The Labor Productivity Gap between the Agricultural and Nonagricultural Sectors, and Poverty and Inequality Reduction in Asia

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The objective of this paper is to examine how agricultural and nonagricultural labor productivities have grown over time and whether the growth pattern affected poverty in low- and middle-income economies in Asia. We first examine whether labor productivities in the agricultural and nonagricultural sectors have converged, finding evidence that they did not as the latter have grown faster. We then confirm that both agricultural and nonagricultural labor productivities have converged across economies and that the convergence effect is stronger for the nonagricultural sector. We have also observed that, despite the relatively slower growth in agricultural labor productivity, the agricultural sector played an important role in promoting nonagricultural labor productivity and thus in nonagricultural growth. Finally, we have found some evidence that the labor productivity gap reduces rural and urban poverty, as well as national-level inequality.

Keywords: agricultural labor productivity, Asia, inequality, labor productivity gap, poverty
JEL codes: C23, I32, J24, O13

I. Introduction

The objective of this paper is to examine (i) how labor productivities in the agricultural and nonagricultural sectors in Asia have grown over time, and (ii) whether the growth pattern—proxied by the labor productivity gap between the two sectors—affected poverty and inequality in low- and middle-income economies in Asia. We focus on these economies because the interaction between the agricultural and nonagricultural sectors has become increasingly important as these

economies have experienced structural transformation. We will first investigate the convergence of labor productivity in the agricultural and nonagricultural sectors with a focus on both intersectoral convergence and within-sector convergence across different economies over time.

The issue of intersectoral convergence versus divergence is reviewed in the literature, which investigates allocations or misallocations of inputs into the agricultural and nonagricultural sectors. For instance, using microlevel data, Gollin, Lagakos, and Waugh (2013) found that a large gap between the two sectors persists, suggesting the misallocation of labor at the macro level. However, the extent of the gap and how it has changed over time differs across economies depending on their initial capital and labor endowments, the stage of economic development, and the nature of their public policies. As the degree of the misallocation of resources in dual-economy settings explains variations in national income and productivity growth (Vollrath 2009), it is important to examine how the gap has changed over time.

To investigate whether the growth pattern impacts poverty and inequality in low- and middle-income economies in Asia, we draw upon the large empirical literature to test the convergence hypothesis in line with the neoclassical growth model: that is, whether poorer economies or regions grow faster than richer economies or regions (Barro 1991, Barro and Sala-i-Martin 1992, Barro et al. 1991). For instance, Barro et al. (1991) and Barro and Sala-i-Martin (1992) used state-level data on personal income for 48 states in the United States (US) during 1940–1963 and found clear evidence of convergence. As for convergence across economies, while the earlier literature suggests that there was convergence across a wide range of economies (Barro [1991] observes 98 economies during 1960–1985) and that the convergence was also observed for productivity growth (Baumol, Nelson, and Wolff 1994), it has been debated whether the convergence occurred for a subset of economies or for different specifications (Levine and Renelt 1992, Quah 1996). The results partly depend on the extent to which the economies are integrated, for instance, through international trade (Ben-David 1996). Given that East and South Asian economies are becoming more integrated, an interesting question is whether productivity converged among Asian economies.

We will also investigate whether the gap is associated with poverty and inequality reduction in rural and urban areas. While the literature has focused on the poverty-reducing effect of agricultural sector income or productivity growth, little is known about whether the gap between agricultural and nonagricultural productivity influences poverty or inequality.[1] A point of departure is that we treat the labor productivity gap as endogenous by using the fixed-effects instrumental-variable (FE-IV) model, where the cropping pattern is used as an instrument. Finally, we

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[1]See Imai, Gaiha, and Bresciani (2016) for the evidence for Asia.

will discuss whether the labor productivity gap will dynamically affect the labor allocation between rural and urban sectors.

Our paper draws upon the following three strands of the literature. The first is the literature on the empirical investigations of the gap between agricultural and nonagricultural productivities in the dual-economy model, consisting of the traditional and modern sectors. A seminal work in this strand of the literature is Gollin, Lagakos, and Waugh (2013), who used both national accounts and household data to show that value added per worker is much higher in the nonagricultural than agricultural sector in developing economies. They call this the "agricultural productivity gap." As Gollin, Lagakos, and Waugh (2013, p. 942) note, the investigation of the agricultural productivity gap has been viewed as an important topic in the early literature on development economics as it can offer valuable insights into the analysis of economic growth and inequality in developing economies (e.g., Lewis 1955, Kuznets 1971). In recent years, the agricultural and nonagricultural sectors have become more integrated within economies through structural transformation, while the agricultural (or nonagricultural) sector of one economy has become more closely linked with the same sector of other economies under globalization. Given the nature of the data that Gollin, Lagakos, and Waugh (2013) used, their analysis is essentially static. However, it is important to analyze the gap in a dynamic context. Drawing upon the panel data of Asian economies, the present study focuses on how agricultural and nonagricultural labor productivities have grown, with their interactions taken into account. It also estimates the effect of the gap on poverty and inequality.

Second, our study is closely related to the large body of the literature on the role of the agricultural sector in development and the reduction of poverty and inequality (e.g., Christiaensen, Demery, and Kuhl 2011). A point of departure of the recent literature (Christiaensen, Demery, and Kuhl 2011; Imai, Cheng, and Gaiha 2017) is that the role of agriculture is captured by dynamic interactions between the agriculture and nonagricultural sectors. The present study extends these arguments and focuses on the effect of the labor productivity gap between the two sectors on poverty and inequality.

Third, the present study is also closely related to the literature on structural transformation, in particular rural transformation (or agricultural transformation), and its effect on development and/or poverty in low- and middle-income economies in Asia and elsewhere (e.g., Reardon and Timmer 2014, Dawe 2015, Barrett et al. 2017). As the structural transformation implies a closer and more intricate relationship between the agricultural and nonagricultural sectors, our empirical investigation of the gap between agricultural and nonagricultural productivity can provide useful insight into the literature on structural transformation.

The rest of the paper is organized as follows. In the next section, we briefly summarize the theoretical foundations underlying our empirical investigation. In section III, we examine the convergence of labor productivity in the agricultural and

nonagricultural sectors. Section IV estimates the effects of the labor productivity gap on poverty, inequality, and the sectoral population share. The final section offers our concluding observations.

II. Theoretical Foundations

Our empirical investigation of the gap between agricultural and nonagricultural labor productivity is associated with a large body of theoretical literature on the dual-economy model, which originated from Arthur Lewis (1954) and was later developed by many authors (e.g., Dixit 1973, Mundlak 2000). More recently, Vollrath (2009) constructs a dual-economy model in which the productivity differences between the two sectors arise endogenously. In Vollrath's model, agricultural production is a constant returns to scale function of labor effort and land (Vollrath 2009, p. 8). Total agricultural production is denoted as

$$Y_t^A = A_t^A F\left(R, E_t^A\right) \tag{1}$$

where Y_t^A is agricultural production at time t (and superscript A denotes the agricultural sector), A_t^A is total factor productivity of the agricultural sector, R is the total amount of land (or resources in general) in the agricultural sector, and E_t^A is the total labor effort: that is, $E_t^A = s_t a_t L_t$. F is a well-behaved function with constant returns to scale. Net income for a representative farmer in the agricultural sector is

$$I_t^A = p_t^A A_t^A F\left(r_t, s_t\right) - \rho_t r_t \tag{2}$$

where r_t is the land employed by the farmer at time t. Each individual has a unit of time, with the share $s_t \in (0, 1)$ allocated to productive work in the agricultural sector and the remaining $1 - s_t$ spent in nonfarm activity at time t. ρ_t is the rental price of land, and p_t^A is the price of agricultural goods relative to manufactured goods.

The manufacturing (nonagricultural) sector is assumed to be perfectly competitive so that labor effort is paid its marginal product (Vollrath 2009, p. 9). The wage rate per unit of effort in the nonagricultural sector is specified as

$$w_t^M = A_t^M w\left(a_t\right) \tag{3}$$

where the wage rate depends on the productivity of nonagricultural sector, A_t^M, as well as on a well-behaved function w of the number of people in agriculture, a_t ($w' > 0$ and $w'' > 0$), given the assumption that the nonagricultural sector is competitive, while the agricultural sector is not. These properties imply that the

nonagricultural wage increases as the number of people in the nonagricultural sector $(1 - a_t)$ decreases. Net income for nonagricultural workers is simply defined by

$$I_t^M = w_t^M s_t \tag{4}$$

Under these settings, Vollrath (2009, p. 11) showed that in equilibrium a dual economy exists where nonagricultural workers allocate more time to productive work than agricultural workers, and the marginal product of a worker is higher for nonagricultural (manufacturing) workers.[2] As a result, gross domestic product (GDP) per capita can be increased by a transfer of labor from the agricultural sector to the nonagricultural sector. Vollrath's model (2009, p. 13) also implies that sustained increases in agricultural productivity will help industrialize the economy, but this will be accompanied by a growing disparity in productivity between sectors. On the contrary, increases in nonagricultural productivity will not only industrialize the economy but also induce agricultural workers to work more efficiently.[3] This model prediction is intuitively valid given close interactions between the two sectors through migration, particularly in emerging economies such as India, the People's Republic of China, and Viet Nam.

The above model would predict, in our empirical context, that the gap in labor productivity between the agricultural and nonagricultural sectors expands as the economy grows. As the gap in labor productivity between the two sectors implies an improvement in relative productivity of the nonagricultural sector, it is likely to reduce poverty. So, we will test the hypotheses directly related to Vollrath (2009) that (i) the labor productivity gap between the agricultural and nonagricultural sectors expands over time, and (ii) the labor productivity gap between the two sectors reduces poverty. As we will discuss later, our empirical results are broadly consistent with Vollrath (2009).

Vollrath's (2009) model also implies that agricultural productivity and nonagricultural productivity interact in a complicated way. However, the model does not explicitly consider the interactions with factors outside the economy. Assuming the concavity of the production function in both sectors, we will empirically investigate whether agricultural productivity will converge or not across Asian economies by taking account of the effect of the lagged nonagricultural productivity on agricultural productivity. The convergence of nonagricultural productivity will also be examined by incorporating the effect of agricultural productivity on nonagricultural productivity. This empirical model is oriented in the literature to test the convergence of economic growth (Barro 1991, Barro and Sala-i-Martin 1992, Barro et al. 1991).

Vollrath (2009) predicts that in the long term the agricultural sector's productivity growth will exacerbate the inefficiencies of a dual economy and

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[2]See Vollrath (2009, pp. 8–11) for details on how equations (1)–(4) will lead to the results.
[3]See Vollrath (2009, pp. 12–13 and the Appendix) for more details.

produce slower overall growth than will nonagricultural sector productivity improvements, and therefore the dual economy will disappear. This is consistent with empirical observations of developed Asian economies such as Japan and the Republic of Korea. While both of these economies improved their agricultural productivity in the late 20th century, the GDP share of the agricultural sector declined as they industrialized and eventually achieved higher overall productivity. In the meantime, the overall inequality of these economies remained relatively low and stable.[4] However, Vollrath (2009) lacks two aspects. First, the effect of the persistence of the dual economy on income distribution is not explicitly analyzed. Second, focusing on the long-term effect, Vollrath's model may not fully capture the positive role of agriculture on economic growth and the reduction of poverty and inequality, which is important in most low- and middle-income economies in Asia such as India. For instance, Ravallion and Datt (1996) used 35 household surveys of India between 1951 and 1991 and found that the growth of the primary sector (mainly agriculture) and the tertiary sector (mainly services) reduced national, rural, and urban poverty significantly, while growth of the secondary sector (mainly manufacturing) increased national poverty. They also showed that rural growth is more important for poverty reduction than urban growth. It is evident that a separate theoretical model is necessary to analyze the effect of a dual economy on income distribution and poverty.

Some authors have explored the relationship between growth and income distribution with a focus on the dual economy (e.g., Robinson 1976, Bourguignon 1990, Fields 1993, Bourguignon and Morrisson 1998). Bourguignon (1990) offers a theoretical ground for Kuznets' hypothesis in detail. The dual economy is modeled in a general equilibrium framework by taking account of the entire distribution, which generates a Lorenz curve rather than summary measures. Bourguignon (1990, p. 219) first derived a proposition that a "necessary and sufficient condition for growth to shift the Lorenz curve of the income distribution upward is that the share of the traditional sector in GDP increases with growth." That is, an increase of the share of the agricultural sector in the growth process tends to reduce inequality. However, as Bourguignon notes, it is unlikely that the agricultural sector share increases with growth. Bourguignon (1990, pp. 226–27) then derives the proposition that a "necessary condition for growth to be unambiguously egalitarian, despite a fall in the GDP share of the traditional sector, is that capital–labor substitution be inelastic in the modern sector," implying that "observing a falling GDP share of the traditional sector, together with elastic capital–labor substitution in the modern sector, is sufficient to rule out unambiguously egalitarian growth in a dual economy." That is, the model predicts that the disparity between the

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[4]The income Gini coefficient of the Republic of Korea declined from 0.34 in 1965 to 0.31 in 1993 (Choo 1991) and that of Japan fell from 0.29 in 1966 to 0.28 in 1998 (based on the Family Income and Expenditure Survey from Moriguchi and Saez 2008). Both economies experienced a decline in the GDP share of agriculture during the respective review period.

agricultural and nonagricultural sectors tends to increase inequality with elastic capital–labor substitution in the nonagricultural (modern) sector. Bourguignon's model motivates our empirical analysis of the relationship between the agricultural–nonagricultural labor productivity gap and inequality and poverty.

III. Convergence of Labor Productivity in the Agricultural and Nonagricultural Sectors

Drawing upon the theoretical discussion in the last section, this section will examine the relationship between agricultural labor productivity and nonagricultural labor productivity with a focus on whether (i) these two converge or diverge over time, (ii) agricultural labor productivity converges across different economies, and (iii) nonagricultural labor productivity converges across different economies. For (ii) and (iii), the intersectoral effects are also taken into account in one case. That is, the effect of lagged nonagricultural labor productivity on agricultural labor productivity is considered. For (iii), the effect of lagged agricultural labor productivity on nonagricultural labor productivity is taken into account. For simplicity, the labor productivity of the agricultural (nonagricultural) sector is defined as value added in the agricultural (nonagricultural) sector divided by the number of workers in the agricultural (nonagricultural) sector.

Table 1 compares labor productivity in these sectors by economy and region, and for Asia as a whole. The comparison is also made for the entire period as well as before and after the year 2000. Table 1 reports labor productivity growth as well as the labor productivity gap as defined by the gap between the logarithm of agricultural value added per worker and the logarithm of value added per worker in the nonagricultural sector. Consistent with earlier literature (e.g., Martin and Mitra 2001, Bernard and Jones 1996), nonagricultural labor productivity is higher in all cases except the Federated States of Micronesia before 2000. Also, the labor productivity gap is higher after 2000 in all cases except Fiji. Our results strongly confirm the labor productivity divergence between the two sectors. That is, nonagricultural labor productivity was higher than agricultural labor productivity to start with and that the gap has expanded over time.

However, there is a great degree of heterogeneity in terms of the speed of divergence. For instance, in a few economies (e.g., Indonesia and the Federated States of Micronesia), the gap has only moderately increased, but in other economies (e.g., Bhutan, India, and the People's Republic of China), the gap dramatically increased after 2000. It is thus safe to conclude that there is no evidence of labor productivity convergence between the agricultural and nonagricultural sectors. This is due to the fact that while agricultural labor productivity has grown substantially since 2000, nonagricultural labor productivity has grown even faster in many economies.

Table 1. **Labor Productivity Growth in the Agricultural and Nonagricultural Sectors, and the Labor Productivity Gap (in level) in These Sectors**

	Total			Before 2000			After 2000		
	Agricultural Labor Productivity Growth[a]	Nonagricultural Labor Productivity Growth[b]	Labor Productivity Gap[c]	Agricultural Labor Productivity Growth[a]	Nonagricultural Labor Productivity Growth[b]	Labor Productivity Gap[c]	Agricultural Labor Productivity Growth[a]	Nonagricultural Labor Productivity Growth[b]	Labor Productivity Gap[c]
South Asia									
Bangladesh	0.33	2.40	0.95	−0.41	1.49	0.82	2.57	5.15	1.39
Bhutan	1.30	7.90	0.66	2.13	8.38	0.29	0.06	7.14	1.28
India	0.66	4.01	0.81	0.37	3.20	0.59	1.53	6.47	1.52
Nepal	0.50	2.62	0.34	0.002	2.78	0.22	1.79	2.29	0.61
Pakistan	1.00	3.29	0.91	0.93	3.33	0.78	1.25	3.15	1.28
Sri Lanka	1.29	3.76	1.40	1.03	3.36	1.21	2.04	4.97	1.99
Total	0.82	3.77	0.88	0.55	3.36	0.71	1.56	4.83	1.34
East and Southeast Asia; Pacific									
Cambodia	2.72	7.25	0.52	1.93	5.66	0.13	3.23	7.99	0.74
PRC	2.96	7.34	0.74	2.78	6.54	0.31	3.51	9.75	2.06
Fiji	0.86	3.63	2.96	0.34	3.99	2.87	−0.66	0.97	1.82
Indonesia	1.40	4.38	1.34	1.09	4.34	1.15	2.32	4.51	1.91
Lao PDR	1.98	5.50	0.33	1.97	3.60	0.10	1.99	7.68	0.62
Malaysia	0.62	4.47	1.78	0.22	4.95	1.50	1.52	3.41	2.52
FSM	0.12	−0.27	1.09	−14.20	−6.31	1.01	0.74	0.19	1.09
Philippines	0.35	1.74	1.72	0.07	1.20	1.64	1.22	3.34	1.97
Timor-Leste	−2.90	4.87	1.08	—	—	—	−2.90	4.87	1.08
Viet Nam	2.19	5.85	1.18	1.70	5.70	0.94	2.70	6.02	1.46
Total	1.15	3.68	1.06	0.96	3.14	0.90	1.48	4.64	1.34
Asia Total	0.84	3.44	1.07	0.24	2.56	0.90	2.04	5.16	1.42

FSM = Federated States of Micronesia, Lao PDR = Lao People's Democratic Republic, PRC = People's Republic of China.
Notes:
[a]Agricultural labor productivity growth = DLog (agricultural value added per worker)
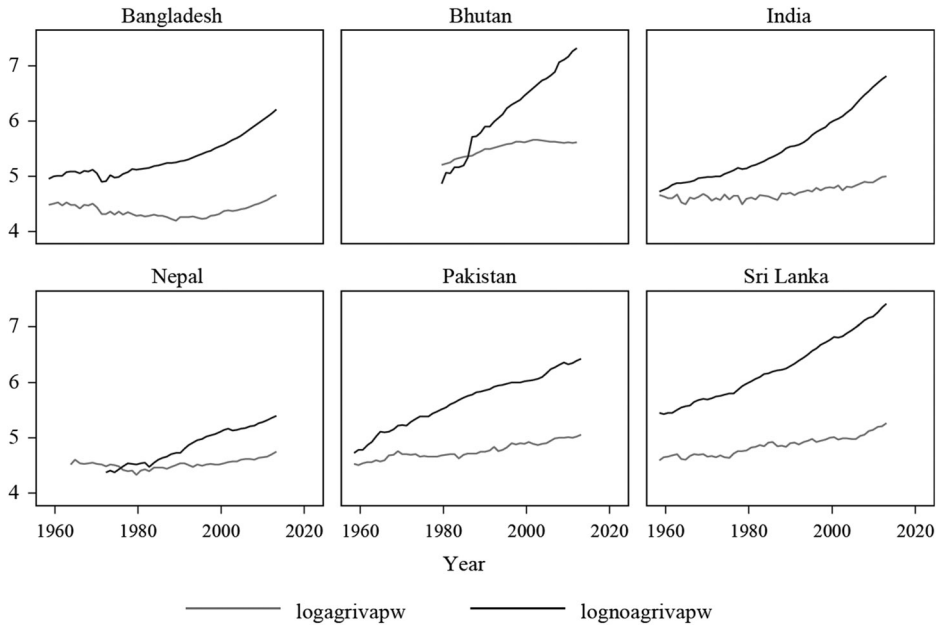[b]Nonagricultural labor productivity growth = DLog (nonagricultural value added per worker)
[c]Labor productivity gap = Log (nonagricultural value added per worker) − Log (agricultural value added per worker)
Source: Authors' calculations based on World Bank. 2016. World Development Indicators 2016. https://openknowledge.worldbank.org/handle/10986/23969.

Figure 1. **The Gap between Nonagricultural Labor Productivity** (nonagricultural value added per worker) **and Agricultural Labor Productivity** (agricultural value added per worker) **in South Asia by Economy**
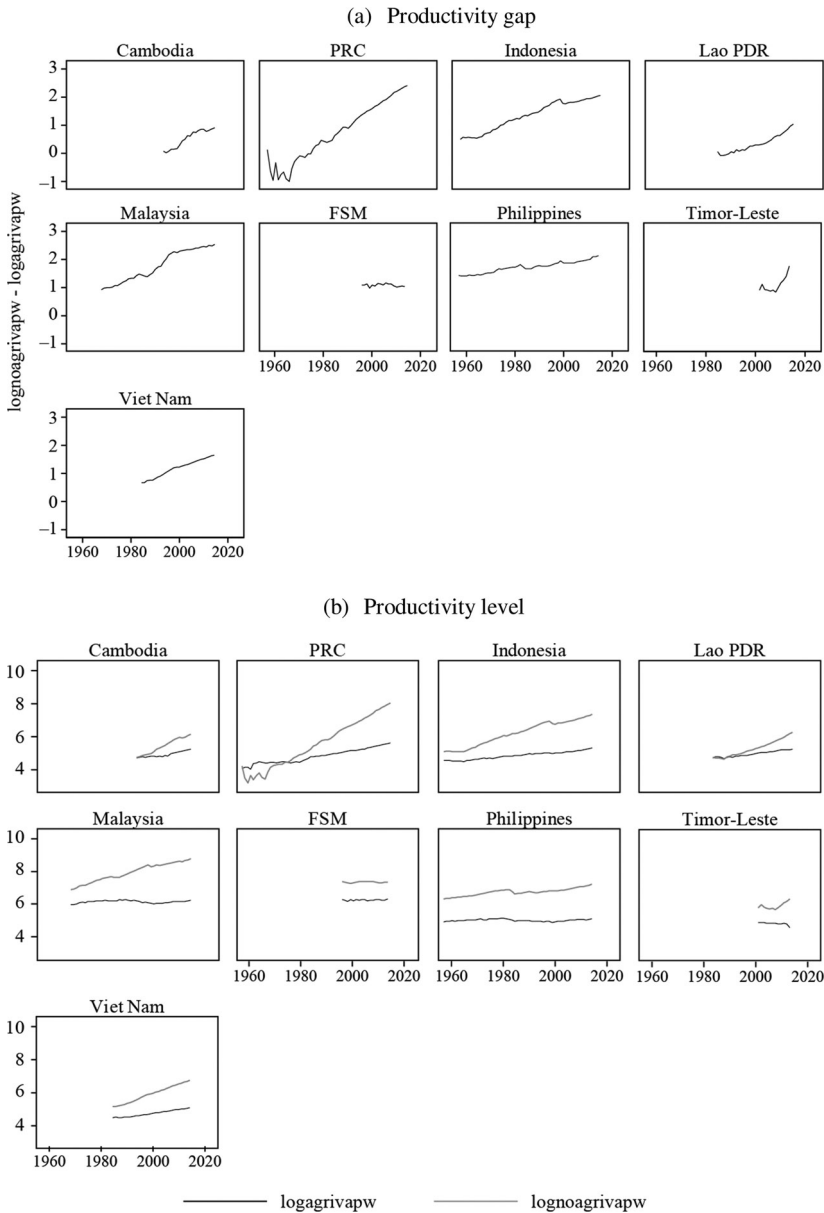

logagrivapw = logarithm of agricultural value added per worker, lognoagrivapw = logarithm of nonagricultural value added per worker.

Source: Authors' calculations based on World Bank. 2016. World Development Indicators 2016. https://openknowledge.worldbank.org/handle/10986/23969.

Figures 1 and 2 confirm these results graphically. Figure 1 plots labor productivity in the agricultural and nonagricultural sectors in South Asian economies over time. The productivity gap was initially small in many economies (in the 1960s and 1970s), but it has expanded over the years. Figure 2 indicates that the above results are broadly similar for East and Southeast Asian economies. If we aggregate these data, the divergence of labor productivity between the agricultural and nonagricultural sectors can be confirmed for all of Asia.

Next, we will examine whether agricultural labor productivity (or nonagricultural labor productivity) has converged across different economies based on the following simple static model (FE model) and dynamic panel model (system generalized method of moments). The idea is similar to Ghosh (2006), who examined the convergence of agricultural productivity among Indian states during 1960–2001. He found that there was significant divergence in labor productivity, particularly after the early 1990s, while there was no significant convergence or divergence in land productivity and per capita agricultural output. To take account

Figure 2. **The Gap between Agricultural Labor and Nonagricultural Labor Productivity in East and Southeast Asia, by Economy**

(a) Productivity gap

(b) Productivity level

FSM = Federated States of Micronesia, Lao PDR = Lao People's Democratic Republic, logagrivapw = logarithm of agricultural value added per worker, lognoagrivapw = logarithm of nonagricultural value added per worker, PRC = People's Republic of China.

Source: Authors' calculations based on World Bank. 2016. World Development Indicators 2016. https://openknowledge.worldbank.org/handle/10986/23969.

of the business cycle, we have taken the 5-year averages and estimate the same models as follows. We have redefined the time periods as $t = 1$ for 1960–1964, $t = 2$ for 1965–1969, . . . , and $t = 11$ for 2010–2014. A selection of the economies is guided by the availability of variables: 37 middle-income and low-income economies have been chosen from Asia and the Pacific.

First, the static model (FE model) is specified as

$$d \log AGLP_{it} = \beta_0 + \beta_1 \log AGLP_{it-1} + \beta_2 T + X_{it} \cdot \beta_3 + \beta_4 d \log NAGLP_{it-1}$$
$$+ \mu_i + \varepsilon_{it} \tag{5}$$

where $d \log AGLP_{it}$ stands for the annual agricultural labor productivity growth at time t for economy i. $\log AGLP_{it-1}$ is the level of agricultural productivity one period earlier in order to capture the convergence effect following the empirical literature to test the Solow growth model. Our main hypothesis for convergence is to test whether β_1 is negative.

T is the linear time trend. X_{it} is a vector of control variables, such as the logarithm of schooling years, the logarithm of share of the mining sector in GDP (in order to capture the economy's resource dependency), and the lagged level of inequality (based on the Gini coefficient). A selection of explanatory variables draws upon the recent literature, which investigated the interactions between agricultural growth and nonagricultural growth (Christiaensen, Demery, and Kuhl 2011; Imai, Cheng, and Gaiha 2017). The average years of total schooling is based on the Barro–Lee data, which has been commonly used in the empirical macroeconomics literature as it is a broad measure of the human capital stock of the economy.[5] It is assumed that as the economy's educational attainment improves, agricultural or nonagricultural labor productivity improves. The GDP share of the mining sector captures the extent to which the economy relies on natural resources, which may undermine sectoral labor productivity. The degree of inequality in various ways influences the sectoral labor productivity. For instance, if there exists a threshold (based on the nutritional requirement) below which workers cannot work efficiently in the labor market, a high level of inequality may undermine either agricultural or nonagricultural labor productivity. $d \log NAGLP_{it-1}$ is the lagged annual nonagricultural productivity growth to capture the transmission effect of labor productivity growth in the nonagricultural sector. This draws upon Vollrath's (2009) model, which showed that nonagricultural labor productivity enhances agricultural labor productivity over time in a dual-economy setting. μ_i is the economy's unobservable fixed effect (e.g., cultural or institutional factors). ε_{it} is an error term. We estimate this model with and without control variables, or

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[5]For more details, see Barro–Lee Educational Attainment Dataset. http://www.barrolee.com/.

the nonagricultural labor productivity growth term, while the results are robust to inclusion (exclusion) of a few other explanatory variables.

As an extension, equation (1) has been estimated using the dynamic panel model (system generalized method of moments) drawing upon the Blundell and Bond (1998) robust estimator:

$$d \log AGLP_{it} = \beta_0 + \beta_1 d \log AGLP_{it-1} + \beta_2 \log AGLP_{it-1} + \beta_3 T$$
$$+ \beta_4 d \log NAGLP_{it-1} + \varepsilon_{it} \tag{6}$$

Here, d denotes the first difference. The lagged dependent variable captures the persistent effect of agricultural labor productivity growth. Control variables have been dropped as they are statistically insignificant.

Exactly the same models can be estimated for nonagricultural labor productivity growth by static and dynamic panel models as in equations (7) and (8). The same models have been applied to subsamples for South Asia and for East and Southeast Asia:

$$d \log NAGLP_{it} = \beta_0 + \beta_1 \log NAGLP_{it-5} + \beta_2 T + X_{it} \cdot \beta_3 + \beta_4 d \log AGLP_{it-1}$$
$$+ \mu_i + \varepsilon_{it} \tag{7}$$
$$d \log NAGLP_{it} = \beta_0 + \beta_1 d \log NAGLP_{it-1} + \beta_2 \log NAGLP_{it-5} + \beta_3 T$$
$$+ \beta_4 d \log AGLP_{it-1} + \mu_i + \varepsilon_{it} \tag{8}$$

In Table 2, the above models are estimated by using the 5-year average data. Here, the presence of convergence effect can be tested by checking whether the lagged agricultural labor productivity (agricultural value added per worker $[t − 1]$) is negative and statistically significant in Cases 1–4, and whether lagged nonagricultural labor productivity (nonagricultural value added per worker $[t − 1]$) is negative and statistically significant in Cases 5–8. The result of a positive effect of agricultural productivity on nonagricultural productivity (Cases 1–4) is important as this is consistent with the prediction of Vollrath's (2009) model that there is diffusion from the agricultural sector. This is important in terms of the literature on structural transformation in Asia (Reardon and Timmer 2014), which suggests that the transformation of the agricultural sector (e.g., commercialization and product diversification) is becoming closely linked to changes in dietary patterns; supply chain and retail revolution; and integrated labor, land, and credit markets. Here, the whole process of structural transformation implies a positive diffusion effect of agricultural labor productivity on nonagricultural labor productivity. However, contrary to Vollrath's prediction, a positive effect of nonagricultural labor productivity on agricultural labor productivity was not observed as many Asian

Table 2. Convergence of Labor Productivity in the Agricultural and Nonagricultural Sectors (Asia, 5-year average)

Model Variables	Dependent Variable: Agricultural Labor Productivity Growth				Dependent Variable: Nonagricultural Labor Productivity Growth			
	Fixed Effects Case 1	Fixed Effects Case 2	Fixed Effects Case 3	SGMM Case 4	Fixed Effects Case 5	Fixed Effects Case 6	Fixed Effects Case 7	SGMM Case 8
Agricultural labor productivity growth ($t-1$)				0.331** (0.141)	0.318*** (0.117)		0.281* (0.160)	0.340** (0.145)
Nonagricultural labor productivity growth ($t-1$)		−0.0401 (0.0555)	−0.100** (0.0418)	−0.154** (0.0779)				0.0136 (0.0756)
Agricultural labor productivity ($t-1$)	−4.27e-06** (1.91e-06)	−3.56e-06 (2.19e-06)	−2.91e-05* (1.45e-05)	−2.61e-06** (1.22e-06)				
Nonagricultural labor productivity ($t-1$)					−0.000111*** (2.28e-05)	−9.56e-05*** (1.77e-05)	−0.000124*** (3.19e-05)	−2.73e-05*** (7.75e-06)
Log share of the mining sector in GDP			0.00377 (0.0101)				0.0119 (0.0202)	
Log schooling years			−0.0366 (0.103)				0.00883 (0.144)	
Inequality index ($t-1$)			0.00424 (0.00259)				0.00850* (0.00430)	
Linear time trend	0.0197** (0.00732)	0.0102** (0.00484)	0.0203 (0.0118)	0.00956** (0.00386)	0.0200*** (0.00655)	0.0268*** (0.00750)	0.0188 (0.0196)	0.00446 (0.00473)
Constant	−0.118 (0.0625)	−0.0144 (0.0462)	−0.138 (0.211)	−0.00652 (0.0377)	0.208 (0.0485)	0.123 (0.0450)	−0.147 (0.200)	0.171 (0.0545)
Observations	177	155	102	155	185	222	123	184
R-squared	0.054	0.033	0.197		0.253	0.160	0.257	
Number of economies	37	37	23	37	37	38	23	37

GDP = gross domestic product, SGMM = system generalized method of moments.
Notes: Robust standard errors in parentheses. ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.
Source: Authors' calculations based on World Bank. 2016. World Development Indicators 2016. https://openknowledge.worldbank.org/handle/10986/23969.

economies were primarily dependent on the agricultural sector during our data period.

In Table 2, we confirm that labor productivity converges in both the agricultural and nonagricultural sectors, and the convergence effect is significant in all the cases except Case 2. This implies "a catching-up effect" in which the economies with relatively low agricultural labor productivity tend to catch up with those having relatively high agricultural labor productivity. The catching up effect is also found for nonagricultural labor productivity.

We have also found that lagged nonagricultural labor productivity growth deters agricultural labor productivity growth (Cases 3 and 4). This is consistent with the theoretical model of Vollrath (2009) that an improvement of nonagricultural productivity induces agricultural workers to work more efficiently. However, the result is reversed when we use the annual panel data in which nonagricultural labor productivity is lagged by 5 years. Here, lagged nonagricultural labor productivity growth is found to promote agricultural labor productivity growth as predicted by the theoretical model.[6]

On the other hand, we have found, based on the 5-year average panel, that lagged agricultural labor productivity growth promotes nonagricultural labor productivity growth (Cases 5, 7, and 8). In Case 8, the lagged agricultural productivity growth is treated as an endogenous variable. Other covariates are mostly statistically insignificant, but a large lagged inequality increases nonagricultural labor productivity growth in Case 7.

We have estimated the same models using the 5-year average data only for South Asia. A statistically significant convergence effect is found in the case of agricultural labor productivity growth. For the cross-sectoral effects, lagged agricultural labor productivity growth is found to promote nonagricultural labor productivity growth. For South Asia, a higher level of inequality tends to reduce overall agricultural labor productivity growth with some lag. Given that inequality can dampen the productivity of the disadvantaged group of agricultural workers or poor smallholders, this is a plausible result.[7] When we replicate the same regressions for East and Southeast Asia, we find that convergence effects are generally found to be significant. For the cross-sectoral effect, lagged agricultural labor productivity growth positively affects nonagricultural labor productivity growth.[8]

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[6]The results based on the annual panel will be provided on request.

[7]For South Asian economies, the Gini coefficient is positively correlated with the agricultural commercialization index based on the extent to which an agricultural product is processed (Imai, Gaiha, and Bresciani 2016); the coefficient of correlation is 0.067. For East and Southeast Asian economies, the correlation is negative with a coefficient of –0.4. This could explain the negative correlation between inequality and agricultural labor productivity for South Asia, though the causality will have to be examined carefully in future studies.

[8]The disaggregated results will be provided on request.

IV. Effects of the Labor Productivity Gap between the Agricultural and Nonagricultural Sectors on Poverty, Inequality, and the Sectoral Population Share

We have so far examined the pattern of (i) the convergence of labor productivity between the agricultural and nonagricultural sectors, and (ii) the convergence of agricultural or nonagricultural productivity across different economies. Overall, agricultural labor productivity growth has promoted nonagricultural productivity growth and the sectoral gap has widened, while the between-economy disparity of the sectoral labor productivity has narrowed. These findings are broadly consistent with the theoretical model of Vollrath (2009).

An interesting empirical question is how this process will dynamically affect poverty and inequality as well as labor allocation across different sectors over time. As we discussed in section II, the theoretical model implies that an increase of the sectoral gap tends to be generally less egalitarian, or that there is an increase in inequality when both sectors grow (Bourguignon 1990). However, it is not straightforward to answer the question because of the difficulty in disentangling the complex causal links from the labor productivity gap between the agricultural and nonagricultural sectors to poverty (or inequality or the sectoral population share). For instance, an increase in the labor productivity gap may imply a divergence: that is, a change toward higher nonagricultural labor productivity (reflecting technological development) and/or lower or more stagnant agricultural productivity. On the other hand, a reduction in the gap may imply a change toward convergence due to stagnant nonagricultural labor productivity and/or an increase in agricultural labor productivity. However, while the larger gap affects poverty or inequality, the higher poverty rates or inequality might also influence the gap. For instance, poor people in rural areas cannot invest in a profitable investment in agriculture that would require a certain amount of investment in physical and human capital (e.g., machinery or high-yielding crops), which hinders the growth of labor productivity in agricultural areas. Thus, there is a need for instrumenting the labor productivity gap because it may be endogenous.

We have tackled the endogeneity by instrumenting the labor productivity gap by (i) the lagged agricultural product diversity index (Imai, Gaiha, and Bresciani 2016) and (ii) the lagged logarithm of the production share of the mining sector in GDP.[9] The first instrument is used as a proxy for agricultural transformation by

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[9]This draws upon Remans et al. (2014), who use an index called the Shannon Entropy Diversity Metric to capture production diversity at the country level using FAOSTAT. It is defined as $H' = -\sum_{i=1}^{R} p_i \ln p_i$ where R is the number of agricultural products and p_i is the share of production for the item, i, available from FAOSTAT. The production share, p_i, is defined in terms of the monetary value at a local price for each product, i. If the country produces more agricultural products, including processed and unprocessed crops, and the monetary value of all products is more evenly divided among different items, the diversity index, H', takes a larger value. On the contrary, if the country produces a smaller number of agricultural products and the monetary value of one or two specific products is large, H' is smaller.

Imai, Gaiha, and Bresciani (2016), and is supposed to affect the labor productivity gap, mainly by influencing agricultural labor productivity. However, the change of the production pattern itself cannot directly influence poverty or inequality. We cannot deny the possibility that the process of specialization could increase poverty, for instance, as there may be less demand for manual labor; but we can reasonably assume that poverty can change through adjustments in farm production or income (per worker). The second instrument could also reduce the labor productivity gap because dependence on the mining sector could deter the overall effort for technological progress in the industrial sector, without directly affecting poverty. The reliance on the mining sector could affect poverty directly (e.g., the impoverishment of manual workers in the mining sector), but we assume that this does not have a direct impact on poverty, particularly in rural areas. We assume that the productivity or income effect is larger than the direct effect on poverty, while we admit limitations in using the second instrument.[10] We have applied the IV model in the panel framework using the FE-IV model, whereby the unobservable country effect is taken into account. Because we focus on the relatively longer-term effect, we use only the 5-year average data.

In the first stage, we will estimate the determinants of the labor productivity gap between the two sectors:

$$Gap_{it-1} = \beta_0 + \beta_1 d \log AGLP_{it-1} + \beta_2 d \log NAGLP_{it-1} + \beta_3 S_{it-1} + \beta_4 Mining_{it-2}$$
$$+ \beta_5 Product\ Diversity_{it-2} + \mu_i + \varepsilon_{it} \tag{9}$$

Here, t stands for each 5-year period: $t = 1$ for 1960–1964, $t = 2$ for 1965–1969, ..., $t = 11$ for 2010–2014. Gap_{it-1} is the first lag of normalized difference between nonagricultural value added per worker and agricultural value added per worker (at purchasing power parity [PPP] in US dollars divided by 1,000). $d \log AGLP_{it-1}$ is the lag of the first difference in log of agricultural value added per worker: that is, the agricultural labor productivity growth during the preceding period. Likewise, $d \log NAGLP_{it-1}$ is the nonagricultural labor productivity growth during the preceding period. S_{it-1} is the lag of schooling years. μ_i is the unobservable country fixed effect and ε_{it} is an error term (independent and identically distributed).

Instruments for the labor productivity gap between the agricultural and nonagricultural sectors are the second lag of the production share of the mining sector ($Mining_{it-2}$) and the second lag of the agricultural product diversity index. These instruments, despite the limitations, are justified on the following grounds. Since the mining sector share is a variable closely associated with the (broadly predetermined) factor endowment of the economy, it will have a direct effect on the economy's labor allocations across different sectors, including the

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[10]These sets of instruments are the best candidates given the data availability.

rural agricultural sector, rural nonagricultural sector (nonmining or mining), and urban nonagricultural sector (nonmining or mining). Depending on the degree of dependence on mining resources, the allocation of labor across sectors and worker efforts in each sector are influenced directly. It is surmised here that the effect of the mining sector share first influences sectoral labor productivity, rather than poverty. While the mining sector share may influence poverty directly (e.g., through the impoverishment of mining workers), we assume that it mainly influences the relative sectoral productivity. The second instrument, the product diversity index, affects agricultural labor productivity directly as more diversified production implies the economy's adoption of profitable and marketable agricultural products (e.g., vegetables, fruits, meat). The index also influences nonagricultural labor productivity as the introduction of these products influences the productivity of the food processing sector. However, it is unlikely that the product diversity index directly affects poverty or inequality. These instruments, despite the limitations, have been validated by specification tests.

In the second stage, poverty is estimated by the (instrumented) labor productivity gap as well as other determinants:

$$Poverty_{it} = \gamma_0 + \gamma_1 \widehat{Gap}_{it-1} + \gamma_2 d \log AGLP_{it-1} + \gamma_3 d \log NAGLP_{it-1} + \gamma_4 S_{it-1}$$
$$+ \theta_i + e_{it} \tag{10}$$

Equations (9) and (10) are estimated using the FE-IV model. Poverty is defined in various ways, including (i) the national poverty headcount, or poverty gap, based on the international poverty line of \$1.9 (extreme poverty) or \$3.1 (moderate poverty) per day at PPP in 2011 (World Bank 2016); (ii) the rural poverty headcount, poverty gap, or poverty gap squared, based on \$1.25 (extreme poverty) or \$2 (moderate poverty) at PPP in 2005; and (iii) the same urban poverty indexes in (ii), based on household data in rural areas.[11] In one case, we have replaced poverty by the Gini coefficient evaluated at the national or subnational level (for rural and urban areas separately). Finally, given the data limitations, we have derived the population share of the rural sector, nonagricultural sector, and urban sector, and used each share as a dependent variable in the second-stage regression (Imai, Gaiha, and Garbero 2017). This aims to examine how the labor productivity gap will influence the labor allocation in the middle to long run. In all cases, the endogeneity of the labor productivity gap is instrumented.

First, we have estimated national poverty in the second stage (the upper left panel of Table 3).[12] In the first stage, one of the instruments, the agricultural product

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[11]The difference in the definitions of rural, urban, and national poverty reflects the data availability. Poverty estimates for (ii) and (iii) have been provided by the Strategy and Knowledge Department of the International Fund for Agricultural Development.

[12]A full set of the regression results will be provided upon request. We provide only the second-stage results in Table 3.

Table 3.   **Effects of the Labor Productivity Gap between the Agricultural and Nonagricultural Sectors on Poverty and Inequality**
(second stage of the FE-IV model)

Variables	Poverty Headcount ($1.9)	Poverty Gap ($1.9)	Poverty Headcount ($3.1)	Poverty Gap ($3.1)	Rural Poverty Headcount ($1.25)	Rural Poverty Gap ($1.25)	Rural Poverty Gap Squared ($1.25)	Rural Poverty Headcount ($2)	Rural Poverty Gap ($2)	Rural Poverty Gap Squared ($2)
Gap ($t-1$)	−0.224	**0.081**	−0.074	−0.394	−1.620**	−1.633**	−1.291	−1.117**	−1.357**	−1.465**
	(0.481)	(0.464)	(0.601)	(0.459)	(0.734)	(0.797)	(2.664)	(0.504)	(0.593)	(0.662)
Agricultural productivity growth ($t-1$)	−3.445	−3.894	−2.793	−3.063	−1.176	−1.537	2.961	−0.904	−1.008	−1.152
	(2.940)	(2.857)	(3.207)	(2.942)	(1.736)	(2.086)	(2.841)	(1.109)	(1.422)	(1.660)
Nonagricultural productivity growth ($t-1$)	0.553	0.395	0.154	0.373	0.159	0.360	−1.132	0.190	0.172	0.214
	(2.366)	(2.309)	(2.615)	(2.358)	(1.073)	(1.313)	(1.172)	(0.679)	(0.886)	(1.040)
Log schooling years ($t-1$)	−1.660	−1.613	−1.746	−1.470	−0.776	−1.368	−8.573**	−0.174	−0.584	−0.932
	(1.085)	(1.023)	(1.224)	(1.056)	(0.888)	(0.931)	(4.119)	(0.592)	(0.704)	(0.799)
Observations	77	77	77	77	45	45	45	45	45	45
R-squared	0.251	0.190	0.170	0.273	0.479	0.557	0.561	0.455	0.506	0.524
Number of economies	11	11	11	11	12	12	12	12	12	12

Continued.

Table 3. Continued.

Variables	Urban Poverty Headcount ($1.25)	Urban Poverty Gap ($1.25)	Urban Poverty Gap Squared ($1.25)	Urban Poverty Headcount ($2)	Urban Poverty Gap ($2)	Urban Poverty Gap Squared ($2)	National Gini	Rural Gini	Urban Gini	Rural Share	Rural Non-agri. Share	Urban Share
Gap ($t-1$)	−19.400	−3.317**	−2.074	−1.864***	−2.058***	−6.854	−4.636***	0.136	−0.0115	−24.46**	30.81***	5.032*
	(12.740)	(1.583)	(1.891)	(0.488)	(0.716)	(4.967)	(1.174)	(0.147)	(0.0971)	(8.294)	(8.281)	(2.535)
Agricultural productivity growth ($t-1$)	26.210*	−0.525	0.316	−0.188	−0.0250	8.909*	6.316	−0.281	−0.198	−12.42	5.940	−5.097
	(14.18)	(1.702)	(1.711)	(1.052)	(1.287)	(5.084)	(3.925)	(0.183)	(0.142)	(21.900)	(17.650)	(7.491)
Nonagricultural productivity growth ($t-1$)	−15.68**	−0.564	−0.749	−0.174	−0.450	−5.528**	−6.143**	0.0261	0.00750	5.547	−9.953	8.586*
	(5.859)	(1.064)	(1.114)	(0.658)	(0.769)	(2.070)	(2.766)	(0.106)	(0.086)	(14.990)	(19.43)	(5.048)
Log schooling years ($t-1$)	−11.65	0.261	−0.702	−0.135	−0.737	−5.265	8.673***	−0.0299	0.234*	46.34***	−39.37***	−8.656
	(13.97)	(1.631)	(2.090)	(0.618)	(1.113)	(7.249)	(2.851)	(0.177)	(0.137)	(8.679)	(8.875)	(7.405)
Observations	44	42	39	43	42	42	77	45	43	24	24	68
R-squared	0.271	0.542	0.428	0.689	0.689	0.256	0.063	−0.003	0.356	0.686	0.629	0.034
Number of economies	12	12	11	12	12	12	12	12	12	6	6	10

FE-IV = fixed effects instrumental variable.

Notes: "Gap" refers to the normalized difference between nonagricultural value added per worker and agricultural value added per worker (at purchasing power parity in United States dollars divided by 1,000). Robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Values inside the parentheses below the column headings are the poverty lines.

Source: Authors' calculations based on World Bank. 2016. World Development Indicators 2016. https://openknowledge.worldbank.org/handle/10986/23969.

diversity in the preceding period, will reduce the labor productivity gap. That is, if the structural transformation in the rural sector progresses and agricultural production is more diversified, then the gap will be reduced, presumably because agricultural sector productivity will catch up with nonagricultural productivity. However, the first lagged agricultural productivity growth increases the gap. This is counterintuitive, but if agricultural productivity growth promotes nonagricultural growth without a lag, the period with faster agricultural productivity growth may even match the period with faster nonagricultural growth. The coefficient estimate of nonagricultural labor productivity growth is negative, but not statistically significant.[13] Education tends to increase the gap.

The question arising from the analysis in the last section is why the labor productivity gap has grown in some economies and not in other economies. It is not easy to provide a definite answer, but our results imply that the agricultural transformation reduces the gap and that improved human capital widens the gap.

In the second stage, we do not find any evidence that the gap influences poverty at the national level with the coefficient estimate being negative (except the second column) and statistically insignificant (the upper left panel of Table 3).[14] We find that the number of schooling years is negative and statistically significant. The F-statistic of excluded instruments is 16.34, which is above the threshold of 10, and the Sargan overidentification test of all instruments is not significant (p-value of 0.331), validating the IV estimation.

Next, we examine whether the labor productivity gap has affected poverty. Because the sample is reduced, the results from the first stage have changed slightly. For instance, nonagricultural productivity growth is now negative and significant, while one of the instruments, the productivity–diversity index, is now positive and significant. So, with a smaller sample, the progress of the agricultural transformation tends to increase the labor productivity gap. The reason is not clear, but in this case the agricultural transformation may have an instant impact on improving both agricultural and nonagricultural labor productivity, with the magnitude of the latter being comparatively larger.

In the second stage, the increase of the labor productivity gap tends to reduce poverty in the rural regions regardless of the choice of poverty thresholds and for all different measures of poverty (e.g., headcount, poverty gap, and poverty gap squared except the third column for extreme poverty gap squared as shown

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[13]The correlation between the labor productivity gap and nonagricultural labor productivity growth is positive with a correlation coefficient of 0.034. The correlation coefficient between the gap and agricultural labor productivity growth is 0.036. Not surprisingly, the correlation coefficient between the agricultural and nonagricultural sector growth terms is high at 0.614. The highest variance inflation factor of the first-stage regression is 2.44, which is below the threshold of 10 and which would justify the inclusion of labor productivity growth in both sectors at the same time.

[14]We have also estimated the second-stage regressions by using the FE model without using IV. In this case, the sample size is larger, but we have found that the lagged labor productivity gap reduces significantly both extreme and moderate poverty, for both the headcount ratio and poverty gap.

in the upper right panel of Table 3). That is, as nonagricultural labor productivity grows faster than agricultural labor productivity, rural poverty significantly declines in every dimension, including the share of the poor, the depth of rural poverty, and inequality among the rural poor. This result may not be consistent with the theoretical prediction by Bourguignon (1990) as the model suggests that the gap between the agricultural and nonagricultural sectors tends to increase inequality given elastic capital–labor substitution assumed in the modern sector. However, Vollrath's (2009) model implies that as nonagricultural labor productivity increases, the efficiency of workers in the agricultural sector improves. If this helps the rural poor escape from poverty, we expect that nonagricultural labor productivity growth has the effect of reducing rural poverty. Here, the test of excluded instruments (F-statistic) is 9.55, which is below the threshold of 10, partly because of the small sample size, and so the results need to be interpreted with caution. The Sargan statistic is not significant, justifying the use of IV.[15]

We have also estimated urban poverty in the second stage of the FE-IV model. The results are shown in the lower left panel of Table 3. We have found that the size of the poverty-reducing effect is much larger for urban poverty than rural poverty. That is, as the gap between nonagricultural and agricultural labor productivity expands, both urban poverty and rural poverty decrease, but urban poverty tends to decline at a much faster rate. However, the results will have to be interpreted with caution, particularly in cases where the F-statistic for excluded instruments in the first stage is low (columns 2 and 3).

Finally, we have estimated the effect of the lagged labor productivity gap on the Gini coefficient at the national, rural, and urban levels. As the sample sizes differ, the result in the first column cannot be compared with the results in the second and third columns. However, after controlling for the endogeneity of the labor productivity gap, we have found evidence that the gap significantly reduces the national Gini coefficient (the lower right panel of Table 3). In this case, the first-stage F-statistic is larger than 10. The result is robust if we do not instrument the labor productivity gap or if we use the smaller sample for which disaggregated inequality data are available.

Using the disaggregated data, we have also estimated the effects of the lagged labor productivity gap on the sectoral population share, drawing upon Imai, Gaiha, and Garbero (2017). The results will have to be interpreted with caution, specifically in the first and the second columns (due to the small sample size) where the specification tests for IV do not validate the specifications. However, we have found some evidence that the labor productivity gap reduces the rural population share and increases the share of the rural nonagricultural sector. When we use a larger sample size, we have found that the lagged productivity gap

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[15]The lagged labor productivity gap is no longer statistically significant in explaining rural poverty for the larger sample in the FE model without IV.

increases the population share of the urban sector significantly. These results are broadly consistent with the theoretical model of Vollrath (2009) where increases in nonagricultural productivity will help industrialize the economy and induce agricultural laborers to work more efficiently, while the share of the agricultural sector declines over time. If this process benefits much of the population in rural and urban areas, inequality is likely to decline over time. However, our result is not consistent with Bourguignon's (1990) model, which implies that the gap between the agricultural and nonagricultural sectors tends to increase inequality.

In sum, we have found that the increase in the lagged labor productivity gap, which is treated as endogenous, will reduce both urban and rural poverty as well as national-level inequality. In particular, there is robust evidence confirming that the labor productivity gap reduces urban poverty evaluated at the poverty threshold of $2 per day.

IV. Conclusions

First, we have examined whether labor productivities in the agricultural and nonagricultural sectors have converged by using the 5-year average panel dataset. We have found robust evidence that nonagricultural labor productivity and agricultural labor productivity did not converge; the former has grown faster and the gap has increased significantly over time.

We have also observed that within Asia (i) agricultural labor productivity has converged across economies, (ii) nonagricultural labor productivity has converged across economies, and (iii) the convergence effect is stronger for the nonagricultural sector. Agricultural labor productivity growth was found to promote nonagricultural productivity growth with some lag. That is, despite the slower growth in agricultural labor productivity, the agricultural sector played an important role in promoting nonagricultural labor productivity and thus in nonagricultural growth. As we used the 5-year average panel data, we can identify the middle- to long-term effects by controlling for short-term fluctuations.

In the second part of the study, we examined whether the labor productivity gap between the agricultural and nonagricultural sectors reduced poverty, inequality, and the sectoral population shares over time. While the results vary depending on the specifications, we have found some evidence that the labor productivity gap reduces both urban and rural poverty over time as well as national-level inequality. The gap also increases the share of the population in the urban sector.

Our results provide the following policy implications. While improvement in agricultural labor productivity also brings about improvement in nonagricultural labor productivity, the latter has increased faster than the former over time, resulting in a gap between the two sectors. The widening gap was found to reduce poverty and inequality. These results are important in light of the literature on structural

transformation in Asia (e.g., Reardon and Timmer 2014; Imai, Gaiha, and Bresciani 2016), which underscores diffusion from the agricultural sector. Our results suggest that as the agricultural sector experiences structural changes, it plays a central role in improving nonagricultural labor productivity and reducing poverty and inequality within an economy. Policy makers need to facilitate the process of structural transformation (e.g., commercialization and product diversification of agriculture; revolutions in supply chain and retail networks; and integration of labor, land, and credit markets) to improve agricultural labor productivity and reduce poverty and inequality.

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