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Economic Rise and Decline in Indonesia – As Seen from Space

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Abstract

Satellite-detected luminosity is sometimes used to proxy for economic activity although only recently within the mainstream economics literature (Henderson et al., 2012). If this method works it holds great promise for developing countries with weak statistical systems that face difficulties in consistently measuring long-term economic change. Regardless of how chaotic are statistical efforts on the ground, viewed from space it may be possible to detect economic change, with high frequency and for small areas. But doubts remain about how much trust can be put in night lights data as a proxy for economic growth since previous validation attempts just compare with other error-ridden measures (Henderson et al., 2012; Chen and Nordhaus, 2011; Kulkarni et al., 2011). This paper uses gold standard data on electrification and economic growth for 5000 sub-districts in Indonesia from 1992 to 2008 to evaluate the reliability of night-light based measures of local economic change. Our results also contribute to debate in the literature about the severity of the shock to Indonesia from the Asian Financial Crisis of 1997 and the subsequent rate of rebound in economic activity.

Keywords: Economic Growth, Luminosity, Measurement Error, Indonesia

JEL: O47, C52, E31

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"*Cities, like cats, will reveal themselves at night"* – Rupert Brooke, *Letters from America,* 1916

I. Introduction

Economic change is hard to measure and thus hard to diagnose. When a country suffers a crisis the priorities of the moment usually do not include accurate statistical measurement of either economic activity (GDP) or household incomes. Moreover, the most crisis-prone countries, in sub-Saharan Africa, have the weakest statistical systems (Deaton and Heston, 2008). Rapidly growing economies also have difficulties with accurate measurement, especially when their statistical systems cannot cope well with the emergence from central planning (Ravallion and Chen, 1999). The difficulties multiply when comparisons are attempted over either time or space, since price indexes are then needed to convert monetary values between time periods or between regions and such indices typically have severe biases (Gibson et al., 2008).

But for the past three decades, one indicator of economic activity – light emissions – has been observed nightly by satellites, for areas smaller than one square kilometre (Croft, 1978). These data are available for the entire surface of the Earth subject to human settlement (between latitudes 65 degrees North and 65 degrees South) and can be aggregated to village, town, city or district level. Since it is possible to compare with the light emitted from the same area in a previous period, these satellite images provide a readily available proxy for changes in local economic activity. Thus regardless of how chaotic are statistical efforts on the ground, viewed from space it is possible to detect economic decline (and improvement), with high frequency and for very small areas.

Changes in light intensity correlate well with dramatic economic changes at the national level, such as the market transitions of the former Soviet countries (Henderson et al, 2009). But there is much less experience with using changes in night lights as a proxy for economic changes at the sub-national level (Ebener et al, 2005). Yet researchers are greatly interested in the causes and consequences of growth at the sub-national level; to test theory (Dercon, 2004), to find geographical poverty traps (Jalan et al, 2002) and to evaluate broader growth-promoting interventions than those possible in cross-country studies (Dercon et al, 2009). Therefore economists and statisticians have invested heavily in methods for forming small-area income estimates (Elbers et al, 2003).

Hence data on night lights could greatly advance research at quite low cost. But economists are not sure if they can trust such data. Previous validation attempts just compare night lights with other error-ridden measures, such as mis-measured GDP growth (Henderson et al, 2009; Chen and Nordhaus, 2010) or crude household asset indicators (Noor et al, 2008). Opportunities to formally test the validity of this approach remain rare due to lack of appropriately detailed data. To fill the gap in the existing literature, this paper uses gold standard data on electrification and economic growth for 5000 sub-districts in Indonesia from 1992 to 2008 to evaluate the reliability of night-light based measures of economic change. Indonesia is, in many ways, an ideal context for such a study because: 1) it electrified rapidly, going from less than 10% of the rural population having access to electricity in 1980 to over 80% in 2001 (Gibson and Olivia, 2010); 2) it is data-rich, with a triennial village census (Olken, 2009) letting us cross-validate ("ground-truth") satellite images of night light with other measures of electricity use; 3) a financial crisis in 1997 caused a collapse in Indonesia's economy after earlier rapid growth (Hill and Shiraishi, 2007); and 4) there is debate about the severity of this shock and subsequent rate of rebound in economic activity due to bias in the price deflators used for long-run comparisons in Indonesia (Olivia and Gibson, 2013).

The rest of this paper is organized as follows. In Sections II, we provide a brief description of the night lights data. Section III describes the village censuses that we use in the paper to validate the accuracy of night lights as a surrogate for economic activity. In section III, we provide a robustness check where we use the patterns of economic growth that are obtained using both the satellite data as well as the village censuses and benchmark them against data on income, expenditure and other proxy measures of welfare derived from Indonesia's longitudinal household survey. Hence, these results allow us to examine how welfare changes as the economy changes over time in Indonesia both at the national and sub-national levels.

II. Night-time Lights Data

Satellite images of the earth at nights use in this paper come from the Defence Meteorological Satellite Program (DMSP). DMSP is a series of weather satellites that capture high resolution images of night lights across the globe every night. These satellites have been circling the earth 14 times per day recording the intensity of Earth-based lights with their Operational Linescan System sensors since the 1970s, with a digital archive beginning in

1992. These sensors are designed for low light detection as they were initially developed to identify clouds that have been lit up by the moon for meteorological reporting. An additional product is that lights from human settlements are recorded, and composite yearly global images have been produced since 1992 that are cloud free. The spatial resolution varies across the globe but is approximately at the 1km^2 equator, with each pixel encoded with a relative measure of its annual average brightness on a 6-bit scale from 0 to 63.All 30 composite night light images available between 1992 and 2009 were downloaded and inter-calibrated using the method described by Elvidge et al. (2009). These images are overlaid with digital map of Indonesia and processed into a series of annual composite images identifying time stable night lights in each year from 1992 to 2009 (Doll, 2008). Using the available sub-district digital boundaries files, we calculate the mean light intensity for Indonesia's sub-districts using a zonal mean function.

Doll et al (2006) and Sutton et al. (2007) suggest that sum light as a good proxy to estimate GDP at the sub-national levels. The logic is that a region with increased business activity has brighter lights at night which leads to higher brightness values in the night-time imagery. Furthermore, greater business activity is likely indicative of relatively greater wealth

Figure 2 illustrates the distribution of mean light intensity for Indonesia across time. The figure itself suggest that lights reflects human economic activity as pointed out by for example Croft (1978), Elvidge et al. (1997), Sutton and Constanza (2002), and Sutton et al. (2007). In Figure 2, unlit areas are black and lights appear with intensity increasing from grey to white. Lights in an area reflect total intensity of income, which is increasing in both income per person and number of people. As can be seen from the Figure, the living standards in Indonesia do not seem to spread equally across the regions – in which we detect the higher concentration of lights in Java in comparisons to other major islands in Indonesia. Not only that Java is the most developed island in Indonesia, it is also has high population densities of around 1,064 person/km^2. Figure 1 also enable us to say something about the path of economic development in Indonesia. Over ther period of 1992 – 2008, the development in Indonesia seems to concentrated on two islands (Java and Sumatra, in which Sumatra starting to catching up with Java). Over the time period being considered, there seems not much economic development happening in the Eastern region of Indonesia, which is consistent with previous studies on lagging behind regions in Indonesia (e.g. Vidyattama, 2012)

Table 2 provides a more detailed distribution of the data, in which it also describes the distribution of digital numbers for 4,900 sub-districts in Indonesia over the period of 1992 and 2008. The temporal patterns of satellite observed night-time lights can be viewed as a way to tracking the economic development process of a nation. In developing countries the lighting may go up and down from year to year in an erratic pattern or it may be more stable showing neither an upward or downward trend. Lighting can be lost following catastrophic event for instance economic collapse. As evidenced from Table 2, changes in night light were quite rapidly during the early 1990s, but then we evidence of dimming of light in the late 1990s as a result of the Asian Financial Crisis that hit Indonesia quite severely. The percentages of the light on a year-on-year basis drop by 2 percent and 5 percent from 1996-1997 and 1997-1998 respectively. Since then, we see a decreasing pattern in the average intensity of light until it drops by almost 13 percent between 2002 and 2003. The slowing down of Indonesia economy could be due to outbreaks of the SARs epidemic in other parts of East Asia which harmed inbound tourist travel (MacIntyre and Resosudarmo, 2003).

Table 2 also shows us the proportion of unlit areas (denoted with Digital Number = 0) has been decreasing over time – in 1992, 67 percent of sub-districts in Indonesia were unlit but this number has been substantially dropped to 39 percent. The top-lit area [those with Digital Numbers above 63] has been increasing over the year, noting that most of sub-districts with high night-light intensity are concentrated on Java Island throughout the year and on some parts of Sumatra during the later years.

III. Village Census Data (PODES)

The second source of data used in this paper is the Indonesian Village Census (PODES). PODES is a long-standing tradition of collecting data at the lowest administrative tier of local government conducted triennially. It collects detailed information on a range of characteristics – ranging from infrastructure to village finance for Indonesia's current 69,000 villages and neighbourhoods. The advantage of using the PODES data for this project is that it provides a complete enumeration of measures electricity use in all villages, towns and cities for the last two decades. It is very rare to find such detailed information especially on infrastructure census at the lowest administrative level for a country. The PODES data thus [illegible]

[illegible]

[1] Since the implementation of decentralization in 2001, the numbers of administrative units in the regions (province, district, sub-district and village) have been increasing tremendously. Prior to the decentralization, the number of provinces was 27, districts 297, sub-districts 4,200 and villages about 65,000. At present, the number of provinces is 33, districts 497, sub-districts about 7000 and villages about 75,000. Given that we are interested in looking at economic growth overtime, we use 1993 as our base for the administrative boundaries. Any newly created administrative regions were coded such that they match with the 1993 conditions.

$$y_i = y_i^* + \varepsilon_i \qquad (1)$$

y_i^*

ε_i

$\sigma_{y^*}^2$ ε_i

σ_ε^2

$$\begin{aligned} x_i &= \beta y_i^* + u_i \\ &= \beta(y_i - \varepsilon_i) + u_i \end{aligned} \qquad (2)$$

[illegible]

[illegible] β

[illegible] β

[illegible]

$$\tilde{\beta} = \left(\frac{\sigma_{y^*}^2 + \sigma_{\varepsilon}^2}{\sigma_{y^*}^2} \right) \hat{\beta} \qquad (3)$$

[illegible] $\hat{\beta}$

[illegible] $\hat{y}_i^*$ [illegible]

$$\hat{y}_i^* = \frac{1}{\tilde{\beta}} x_i \qquad (4)$$

[illegible] $\tilde{\beta}$ [illegible]

[illegible]

[illegible]

VI. Conclusions and Discussions

[2] In a recent ERA 2010, the department itself scores a "4" (=performance above world standard), equally with the University of Melbourne and Australian National University.

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Figure 1. Night Lights for Indonesia, Selected Years

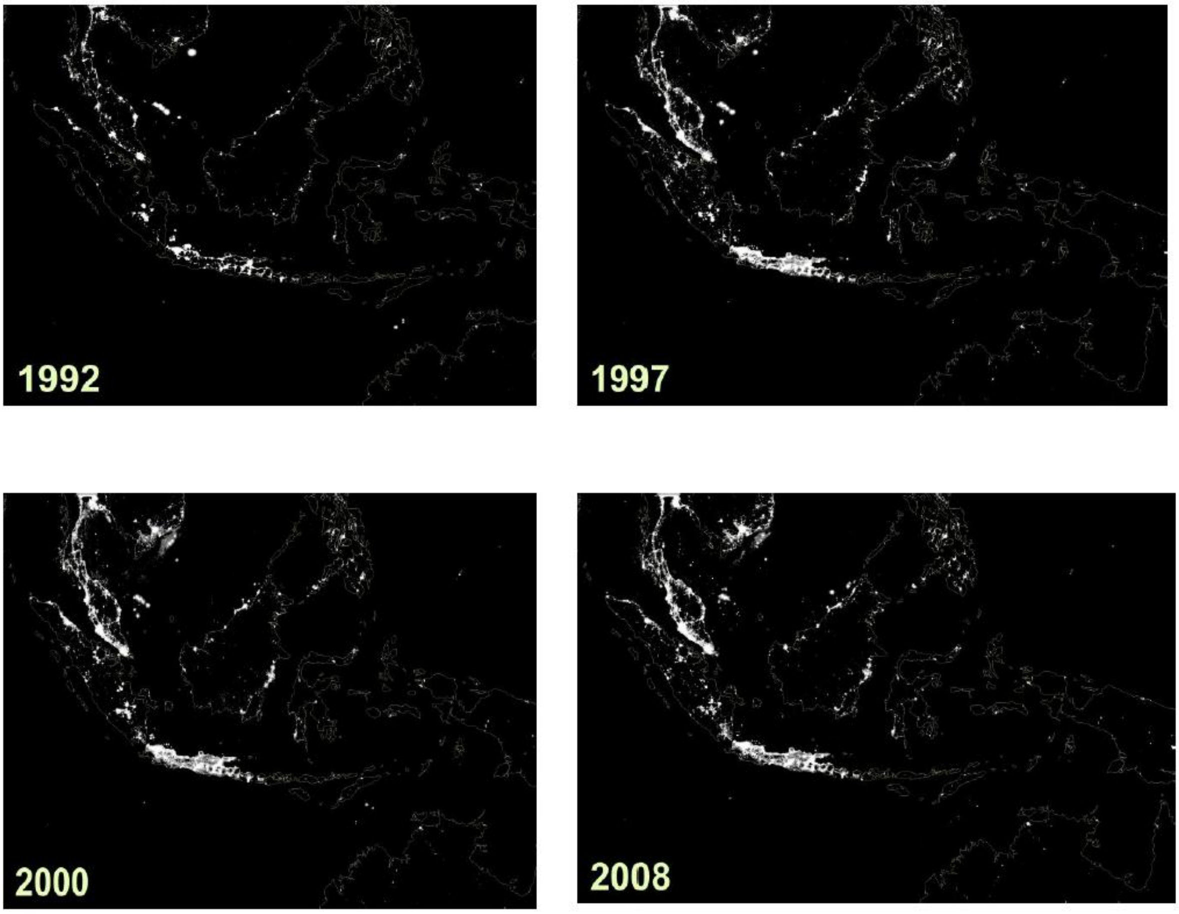

Table 1. Night Lights Data for Indonesia, 1992 - 2010

Year	Average Digital Number [DN]	% Change [Year-on-year]	% of observations with the following digital numbers: [DN 0]	[DN 1-2]	[DN 3-5]	[DN 6-10]	[DN 11-20]	[DN21-60]	[DN 61-63]	*N*
1992	4.54	n.a.	66.66%	5.32%	7.00%	9.73%	4.81%	4.96%	1.52%	*4,877*
1993	5.94	30.72%	50.53%	8.09%	12.34%	15.43%	5.97%	5.50%	2.14%	*4,877*
1994	6.28	5.68%	45.48%	13.90%	10.38%	14.85%	6.90%	6.06%	2.43%	*4,877*
1995	7.51	19.61%	44.63%	7.65%	11.16%	17.68%	8.54%	7.55%	2.81%	*4,877*
1996	7.52	0.11%	43.11%	7.96%	12.31%	18.34%	8.22%	7.08%	2.98%	*4,877*
1997	7.37	-2.02%	37.43%	11.78%	15.05%	18.02%	7.99%	7.12%	2.62%	*4,877*
1998	7.01	-4.83%	38.79%	11.29%	13.94%	19.81%	7.12%	6.54%	2.50%	*4,877*
1999	7.15	1.95%	38.99%	10.83%	10.99%	21.80%	8.34%	6.86%	2.19%	*4,877*
2000	7.23	1.15%	36.26%	9.69%	14.12%	22.70%	8.36%	6.95%	1.92%	*4,877*
2001	7.47	3.37%	34.62%	10.28%	14.01%	23.03%	8.87%	7.10%	2.10%	*4,877*
2002	7.88	5.44%	34.68%	10.34%	12.73%	22.15%	9.90%	7.91%	2.29%	*4,877*
2003	6.86	-12.99%	35.50%	12.10%	18.10%	18.38%	7.19%	6.85%	1.88%	*4,877*
2004	7.30	6.45%	33.92%	11.43%	17.58%	19.95%	7.94%	6.94%	2.25%	*4,877*
2005	6.68	-8.52%	34.33%	12.54%	20.91%	17.02%	6.80%	6.86%	1.54%	*4,877*
2006	7.64	14.47%	35.10%	10.69%	16.08%	19.58%	8.62%	7.44%	2.49%	*4,877*
2007	7.59	-0.72%	36.36%	10.41%	16.27%	18.69%	8.22%	7.77%	2.28%	*4,877*
2008	8.21	8.26%	39.08%	7.47%	13.00%	20.25%	9.34%	7.70%	3.16%	*4,877*
2009	8.18	-0.48%	39.03%	7.21%	13.87%	19.71%	9.20%	8.48%	2.51%	*4,877*

* Summary statistics are aggregated by sub-disctricts (*kecamatan)*

** Figures are calculated within satellite-years, averaged across satellites within a year

	Podes 1993	Podes 1996	Podes 2000	Podes 2003
Regional Income (*in 000 Rp*)	n.a.	210,000	n.a.	519,000
Number of Households	8513.53	9190.15	9831.88	10881.51
Population	40595.62	42893.67	42702.99	45258.00
Area (in km^2)	353.74	344.83	351.66	419.78
Population density (people per sq km)	168.45	170.86	160.00	167.29
Main source of income: agricultural sector	0.88	0.86	0.86	0.84
Village infrastructure				
Asphalt road	0.56	0.58	0.56	0.56
Gravel road	0.20	0.21	0.25	0.26
Dirt road	0.15	0.14	0.12	0.12
# of electricity subscribers (HHs)	3836.58	4918.89	6604.74	7251.06
Proportion of HHs subscribed to electricity	0.35	0.44	0.58	0.59
Drinking water source:				
Piped	0.11	0.13	0.12	0.13
River	0.11	0.10	0.09	0.08
Well	0.56	0.52	0.51	0.51
Cooking fuel used by the majority of the population:				
LPG	0.01	0.01	0.01	0.02
Kerosene	0.01	0.18	0.23	0.31
Wood	0.15	0.81	0.75	0.66
Number of observations	4877	4877	4877	4877