensity. In South Asia's case, GDP predicted using these methodologies closely tracks National Accounts GDP at the aggregate level, and provides a granular picture of GDP at subnational levels. Nightlight intensity also yields new insights on recent economic developments. Thus, the major shocks experienced by Nepal in 2015 had very different impacts across districts. In Afghanistan, local surges in conflict reduced local growth for up to one quarter. And in India demonetization had a short-lived effect at the aggregate level, but a noticeable impact on rural, unbanked and informal districts. To improve economic measurement in South Asia, a greater reliance on big data may help, but a clear agenda toward stronger statistical systems is a necessity.

PHOTO: NASA Earth Observatory images by Joshua Stevens

The measurement of economic activity is imprecise by nature

Properly capturing economic activity is particularly challenging in developing countries. Gross Domestic Product (GDP), the most standard measure of economic activity, is defined as the value of all final goods and services produced within the country during a given period, net of the value of inputs. With pervasive informality, many final goods and services, as well as many inputs, escape the scrutiny of statistical agencies. Even in the formal sector, businesses and individuals may understate their earnings to avoid taxation and regulation. Since not all economy activity can be precisely captured, GDP data is necessarily based on estimations and extrapolations.

Skepticism about official growth figures is often amplified by data gaps, inconsistencies and revisions. Few countries in South Asia produce quarterly GDP estimates, making it difficult to identify trend breaks. Subnational estimates, when they exist, are made available with substantial delays. In some countries these subnational estimates do not add up to national figures. National Accounts revisions, aimed at strengthening GDP estimates, can change growth stories dramatically. And on occasion, statistical agencies are insufficiently insulated from political interference, which amplifies concerns about the relevance of the official data.

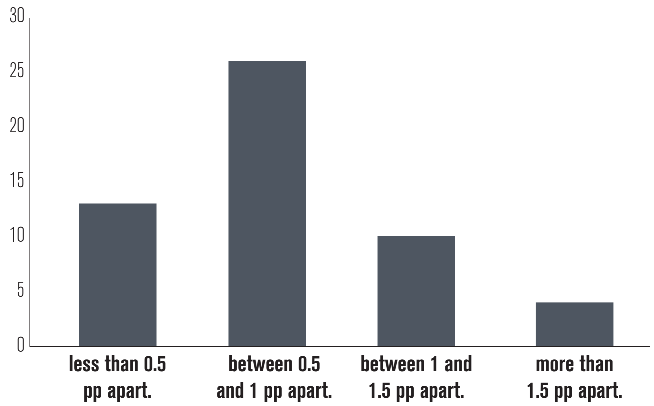
South Asian researchers and practitioners are well-aware of these measurement challenges. Respondents to a survey conducted for this report see a sizeable gap between GDP estimates and reality. Half of them expect actual growth to be between half a percentage point and one percentage point apart from first estimates. And one third believe that the gap is even larger. Regardless of what the real growth rate is, final figures are often quite different from preliminary estimates. India has a better statistical infrastructure than many other countries, but even there the first GDP growth estimate has on average been revised upward by 0.5 percentage points. The average absolute correction (positive or negative) since FY2004 has been 0.7 percentage points.

The rise of big data offers an opportunity to strengthen the measurement of economic indicators such as price indices and GDP levels. For example, insightful price indices have been developed on the basis of "scraping" the internet. These indices cover a very large number of products and points of sale, they can be updated daily, and they are cheap to maintain. Similarly, satellite imagery and especially luminosity observed from outer space have been shown to generate good proxies for economic activity. Measures of economic activity based on night-time light (or nightlight for short) have some crucial advantages over surveys and censuses. These measures capture economic activity regardless of whether it is formal or informal, they do so with a very high level of spatial granularity, and they are available nearly in real time. Importantly nightlight data is cheap to acquire and is not subject to political interference.

Figure 33: Researchers and practitioners see a gap between estimated and actual growth.

Compared to the initial GDP growth estimate, the actual GDP growth in your country has in general been

Number of answers

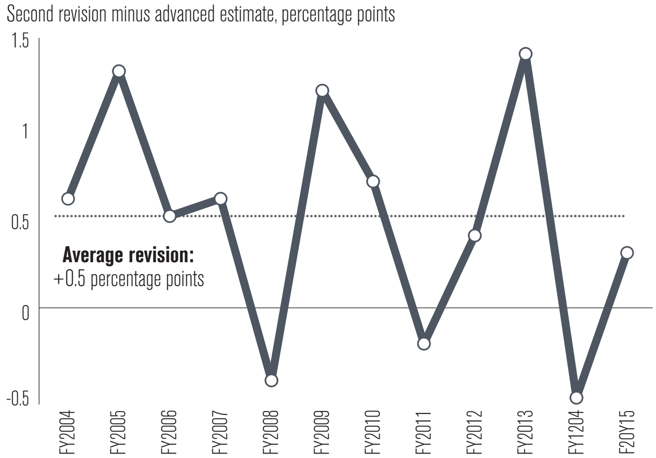


Source: World Bank South Asia Economic Policy Network.

Figure 34: Preliminary GDP growth rates can be revised substantially.

Revisions of GDP estimates in India

Second revision minus advanced estimate, percentage points



Source: Sapre and Sengupta (2017).

Nightlight and economic activity

The correlation between nightlight intensity and GDP levels is by now well established. Part of the correlation captures the fact that access to electricity, and the reliability

Measuring nightlight is challenging

Nightlight data at the global level is a byproduct of the Defense Meteorological Satellite Program (DMSP), a meteorological initiative of the US Department of Defense. Since 1976, this program includes a main weather sensor, the Operational Linescan System (OLS). The satellites follow an oscillating low orbit at a mean altitude of approximately 833 kilometers, with nightlight captured daily between 8:30 PM and 9:30 PM. The OLS sensor has the unique capability of detecting city lights, gas flaring, shipping fleets, and fires. An algorithm developed by the National Geophysical Data Center (NGDC) of the National Oceanic and Atmospheric Administration (NOAA) allows to identify stable lights. The treatment of the data includes removing sunlit, glare and moonlit data. Observations with clouds are also excluded as well as lighting features from the aurora in the northern hemisphere. The resulting global composites are known as DMSP-OLS stable nightlights (Elvidge et al. 1997).

Data collected by six DMSP-OLS satellites for years 1992 to 2013 has been made publicly available. The design of the OLS sensor onboard DMSP has not changed significantly since 1979, and new satellite deployments aim at ensuring data collection continuity, given sensor aging (Elvidge et al. 2013). Overlapping years, when data is available from two satellites, are particularly useful to check the comparability of measured nightlight intensity. Due to the absence of onboard in-flight calibration, differences caused by sensitivity discrepancies between satellite instruments are addressed by inter-calibrating the data (Elvidge et al. 2009).

The release of DMSP-OLS nightlight data was discontinued in 2013, at which point a new data product became available. In 2011, NASA and NOAA had deployed the Suomi National Polar Partnership (SNPP) satellite with the Visible Infrared Imaging Radiometer Suite (VIIRS). Data from SNPP-VIIRS has a resolution of approximately 0.5 km^2, a wider radiometric detection range solving over-saturation at bright core centers, and onboard calibration, all features that were missing in DMSP-OLS (Elvidge et al. 2013). Yet, the data publicly available is still raw, as some temporary lights and background noise remain.

Several strategies can be considered to clean the VIIRS data. A first approach consists in removing individual nightlight observations below a certain intensity threshold. This threshold is defined by sampling nightlight data from places known to lack human activity, such as natural parks and mountain ranges (Ma et al. 2014). The second approach consists in removing all observations from areas seen as a “background noise mask”. These areas are identified by first removing outlier observations from each location, and then clustering the remaining observations based on their intensity. In practice this approach amounts to removing all observations from areas distant from homogenous urban cores. The third approach also involves removing all observations from locations with background noise, but the way these locations are identified is different. For 2015, an annual composite of stable VIIRS nightlight was released (Elvidge et al. 2017). Locations with background noise are identified by comparing the raw data with the stable annual composite. Once this is done, data from these locations can be removed from all VIIRS monthly data.

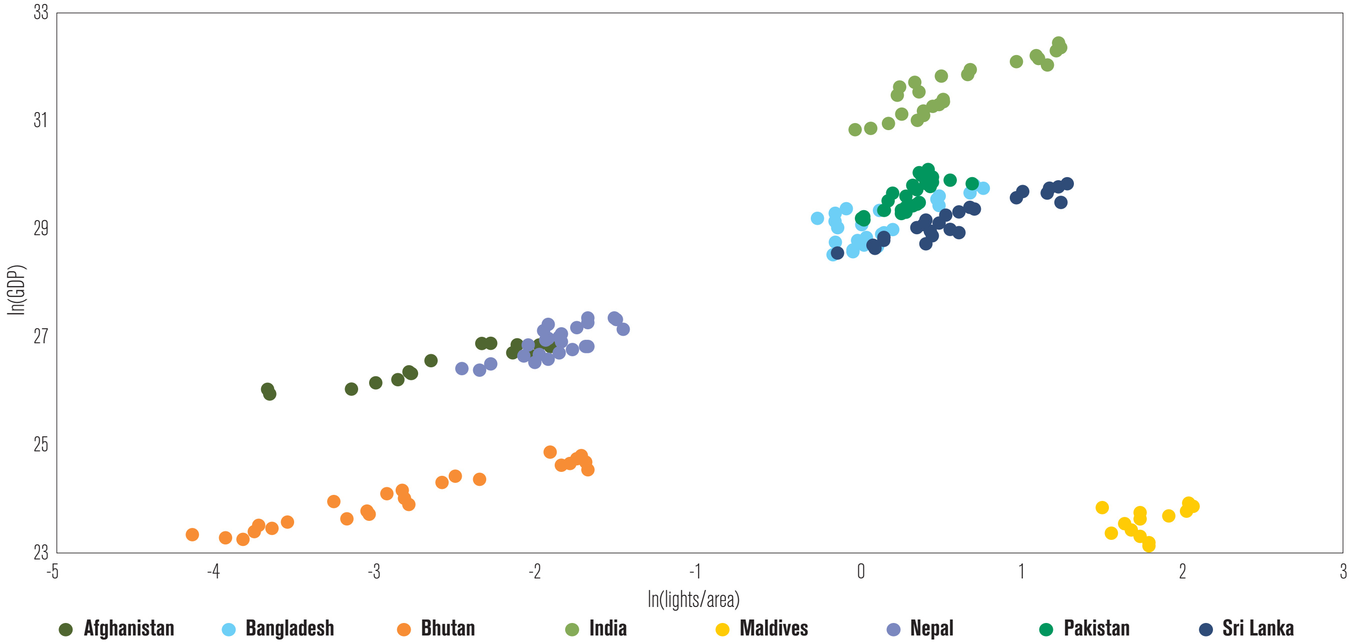
A final challenge is to link the DMSP-OLS annual data with the VIIRS monthly data to generate a longer annual series of nightlight data from 1992 to the present. But this can easily be done by taking advantage of the overlap between the two data sources in 2013.

of power supply, increase as countries develop. Another part of the correlation is due to the fact that, among those who have access, electricity consumption increases with income levels. The overall correlation is typically computed between the level of GDP and nightlight intensity per unit of surface, with both variables measured in logs. While a similar pattern can be observed around the world, there is also variation across countries. In the South Asia region, the correlation coefficient for Bhutan is 0.97, and it is statistically significant at the 1 percent. The coefficient reaches 0.90 in India, with the same statistical significance. But the correlation coefficient is not statistically significant in Maldives, which stands out as the exception to the general pattern in the region.

The relationship between economic activity and nightlight intensity in South Asia is quantitatively similar to that observed in other regions. This relationship is typically estimated assuming a constant elasticity between the two variables. This approach was introduced in a seminal academic paper by Henderson et al. (2012), whose goal was to develop a comprehensive framework to improve the reliability of GDP estimates for developing countries. Using that framework, it appears that the relationship between GDP levels and nightlight intensity observed elsewhere in the world also holds in South Asia’s case. Analyses like those conducted by Henderson et al. (2012) can thus be applied to the measurement of the region’s economic activity.

Figure 35: GDP levels and nightlight intensity are correlated.

Nightlight intensity and economic activity, 1992-2016



Note: For Maldives only the years 2001 to 2013 are covered.

The strength of the relationship between economic activity and nightlight intensity declines steadily with economic development. A simple intuition for this pattern is that power supply is a more binding constraint to economic activity in poorer countries. In these countries, the expansion of access to electricity and the improvement of its reliability can have a substantial impact on living standards. But increases in generation capacity are unlikely to have a dramatic effect in rich countries, where access is universal and blackouts almost unheard of. In practice, the percentage change in GDP associated with a one percent change in nightlight intensity is estimated at 0.31 for countries in the poorest decile, and at 0.27 for countries in the second poorest decile. While the estimated elasticity fluctuates around 0.20 for most of the other deciles, it becomes statistically insignificant among OECD countries.

The relationship is weaker when power infrastructure is limited. The simple intuition outlined above implies that the relationship between economic activity and nightlight intensity should be weaker if installed power generation capacity remained unchanged. For the sake of the argument, consider a region without access to electricity, hence totally in the dark. In that region changes in economic activity are necessarily independent of nightlight intensity, because there is no nightlight to begin with. Countries with the lowest generation capacity, or with the lowest electricity consumption, are countries where many households and firms are in the dark. Not surprisingly the estimated elasticity is low in these countries. But the elasticity would increase substantially if generation capacity expanded to match that of countries at the next level.

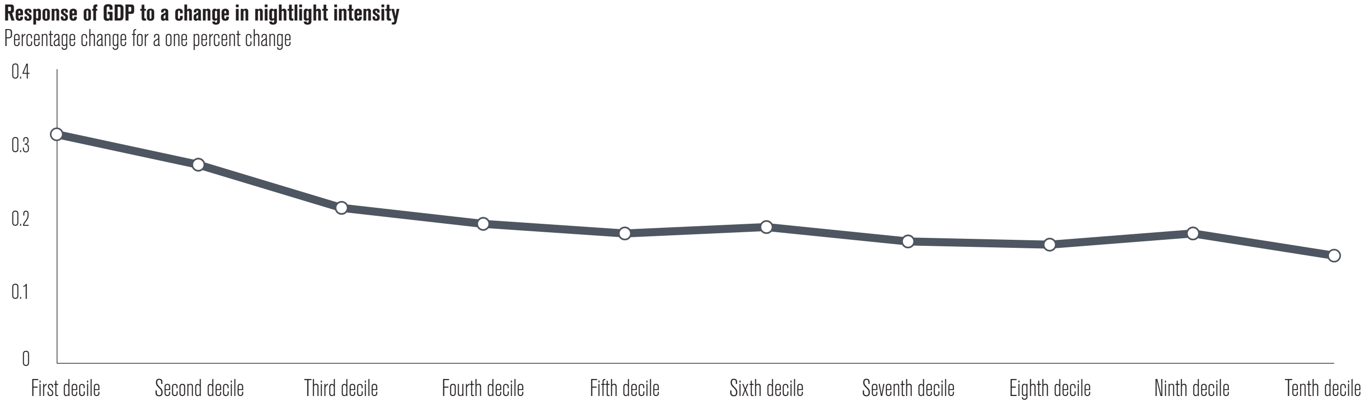
Table 2: The relationship is similar in South Asia and elsewhere.

	World ln(GDP)	World without South Asia ln(GDP)	South Asia ln(GDP)
ln(lights/area)	0.267*** (0.0303)	0.266*** (0.0314)	0.248*** (0.0491)
Observations	3,966	3809	157
Countries	187	179	8
(within country) R^2	0.788	0.782	0.971

Note: The following regression is estimated: , where is the natural logarithm of GDP of country i in year t measured in constant local currency, is the natural logarithm of lights per km^2 , is a country-fixed effect and is a year fixed-effect Robust standard errors, clustered by country, are in parentheses. *** p<0.01

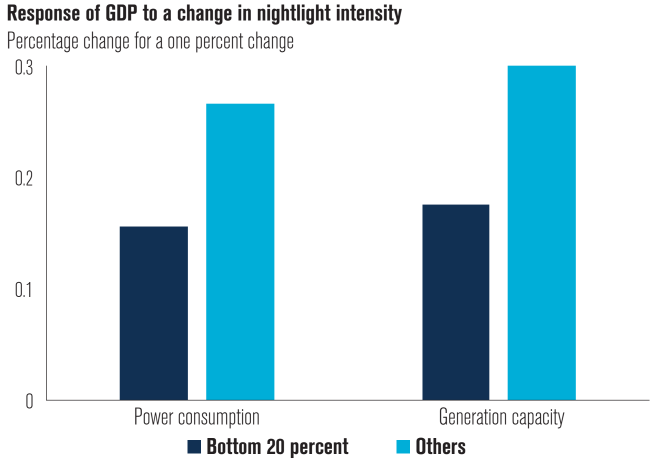
Nightlight intensity is more strongly correlated with economic activity in manufacturing and in services than in agriculture. The sector of activity that is typically in the dark is agriculture. In developing countries, including South Asia, access to electricity is especially low among farmers. And even when they have access, farmers tend to use the electricity for activities such as water pumping, which do not generate nightlight. Data analysis confirms this intuition. When considering a large cross-section of countries covering the whole world, the relationship is statistically significant for all three sectors, but it is weaker for agriculture. When focusing on South Asia only, the relationship becomes statistically insignificant for the agricultural sector.

Figure 36: The relationship is stronger in poorer countries.



Note: We estimate the same regression as in Table 2 with interaction terms for income decile (based on PPP adjusted GDP per capita) and nightlight intensity.

Figure 37: The relationship is weaker when power infrastructure is limited.



Note: We estimate the same regression as in Table 1 on two sub-samples – the bottom 20 percent of power consumption/generation capacity and the remaining 80 percent.

Nightlight intensity and GDP growth

The relationship between nightlight and economic activity is weaker in the short-term but it is still significant, and stronger in South Asia. When considering longer periods of time, economic growth is accompanied by improvements in energy infrastructure. In this context, the strength of the relationship between economic activity and nightlight intensity should not come as a surprise. But infrastructure changes relatively little in the short term. From a statistical point of view, long-term changes in nightlight intensity provide information on fundamental trends in the economy, while short-term changes are "noisier". One consequence of relying on noisier data on nightlight intensity is the "attenuation" of the estimated relationship. But despite this attenuation effect, the relationship between annual changes in GDP and annual changes in nightlight intensity remains significant both in a large cross-section countries and for South Asia.

Figure 38: The relationship is especially weak in the agricultural sector.

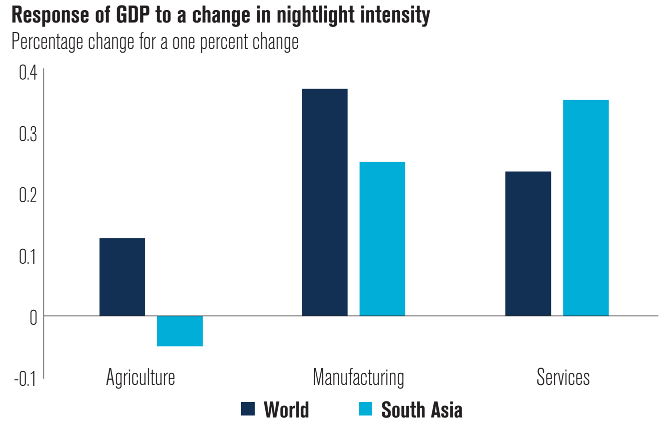


Table 3: The short-term relationship is stronger in South Asia than elsewhere.

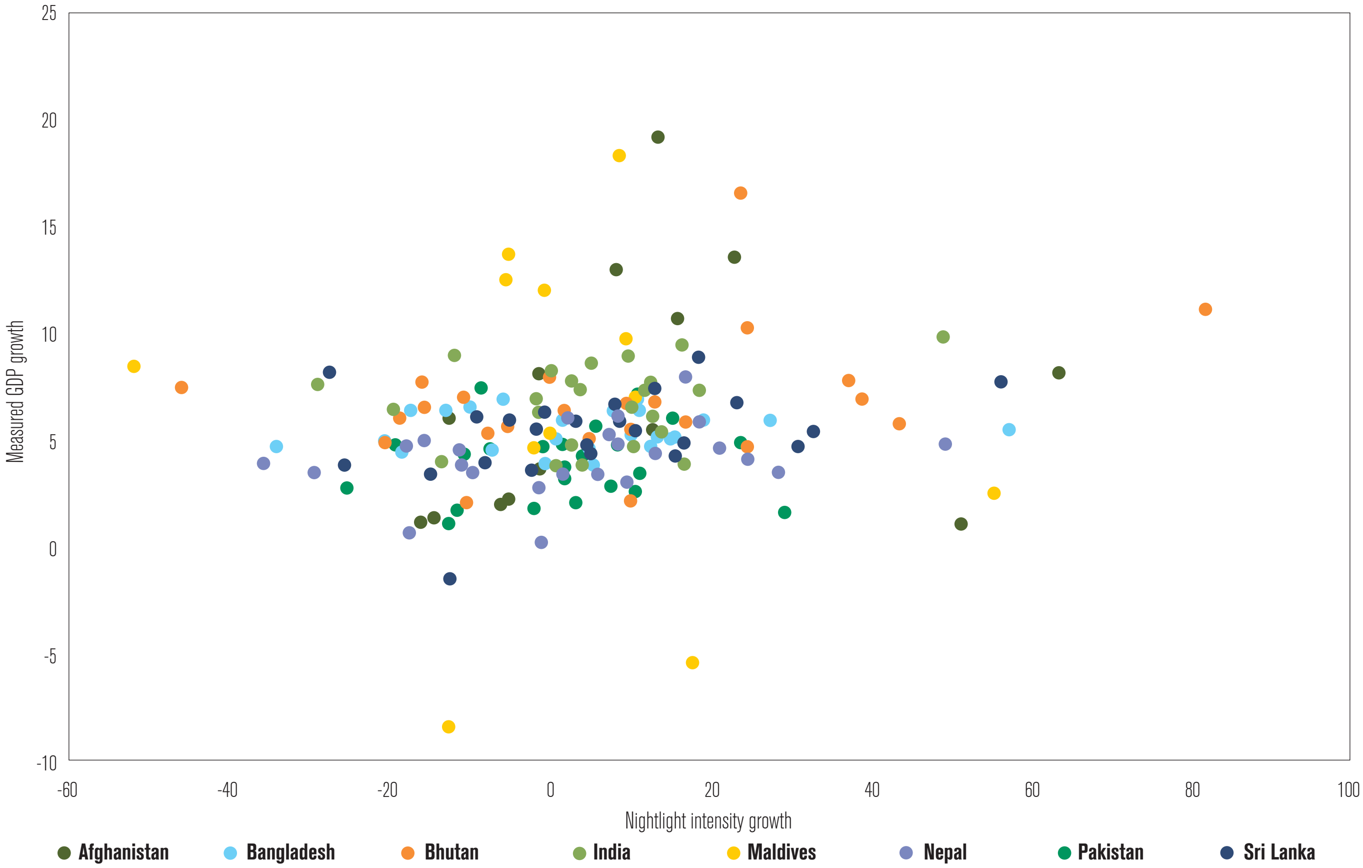
	World Δln(GDP)	World without South Asia Δln(GDP)	South Asia Δln(GDP)
Δln(lights/area)	0.0547*** (0.0161)	0.0557*** (0.0166)	0.0741*** (0.0154)
Observations	3,778	3,629	158
Countries	187	179	7
(within country) R^2	0.094	0.096	0.338

Note: The following regression is estimated: $\Delta \ln (GDP_{i,t}) = a + b_i + c_t + \delta \Delta \ln (light_{i,t}) + \varepsilon_{i,t,}$ where ln ($GDP_{i,t}$) is the natural logarithm of GDP of country i in year t measured in constant local currency, ln ($light_{i,t}$) is the natural logarithm of lights per km^2, b_i is a country-fixed effect and c_t is a year fixed-effect. The regressions in the first and second column are estimated using data until 2013. The regression in the thrid column is estimated using data until 2016 and excludes Maldives. Robust standard errors, clustered by country, are in parentheses. *** p<0.01.

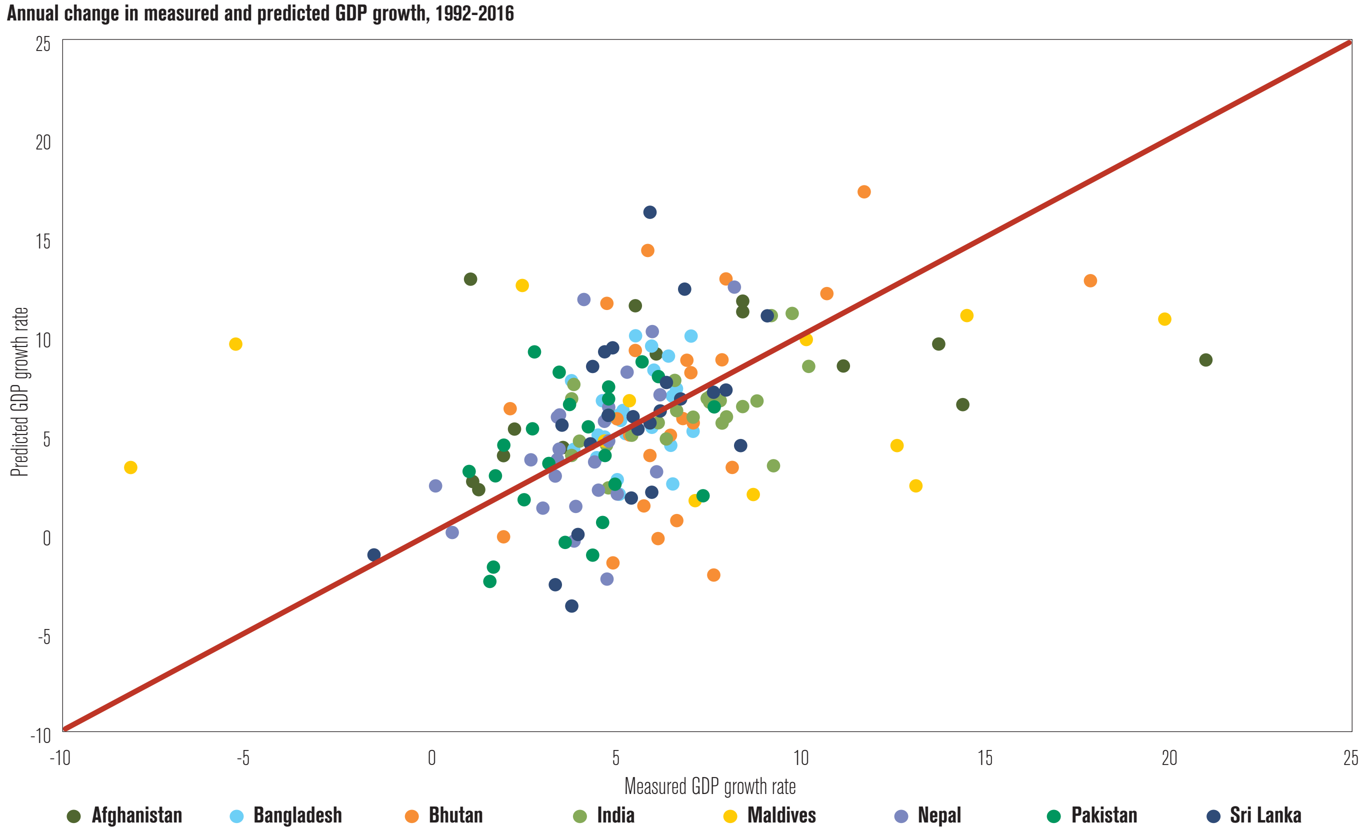
Predictions of short-term changes in economic activity based on short-term changes in nightlight intensity are informative, albeit not very precise. The observed relationship between changes in the two indicators varies across countries. For instance, the correlation

Figure 39: Short-term changes in nightlight intensity carry information and not only noise.

Annual Change in nightlight intensity and in GDP, 1992-2016

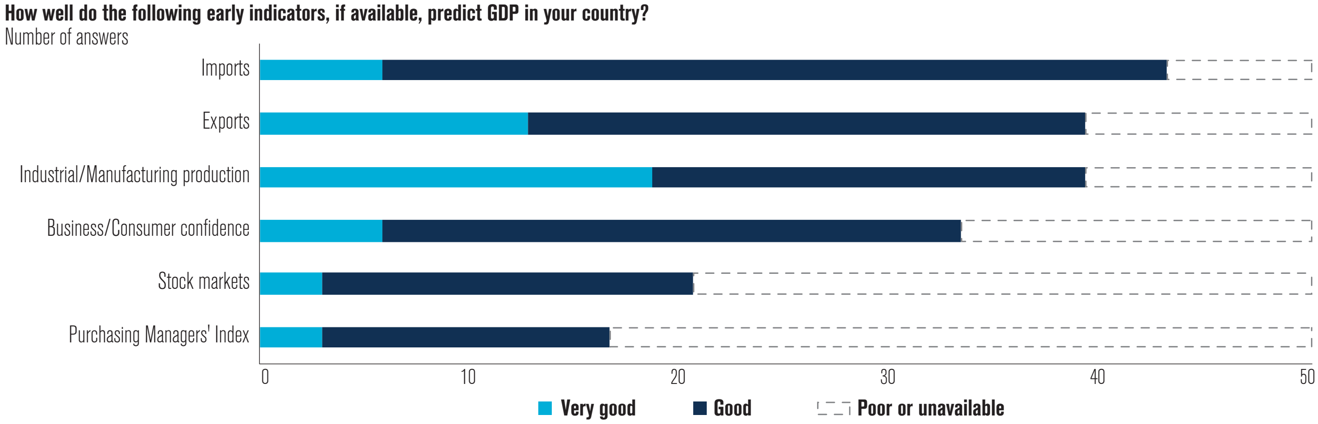


Annual change in measured and predicted GDP growth, 1992-2016



Note: For Maldives only the years 2001 to 2013 are covered.

Figure 40: Several lead indicators are used to forecast GDP growth.



Source: World Bank South Asia Economic Policy Network.

Table 4: Nightlight is a good lead indicator for annual GDP growth.

Indicator	Country coverage	Observations	Correlation with GDP
Business/Consumer Confidence	India, Sri Lanka, Pakistan	16	0.64**
Manufacturing production	India, Sri Lanka, Pakistan, Bangladesh	40	0.44***
Nightlight intensity (shorter sample)	India, Sri Lanka, Pakistan, Bangladesh, Nepal, Bhutan	60	0.35***
Industrial production	India, Sri Lanka, Pakistan	56	0.34*
Nightlight intensity (longer sample)	India, Sri Lanka, Pakistan, Bangladesh, Nepal, Bhutan	144	0.30***
Exports	India, Sri Lanka, Pakistan, Bangladesh, Nepal, Bhutan	131	0.28***
Stock market indices	India, Sri Lanka, Pakistan, Bangladesh	67	0.21*
Services/Manufacturing PMI	India, Sri Lanka	14	0.24
Imports	India, Sri Lanka, Pakistan, Bangladesh, Nepal, Bhutan	150	0.17**
Banking credit	India, Sri Lanka, Bangladesh	44	0.08

Note: All indicators are in growth rates; for Business/Consumer Confidence and Service/Manufacturing Purchasing Managers' Index we also tested levels and demeaned levels but did not find a significant relationship *** p<0.01, ** p<0.05, * p<0.10.
Source: GDP data from World Bank and all other data retrieved from Trading Economics.

coefficient between the two variables is 0.35 in Sri Lanka, and it is statistically significant at the 10 percent level. But the correlation coefficient is only 0.1, and insignificant, in Bangladesh. Despite these relatively low correlation coefficients, predictions of changes in economic activity based on nightlight intensity bear some resemblance with actual changes in GDP. This can be seen by using the relationship estimated in levels to predict GDP based on nightlight intensity, and then deriving a predicted GDP growth rate per country and per year. The correlation between these predicted growth rates and actual growth rates is 0.46 for South Asia as a whole. It exceeds 0.5 in India, Nepal, and Sri Lanka.

While changes in nightlight intensity are noisy, other lead indicators generally used to predict changes in GDP tend to be noisy as well. Despite their broad acceptance in the profession, changes in standard lead indicators also display a weak correlation with changes in GDP in the short run. In a survey for this report, South Asian researchers and advisors reckoned that data on imports and exports contain valuable information about changes in economic activity. Only few, however, thought that these variables contain a lot of information. Industrial and manufacturing production were also seen as informative, as were business and consumer confidence indicators. Stock market indices and the Purchasing Manufacturers Index (PMI) were deemed less informative.

Despite being noisy, the change in nightlight intensity is a better predictor of GDP growth than many standard lead indicators. One way to see this is to compute the correlation between annual changes in GDP and annual changes in lead indicators in the same year. In line with the views of regional researchers and advisors, changes in business and consumer confidence indices and in manufacturing production have the highest correlation with annual changes in GDP. But changes in nightlight intensity are also highly informative, as shown by the fact that their correlation with annual changes in GDP is statistically significant at the one percent level. And the correlation remains strong across different sample periods. Exports, imports, industrial

A survey of studies using nightlights in South Asia

Nightlight intensity is strongly correlated not only with GDP, but also with several other socio-economic indicators. Thus, Proville, Zavala-Araiza and Wagner (2017) uncover a clear relationship with electricity consumption and with carbon dioxide emissions, followed by a somewhat weaker relationship with population, methane emissions, and poverty. Ghosh et al. (2010a) focus on the size of the informal economy. By comparing economic activity as captured by nightlight data with official GDP estimates, they conclude that India's informal economy and remittances are much larger than is generally acknowledged. Nightlight intensity has also been used to estimate electrification rates at local levels (Min 2011). Based on this approach, it has been suggested that close to half of the rural population of South Asia lacks access to electricity (Doll and Pachauri 2010).

The high degree of correlation between nightlight intensity and GDP has been shown to hold even at the subnational level (Bhandari and Roychowdhury 2011). This insight has been exploited to generate a range of subnational economic indicators which are not readily available otherwise (Ebener et al. 2005; Ghosh et al. 2010b; Sutton, Elvidge and Ghosh 2007).

Around the world, the use of nightlight data is common in studies dealing with urbanization dynamics. In India, significant changes in urban proportion have been observed in Tamil Nadu, Kerala and Punjab (Pandey, Joshi, and Seto 2013). While the loss of agricultural land to urban expansion has been slow, it appears that it has steadily accelerated over time (Pandey and Seto 2015). There is also evidence of increasing nightlight intensity along the peripheries of major Indian cities (Chand et al. 2009). The growing importance of the urban fringe may explain why measures of urbanization based on nightlight intensity are quite different from those relying on administrative definitions or on land classification by type of use (Ellis and Roberts 2015; Li and Galdo 2017).

Nightlight intensity has also been used to study long-term growth. In India, nightlight data from 2000 to 2010 provides evidence of both absolute and conditional convergence among rural areas (Chanda and Kabiraj 2016). Nightlight data also suggests that there is convergence at the district and state level (Tewari and Godfrey 2016). This in contrast with findings based on GDP data, according to which there is divergence or, at best, neither convergence nor divergence. It also appears the growth of secondary cities has been more conducive to poverty reduction than that of large metropolitan areas (Gibson et al. 2017). And in Pakistan, there are signs of convergence, albeit slow, between the richest and poorest provinces of the country (Mahmood, Majid and Chaudhry 2017).

Finally, another line of research has focused on the consequences of economic shocks. A study on the impacts of the 2015 earthquakes and trade disruption in Nepal finds that aggregate impacts were more modest than suggested by the data, but could be quite significant in specific localities (Galdo, Kitzmuller, and Rama 2017).

production, and stock market indices contain some information, but less than the other lead indicators. Also consistent with the views of regional experts and advisors, the relationship is not statistically significant for the PMI. And it is not significant for banking credit either.

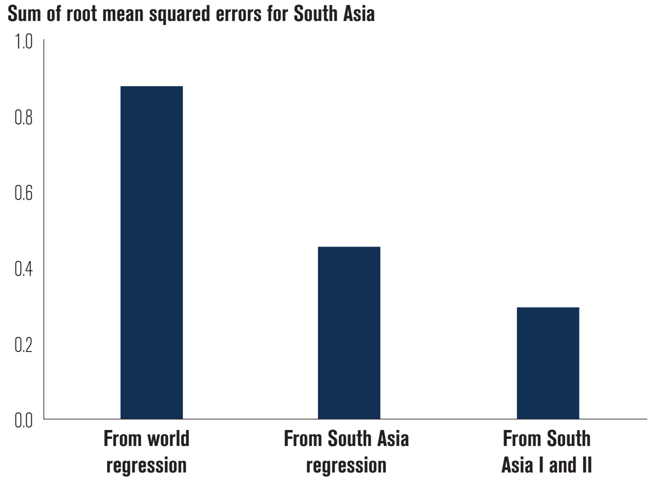
Using nightlight for prediction

Three methodologies have been proposed to predict GDP levels or to forecast GDP growth rates based on nightlight data. These three methodologies, identified by a shorthand name for expositional clarity, are as follows:

- The **elasticity approach** builds on the long-term relationship between GDP levels and nightlight intensity. There can be variations of this approach in practice, depending on the assumptions that are made about the nature of the relationship. For instance, it can be assumed that the relationship is the same for all countries, or that it varies across individual countries, or across groups of countries (Henderson et al. 2012). On the basis of the estimated elasticity, this approach allows predicting GDP levels for each year. Or annualized GDP levels for each month, if monthly data on nightlight intensity is used instead.

- The **spatial approach** uses nightlight intensity to distribute aggregate GDP across states, provinces or districts. To take into account the weak relationship between nightlight intensity and economic activity in the agricultural sector, this second approach first splits aggregate GDP by sectors. Agricultural GDP is allocated to subnational levels based on the distribution of the rural population, whereas non-agricultural GDP is allocated based on the distribution of nightlight intensity (Ghosh et al. 2010b; Bundervoet et al. 2015). Adding up the estimates for the agricultural and non-agricultural sectors, this approach yields predictions of GDP with a potentially high level of spatial granularity.

Figure 41: Allowing for differences across countries increases precision.



	World ln(GDP)	South Asia ln(GDP)	South Asia I ln(GDP)	South Asia II ln(GDP)
ln(lights/area)	0.267*** (0.0303)	0.273*** (0.0481)	0.169* (0.0611)	0.350*** (0.0110)
Observations	3,966	178	78	100
Countries	187	8	4	4
(within country) R^2	0.788	0.976	0.987	0.994

Note: South Asia I includes Afghanistan, Bangladesh, India and Maldives. South Asia II includes of Bhutan, Nepal, Pakistan, and Sri Lanka. All regressions expect the first are estimated from 1992 to 2016. The regression specification is the same as before. * p<0.1 and *** p<0.01.

- The **lead approach** builds on standard practice in short-term macroeconomic forecasting. A relationship is estimated between annual changes in GDP and contemporary or lagged changes in lead indicators considered informative, such as the industrial production index, or the Purchasing Manufacturers Index. The estimated relationship is used to predict changes in GDP when information on the lead indicators becomes available (Armstrong 2001). In this approach nightlight intensity is simply treated as one more lead indicator. This third approach is especially suited for improving short-term macroeconomic analysis.

A series of relatively simple empirical exercises allows assessing the performance of these three methodological approaches. By the same token, these exercises show the potential of data on nightlight intensity to yield new economic insights.

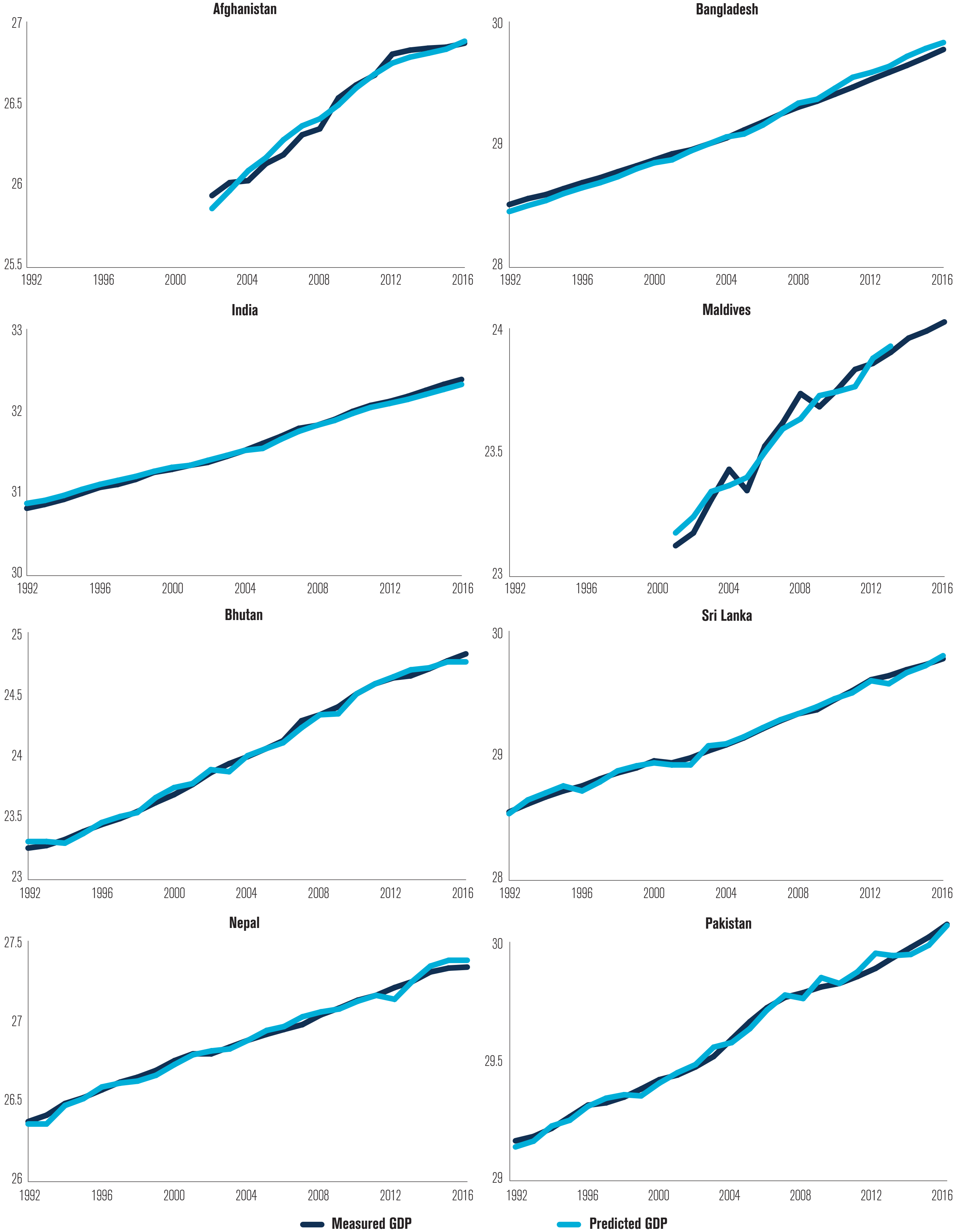
When using the elasticity approach, allowing for differences across groups of countries increases precision in the estimation of national-level GDP. Predicting economic activity in South Asia based on a naïve world-level analysis that treats all countries alike results in rather large errors. In India, for example, GDP predicted using this naïve approach increasingly lags behind the observed GDP. Predicting GDP based on a relationship estimated only for South Asian countries results in a much better fit. But even then, there are periods in which predicted and actual GDP show considerable deviation, at least in some countries. Visual inspection of the data reveals that South Asian countries can be sorted into two groups displaying clearly different relationships between GDP levels and nightlight intensity. Estimating the relationship allowing for this difference yields predicted levels of GDP that track National Accounts GDP very closely.

When using the spatial approach, nightlight intensity predicts GDP at subnational levels relatively well. The performance of the spatial approach can be assessed for India, where data on economic activity at subnational levels is available. The number of observations that can be used for this assessment is maximized when using GDP data at the state level for FY2014, and at the district level for FY2005. Applying the spatial approach, the correlation between predicted and actual GDP at the state level is 0.85. And it only falls to 0.83 at the district level.

The relatively good performance of the spatial approach in India's case gives some confidence that it can be applied to countries without subnational GDP estimates. The same procedure is followed in each of the countries in South Asia, at the level of the district or its equivalent. The only information needed to do this is the breakdown of GDP between agricultural and non-agricultural sectors, the distribution of the rural population by district, and an estimate of nightlight intensity also by district. To facilitate comparisons across space, predicted GDP at subnational levels is measured in per capita terms, with population figures at the district level coming from population censuses. It appears that all South Asian capitals, including Kabul, are in the highest bracket of GDP per capita. Economic centers like Karachi and Chittagong are clearly recognizable and belong to the highest income districts as well. In Sri Lanka, coastal districts appear richer than others, which can be expected in the West but is surprising in the East and North. In India, richer districts are geographically scattered, but most prominent in the Northwest.

Nightlight intensity alone is a poor lead indicator for quarterly GDP growth. Since monthly nightlight data is publicly available only since April 2012, the performance of the lead forecast approach can only be assessed over the last five years or so. And it can only be assessed in the cases of India and Sri Lanka, as these are the only two countries in the region that produce quarterly GDP estimates. A first step, for these two countries, is to compare the correlation coefficients between quarterly GDP and various defensible lead indicators, including nightlight intensity. Some indicators have a high and significant correlation, especially

Figure 42: GDP predicted based on the elasticity approach closely tracks measured GDP.



Note: Predicted GDP based on South Asia I and South Asia II regression (see Figure 41).

Figure 43: In India, nightlight intensity predicts subnational GDP relatively well.

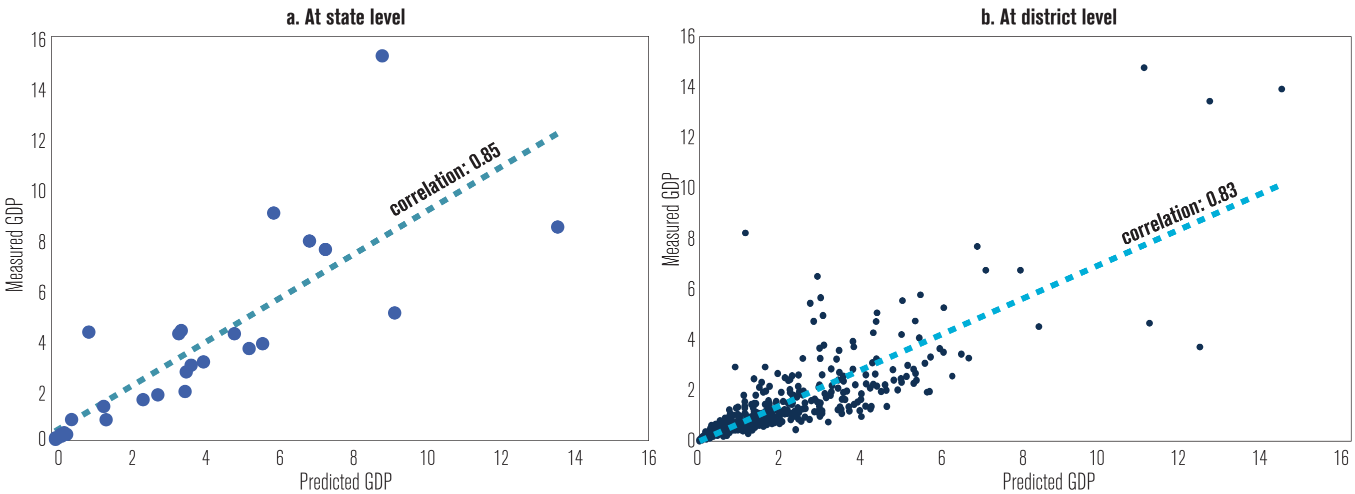
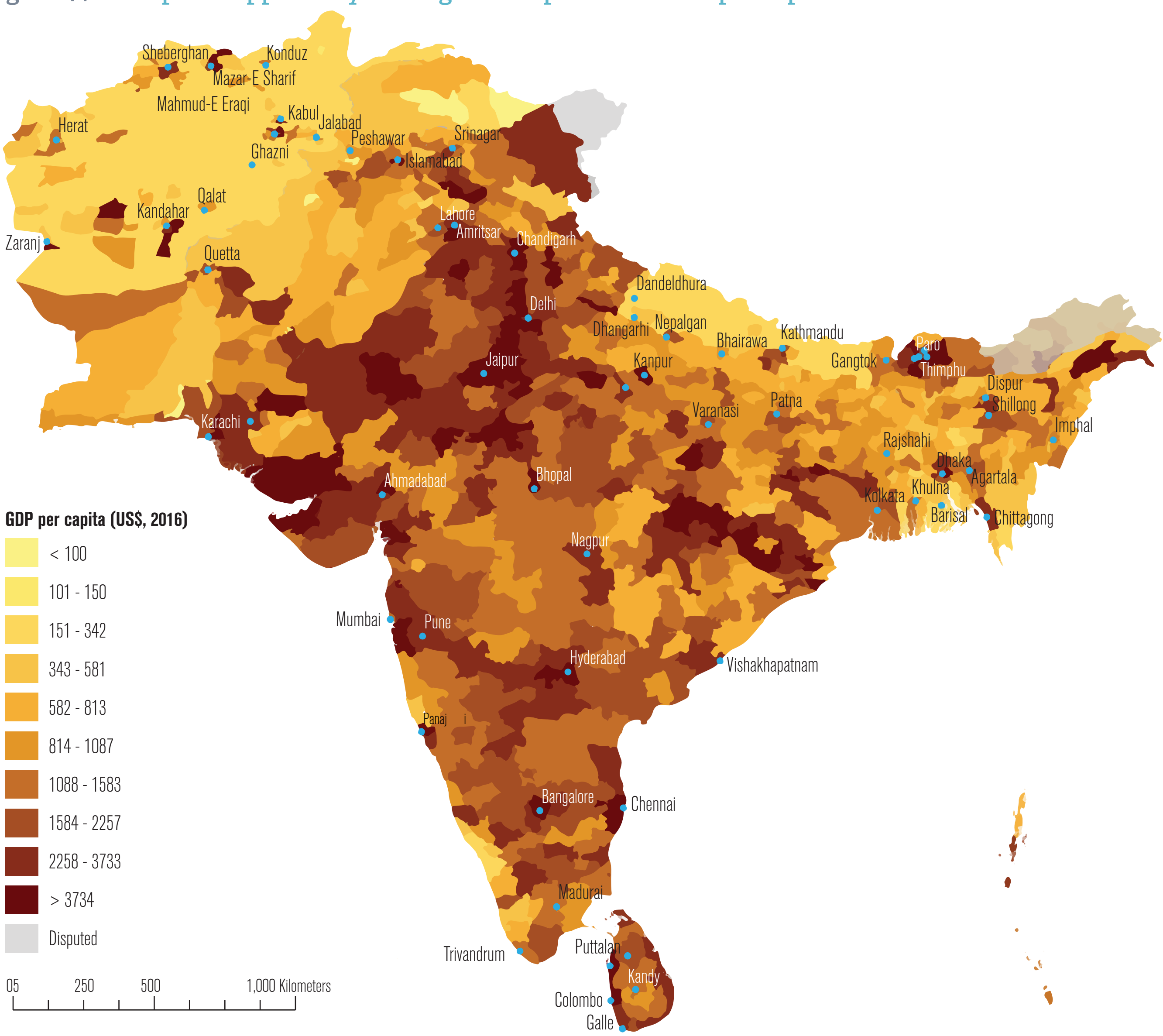


Figure 44: The spatial approach yields a granular picture of GDP per capita in South Asia.



Note: The boundaries, colors, denominations and any other information shown on this map do not imply, on the part of the World Bank Group, any judgment on the legal status of any territory, or any endorsement or acceptance of such boundaries.
Source: WDI, South Asia Spatial Database (Li et al. 2015), DMSP-OLS, VIIRS, and World Bank staff calculations.

Table 5: Nightlight intensity is a poor lead indicator for quarterly GDP growth.

Indicator	Correlation with GDP		
	Observations	Contemporaneous	Lead
Manufacturing production	51	0.71***	0.56***
Industrial production	135	0.49***	0.43***
Exports	129	0.35***	0.30***
Business Confidence	39	0.32***	0.30**
Banking credit	97	0.32***	0.12
Stock market index	111	0.39*	0.43*
Services PMI	33	0.04	-0.05
Manufacturing PMI	32	0.07	-0.05
Nightlight intensity	36	-0.23	-0.03

Note: All indicators are in growth rates; for Business Confidence and Service and Manufacturing Purchasing Managers' Index we also tested levels and demeaned levels. For the first two the relationship is not significant, for the latter the relationship remains significant but weaker then for growth.
Source: All other data retrieved from Trading Economics.

Table 6: The lead indicator approach helps improve GDP growth forecasts.

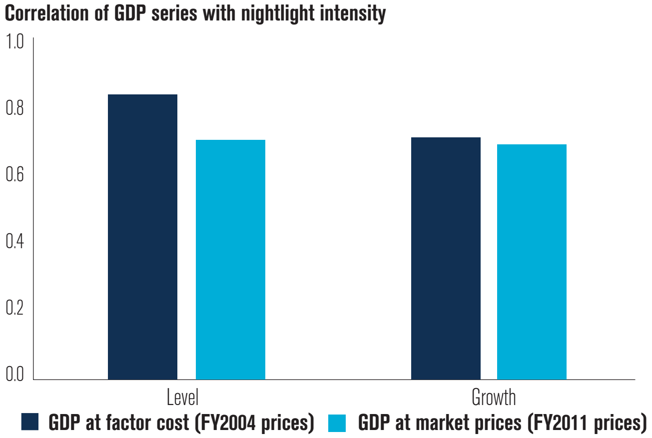
Forecast Evaluation		India		Sri Lanka	
		RMSE	MAE	RMSE	MAE
Simple benchmarks					
naïve	$\Delta GDP_{(t-1)}$	1.0	0.9	1.8	1.6
AR(1)	$\alpha GDP_{(t-1)}$	2.0	1.7	3.0	2.8
Single-variable models					
(1)	X_t = Industrial production	1.9	1.7	1.5	1.4
(2)	X_t = Manufacturing production	2.7	2.5		
(3)	X_t = Night lights growth	1.5	1.1	2.4	2.1
(4)	X_t = Export growth	2.2	1.9	2.9	2.6
(5)	X_t = Loan growth	0.7	0.5	6.8	6.0
(6)	X_t = PMI	1.1	0.9		
(7)	X_t = Business confidence	1.4	1.0		
Two-variable models					
(8)	X_t = Loan growth, industrial production	0.7	0.5		
(9)	X_t = Loan growth, manufacturing production	0.7	0.5		
(10)	X_t = Loan growth, nightlight growth	0.6	0.4		
(11)	X_t = Loan growth, export growth	1.7	1.6		
(12)	X_t = Loan growth, PMI	1.5	1.2		
(13)	X_t = Loan growth, business confidence	1.5	1.1		
(14)	X_t = Industrial production, nightlight growth			1.5	1.3
(15)	X_t = Industrial production, export growth			2.3	1.9
(16)	X_t = Industrial production, loan growth			6.9	6.4

Estimation Period: 2013Q2-2015Q4
Evaluation Period: 2016Q1-2017Q2
Forecasting Model: $\Delta GDP_t = \alpha\, \Delta GDP_{t-1} + \beta\, X_t + \varepsilon_t$
Note: RMSE = root mean squared error, MAE = mean absolute error.
Source: All other data retrieved from Trading Economics and World Bank staff calculations.

manufacturing and industrial production. Nightlight intensity, however, is not correlated over the whole sample period. While for India it is highly and significantly correlated over some periods, it never is for Sri Lanka.

However, in combination with other lead indicators nightlight intensity helps improve the precision of GDP growth forecasts. The lead indicators that individually forecast quarterly GDP growth the best, are banking credit in India and industrial production in Sri Lanka. A simple model combining each of these two lead indicators with nightlight intensity outperforms all other models combining these indicators with another. This model also does better than the naïve model based on GDP growth in the previous

Figure 45: In India both the old and the new GDP series are highly correlated with nightlight intensity.



Note: the correlations have been calculated using quarterly GDP data from the first quarter of FY 2011 to the second quarter of FY 2014. GDP at Factor Cost (FY2004) refers to the old GDP series, whereas GDP at market prices refers to the new GDP series.

quarter. In India, the model with banking credit and nightlight intensity has a 40 percent lower root mean squared error (RSME) over the forecast horizon than the naïve model. In Sri Lanka, the model with industrial production and nightlight intensity beats the naïve model by 15 percent.

Shedding light on recent economic episodes

Changes in nightlight intensity provide valuable insights on recent economic episodes whose assessment has so far been blurred by the lack of data. In recent years, South Asian countries have experienced relatively large shocks and innovations whose consequences are not fully understood yet:

- In 2015 India and Sri Lanka introduced **statistical revisions** that substantially changed the narrative about economic growth. Changes in the National Accounts methodology made a substantial difference in the reported GDP levels, generating debate on whether the old or the new series is closer to reality.

- Also in 2015, Nepal suffered two major **economic shocks**: a series of earthquakes, followed within months by a massive disruption of trade with India. Official statistics suggest that economic activity was severely affected. But the statistical system of Nepal is relatively weak, which raises questions about the real magnitude of the economic slowdown.

- In the same year, Afghanistan saw one of the most violent **conflict outbreaks** since the fall of the Taliban, the Battle of Kunduz. But this was by no means the only conflict episode experienced by the country. It is reasonable to assume that conflict affects economic activity, but there is not much evidence to determine by how much.

- Finally, in 2016 India went through demonetization, a **policy intervention** that withdrew large amounts of currency from the economy. While this intervention has potential benefits in the medium term, in the short term it might have affected economic activity. But it is difficult to tell what the short-term impact was, or how it was distributed across population groups.

Statistical revisions

In India and Sri Lanka GDP figures estimated based on both the old and the new methodologies overlap for quite some time. In India, data on quarterly GDP at market prices with base year FY2011 is available since the first quarter of FY2011, whereas quarterly GDP estimates at factor cost with base year FY2004 were only discontinued in the second quarter of 2014. Thus, the two series overlap for 14 quarters. In Sri Lanka, quarterly GDP at market prices with base year 2010 is available since the first quarter of 2010, whereas quarterly GDP at market prices with base year 2002 was still released until the last quarter of 2015. In this case, the two series overlap for 24 quarters.

The correlation between the old and new GDP series while they overlap allows assessing whether the two series tell a similar story. This type of analysis has been conducted in numerous opportunities. The innovation is to analyze the correlation between each of the two series and data on nightlight intensity. This exercise can help determine which of the two series captures economic activity better.

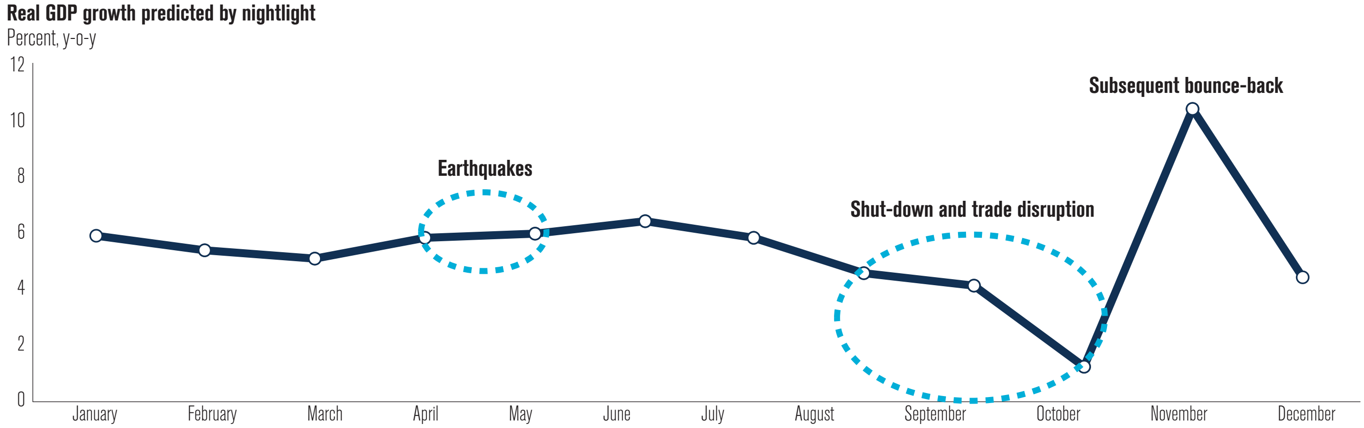
In the case of Sri Lanka, the exercise is unfortunately inconclusive. The correlation coefficient between the two quarterly GDP series is only 0.15, confirming that they tell very different stories. Moreover, none of the two quarterly GDP series is positively correlated with quarterly nightlight intensity.

In India, on the other hand, the old and the new quarterly GDP series are highly correlated, and they do a good job at tracking economic activity as measured by nightlight. If anything, the correlation coefficient with nightlight intensity is slightly higher for the old series, both when considering variables in levels or their changes. But the difference with the correlation coefficients obtained with the new series is not statistically significant. Importantly, the correlation coefficients between GDP series and nightlight intensity are high in absolute terms (in the order of 0.7 to 0.8), suggesting that India's National Accounts provide a relatively accurate picture of economic activity on the ground.

Economic shocks

With two major earthquakes in April and May, and a severe disruption of trade with India from August onwards, the

Figure 46: Trade disruption had a much larger impact on economic activity than the earthquakes.



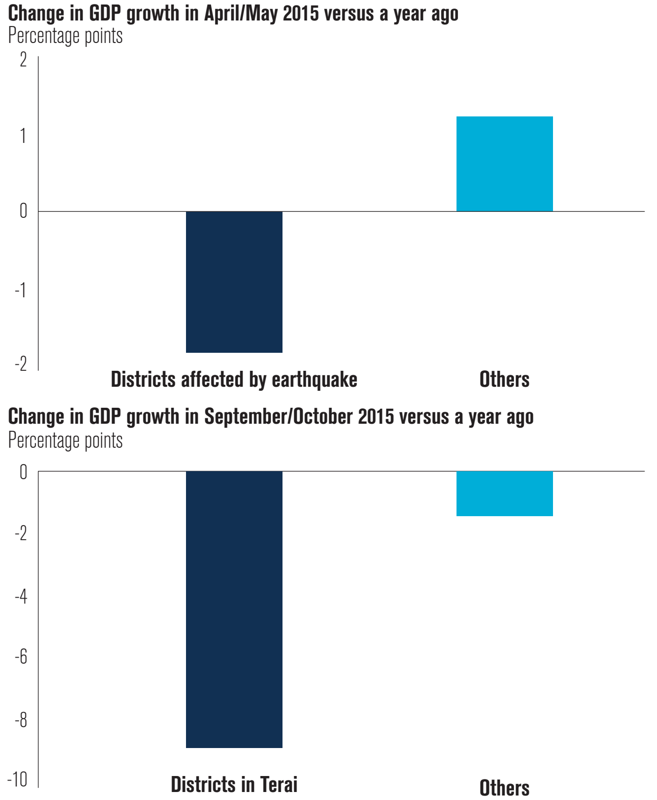
year 2015 was no doubt Nepal's most turbulent since the end of its armed conflict. The two earthquakes killed about 9,000 people, injured at least twice as many, and destroyed uncountable houses and buildings. Later in the year, dissatisfaction among the Madhesi minority about their representation under the new federal arrangements triggered protests that culminated in the complete shutdown of international trade with India. Official statistics put GDP growth for fiscal year 2015 - which started in July 2014 and covers the earthquake - at 3.3 percent and for fiscal year 2016 covering the trade disruption at 0.4 percent.

Based on monthly nightlight data, the economic impact of the 2015 shocks was smaller than official statistics suggest. The earthquakes affected most severely rural areas that were characterized by low nightlight intensity even in good times. The fact that these areas were mostly in the dark suggests that even if local impacts were large in relative terms, they may not have made a major difference at the aggregate level. The impact of the trade disruption, on the other hand, was massive. Based on the elasticity approach, from June to October 2015 the GDP growth rate of Nepal declined by 4 percentage points. But economic activity bounced back strongly in November, and over the full year the GDP growth rate might have declined by less than 2 percentage points.

The shocks had a more substantial impact at the local level. This can be seen by using the spatial approach to estimate GDP by district, and then comparing the performance of districts directly affected by the shocks to that of unaffected districts. However, instead of spatially distributing the official annual GDP, the methodology is applied to the monthly GDP estimated using the elasticity approach. This way of proceeding allows to assess local economic activity on a monthly basis.

In comparing growth rates at the district level, it is important to keep in mind that the locations most affected by the earthquakes, or most affected by the trade disruptions,

Figure 47: The GDP impacts of the shocks were substantial at the local level.

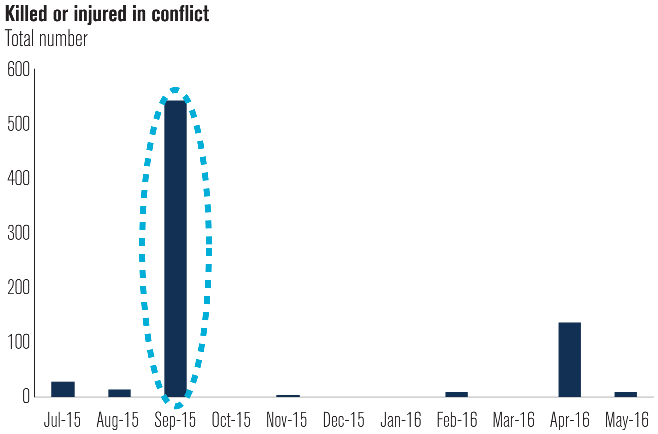


Note: Monthly predicted GDP is distributed across districts according to the spatial approach. The rates reported are the median growth rates among districts.

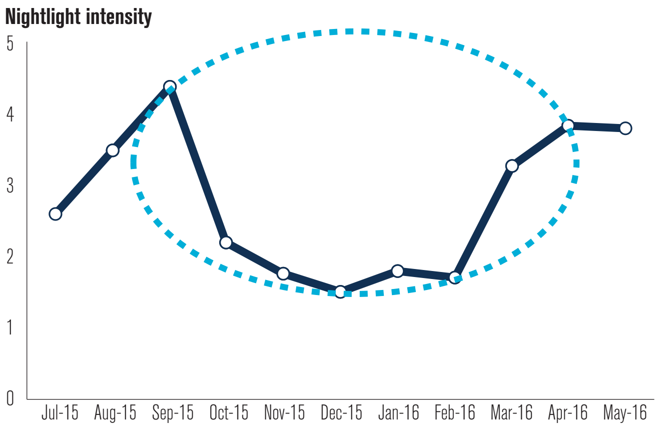
could be systematically different from other locations. As a result, they could grow at a different pace even in normal times. To address this possible bias, a "differences-in-differences" approach can be used.

The first difference is between the annual growth rate of local GDP in the two months following the shock and the annual growth rate in the same two months of the previous year. The two months considered are April and May in the

Figure 48: The deadly attack on Kunduz had a lasting impact on nightlight intensity.



Source: CSCW and Uppsala Conflict Data Program.



case of the earthquakes, and September and October for the trade disruptions. Growth rates are computed relative to the same two months one year earlier. This first difference can be called a growth shock, for brevity. The second difference is between the growth shocks experienced by affected and unaffected districts. The median growth shock across districts in each group is used for the comparison.

Based on this exercise, in April and May 2015 districts affected by the earthquakes experienced a decline in their local GDP by 1.8 percentage points, while unaffected districts grew slightly faster than before. And in September and October 2015, districts in the Terai region closer to India contracted by 9.0 percentage points, whereas the rest of the country saw GDP growth decline by a more modest 1.4 percentage points. These results confirm, once again, that the impact of the trade disruption was much more severe than that of the earthquakes.

Conflict outbreaks

On September 28, 2015, after a battle that had lasted for several months, the Taliban overran the Afghan military forces and took control of the city of Kunduz. During September alone, more than 500 people were killed or injured. The city was recaptured by government forces in a counter-offensive on October 1, but three days later the Taliban claimed to have regained control of most of it. Heavy fighting continued for several days before the Taliban finally withdrew on October 13. Nightlight data reveals that the battle for Kunduz had a strong and long-lasting effect on economic activity. Nightlight intensity declined strongly in October and remained low until March 2016.

A more systematic analysis of the impact of conflict on economic activity can be conducted combining nightlight data with conflict data at the district level. The number of casualties scaled by the local population provides a defensible measure of the local intensity of conflict. In parallel, the elasticity approach can be used to predict GDP at the district level, based on local nightlight intensity. With this information, it is possible to estimate whether surges in local conflict affect local GDP in the same month, quarter or year. The results suggest that one more dead or injured per 1000 people reduces local GDP growth by 9 percentage points in the same month. While the impact of conflict is not statistically significant over a one-year period, it is still sizeable and significant when the reference period is the quarter.

Policy interventions

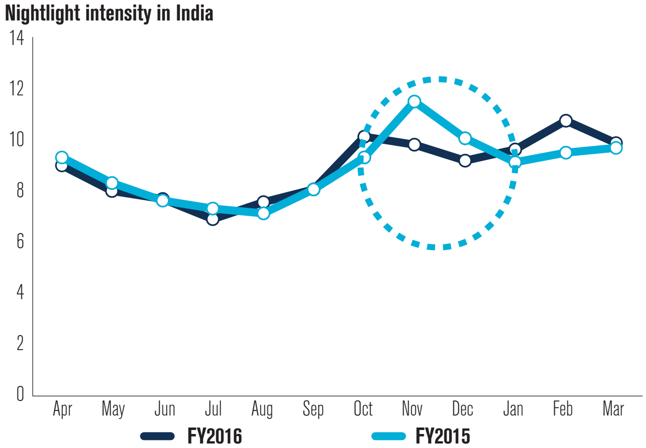
In early November 2016, all 500 and 1,000 rupee banknotes were declared invalid in India. During several months, liquidity was severely constrained. Demonetization, as it came to be known, aimed at curbing corruption and encouraging the use of electronic payments. There is clear agreement that it will take time to assess the extent to which these benefits materialized. But there is considerable

Table 7: Across districts, conflict reduces GDP growth for up to a quarter.

	2005-2016				2014-2016			
	Annual GDP growth	Annual GDP growth	Annual GDP growth	Annual GDP growth	Quarterly GDP growth	Quarterly GDP growth	Monthly GDP growth	Monthly GDP growth
Killed and injured (per 1000)	-1.194 (2.343)	-2.009 (3.025)	-1.306 (1.280)	0.986 (2.141)	-6.940** (2.370)	-5.541** (2.572)	-9.291** (3.309)	-8.675** (3.309)
District and year FE	no	yes	no	yes	no	yes	no	yes

Note: The regression is estimated for Afghan districts. GDP is predicted using night lights as described above. The number of injured and killed is from the CSCW and Uppsala Conflict Data Program.

Figure 49: The negative impact of demonetization was short-lived at the aggregate level.



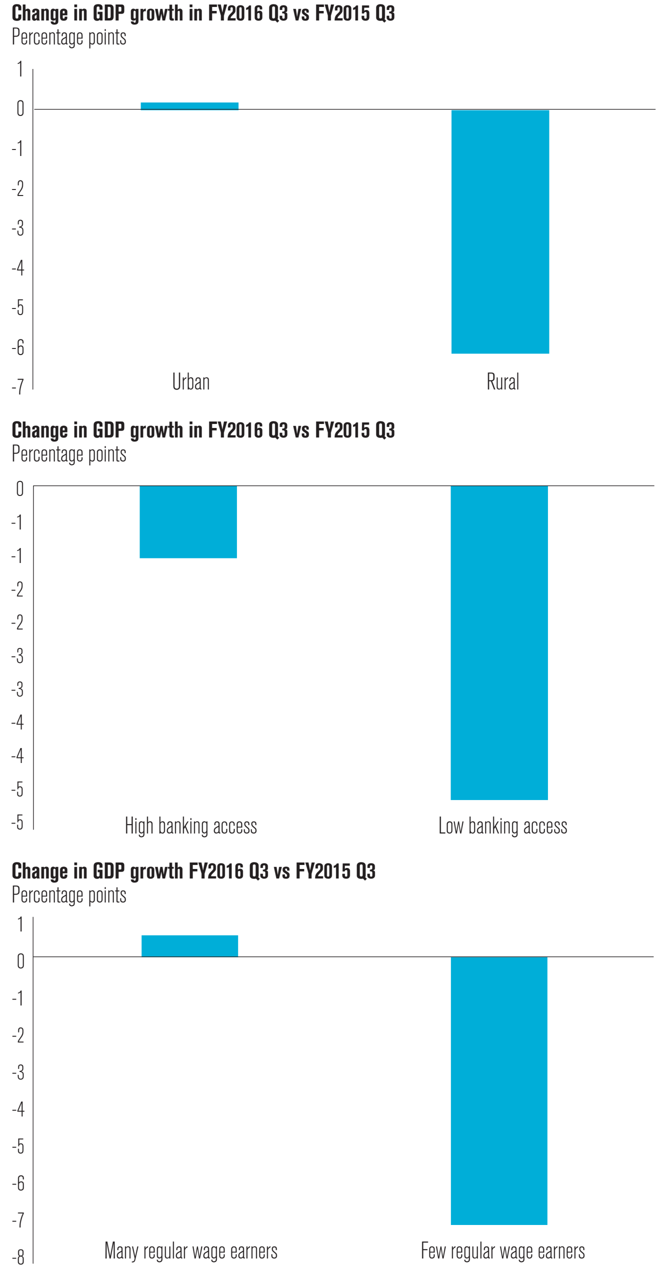
disagreement on how large the short-term cost of demonetization was, and which population groups were most affected. The shortage of relevant data partly explains why these issues are still being so lively debated. Nightlight data provides interesting insights in this respect.

At the aggregate level, a comparison of nightlight intensity in FY2015 and FY2016 suggests that demonetization had a small and short-lived effect on economic activity in India. There is a dip in nightlight intensity, but it only lasts for about two months.

On the other hand, the local impact was large in more informal districts, where cash must have played a more important role in supporting transactions. Identifying informal areas is not straightforward, but it seems safe to assume that informality is higher in rural districts, in districts with low access to finance, and in those where regular wage workers account for a lower share of total employment. The spatial approach is used to estimate quarterly GDP at the district level, based on local nightlight intensity and rural population. Local GDP levels are then used to compute local growth rates, and to assess how they were affected by demonetization.

In India's case there is evidence that poorer states grow more slowly, and these poorer states may also be characterized by higher levels of informality. If so, just comparing growth rates across formal and informal districts would overestimate the impact of demonetization. To address this possible bias, much the same as in Nepal's case, a "differences-in-differences" approach can be used. The first difference is between the local GDP growth rate in the third quarter of FY2017 and in the previous year (considering the average growth rate of the three previous years instead did not change the results). As before, this first difference represents a growth shock. The second difference is between the growth shocks experienced by more and less informal districts.

Figure 50: The performance of more informal districts was temporarily worse after demonetization.



Note: Quarterly GDP is distributed across districts according to the spatial approach outlined above. The rates reported are the median growth rates among districts. The socio-economic variables are from the South Asia Spatial Database (Li et al. 2015).

The results suggest that more informal districts performed worse. The difference in local growth relative to a normal year was very small in urban districts, as well as in those with greater access to finance and with more prevalent regular wage employment. On the other hand, more informal districts experienced drops in local GDP in the range of 4.7 to 7.3 percentage points. These shocks were temporary, so that their impact on the annual GDP of the affected localities was probably modest. But in the short term the local impact was sizeable.

Toward stronger statistical systems

Data on nightlight intensity, and big data more generally, have the potential to improve substantially the measurement and understanding of economic developments. Nightlight data captures informal economic activity, it is available at high levels of spatial disaggregation, it can be obtained in almost real time, it is relatively cheap to acquire, and it is not subject to politically-motivated interference. The same can be said of other forms of big data, from land classification to cell phone traffic, and from administrative databases to internet scraping. New technologies provide the opportunity for a qualitative jump in the amount and type of data that can be processed. Integrating "old" and "new" sources, as was done in the analyses above, provides new insights, and could support a greater emphasis on evidence-based decision making. This is an especially promising prospect in developing countries, where capturing the informal sector is very challenging.

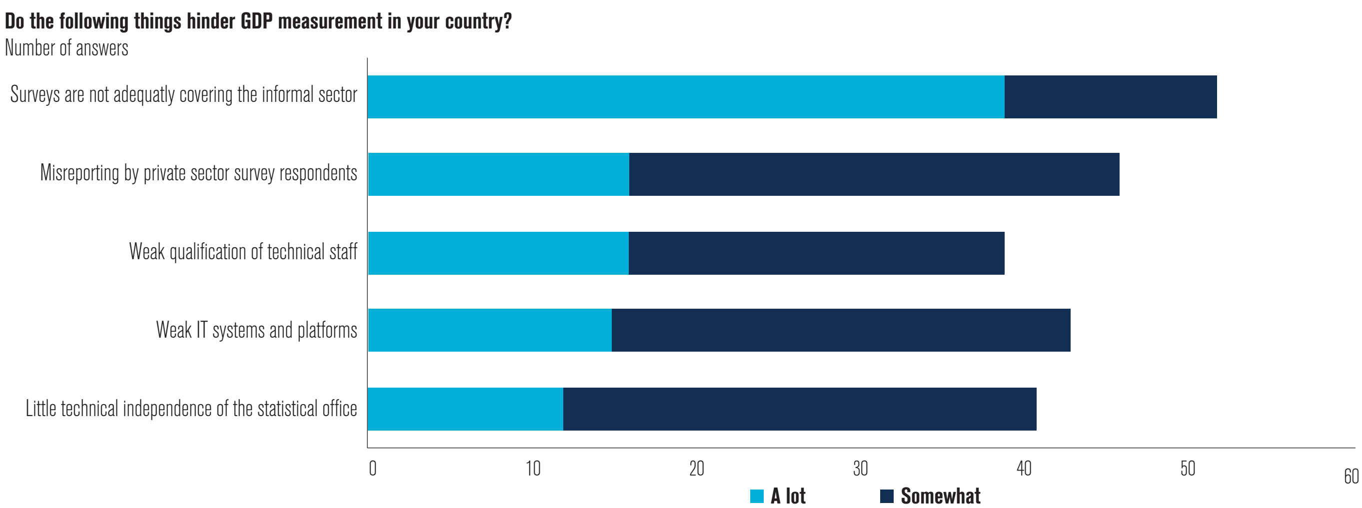
However, the "data revolution" under way requires more than just a good grasp of technology: it is, above all, an institutional reform agenda. Statistical agencies are a much more central part of the service delivery machinery than is generally acknowledged. The availability of high-quality data, which can be easily accessed without impinging on privacy or breaching confidentiality, is an extremely valuable public good. Tech-savvy private sector players are an important part of the data architecture of a country. They help push the frontier with their innovations, and develop new products for subsets of customers who can afford them. But the provision of reliable high-quality data as a public good is likely to remain with statistical agencies for the foreseeable future. The "data revolution" requires their institutional and technological upgrading, so that they can play this role effectively.

There is a long tradition of economic measurement based on censuses and surveys, and South Asian economists and statisticians were at the forefront of this approach. As of late, efforts to modernize statistical systems have mostly emphasized a deepening of this model: more frequent surveys, standardized definition of variables, piloting of new questionnaires, capture of responses through tablets rather than paper questionnaires… There has generally been less emphasis on other potential upgrades, including the systematic geo-referencing of data, or the linking of government databases. It is as if new rooms were being piled up on top of an old building to accommodate new functions, rather than a new modern building being designed with its updated functions as the organizing principle.

Researchers and practitioners in South Asia are well aware of the challenges faced by statistical agencies in their countries. In a survey conducted for this report, views were sought on the obstacles GDP measurement faced in their country. The inadequacy of survey instruments to capture the formal sector was seen as the most important challenge, closely followed by misreporting by survey respondents in the formal sector. Technological challenges were mentioned, but they did not come at the top of the list. Constraints which are more institutional in nature, such as the poor qualification of technical staff and the limited independence of their offices, were also seen as key obstacles. These responses suggest that an integrated response is needed to make statistical measurement more credible, and that technology is not the silver bullet that will solve all problems.

In developing countries, the upgrading of statistical agencies has often been approached in an

Figure 51: GDP measurement faces challenges that can be overcome.



Source: World Bank South Asia Economic Policy Network.

South Asians were pioneers in economic measurement

From the 1960s to the 1980s, distinguished economist and statisticians from the region were at the forefront of statistical development and the adoption of new metrics. Instruments and indicators which are widely used by now are connected to South Asia to a much greater extent than is generally recognized. Indeed, the priority given these days to the fight against poverty and the improvement of living standards more broadly could be easily taken for granted. But it was not always this way. A few South Asians were instrumental in articulating this agenda, and developing the measurement tools needed to make it operational.

Mahbub ul Haq (1934-1988) was a Pakistani economist. He studied at Cambridge University – where he developed a lifelong friendship with Indian economist Amartya Sen, a Nobel-Prize winner – and subsequently at Yale and Harvard Universities. In the 1960s, while still in his 20s, he became the Chief economist of Pakistan. He had a keen interest in the distribution of income and wealth, conducting research on how two dozen family groups had come to dominate Pakistan's economy.

In the 1970s, ul Haq served as the chief economic adviser to Robert McNamara, the President of the World Bank. There he influenced the World Bank's development philosophy for several decades to come. Ul Haq helped convince McNamara that development should focus on raising living standards and that poverty alleviation could be a cause, rather than a consequence, of economic development. This view was embraced by McNamara in his watershed "Nairobi address", in 1973.

In 1988, after having served as Finance Minister of Pakistan, ul Haq worked with the United Nations Development Program, where he led the establishment of the Human Development Report. In the process, he articulated the now-popular Human Development Index (HDI), a measure of economic and social development that combines monetary and non-monetary dimensions of wellbeing. The HDI is arguably the precursor of modern Multidimensional Poverty Indices.

Prasandra Chandra Mahalanobis (1893-1972) was an Indian scientist and statistician. Born in what is nowadays Bangladesh, he did his undergraduate courses in Calcutta and then studied at the University of London. In 1932, together with two other university professors, he created the Indian Statistical Institute (ISI), registered as a non-profit learned society. After India's independence, ISI was declared as an institute of national importance, with the rank of a university.

At ISI, Mahalanobis conducted pioneering studies in anthropometry, examining the role of caste in stunting. In the process he developed a new multidimensional distance metric, nowadays known as the Mahalanobis distance. But his best-known contribution was the development of the modern household survey. Mahalanobis was keen to produce a credible snapshot of living standards at the district level, and this at a time when many Indian districts did not even have a road connecting them.

In the words of Angus Deaton, another Nobel Prize-winner, India became "the motherland of household surveys". The approach developed by Mahalanobis was subsequently scaled up by the World Bank, under the Living Standards Measurement Project. It did not take long to realize that surveys of this sort could provide the basis for reliable poverty measurement. Another distinguished Indian economist who was by then working with the World Bank, Montek Singh Ahluwalia, contributed to the development of the seminal "one-dollar-a-day" metric.

In all these ways, distinguished South Asians shaped the notion that living standards could be credibly measured even in poor countries with very large informal sectors. Their approaches shaped statistical development for several decades. It can only be hoped that a new generation of South Asian economists and statisticians will play a similar role now, when new technologies and the availability of big data pave the way to revamping economic measurement.

"extractive mode", rather than with a reform mindset. Quite often a donor or an international organization is interested in a specific metric, a trust fund is mobilized to cover the cost, and a new survey is conducted. The Sustainable Development Goals, with their long list of policy-relevant indicators, represent an important step forward, as they implicitly benchmark the statistical systems in terms of what they are expected to deliver. But in other development areas the international community has been more ambitious. Entire programs have been designed to help developing countries liberalize international trade, unbundle infrastructure sectors, or revamp social security systems. These programs combine policy dialogue, technical assistance and sizeable financial resources under the form of a long-term engagement. But such programs have been the exception more than the rule when it comes to statistical upgrading.

Building trust in citizens that official statistics do not come "out of the blue" is an integral part of the development agenda, but this requires a clear strategy. The first step is upstream, by enshrining the technical independence of statistical agencies and by clarifying their reporting lines to the rest of the government. Also upstream is the adoption of rules striking the right balance between access to information and the protection of privacy. Then comes the statistical development strategy of the country, a compact that needs to be brokered at a high level, as an integral part of the country's overall growth strategy. The next step concerns business process engineering, designing an institutional form that brings together the multiple sources of data available, including big data, in a way that ensures their alignment with the strategy. Caricaturing slightly, technology is the final step in this chain; a very important step, but not the driver of the process.

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