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# **Intersectoral Migration in Southeast Asia: Evidence from Indonesia, Thailand, and the Philippines**

**Rita Butzer, Yair Mundlak, and Donald F. Larson**

Using time-series data spanning three decades, we examine the determinants of sectoral migration in Indonesia, Thailand, and the Philippines. We used a principal-components algorithm to address the problems associated with trended and intercorrelated explanatory variables. Migration rates in the three countries are low relative to other developing countries, with the consequence of persistent intersectoral income differentials. Even so, the rate of migration has been responsive to the income ratios in each country. The migration rates were also affected by the absorbing capacity of nonagriculture, as indicated by several measures. In contrast to other studies, policy variables consisting of indicators of physical and human capital had little impact on the migration rate separate from that captured by relative incomes.

*Key Words:* agriculture, Indonesia, labor, migration, Philippines, Thailand

Beginning with Lewis, the flow of labor resources from agriculture has been an important consideration in models of economic development. Since Todaro's article, well-formulated models have been available to guide empirical measurement of the process of sectoral migration. In practice, rates of migration and rates of natural population growth tend to be similar, so the accumulated effects of migration occur over decades. However, using long time-series measures of sectoral migration poses special difficulties for researchers, because some of the explanatory variables are trended and intercorrelated. Omitting correlated variables runs the risk of specification error, a problem formulated by Theil in 1957. In the present article, we describe the flow of labor resources from agriculture to other sec-

tors of the economy in Indonesia, Thailand, and the Philippines over three decades and examine factors that determine the rate of migration. To mitigate the problems associated with intercorrelated variables, we employ principal components, using the algorithm given in Mundlak, which imposes parameter restrictions as a substitute for the elimination of specific variables.

The three countries we study are geographically close and share similar climate and other characteristics; however, growth experiences have differed. In a companion paper (Mundlak, Larson, and Butzer), we consider sources of growth and productivity in the three countries in which the stock of agricultural labor plays a key role. In all three countries, economic growth and growth in agricultural income have been associated with an out-migration of labor from agriculture. However, as with growth, country experiences differ in key ways.

The share of agriculture in total employ-

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Rita Butzer is a visiting fellow, Department of Economics, Harvard University; Yair Mundlak is a professor emeritus, The University of Chicago and The Hebrew University of Jerusalem; and Donald F. Larson is a senior economist, Research Group, World Bank.

ment is shown in Figure 1. The shares were very high in the 1960s and 1970s (over 50% for Indonesia and the Philippines and over 70% for Thailand) and fell over time. Nonetheless, in the late 1990s, the agricultural sector still employed nearly 40% of workers in the Philippines and Indonesia and 50% in Thailand. In developed economies, these shares level off at 2%–3% (Larson and Mundlak). Although the shares in Indonesia, Thailand, and the Philippines have decreased rather steadily over the past three decades, the pace of the allocation of labor resources from agriculture to other sectors of the economy has been relatively slow, with some indications of speeding up in the past decade. We examine this process of reallocating labor.

### Migration From Agriculture

#### Framework

The change in the sectoral composition of the labor force is the outcome of migration from agriculture conditioned by births and mortality rates. We describe the analysis of this process, using the framework in Mundlak and Larson and Mundlak (1979). These authors also provide a review of the literature relevant to the approach taken in the present article. We summarize herein the material pertinent for the empirical analysis. Intersectoral labor allocation is analyzed within the framework of occupational choice. The postulation is that, at any time, the individual maximizes his remaining-life utility by, among other things, choosing his occupation. The choice is made from a feasible set of occupations, which are characterized by the trajectory of their income and the uncertainty attached to it. We concentrate on the binary choice between agricultural and nonagricultural work. The two sectors are not homogeneous, but in most of the discussion this fact is ignored. Because nonagricultural employment often requires moving to other areas, the cost of migration involves additional elements to those attached to the change of occupation alone.

Data on off-farm migration in Indonesia, Thailand, and the Philippines are not avail-

able; thus, they are inferred from changes in intersectoral allocations of labor. It is assumed that, without migration, agricultural labor would grow at the same rate as total labor. Deviations from this rate are attributed to migration. Migration was calculated as

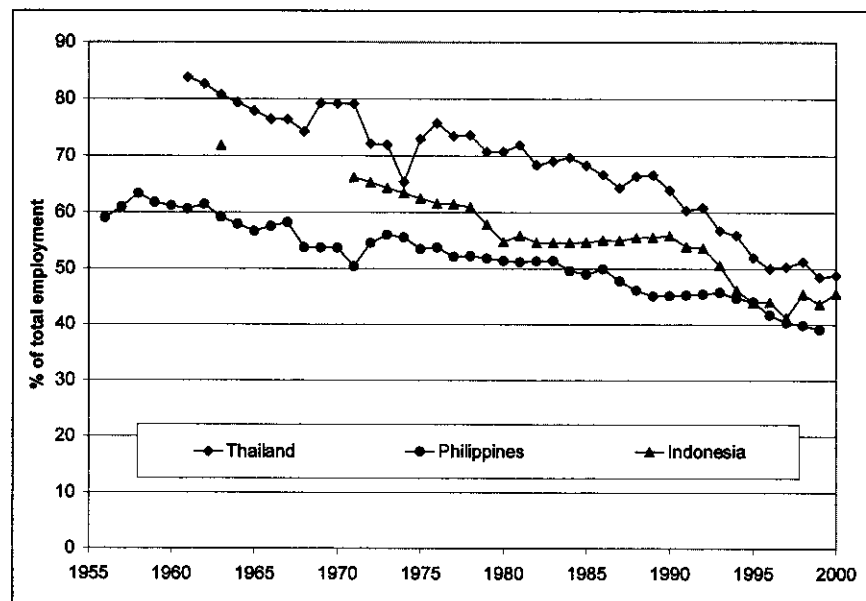
$$(1) \quad M_t = [L_{At-1}(1 + n_t)] - L_{At}$$

$$m_t = M_t/L_{At-1}$$

where  $M$  is the number of migrants (outflow of workers from agriculture to nonagriculture),  $L_A$  is agricultural labor,  $n$  is the rate of growth of the total labor force, and  $m$  is the ratio of migrants to agricultural labor. In practice, we calculate  $n$  from  $n_t = (L_t - L_{t-1})/L_{t-1}$ , where  $L$  is total labor. Similarly, define the growth rate of the agricultural labor force as  $n$  from  $n_{At} = (L_{At} - L_{At-1})/L_{At-1}$ , then  $m = n - n_A$ . Thus, the rate of migration out of agriculture is the difference between the growth rate of total and of agricultural labor.

Ideally, we would like to use data on labor to calculate migration rates as shown above. However, the country sources do not report data on agricultural labor but rather agricultural employment. Annual sectoral labor data are available from the Food and Agriculture Organization and the World Development Indicators of the World Bank, which are constructed from census data. Such data, however, are collected every 10 years and the annual series are obtained with straight-line interpolations. Thus, migration rates calculated from these data do not actually measure the annual variation that we hope to explain. We therefore have chosen to use employment data from the country sources to calculate migration rates. This choice is the outcome of the data limitation but is not an ideal one.

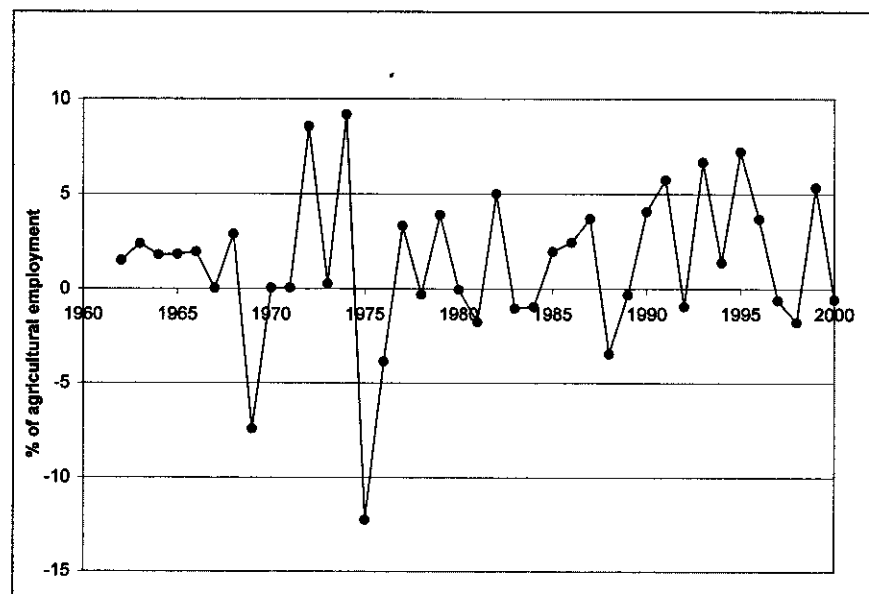
The constructed migration series are plotted in Figures 2–4. The migration rates are volatile to the point that it is difficult to discern any trends. It is to be noted, however, that most of the observations are in the positive part of the graphs, which indicates positive migration over the entire period. The volatility comes from two sources. First, the use of data on employment rather than data on labor brings the demand for workers (and, hence,



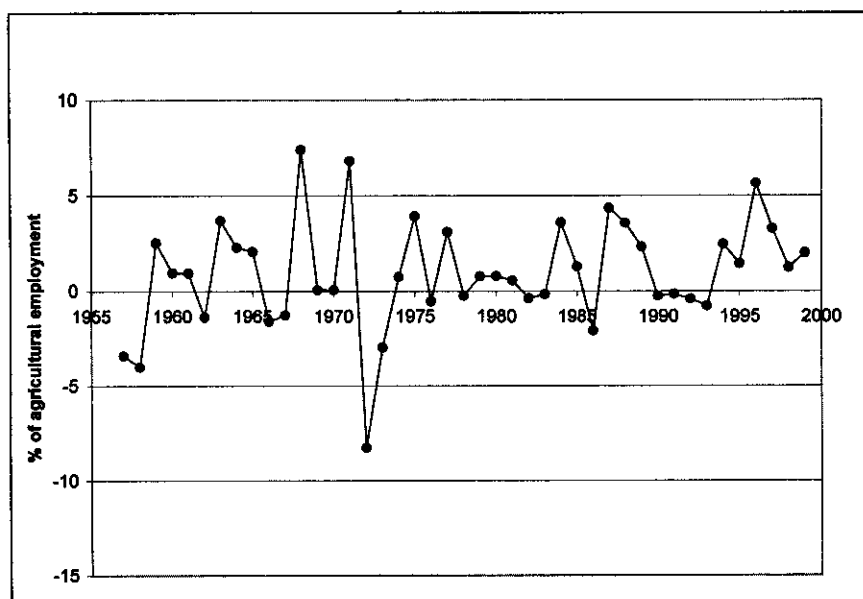
**Figure 1.** Agriculture's Share of Total Employment

shocks to that demand) into the constructed migration series, and, second, annual data tend to be more erratic; nevertheless, the trend still prevails. This is seen in Table 1, which presents decade averages of the migration rates. The migration rates are relatively low by international standards and are consistent with

the slow change in the share of agriculture in employment discussed earlier and seen in Figure 1. The average migration rates are greater than 2% in only two cases (Indonesia and Thailand during the 1990s). Comparing the rates with those for Asian countries from the study by Larson and Mundlak, we see that mi-



**Figure 2.** Migration from Agriculture in Thailand



**Figure 3.** Migration from Agriculture in the Philippines

gration was somewhat slower in Indonesia, Thailand, and the Philippines than in other Asian countries.<sup>1</sup> We should also note from this table the considerably lower migration rates in the 1980s in Thailand and Indonesia. We now turn to identifying factors that determine these rates of migration.

#### Formulation

The analytic framework is summarized in the form of the migration equation:

$$(2) \quad m_t = \beta_0 + \beta_1 \ln(RI_{t-1}) + \beta_2 \ln(RL_{t-1}) + \beta_3 S_{t-1} + \mu$$

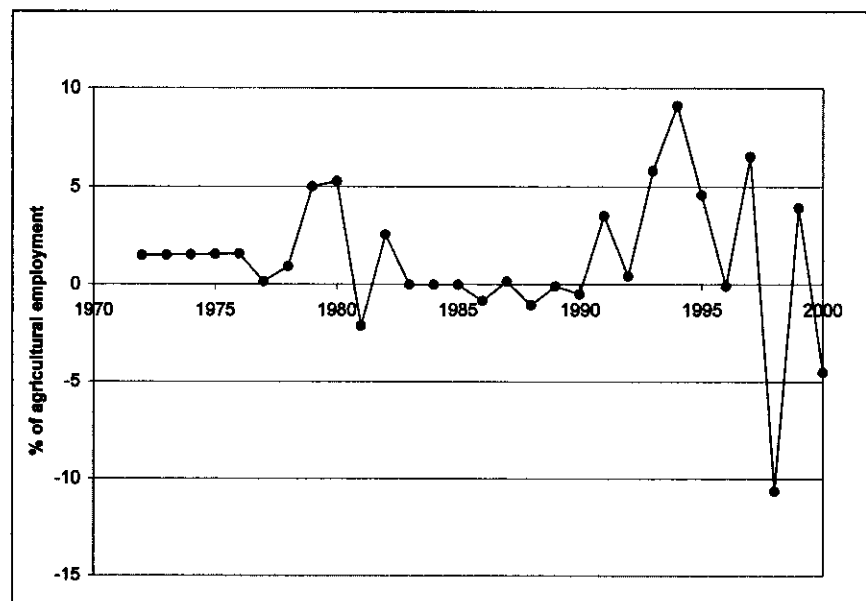
where  $m$  is defined above,  $RI = I_N/I_A$  is the income ratio (the ratio of gross domestic product [GDP] per worker in the nonagricultural sector to that in the agricultural sector),  $RL = L_N/L_A$  is the ratio of employment in the nonagricultural sector to that in the agricultural sector, and  $S$  represents other attributes and exogenous state variables.

<sup>1</sup> Migration in Indonesia, Thailand, and the Philippines was also far slower than in Latin America where rates were close to 2% in the 1960s and over 2% in the 1970s and 1980s (Larson and Mundlak).

We isolate the income and labor ratios from the other variables for the following reasons. The income ratio is assumed to be the major incentive faced by the potential migrant. In applying the formulation to the market, we need to consider the size of the labor force in the two sectors. The number of migrants depends on the size of the labor force in agriculture (the origin); the larger the labor force in agriculture, the more migrants can be expected under a given economic environment. The actual number may also depend on the ease of finding work in nonagriculture. In the absence of strong unemployment there, it is expected that the larger the labor force in the destination, the easier it is to get a job. The formulation assumes that the migration rate depends only on the composition of the labor force (the ratio of labor in nonagriculture to agriculture) and not on the size of the total labor force. The variables covered by  $S$  are discussed below.

#### Variables and Data

The choice over whether to migrate is strongly influenced by incentives, the main one being sectoral income. The basic idea is that labor, like other resources, flows from low to high-



**Figure 4.** Migration from Agriculture in Indonesia

income occupations.<sup>2</sup> As such, this is a qualitative property, and to test it would require a comparison of data with and without a sectoral income gap. The data do not appear in this dichotomy form and instead show variability. The empirical analysis, as formulated in Equation (2), is designed to examine the impact of such variability on the migration rate. It thus tests a much stronger proposition:

**Proposition:** The larger the income gap between the sectors, the stronger the migration rate. In other words, the income gap affects the pace of the resource allocation.

We measure the incentive by income and not by wages. When it comes to long-term decisions, such as the migration out of agriculture, income is thought to be a more informative measure of the future prospects than wages. Wages are the more important component of income but are not the only component. The nonwage component of income (e.g., the rent on land and returns to capital, both physical and human) may be influential in the migration decision. In addition, in our

particular case there is a basic problem with the wage data. As indicated by Mundlak, Larson, and Butzer, the published wages are daily rates. To convert them to annual figures, it is necessary to know the number of working days, but this information is not available.

The intersectoral income differential is measured by the ratio of income in nonagriculture to that in agriculture.<sup>3</sup> Evidence from cross-country studies shows that, as countries develop, the income differential decreases. "In middle and high income countries, the [income] ratio is almost equal to 1 and, as the data show, this statement was as true in 1950 as it is today." (Larson and Mundlak). This finding summarizes a long-run process whereby migration of labor from agriculture to nonagriculture will lessen the gap in productivities. As the supply of labor in agriculture decreases, the shadow price of agricultural labor will rise, leading to investment in labor-saving techniques in agriculture. Increased stocks of capital (human and physical) en-

<sup>2</sup> This is the essence of the dual economy model of Lewis and Ranis and Fei.

<sup>3</sup> Income is calculated as GDP (in constant prices) per worker, where nonagricultural GDP is the difference between total GDP and GDP in agriculture (and similarly for nonagricultural employment).

**Table 1.** Average Migration Rates for Selected Periods

	Decade Averages (Percentage Per Annum)				Period of Analysis	Period Averages (Percentage Per Annum)
	1960s	1970s	1980s	1990s		
Thailand	0.61	0.89	0.55	3.09	1962–1999	1.32
Philippines	1.32	0.35	1.39	1.45	1962–1998	1.11
Indonesia		1.72	0.39	2.27	1972–1999	1.44
Asia	1.07	1.40	1.80	NA		

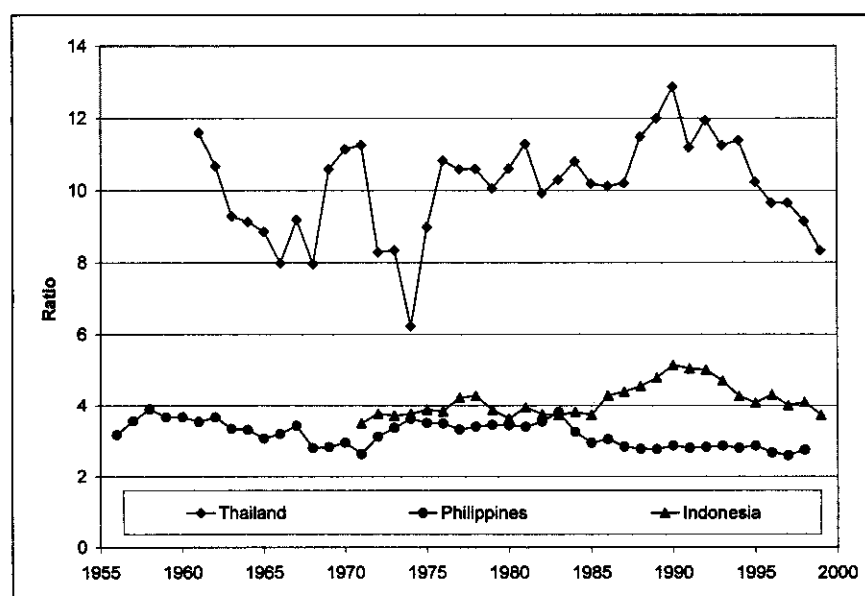
Note: Asia decade averages taken from Larson and Mundlak. NA, not applicable.

hance the productivity of the labor remaining in agriculture.

Our current analysis deals with annual variations and in this sense differs from the cross-country analysis based on period averages, which are subject to less variability. Figure 5 shows that the productivity in nonagriculture has been much higher than that in agriculture. In part, this may reflect the problem of the labor data, which may overstate the labor in agriculture and understate that in nonagriculture (for details, see Mundlak, Larson, and Butzer). We continue herein to review the data, ignoring this possible data problem. An increase in the income differential occurs when nonagricultural productivity grows at a faster rate than agricultural productivity. For most of the study period, agricultural productivity increased but at a slower pace than that

of nonagriculture. It is important to keep in mind that the productivity measure is an outcome of the effect of the economic environment on output and the labor input. Because the economic environment varied across countries and over time, the pattern of the income gap was not uniform for the three countries.

In Indonesia, the difference in the sectoral incomes actually increased throughout the 1970s and 1980s, peaking in 1990 before decreasing back to the early 1980s levels, despite the consistent positive growth in agricultural GDP. Agricultural productivity in Indonesia increased by 25% between 1971 and 1980 but then remained stagnant throughout the 1980s. Agricultural GDP was increasing but at the same rate as agricultural employment. Non-agricultural sectors grew rapidly after 1985, widening the existing income differential.

**Figure 5.** Ratio of Average Incomes per Worker, Nonagriculture to Agriculture

**Table 2.** Decade Average Nonagriculture to Agriculture Income Ratios

	1960s	1970s	1980s	1990s
Thailand	9.47	9.63	10.69	10.57
Philippines	3.29	3.29	3.19	2.79
Indonesia		3.88	4.07	4.44
Asia	3.37	3.31	3.57	

Note: Asia decade averages taken from Larson and Mundlak.

Since 1990, the gap decreased as agricultural productivity increased by over 40% (due to decreases in agricultural employment) before the crisis in 1997.

The sectoral income gap is extremely high in Thailand and has remained so throughout the past three decades, although it declined steadily during the later 1990s. Agricultural productivity in Thailand increased by 17% in the 1970s and by only 12% in the 1980s as the commodity boom ended and prices stagnated. The nonagricultural sector grew rapidly after the influx of foreign direct investment in the late 1980s. From 1990 to 1999, agricultural employment decreased, and agricultural productivity increased by over 55%, contributing to the decline in sectoral income differentials.

In the Philippines, the income ratio increased over part of the study period (1975–1984) and stayed above 2.5. Much of the movement in the income ratio was due to slow growth in nonagricultural productivity, particularly since the early to mid-1980s, when the Philippines experienced a series of political and economic crises. Agricultural productivity in the Philippines increased 25% over the past three decades, but most of the growth occurred in the 1960s as a result of the green revolution. Agricultural GDP actually decreased in the early 1980s. Agricultural employment has continued to increase throughout the study period. Still, the gap declined from 1983 on.

To sum up, there is a tendency for the income gap to decline in the more recent years in the three countries. This was still not sufficient to affect the decade averages of the gap as shown in Table 2, but it is expected that these countries will follow the development that took place in other countries and the gap

will eventually decrease substantially. We can compare these trends to those for Asian countries in the Larson and Mundlak study. The slow rate of migration from agriculture to nonagriculture plays a significant role in these trends. Migration has not yet been sufficient to close the income gap between the sectors. Conversely, given that the income gaps are still rather large, it is not surprising that migration rates have not decreased in the 1990s.

The vector  $S$  in Equation (2) consists of other variables that may affect the migration decision. We think of two groups: one related to incentives and the other consisting of variables representing infrastructure, which may bear on the cost of migration. The latter group contains trended variables, whereas the migration rates show high variability. Thus, the onus of the explanation is on the first group. We therefore list several variables that might have affected migration and leave it for the data to determine their relevance in our case.

As for the incentives, the income ratio may not fully summarize the opportunities and their stability. We therefore consider other variables that reflect the attractiveness of the two sectors. It is worth noting at the outset that several of the variables we consider have a direct role in determining agricultural income and productivity, which we attempt to measure in Mundlak, Larson, and Butzer. However, for reasons given below, we expect these factors to play an additional role in migration as well.

A natural variable is the terms of trade of agriculture as measured by the ratio of sectoral prices, agriculture to nonagriculture.<sup>4</sup> The price ratio affects the relative profitability of agriculture, and thus a decline in the price is expected to encourage migration. The condition in agriculture can also be viewed in the ability of the agricultural sector to support its expanding labor force. For that purpose, we use the ratio of agricultural population to agricultural land as a measure of agricultural density. It is expected that the more densely populated the agricultural sector, the greater

<sup>4</sup> The price ratio is the ratio of the GDP deflator in agriculture to that of nonagriculture. The GDP deflator is derived from the ratio of GDP in nominal prices to GDP in constant prices.



the incentive to migrate out of agriculture. This can be viewed as a measure of the push side.

On the pull side, we try several measures related to the prospect of finding work in nonagriculture. Unutilized capacity in nonagriculture is approximated by the difference between the peak of previous per capita output and current per capita output divided by the peak value. If the current value exceeds the peak value, the unutilized capacity is zero. An alternative measure is the growth rate of output in the nonagricultural sector. Periods of fast growth are presumably more attractive for migration. A more direct measure is the growth rate of the nonagricultural labor force. We also tried the difference in the growth rates of output in nonagriculture to that in agriculture.

Turning to the second group of variables, the rate of migration is also affected by the cost of migration. This cost is negatively related to the degree of integration of the rural areas with labor markets. Such integration depends on the state of the physical infrastructure, such as roads and telecommunications. Education may also reduce the cost of migration, probably through the ability to obtain and digest information; thus, we expect a positive effect on migration. The education variable also reflects the demand preferences for skilled labor. Labor and technology are not homogeneous, and, with the changes in technology, there is an increasing demand for skilled labor; this supplements the effect of education on the migration cost.

Certain public health issues, such as the spread of infectious diseases, can be viewed in terms of the cost of migration and the incentives to migrate. The prevalence of roads, telecommunications, education, and health depends on the investments in such activities. This investment originates mostly in the public sector, and we therefore refer to this group as the policy variables. The impact of public goods on the migration rate, however, might be ambiguous. On one hand they reduce the migration cost, but, on the other hand, they increase the labor productivity in agriculture, as well as in nonagriculture, and thereby might reduce the income gap. In that case, the net

effect is uncertain. Moreover, the empirical scope for these variables in time-series analysis of the migration equation is rather limited. Migration is subject to annual variations, whereas these explanatory variables are strongly trended and highly intercorrelated.

### Regression Results

The migration equation was estimated separately for each country, and the results are reported in Tables 3–5. The time period varied depending on data availability. The explanatory variables were lagged one period and expressed in natural logs, except when noted. As we saw in earlier figures, migration rates for some years were negative; therefore, the dependent variable is migration rate ( $m$ ). Recall that the migration rate was calculated from the employment data, rather than the labor force, and the resulted series are volatile.<sup>5</sup> Because some of the explanatory variables are trended and intercorrelated, the explanatory power of the regressors is not high. The regression did not sustain all the contemplated variables and the exercise amounted to a search of relevance of the various variables in explaining the data. We report results obtained by ordinary least squares (OLS) and by principal components (PC). As mentioned earlier, the latter was used to impose restrictions on the parameter as a substitute to the elimination of specific variables. Such a procedure reduces the specification error due to omission of regressors (Theil). The statistical rank reported in the tables is obtained as the difference between the number of regressors and the number of restrictions imposed on the parameters.<sup>6</sup> Throughout, the Durbin-Watson statistics did not flag a serial-correlation problem.

The most important and most robust result is the positive impact of the income ratio on the migration rate. The numerical value of the

<sup>5</sup> The data problems are discussed in Mundlak, Larson, and Butzer.

<sup>6</sup> The PC method used followed the algorithm in Mundlak (1981). The level of significance was 10%. A statistical rank of 3 means that three linear combinations of the variables summarize the information contained in the regressors.

**Table 3.** Principal components regression results for Thailand, 1962–1999

	Estimate	t-Score	Estimate	t-Score
Intercept	–28.59	–3.43	–34.17	–3.52
Income ratio	13.59	3.59	15.42	3.68
Employment ratio	1.64	3.59		
Unutilized capacity	–9.13	–3.59	–12.78	–0.52
R-square	0.26		0.30	
D-W statistic	2.17		2.04	
Statistical rank	1		2	
Means				
Migration	1.322		1.322	
Unutilized capacity	0.009		0.009	
Elasticities				
Income ratio	10.28		11.67	
Employment ratio	1.24			
Unutilized capacity	–0.06		–0.09	

Note: The elasticities were calculated at mean migration rates.

**Table 4.** Principal Components and Ordinary Least-Squares Regression Results for the Philippines, 1962–1998

Estimation Method	OLS		OLS		PC	
	Estimate	t-score	Estimate	t-score	Estimate	t-score
Intercept	–4.45	–0.91	–18.21	–1.93	–17.20	–1.87
Income ratio	4.31	0.99	8.50	1.74	5.58	1.25
Ratio of GDP deflators	–2.84	–0.77	–5.32	–1.47	–6.79	–2.19
Growth rate of industrial employment	0.21	2.62	0.16	2.07	0.14	2.19
Mean years of schooling			4.69	1.69	6.01	2.36
Growth rate differential			0.22	1.71	0.17	2.54
R-square	0.22		0.35		0.30	
D-W statistic	2.15		2.08		0.10	
Statistical rank					3	
Significant level					0.15	
Means						
Migration	1.112		1.112		1.112	
Growth rate of industrial employment	3.308		3.308		3.308	
Growth rate differential			1.338		1.338	
Elasticities						
Income ratio	3.88		7.64		5.02	
Ratio of GDP deflators	–2.55		–4.79		–6.11	
Growth rate of industrial employment	0.63		0.49		0.41	
Mean years of schooling			4.22		5.40	
Growth rate differential			0.27		0.20	

Note: The elasticities were calculated at mean migration rates.

**Table 5.** Principal Components and Ordinary Least-Squares Regression Results for Indonesia, 1972–1999

Estimation Method	OLS		OLS		PC	
	Estimate	t-score	Estimate	t-score	Estimate	t-score
Intercept	-13.78	-1.60	-11.55	-1.64	-18.42	-5.66
Income ratio	10.22	1.73	2.88	0.45	10.80	6.17
Unutilized capacity	-35.96	-2.46	-35.89	-2.69	-12.12	-2.18
Inflation rate	0.11	1.96	0.09	2.21	0.05	1.85
Mean years of schooling			3.88	1.61	0.90	2.60
Growth rate of nonagricultural employment			0.55	4.84	0.56	6.06
R-square	0.31		0.67		0.61	
D-W statistic	2.04		2.38		2.54	
Statistical rank					2	
Significance level					0.10	
Means						
Migration	1.442		1.442		1.442	
Unutilized capacity	0.021		0.021		0.021	
Inflation rate	13.495		13.495		13.495	
Growth rate of nonagricultural employment			5.170		5.170	
Elasticities						
Income ratio	7.09		2.00		7.48	
Unutilized capacity	-0.52		-0.52		-0.17	
Inflation rate	1.03		0.85		0.42	
Mean years of schooling			2.69		0.62	
Growth rate of nonagricultural employment			1.96		2.01	

Note: The elasticities were calculated at mean migration rates.

income-ratio coefficient varied somewhat in the various experiments, but on the whole the coefficient was significant. This is empirical validation of the proposition stated above and is consistent with other studies with a similar specification. The elasticity with respect to the income ratio (computed at the mean value of the migration rates) varied in the range of 10–12 in Thailand, 4–8 in the Philippines, and 7 for Indonesia.<sup>7</sup> These are high values, but it should be noted that the impact of a 10% change in the migration rate on the sectoral employment is by far smaller. We turn now to review the role of the other variables.

The labor ratio was practically irrelevant with a few exceptions, one of which is shown for Thailand. But even there the importance is marginal. Instead, what seems to be important

is the absorbing capacity of nonagriculture. This is revealed by several indicators. The unutilized capacity in nonagriculture was important in Indonesia and in Thailand. During most of that period, the measure of unutilized capacity, which was not lagged, was zero, and as a result the mean value is low, but in some years it was quite high. The peak value for this variable in the study period was 0.12 in Thailand and 0.16 in Indonesia. The elasticities reported in the table are calculated for the mean values. During years of high-unutilized capacity in nonagriculture, the elasticities would be considerably higher. For the extreme values reported above for the study period, the elasticities would be higher by an order of magnitude of 10-fold.

In the Philippines, the nonagricultural sector did not develop fast enough to attract and absorb labor from the agricultural sector, an issue raised by Balisacan, Debuque, and Fuwa. To take account of this fact, we used data on

<sup>7</sup> Let  $m = b \ln x$ ; then the elasticity of  $m$  with respect to  $x$  is  $\delta \ln m / \delta \ln x = b/m$ . The results reported in the article are obtained at the mean value of  $m$ .

the growth rate of employment in the industrial sector. This variable has a strong positive effect on migration.<sup>8</sup> We did not have a similar measure for the other countries. We therefore used the growth rate of nonagricultural employment. This variable enters the calculation of the migration rates; therefore, its effect should be interpreted with caution. This was done for Indonesia where the coefficient is positive and significant. Note, however, that its introduction did not affect the coefficient of the income ratio much, and its effect on the other coefficients is not substantive. The interpretation is that the variable picked up some of the noise in  $m$  that comes from the use of the employment data in the calculation of the migration rates. The results for Thailand were less meaningful. We also tried the difference in the growth rates of output between nonagriculture and agriculture. This variable had a marginally positive effect only for the Philippines.

The terms of trade of agriculture, measured by the price ratio, were relevant in the Philippines, where the variable varied much over the study period, unlike in Thailand and Indonesia. The sign of the coefficient is negative, meaning that the migration rate is higher in years when the terms of trade of agriculture are low. We tried a population density variable (the ratio of population to agricultural land). The variable did not have explanatory power. Inflation was empirically relevant in Indonesia with a positive coefficient; it seems that the heating up of the economy was supportive to migration. There can be various interpretations to the role of the inflation rate, but the finding is not so strong that it justifies diving into the discussion of this subject here.

Finally, the public good, or policy, variables discussed above had little impact. These variables are trended and thus had only weak correlations with the migration rate. The most

pronounced effect is education in the Philippines, obtained in the PC regression. It was possible to force some of the policy variables in other regressions using the PC procedure but at the cost of reducing the level of explanation. This means that the contribution of these variables to the explanation, conditional on the other regressors, is negligible or negative. This result may reflect the data problem, but it may also be due to the fact, discussed above, that the impact of the public goods on the migration rate might be ambiguous. In a cross-country study (Larson and Mundlak), education showed a robust positive impact on the migration rate. That study does not include measures of physical infrastructure, such as road length or health conditions, so it is not strictly comparable to the current study. It does, however, contain year and geographic dummies that may confound some of the impact of the infrastructure. To conclude, we refrain from generalizing our empirical results on the role of the policy variables.

## Conclusions

The labor migration from agriculture is related to the dynamics of sectoral allocation of labor. Our article examines the process in Indonesia, Thailand, and the Philippines. The migration rates from agriculture to nonagriculture are relatively low compared with those of other countries; thus, labor surpluses have not been reallocated at a fast pace to other sectors of the economy. The effect of these low migration rates on the persistence of the intersectoral income differentials is obvious. Even so, the rate of migration has been responsive to the income ratios in each country. The migration rate was also affected by the absorbing capacity of nonagriculture, as indicated by several measures. The policy variables consisting of indicators of physical and human capital had little impact on the migration rate separate from that captured by relative incomes.

Unfortunately, the data yield migration series that contain a considerable amount of variability for which we have not been able to account. This variability may be due to data

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<sup>8</sup> The labor data in the Philippines is reported for three sectors: agriculture, industry, and services. Thus, industrial employment is not the same as nonagricultural employment. In 1960, approximately 50% more people were employed in services than in industry. By 1971, employment in services was double that in industry, and by the late 1990s it was nearly triple.

problems or perhaps to economy-wide shocks. This remains part of the puzzle of migration in Indonesia, Thailand, and the Philippines.

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- ery but does not include Simple Agricultural Processing Products. National income accounts were obtained in constant and current market prices (in baht) from the Office of The National Economic and Social Development Board.
- Employment (agricultural, total)*. Data on employment comes from the National Statistical Office, *Report of the Labor Force Survey*. Round 2 (July-September) was used for 1969-1983, and Round 3 (August) was used from 1984 on. No data were reported for 1970, so straight-line interpolation was used to estimate the data. For 1961-1968, data obtained from Coxhead and Plangraphan (1998) were used.

## Philippines

*Gross Domestic Product (agricultural, total)*. The agricultural GDP series includes Forestry and Fishery. National accounts were obtained in constant and current market prices (in pesos) from the Economic and Social Statistics Office, National Statistical Coordination Board.

*Employment (agricultural, industrial, and total)*. Data on employment come from the Labor Force Survey, National Statistics Office. When available, data from the October survey were used. Sectoral data were not reported in 1964, 1969, and 1979. For these years, the ratios of sectoral employment to total employment were estimated using straight-line interpolations. Agricultural and industrial employment figures were then calculated from these estimates.

*Education*. Economy-wide human capital is proxied by the mean school years of education of the total labor force. This data series was constructed by Nehru, Swanson, and Dubey from enrollment data using the perpetual inventory method and is available up to 1987. Data for 1988-1998 are forecast by fitting the series using an OLS regression of human capital on time.

## Indonesia

*Gross Domestic Product (agricultural, total)*. The GDP series in current and constant prices were obtained from various issues of *Statistik Indonesia* (the Statistical Yearbook of Indonesia), Badan Pusat Statistik (BPS). The agricultural GDP series includes Forestry & Fishery.

*Employment (agricultural, total)*. The *National Labour Force Survey* contains data on population aged  $\geq 10$  years who worked by main industry. These were obtained from various issues of *Statistik*

## Appendix: Data Sources

### Thailand

*Gross Domestic Product (agricultural, total)*. The agricultural GDP series includes Forestry & Fish-

*Indonesia, BPS.* Data for the missing years of 1972–1975, 1979, and 1983–1984 were estimated using straight-line interpolations of the ratio of agricultural employment to total employment, as well as the total employment series. Agricultural employment was then calculated from these estimates. Employment data reported for 1998–1999 were for population of aged  $\geq 15$  years, so the annual changes in this series were calculated and applied to the previously mentioned employment series (age 10+) to obtain estimates for these years.

*Consumer Price Index.* Data on the consumer

price index of 17 capital cities in Indonesia are reported in the *International Financial Statistics* of the International Monetary Fund. Data were converted to a base year of 1993.

*Education.* Economy-wide human capital is proxied by the mean school years of education of the total labor force. This data series was constructed by Nehru, Swanson, and Dubey from enrollment data using the perpetual inventory method and is available up to 1987. Data for 1988–1998 are forecast by fitting the series using an OLS regression of human capital on time.

