Measuring population mobility speed from space

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Abstract

Ad-hoc population dynamics in Krugman's type core and periphery models adjust population share of a region, based on its real wage rate deviation from national average, at pre-specified speed of population mobility. Whereas speed of population mobility is expected to be different across countries, for geographical, cultural, technological, etc. reasons, one common speed is often applied in theoretical and simulation analysis, due to spatially patchy, and temporally infrequent, availability of sub-national regional data. This article demonstrates how, increasingly available, high definition spatio-temporal remote-sensing data, and their by-products, can be used to measure speed of population mobility in national and sub-national level.

Keywords: regional data, regional migration
JEL classification: R10, R23

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Measuring Population Mobility Speed from Space

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Ad-hoc population dynamics in Krugman's type core and periphery models adjust population share of a region, based on its real wage rate deviation from national average, at pre-specified speed of population mobility. Whereas speed of population mobility is expected to be different across countries, for geographical, cultural, technological, etc. reasons, one common speed is often applied in theoretical and simulation analysis, due to spatially patchy, and temporally infrequent, availability of sub-national regional data. This article demonstrates how, increasingly available, high definition spatio-temporal remote-sensing data, and their by-products, can be used to measure speed of population mobility in national and sub-national level.

(JEL R10, R23)

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Unavailability of high definition spatio-temporal data regularly poses major limitations on quantitative analyses of sub-national regions in the social sciences. For instance, the population census, a major source of information on population mobility, is usually carried out once in a decade in developing countries. Although national statistics are often available on a yearly basis through the interpolation and/or extrapolation of sample surveys and administrative data, statistics at finer or lower administrative levels are generally available only at much lower temporal frequency. This is because the spatial and temporal costs of ground-based surveys are both marginally high. In other words, each can only be improved at the expense of the other. At a particular cost level, therefore, a study of sub-national inter-regional mobility has to choose between covering large areas less frequently and focusing on smaller regions more frequently.

Time series sub-national regional population data is a prerequisite in inter-regional population mobility analysis. The spatio-temporal resolution of such data inevitably imposes significant constraints on a population mobility study. In a study of migration from the rural areas of the upper Midwest region of the USA (Sjaastad 1962), for example, between 1% and 5% of the regional population of several age ranges were reported to have emigrated from those regions in the 1950s and 1960s. The spatial coverage involved a part of USA whereas the temporal frequency was decadal. For 11 regions in the UK between 1981 and 2000, Hatton and Tani (2005) reported a decadal population mobility of between −0.73% and 0.71%. Here, the temporal frequency is likewise decadal. The spatial resolution, however, applies to the whole UK, albeit divided into 11 regions, or approximately 22 thousand square kilometers. In analyzing inter-provincial migration in Vietnam from 2004 to 2009, Nguyen-Hoang and McPeak (2011) could use semi-decadal frequency only because of a census question that asked where the respondent had lived five years earlier. The average spatial resolution of the data is approximately 3,450 square kilometers because there are 96 provinces in Vietnam in 2009. A province that manages to receive a disproportionately high share of foreign direct investment (FDI) is reported to have a net-inflow rate of more than 300% between 2004 and 2009. Yang (2004) studies two-year inter-provincial migration in Thailand from 1998 to 2000. However, the household income data used in this study is based on a sample survey of merely 10,000 to 20,000 out of a total of more than 15 million households for the whole of Thailand. The emigration data, organized by village, numbered between about 50,000 and 60,000 households, but the data on destination is limited to the most common one. As a result, Yang (2004) has a relatively high temporal frequency but significantly patchy spatial coverage.

Obviously, other kinds of data, or factors influencing population mobility, are also necessary. The regional wage rate, for instance, is technically more difficult and financially costly to produce and obtain. At the prevailing pace of the advancement of transportation technology, and relatively high spatio-temporal marginal costs, it is unlikely that high definition spatio-temporal ground-based data can soon become widely available at an affordable cost.

To overcome such limitations of ground-based data, this article offers an innovative approach that takes advantage of remote-sensing data and their by-products. The data and information are derived from but not limited to satellite imageries that have low marginal, spatial, temporal, processing, and distribution costs. Spatially, it does not take much additional cost for a satellite stationed several hundred kilometers in space to capture images of a district, a state, a country, or an entire continent. Temporally, many satellites can cover the whole globe in a matter of day, incurring not so different additional cost as if the satellites observed the same spot all day long.

Using two sets of high definition spatio-temporal data sets, namely, gridded global population data LandScan, and nighttime light DMSP-OLS, this article demonstrates how the population mobility speed can be estimated at different administrative levels in 10 ASEAN countries. We have selected the ASEAN countries to explain and demonstrate our methodology because they form a region with which we are most familiar. But, in fact, with the spatio-temporal coverage of the above data sets, we can apply our methodology to any other country, region or community that is larger in area than about 1 km by 1 km.

The rest of this article is structured as follows. Section I describes LandScan and nighttime light DMSP-OLS. Section II presents, mostly, visualized statistical summaries of population mobility data derived from LandScan. Section III assesses the results of our estimates. And Section IV concludes with a discussion of the scope and implications for further research.

I. The Data – From Ground to Space

Theoretically, macro factors, such as real wage rates, unemployment rates, distances, and micro factors, including age, languages, culture, etc., are hypothesized to have impacts on inter-regional migration (Sjaastad 1970; Harris and Todaro 1970; Barro and Sala-i-Martin 1992; Fujita et al. 2001). Nevertheless, none of these kinds of data, which are obtained from ground-based surveys, is available with high spatio-temporal definition and global coverage. Since our objective is to measure population mobility speed, for selected countries or sub-national regions, we cannot rely on spatially patchy and temporally infrequent ground-based data. Instead, we use high definition remote-sensing data. The problem is, remote-sensing data is spatio-temporally high definitive but it is not generally collected or designed to suit most requirements of social science. To solve this problem, we provide a theoretical formulation of inter-regional population dynamics which only require data that can be met by available remote sensing data.

Fortunately, we can begin with the inter-regional population mobility dynamics surrounding Krugman's type core and periphery model that only requires real wage rate and population figures (Fujita et al. 2001). Equation (1) is the, most common form of ad-hoc population dynamics used in Krugman's type core periphery models.

(1) $$\dot{\lambda} = \gamma(\frac{\omega_r}{\bar{\omega}_r} - 1)\lambda_r$$

where … λ_r and $\dot{\lambda}_r$ are population share and its rate of change in region r. ω_r and $\bar{\omega}$ are real wage rate in region r, and its average. γ is the speed of population mobility.

From equation (1), it is easy to see that the regional population share, and the wage rate and its average often depend on a subjectively selected geographical unit of analysis – a problem called the Modifiable Arial Unit Problem (MAUP) which has been clarified and discussed in detail, for instance, in Briant et al. (2010). We will later address this problem in our estimation. But there are reasons other than MAUP for finding different mobility speeds. Economically, if similar transport technology is utilized, the transport costs should differ among countries because of different relative prices. Furthermore, non-economic factors, such as languages, cultures, preferences, etc. should also affect mobility. For instance, Recchi (2008) reports a much lower mobility among EU states than in USA, even if the geographical scale is much smaller. Nevertheless, in practice, many geographical simulation models that adopt the ad hoc population dynamics formulated by Krugman's type core and periphery model uses one common inter-regional population mobility (Kumagai et al. 2013). One potential contribution of this article would be the estimation of different inter-regional population mobility for different countries, or sub-national regions, with consistent data and methodology.

A. Population Data – LandScan

From equation (1), the population and real wage of sub-national regions, ideally in the form of annual data, are needed in order to compute the population mobility speed. The population data requirement can be met by the global grid population data of LandScan that was developed and made available, for a fee, by Oak Ridge National Laboratory. Annual data is available continually from 2000 onwards. The spatial resolution of LandScan is 30" or approximately 1 km at the equator. It represents ambient, or daytime, average population. LandScan uses a multi-variable dasymetric modeling approach to disaggregate census counts within an administrative boundary (Bhaduri et al. 2007). This approach, also known as smart interpolation, uses high definition satellite imageries, including those with sub-meter resolution, to distribute official population figures over national boundaries. National population figures aggregated from LandScan often agree with official data, because the latter are, whenever possible, used to construct the former. This is not the case at sub-national level. However, in this paper, we do not try to justify our use of LandScan by comparing it to official figures. It is not also our aim to evaluate which reflects reality better. We believe that each data has its own strengths and weaknesses. Our aim is demonstrate what can be done with different datasets.

B. DMSP-OLS Nighttime Light: A Proxy of Wage Rate

For the regional wage rate, however, there is no straightforward remote sensing data. Still, there is potentially some remotely sensed data. For instance, nighttime light data, observed by DMSP-OLS, has in recent years been used to estimate spatial high definition regional products. The DMSP-OLS nighttime light data is generated from data satellite imageries collected by the US Air Force Weather Agency and processed by the NOAA's national Geophysical Data Center. The usage of this data in social sciences may be traced to Croft's suggestion that was made in his seminal paper in 1978. Over the years, many studies related to environment sciences have used DMSP-OLS nighttime light data to measure economic activities on the ground. These include Doll et al. (2006), Gosh et al. (2010). In economics, in particular, Henderson et al. (2012) shows how the intensity of nighttime light, observed from outer space, can be used to estimate growth of Gross Domestic Products (GDP) beyond national boundaries. Keola et al. (2015) argues that nighttime light data is more closely associated with non-agricultural value-added, and if used with developing country data, where majority of regions are without observable nighttime light, will generate spatially patchy results. This particular point is important here because spatial economics, or the new economic geography – the basis of simulation models that often use ad-hoc population mobility – assumes agricultural income to be numeraire, and focuses on non-agricultural income as a principal reason for inter-regional mobility.

Existing studies generally estimate some independent variable using nighttime light data. This article will use nighttime light directly to represent the wage rate for the following reasons. First, nighttime light has been repeatedly found to be highly correlated with economic activities on the ground at the national and sub-national levels. Second, the estimation of mobility speed in this study will be carried out within national boundaries at most, thus precluding the need to account for different levels of economic activity on the ground. For the ad hoc dynamics to be applied here, the deviance from the national average, rather than an absolute level of regional income, is regarded as the cause of population mobility. Third, we understand that regional income is different from the regional wage rate because income gaps exist. Nevertheless, to the best of our knowledge, no remotely sensed or ground-based data can perfectly substitute for the regional wage rate with the spatio-temporal definition and coverage needed for our study.

Here we use the sum of the intensity of nighttime light divided by the number of people in a geographic region to represent its average wage rate.

Before moving to the statistical summaries in Section II, we present here a visual presentation of what can be expected from the remote sensing data set used. Fig. 1, which covers Cambodia, Laos, Myanmar, Vietnam and Thailand, 2001–2011, illustrates the population change rate, within a national boundary, at the sub-national administrative unit level 2 (ADM2), as defined in the 2009 version of the Global Administrative Unit Layer (GAUL). The following observations may be derived from Fig. 1. For Myanmar, whereas no ADM2 has less population in 2001 than in 2001, increase in regions along Thailand and China are much larger. The fact that ADM2 used in aggregation for Myanmar is larger than there rest is likely to be the reason that all region gains, because fertility can cover loss from emigration easier. Many regions along border with Thailand doubled population during the course of a decade. For Laos, net loss of population is observed in ADM2 of mountainous regions along border with Vietnam. Population in ADM2 along border with Thailand increased population. Cambodia shows substantial increase of population in regions along border area of both Vietnam and Thailand. Regions along the highway towards the newly developed Southern port city of Sihanouk Ville, also increased population substantially. Vietnam shows population concentration towards its two cores, Hanoi in the North, and Ho Chi Minh in the South. But interestingly, Vietnam's border regions with Laos also increased population substantially.

In this connection, Fig. 1 have captured well many clusters of cross-border economic activities that have developed since the 1990s. Indeed, many spots, along Myanmar and Thailand, Laos and Vietnam, Thailand and Cambodia have double their population between 2001 and 2011. Further details of development activities in these border regions are available in Ishida (2013). Since the resolution of LandScan is approximately 1 km by 1 km at the equator, the change in population share of administrative units of any size and shape larger than this can, in principle, be computed.

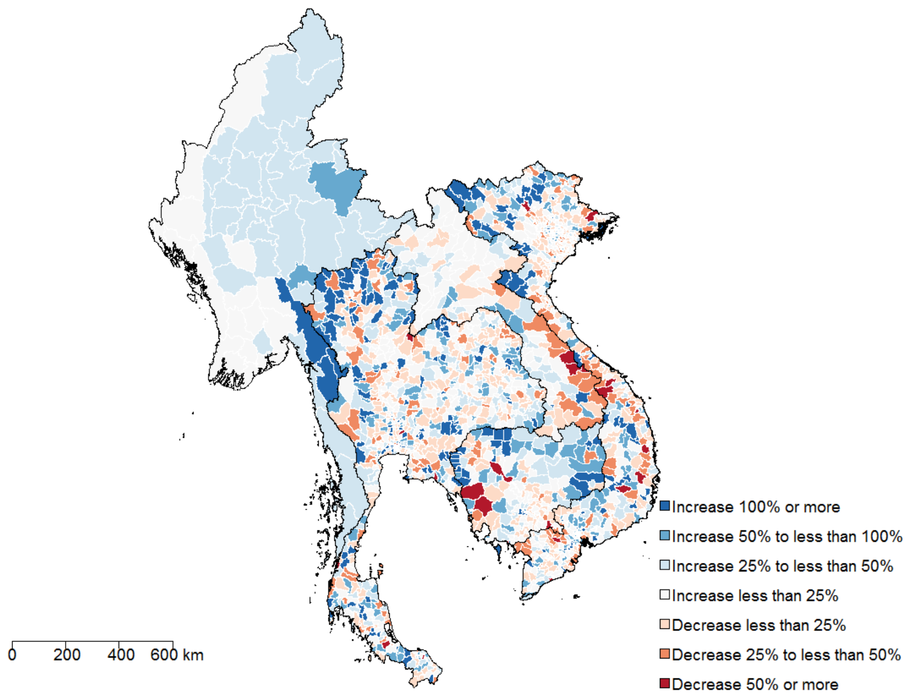

FIGURE 1. POPULATION CHANGE RATE IN CAMBODIA, LAOS, MYANMAR AND VIETNAM BETWEEN 2001 AND 2011

Notes: By authors based on LandScan and GAUL (2009).

II. Statistical Summaries

The number of ADM2 multiplied by the period of study, 11 years (2001 to 2011, inclusive), is about 28,000. The statistical summaries in this section are mostly presented in figures.

TABLE 1—STATISTICAL SUMMARIES OF DATA BY ADM2

ADM0	POPULATION (1000 PERSONS)			AREA (KM^2)		
	Min.	Mean	MAX.	Min.	Mean	MAX.
BN (38)	0.0	9.8	72.7	0.1	155.5	805.1
KH (187)	0.0	7835	358.2	2.2	976.3	5,405.0
ID (444)	0.0	529.8	512.3	11.0	4,282.0	44,560.0
LA (139)	1.3	44.7	202.8	38.9	1,664.0	4,552.0
MY (133)	0.0	184.8	1,679.0	0.85	2,496.0	21,190.0
MM (64)	157.1	724.1	1,953.0	74.8	10,480.0	50,800.0
PH (82)	6,481.0	1,097.0	13,730.0	202.1	3,628.0	14,610.0
SG (9)	47.4	497.3	1,237.0	4.3	66.4	218.6
TH (813)	0.0	79.6	701.8	1.6	636.0	4,843.0
VN (658)	17.0	128.5	634.6	2.1	500.5	3,715.0

Notes: Number of ADM2 in (), except for Singapore where it is of ADM1.

Source: Computed by authors based on LandScan (2001-2011) and GAUL (2009).

First, Table 1 summarizes the population and area of ADM2 in ASEAN, using administrative boundaries from GAUL (2009). Note that the number of ADM2 does not tally with the number given by official sources. For that matter, the ADM2 number can hardly be the same over the study period. Administrative boundaries at lower level, ADM2 for instance, changes frequently in developing countries. Study using official statistics usually adjusts this manually, resulting in some samples being discarded. One major benefit of using remote-sensing data is that one does not need to worry about the consistency of administrative boundaries. Administrative boundaries at any point in time can be used to cut and aggregate data. This article uses administrative boundaries from GAUL (2009) to aggregate population and nighttime light data at ADM2 for ASEAN between 2001 and 2011.

As one set of administrative boundaries is used to compute regional data for the study period, certain ADM2 in some countries have no population. These boundaries define how many persons there are in each ADM2. As was noted in Section I, MAUP is a well-known and much discussed problem in analysis using administrative boundaries.

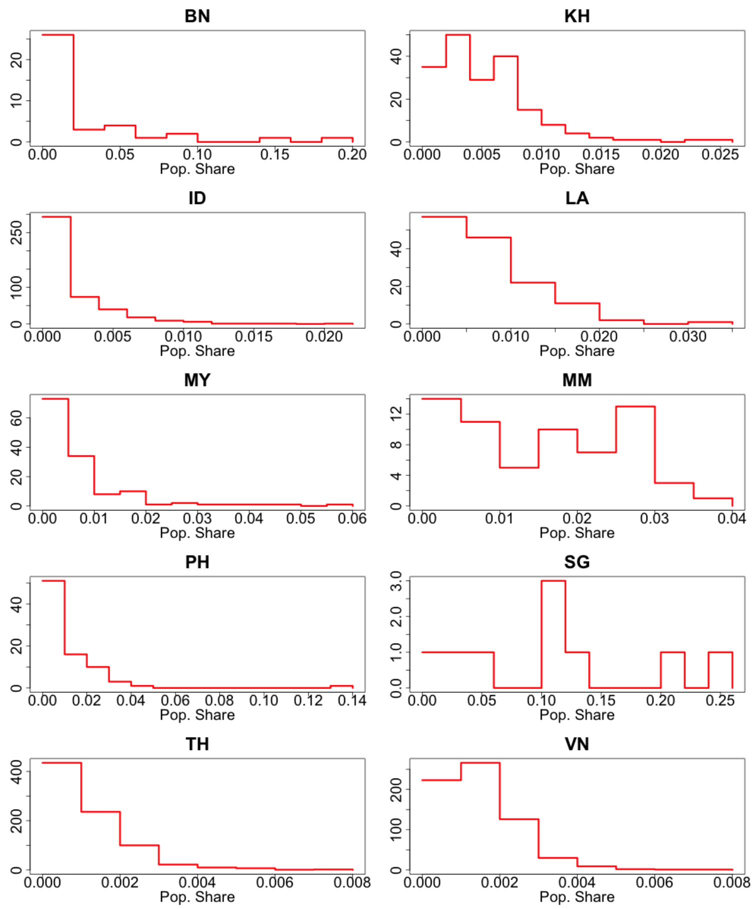

FIGURE 2. FREQUENCY OF POPULATION SHARE BY ADM2 IN ASEAN (2001-2011)

Notes: By authors based on LandScan and GAUL (2009). Brunei (BN), Cambodia (KH), Indonesia (ID), Laos (LA), Malaysia (MY), Myanmar (MM), Philippines (PH), Singapore (SG), Thailand (TH), Vietnam (VN).

Fig. 2 depicts the frequency of population share of ADM2 in ASEAN between 2001 and 2011. For the two city states, Brunei and Singapore, the population share in ADM2 is much larger than the rest, due to their small number of ADM2. Brunei and Singapore have about 38 and 8 ADM2 respectively; other ASEAN countries have mostly more than a hundred. The largest ADM2 in Brunei and Singapore accounts for more than 20% of total population.

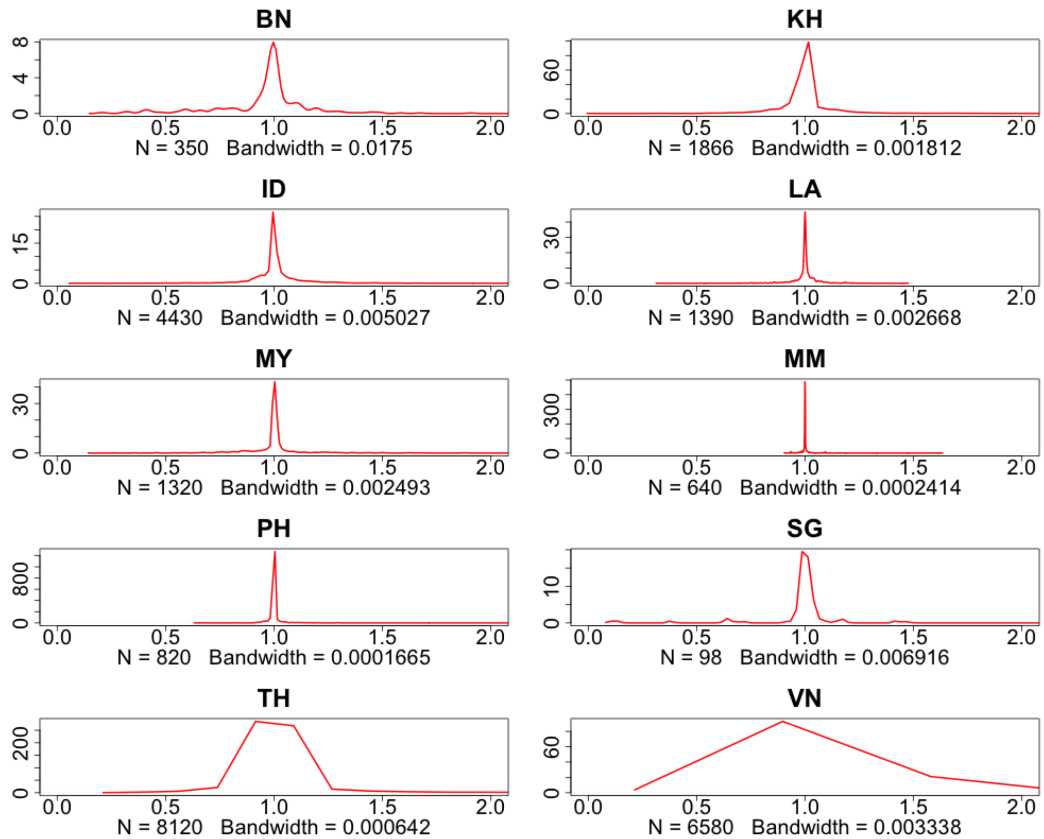

FIGURE 3. KERNEL DENSITY OF REGIONAL POPULATION SHARE CHANGE BY ADM2 IN ASEAN BETWEEN 2001 AND 2011

Notes: See Fig. 2.

In the other countries, only the largest ADM2 in the Philippines accounts for more than 10%. These figures decline to between less than 1 to a few percent for the rest of ASEAN. Some obvious differences among economically advanced and newer ASEAN members can be observed. Myanmar, Cambodia and Laos have more ADM2 with mid- to lower-mid-scale population share, that is, lower levels of concentration that are associated with being less industrialized.

Lastly, Fig. 3 shows the kernel density of the rate of population share change in ADM2 in ASEAN between 2001 and 2011. A value of 1 along the x-axis means an unchanged population share. The range of the x-axis is set between 0 and 2 for all countries for easier visual cross-country comparison. Naturally, the population share change of ADM2 in all ASEAN countries is centered on 1. Even so, Vietnam and Thailand stand out in terms of the number of ADM2 whose share has increased or declined by more than 10%. This can be observed from the larger deviation from 1 for Vietnam and Thailand in Fig. 3. For the rest of ASEAN, most ADM2 changes involved gaining or losing only a few percent of their population shares. The range of change is much smaller for Myanmar and Laos while only in Cambodia have some of ADM2 lost their entire.

Note that whereas the population share is computed within national boundaries, real world population mobility includes cross-border movement. This is particularly true in ASEAN. In Thailand alone, more than one million Burmese and about 200,000 Cambodian and Lao nationals are legally registered as foreign workers. If illegal migrants are included, the figure could be several times higher. Several hundred thousand people daily commute to work between Malaysia and Singapore, a fact that is not assumed away by this study. Indeed, smaller or higher changes of ADM2 population shares in particular countries can happen in two ways. The first is when there is really not much movement between domestic regions. The second is when there is relative larger uniform migration to/from foreign countries. Myanmar, Laos and, to a certain extent, the Philippines are likely to fall into this latter instance. By the same token, a large increase in population share in some countries can be a result of inflows from foreign countries. In addition, the upper bounds of the percentage of population share in Myanmar and Laos reach about 50–60%, much higher than in the rest of ASEAN.

III. Estimated Results and Discussions

The main objective of this article is to estimate sub-national regional population mobility speed as formularized in Fujita et al. (1999), and Barro and Sala-I-Martin (1992). Our estimation formulation is expressed in equation (2).

$$\dot{\lambda}_r^t = \alpha \frac{\omega_r^t}{\bar{\omega}_t} + \begin{pmatrix} \beta_1 \\ \beta_2 \\ \vdots \\ \beta_i \end{pmatrix} k_i + \epsilon_r^t \tag{2}$$

Here, $\dot{\lambda}_r^t$ is the change of population share of region r, that would happen in the next term (t+1), computed specifically as $\frac{\lambda_r^{t+1}}{\lambda_r^t}$. The first term on the right hand side, $\frac{\omega_r^t}{\bar{\omega}_t}$, is the deviation of the wage rate in region r, from the national average. Note that the change of regional population and deviation of wage rate from national average is already computed as percentage change; hence, it is unnecessary to take its log form even if we assume a constant percentage change relationship. $\beta_i k_i$ are many control variables. Barro and Sala-I-Martin (1992), for example, includes the population density of region r, surrounding regions, and climatic condition as control variables for inflow/outflow to/from each region. We include some of these, but add others that we consider necessary for ASEAN. Details about control variables are discussed in the next section. ϵ_r^t is an error term.

Moreover, most countries have more than one level of sub-national administrative levels. MAUP suggests that the choice of sub-national administrative level may affect the estimated results of inter-regional mobility speed at the national level. Using remote sensing data means that data can be prepared, or computed, for any administrative level that has data of its boundaries and a shape and size into which a one-square kilometer grid can fit. We discuss the results of our population mobility estimation by ADM1 and ADM2 under sub-sections A. and B., below. Under sub-section C, we analyze how the level of per capita wage rate affects mobility speed among sub-national regions.

A. National Mobility Speed Estimated by ADM1 DATA

Here, the regional population share and the per capita nighttime light are computed by boundaries of ADM1 for 10 ASEAN countries. Table 2 shows the results of OLS estimation with data aggregated by ADM1 according to four different specifications. (1) and (2) regress the population change rate, whereas (3) and (4) regress the population share change rate over per capita nighttime light deviation from the national average. Each specification includes a year dummy in order to control for different measurement settings of nighttime light. Concretely, data for the intensity of nighttime light used in this study takes values between 1 and 63 for each year. A value of 1 does not necessarily mean the same value across different years. In essence, this is similar to how nominal money values must be denominated by prices in time series analysis. Henderson et al. (2012) [17] and Keola et al. (2015) control for this difference in measurement of nighttime light with a year dummy, whereas Tanaka and Keola (forthcoming) estimate a deflator using official data. Specification (2) and (4) introduce population density as another control variable.

We see that except for Brunei, all specifications yield mostly the same speed of inter-regional mobility, computed as the elasticity of deviation of per capital nighttime light from the national average. For Laos, Malaysia, Myanmar and Thailand, though, the elasticity is not statistically significant. This may be a result of MAUP. For instance, and for whatever reason, if inter-regional population mobility happens only within ADM1, estimating it with data aggregated by

ADM1 would yield mobility speed of 0. The same problem persists if population change in each ADM1 is uniform, for example, because the same proportion of population leaves for, or comes from other countries. In any case, it may not be feasible to undertake a significant measure of inter-regional population mobility speed without sufficient variation in regional population change.

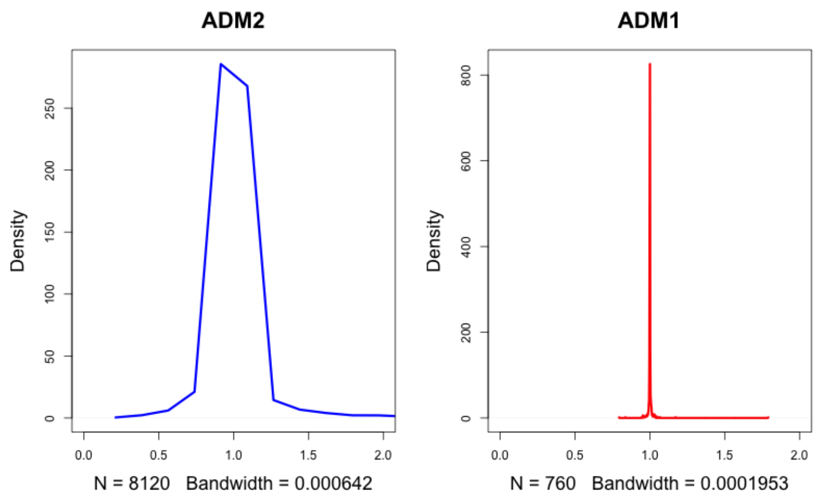

FIGURE 4. KERNEL DENSITY OF REGIONAL POPULATION SHARE CHANGE IN THAILAND BY ADM2 AND ADM1 BETWEEN 2001 AND 2011

Notes: See Fig. 2.

Fig. 4 illustrates the kernel density of population share change in Thailand between 2001 and 2011. Clearly, the population share change by ADM1 is very small; only few ADM1 have increased their share substantially. In contrast, the population share by ADM2 shows variation of between 0.3 and 1.3. Briant and Lafourcate (2010) suggest that using smaller geographic units will help to address MAUP. Next, we will estimate population mobility using data aggregated by ADM2.

TABLE 2—NATIONAL MOBILITY SPEED ESTIMATED BY ADM1 DATA

Country	IV / DV	(1) Pop. Change	(2) Pop. Change	(3) Pop. Share Change	(4) Pop. Share Chang	Pop. Share Change Adjust R Sq. and Number of Obs. (1)	(2)	(3)	(4)
BN	Wage Dev.	0.04794.	0.072961*	0.04725.	0.071861*				
		(0.02816)	(0.030480)	(0.02767)	(0.029942)	0.9964	0.9967	0.9965	0.9967
			0.012357.		0.012155.	29	28	29	28
	Pop. Density		(0.006859)		(0.006737)				
KH	Wage Dev.	0.012950*	0.014316*	0.012749*	0.014093*				
		(0.006355)	(0.006326)	(0.006256)	(0.006228)	0.9727	0.9732	0.9726	0.9732
			-0.018129*		-0.017836*	200	199	200	199
	Pop. Density		(0.008281)		(0.008152)				
ID	Wage Dev.	0.01398***	0.012124***	0.013777***	0.011957***				
		(0.00353)	(0.003581)	(0.003501)	(0.003551)	0.9969	0.9969	0.9969	0.9969
			-0.004767*		-0.004720*	319	318	319	318
	Pop. Density		(0.001937)		(0.001921)				
LA	Wage Dev.	-0.0002193	0.002467	-0.0002041	0.002409				
		(0.0017202)	(0.002329)	(0.0016687)	(0.002260)	0.9969	0.9969	0.9969	0.9996
			-0.005169.		-0.005029.	156	155	156	155
	Pop. Density		(0.003044)		(0.002953)				
MY	Wage Dev.	0.015016	0.013906	0.014623	0.013514				
		(0.009578)	(0.009825)	(0.009364)	(0.009604)	0.9973	0.9973	0.9973	0.9973
			-0.001613		-0.001611	139	138	139	138
	Pop. Density		(0.003016)		(0.002949)				
MM	Wage Dev.	0.004785	0.003676	0.004370	0.003379				
		(0.006004)	(0.006070)	(0.005462)	(0.005523)	0.9968	0.9968	0.9972	0.9972
			-0.005056		-0.004521	154	153	154	153
	Pop. Density		(0.004303)		(0.003915)				
PH	Wage Dev.	0.003566.	0.0040562.	0.003564.	0.0040498*				
		(0.002018)	(0.0020560)	(0.002004)	(0.0020418)	0.9999	0.9999	0.9999	0.9999
			-0.0009221		-0.0009135	159	158	159	158
	Pop. Density		(0.0007689)		(0.0007636)				
SG	Wage Dev.	0.04449*	-0.007016	0.04770*	-0.006462				
		(0.01762)	(0.040931)	(0.01868)	(0.043402)	0.9946	0.9946	0.9937	0.9937
			-0.045355		-0.047695	79	78	79	78
	Pop. Density		(0.032572)		(0.034538)				
TH	Wage Dev.	0.0006495	0.001000	0.000646	0.0009951				
		(0.0015508)	(0.001575)	(0.001540)	(0.0015646)	0.999	0.999	0.9999	0.999
			-0.001787		-0.0017784	749	748	749	748
	Pop. Density		(0.001423)		(0.0014133)				
VN	Wage De	0.013281***	0.014314***	0.013060***	0.014073***				
		(0.002874)	(0.002886)	(0.002826)	(0.002838)	0.998	0.9981	0.9981	0.9981
			-0.004497**		-0.004410**	629	628	629	628
	Pop. Density		(0.001683)		(0.001655)				

Significant codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Notes: (1) Without control for area share. (2) With control for area share. OLS estimation without constant term for both specifications..

B. National Mobility Speed Estimated by ADM2 DATA

To avoid errors that may arise if ADM1 is not an appropriate geographical unit of analysis, we now estimate mobility speed from data aggregated by ADM2. The results for each of the 10 ASEAN countries are presented in Table 3.

TABLE 3—NATIONAL MOBILITY SPEED ESTIMATED BY ADM2 DATA

Country	IV / DV	(1) Pop. Change	(2) Pop. Change	(3) Pop. Share Change	(4) Pop. Share Chang	Pop. Share Change Adjust R Sq. and Number of Obs. (1)	(2)	(3)	(4)
BN	Wage Dev.	0.02718 (0.01902)	0.03141. (0.01898)	0.02675 (0.01885)	0.03096 (0.01881)	0.7813 339	0.7842 338	0.7795 339	0.7825 338
	Pop. Density		0.02909* (0.01236)		0.02897* (0.01225)				
KH	Wage Dev.	-0.0002011 (0.0004815)	-0.0003442 (0.0004814)	-0.0001963 (0.0004767)	-0.0003380 (0.0004766)	0.7566 1855	0.7582 1854	0.7543 1855	0.756 1854
	Pop. Density		-0.027802*** (0.0074935)		-0.027524*** (0.0074192)				
ID	Wage Dev.	0.043039*** (0.002014)	0.042739*** (0.002026)	0.044033*** (0.002036)	0.043740*** (0.002049)	0.9178 4419	0.9178 4418	0.9152 4419	0.9152 4418
	Pop. Density		-0.002974 (0.002244)		-0.002899 (0.002268)				
LA	Wage Dev.	0.0013483 (0.0009138)	0.0007848 (0.0009193)	0.0013041 (0.0008914)	0.0007565 (0.0008968)	0.9949 1379	0.9949 1378	0.995 1379	0.995 1378
	Pop. Density		0.006180*** (0.0015253)		0.006005*** (0.0014880)				
MY	Wage Dev.	0.02488*** (0.00452)	0.024278*** (0.004528)	0.02417*** (0.00440)	0.023585*** (0.004407)	0.9425 1309	0.9426 1308	0.9427 1309	0.9428 1308
	Pop. Density		-0.008097. (0.004425)		-0.007807. (0.004307)				
MM	Wage Dev.	0.003315** (0.001171)	0.003203** (0.001165)	0.003058** (0.001069)	0.002956** (0.001063)	0.9975 629	0.9975 628	0.9978 629	0.9978 628
	Pop. Density		-0.003944** (0.001394)		-0.003576** (0.001272)				
PH	Wage Dev.	0.04304*** (0.01011)	0.064051*** (0.011232)	0.042258*** (0.009919)	0.062860*** (0.011020)	0.968 809	0.9686 808	0.9679 809	0.9685 808
	Pop. Density		-0.032829*** (0.007956)		-0.032187*** (0.007806)				
SG	Wage Dev.								
	Pop. Density								
TH	Wage Dev.	0.247785*** (0.004836)	0.246371*** (0.004845)	0.246199*** (0.004804)	0.244796*** (0.004813)	0.6224 8190	0.6231 8108	0.6221 8109	0.6228 8108
	Pop. Density		-0.030539*** (0.007813)		-0.030331*** (0.007762)				
VN	Wage Dev.	0.009838 (0.020628)	0.0001375 (0.0207329)	0.009564 (0.020057)	0.000138 (0.020159)	0.06114 6569	0.06348 6568	0.06255 6569	0.06488 6568
	Pop. Density		-0.136051*** (0.0325946)		-0.132201*** (0.031692)				

Significant codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
Notes: (1) Without control for area share. (2) With control for area share. OLS estimation without constant term for both specifications..

First, as suggested by Briant and Lafourcate (2010) , the estimated results are significant for more countries. Significant results include about 0.003 for Myanmar, 0.02 for Malaysia, 0.03 for Brunei, though not so significant, 0.04 for Philippines, and as high as about 0.2 for Thailand. We add 0.04 for Singapore which does not have ADM2. Finally, the result for Vietnam is insignificant. All this suggests that the appropriate level geographic unit of analysis may be different for different countries.

Second, there is an inverse relationship between population density with regional population share for most countries. To put it differently, people tend to migrate to regions with low population density, or away from regions with high population density. Vietnam has a very large value of positive effect of population density on regional population share, suggesting that land-intensive agriculture may still play an important role in regional population mobility. In contrast, the effect of population density on regional population share is positive for Brunei and Laos which have relatively large land areas for their population sizes. Although it is not significant, the effect of population density on population share in Indonesia is also positive.

Third, for countries known to have experienced a high proportion of cross-border emigration, both the effect of per capita nighttime light deviation from the national average, and population density take very small values. The mobility speed of Myanmar is 0.003, or about a tenth of that of other countries. The effect of population density is about -0.008, between one fifth and one third of that of other countries. Countries that have received large numbers of legal and illegal migrant workers, however, such as Thailand, have extremely high mobility speed. For Thailand, the value is 0.2, about 10 times larger than that of most ASEAN countries.

Furthermore, it is logical to expect mobility to change over time. Transport costs have steadily declined since the Industrial Revolution. If the assumption holds that richer countries have smaller regional gaps, equation (1) should yield lower inter-regional mobility speed for regions with higher income levels. In sub-section C., below, we analyze the income level effect on inter-regional mobility speed.

C. Income Level and Mobility Speed

From the results presented under A. and B., above, we observe that inter-regional mobility speed is not the same for the 10 ASEAN countries. Different speeds may arise from the selection of geographic unit of analysis, that is, ADM1 and ADM2 are not consistent across countries. But the cases of Thailand and Vietnam, which have comparable land areas and number of ADM2, suggest that other factors may have an impact on inter-regional mobility speed. These can include the level of development, culture, available means and costs of transport, and so on. Here, we pay particular attention to the effect of income level. We do so by making full use of the flexibility permitted by remote-sensing data; we estimate the mobility speed in ADM1 based on data aggregated by ADM2. We simply constrain estimation (4) in Table II into each ADM1. As there are about 300 ADM1 in our data set, we present the estimated results not in a table but as a graph in Fig. 5.

The relationships obtained between per capita nighttime light and speed of inter-regional mobility can be divided into three groups. No clear trends are observed for the first group of Brunei and the Philippines. In the second group Cambodia, Indonesia, Laos, Malaysia, Myanmar, and Singapore, there is a clear inverse relationship between per capita nighttime light and mobility speed by ADM1. For the third group of Vietnam and Thailand, with the most numerous ADM2 in ASEAN, there are more regions having about the same speed although a trend of decline is present.

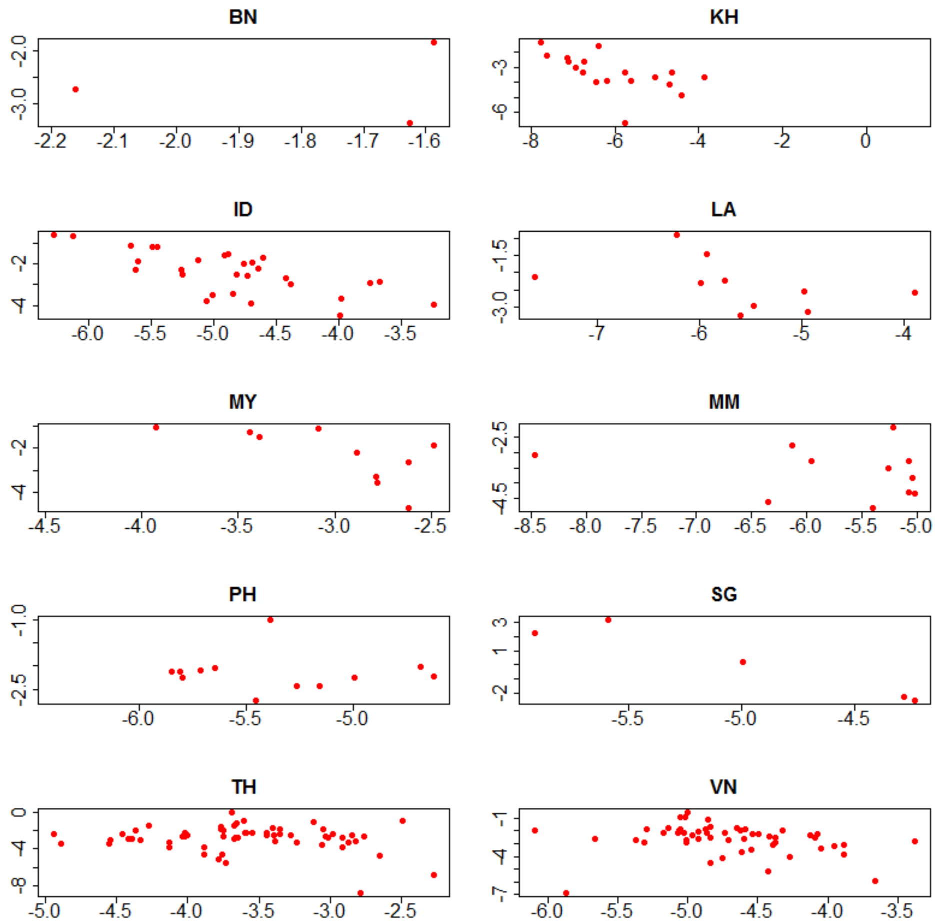

FIGURE 5. PER CAPITAL NIGHTTIME LIGHT AND MOBILITY SPEED AT ADM1

Notes: Horizontal axis is log of per capita nighttime light, and Vertical axis is mobility speed by ADM1.

IV. Conlusions

The objective of this article is to measure sub-national inter-regional population mobility in any country in the world using a consistent data set with global coverage. To the best of our knowledge, this objective cannot be attained with existing ground-based data. Consequently, we choose to use remote-sensing data which is spatio-temporally definitive, and with global coverage. We assemble sub-national regional population from LandScan, and use per capita nighttime light from DMSP-OLS as a proxy for the real wage rate. We have demonstrated we can estimate inter-regional mobility speed for any sub-national administrative level provided its boundaries are available and are larger than 1 km x 1 km.

It would appear from our results that our approach and methodology may be informative in pointing to future research applications and directions. First, whereas this article computes sub-national regional mobility for 10 ASEAN countries using LandScan and DMSP-OLS, the increasing availability of other forms of remote-sensing data means that our basic methodology can be applied far beyond ASEAN to include other developing countries in Asia and Africa, for example, that often have even less ground-based data.

Second, this paper demonstrates that the estimated inter-regional mobility speed is affected by the choice of geographic unit of analysis, or MAUP. We observe at least two different MAUP. There is the MAUP that is related to the appropriate scale of administrative boundary. We observe that estimates for different countries can best be made with different level of ADM because inter-regional population mobility occurs at different levels in different countries. In other words, using ADM1 data would not yield meaningful mobility speed if most movement happens within ADM1. The other MAUP is related to the appropriate grouping of regions. The problem would not exist if migration data includes information on the origins and destinations of migration. It is rare, however, to be able to find such comprehensive migration data with global coverage. Without information on origin and destination, one needs to establish a geographic scope that matches actual regions among which migration actually happens. It may be a potentially rewarding research to develop an algorithm from remotely sensed data that facilitates such matching. More generally, it would advance research in the direction of utilizing remote sensing data in the social sciences.

Third, we have shown that deviation, and to level, of per capita nighttime light affect inter-regional population mobility. Yet, we have not placed the results in a specific geographical context – which can probably be variously accomplished by considering the spatial distribution of those effects.

We have a final comment related to the potentially great complementarity between ground-based data and remote sensing data. In essence, one cannot go back in time to replicate a previous field survey in order to extract additional spatio-temporal information. Yet, this disadvantage can be overcome with the imaginative use of remote sensing data. If one can establish statistically significant relationships between ground-based data and remote-sensing data, then one will be able to compute necessary information about the past for any selected location, provided that necessary remote sensing data is achieved and accessible. In short, while ground-based data can add humanly sensed information to remote sensing data, remotely sensed data can be used to interpolate/extrapolate spatially patchy and temporally infrequent ground-based data. It would well be an important research endeavor to tapping such possibilities for more sophisticated and rigorous applications in social science analyses.

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