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The declining share of agricultural employment in China: How fast?

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ABSTRACT

Between 1962 and 2013, China's agricultural employment share declined from 82% to 31%. The transfer of workers out of low-productivity agriculture is a fundamental pillar of China's aspirations to progress and eventually become a high-income economy. We hypothesize that the drivers of this decline have been the increase in income per capita, industrial value added, foreign direct investment and domestic credit. We use an Autoregressive Distributed Lag Model to test the strong exogeneity of the regressors. This is confirmed by the data and hence we use our model for forecasting. Results indicate that the share of employment in agriculture in China will decline to about 24% by 2020, the end of the 13th Five-Year Plan (2016–2020). We also estimate that China's employment share will reach 5%, the share observed in today's rich economies, by 2042–2048.

1. Introduction

The purpose of this paper is to model the determinants of China's agricultural employment share, and use them to forecast this share up to the year 2020, the end of the 13th Five-Year Plan (2016–2020). We also ask when the share will become 5%, about the same as in most high-income countries today. This exercise is relevant for four related reasons. First, the share of employment in primary agriculture was still 31% in 2013 (about 240 million workers) and, until recently, this sector was the country's largest employer (Fig. 1). China's aspirations to become a high-income economy will be reflected in, among other things, a much lower share of agricultural employment.

Second, the Chinese Communist Party (CCP) set an ambitious reform agenda for the 12th Five-Year Plan (2011–2015) and the reforming process is expected to continue during the 13th Five-Year Plan (2016–2020). Planned reforms include increasing the role of markets in resource allocation, modernizing the tax system, relaxing and eventually eliminating the *hukou* system, and creating an open-door policy (i.e., allow the international mobility of productive factors).[1]

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[1] Employment-related questions are at the center of the reform agenda approved in November 2013 by the 18th National Congress of the CCP. In the Spring of 2014, China's top economic planning body gave the first steps toward preparing the 13th Five-Year Plan covering 2016-2020, which will decide how to implement the ideas discussed in the 18th National Congress. There is agreement that China needs to change its growth model into one that is less capital- and energy-intensive, yet it needs to continue achieving high growth rates to generate employment in industry and services to absorb 240 million agricultural workers. This was reflected clearly in 2013 recent speech by Premier Li Keqiang (Hongbin and Xiaoping, 2013).

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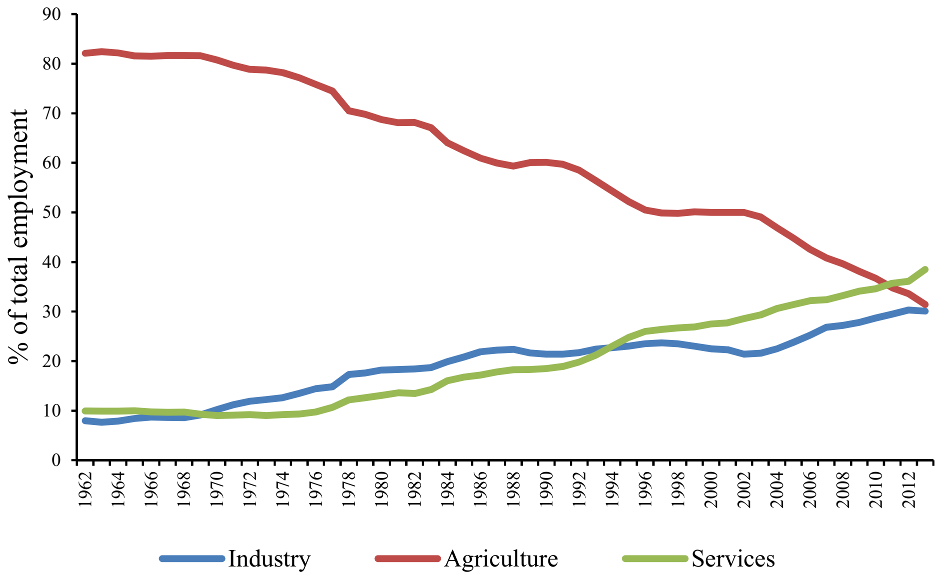

Fig. 1. Sectoral employment. Authors' calculations based on data from Comprehensive Economic, Industry and Corporate Data (accessed August 1, 2014). Industry refers to the secondary sector: manufacturing, construction, mining and quarrying, and utilities.

Third, this paper is related to the debate on whether or not China has reached the Lewis Turning Point, that is, the stage of development where the agricultural surplus labor disappears, and labor shortages and wage increases come about. Authors such as Cai and Wang (2008), Das and N'Diaye (2013) or Zhang et al. (2011) argue that China has already crossed, or it is about to cross, the Lewis Turning Point. On the other hand, Minami and Ma (2010) argue that there are no signs that the gaps between rural-urban incomes and between skilled-unskilled wages are narrowing, while Yao and Zhang (2010) showed that an increase in the demand for labor in China does not lead to an increase in the wage rate; both taken as signs that China has not crossed the Lewis Turning Point. Finally, there are studies that argue that the existence of surplus labor in rural areas is compatible with increasing rural migrant wages in urban areas, as a result of labor market segmentation and of constraints on rural-urban migration (Knight et al., 2011); or as a result of government policies such as the abolition of agricultural taxes, the granting of direct price subsidies to agricultural products, or the increase in urban minimum wages (Golley and Meng, 2011). Data show that China's agricultural employment level was still increasing up to the mid-2000s, although the share in total employment had been declining for a long time (Fig. 1).[2] From 2008 onward, both the agricultural employment level and the share have been decreasing. Our results offer insights that help understand the drivers of China's agricultural employment and, therefore, contribute to this debate.

Finally, labor in traditional agriculture operates at much lower productivity levels than in other sectors (Herrendorf and Schoellman, 2012). Indeed, as Fig. 2 shows, labor productivity in China's agricultural sector is substantially lower than in industry and services.[3] Moreover, as productivity growth is slower in agriculture, the gap with the other sectors has been widening significantly, particularly since the early 1990s.[4] Therefore, and as noted above, the speed at which the transfer of labor out of agriculture takes

[2] While in India, for example, the agricultural employment share is declining but the absolute number of workers in agriculture is still increasing.

[3] Wong (1987) argues China's labor productivity was very low during 1964 -1973, the period during which the commune movement and Cultural Revolution were at their peaks. China ran into economic and political difficulties in 1957. The Communist Party decided to launch the "Great Leap Forward" in 1958. One objective behind it was to significantly increase (double in many cases) both industrial (steel sector in particular) and agricultural production in a short period of time. A second objective was to introduce a new form of human organization, the commune, supposed to dismantle the traditional Chinese family, as well as to accelerate the country's modernization. During 1958, the rural population (and part of the urban population) was swept into about 26,000 giant communes, each containing 5,000-65,000 people. Commune labor was used for a combination of farming and non-agricultural tasks and great masses were used for irrigation and dam-building projects. The commune system did not achieve its objective of providing the base for rapid agricultural improvement. Food shortages appeared in 1959-1960, leading to famine and massive imports of food grains from Canada and Australia. Apart from bad weather, mismanagement and low morale also contributed to the problem. The Great Leap Forward ended in 1961. We are also grateful to a referee for pointing out that during Mao's days, the objective was to improve land productivity in agriculture. This is consistent with Lewis (1978): "..the only way to avoid mounting urban unemployment is to persuade more people to remain in the countryside…our agricultural economics is based on the assumption that numbers in agriculture will decline as economic development proceeds; our policies are therefore set towards helping to reduce the number of men per acre. Instead, we shall need for the next three or four decades agricultural policies aimed at absorbing more men per acre." (p. 241)

[4] China experienced rapid population growth during the 1960s and the 1970s. Tang and Stone (1980) document that "China's rural population increased from approximately 500 million in 1952 to 780 million in 1977, which added 150 million workers to China's agricultural labor force during 1950-1983" (p. 43). This resulted in labor-intensive farming.

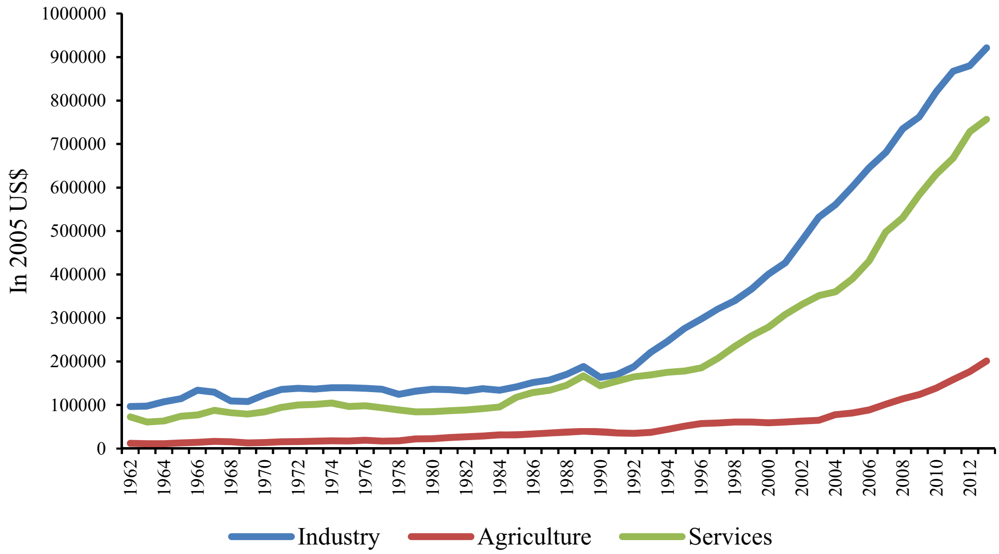

Fig. 2. Sectoral productivity (sectoral value added/sectoral total employment). Authors' calculations based on data from Comprehensive Economic, Industry and Corporate Data (accessed August 1, 2014). All three sectors are gross value added as % of GDP. Industry refers to the secondary sector: manufacturing, construction, mining and quarrying, and utilities.

place is fundamental for China's aspirations to become a high-income economy in the decades ahead.

The remainder of the paper is structured as follows. Section 2 discusses, for comparison purposes, historical trends in employment in the agricultural sector in developed countries. Section 3 discusses the empirical strategy, an autoregressive distributed lag model, and test the significance of a number variables that explain the evolution of the Chinese agricultural employment share. Section 4 shows the estimation results. Section 5 provides strong exogeneity tests and forecasts of China's agricultural employment share. We find that the share of employment in agriculture will decline to about 24% by 2020, and that it will reach 5%, the share observed in today's rich economies, by 2042–2048. Finally, Section 6 summarizes the main findings.

2. Trends in the agricultural sector in China and selected developed economies

The secular decline in the shares of agricultural value added (in GDP) and employment (in total employment) is a key aspect of economic development (Syrquin, 2008). Commonly termed structural transformation, the movement of resources out of the agricultural sector into industry and services, as economies grow richer, is a stylized fact ascribed to forces of demand and supply. On the demand side, demand for food is relatively inelastic. Thus, as income per capita increases, expenditures are diverted from agricultural products to manufactured goods and services. As the country further develops, demand shifts increasingly toward services so that the share of expenditure devoted to manufactured goods stabilizes and then, ultimately, falls in relative terms. As a result, the employment share of manufacturing also stabilizes and eventually falls. On the supply side, the growth of labor productivity in agriculture, due to a whole range of technical innovations, induces a shift of employment out of this sector. The combined effects of demand- and supply-side factors account for the large-scale shift of employment into manufacturing during the industrialization phase of the development process, while the productivity growth differential between manufacturing and services appears to be the key determinant of the subsequent deindustrialization phase.[5]

With a few historical exceptions, structural transformation has been a slow process. Table 2.2 of Maddison (1982), provides the shares of employment in agriculture in 1700 for two countries, the Netherlands and the UK, 40% and 60%, respectively. By 1890, the shares had declined to 33% and 16%, and by 1979 to 5.5% and 2.5%, respectively. Additional data provided in Table C5 by Maddison (1982) indicate that between 1870 and 1979, the agricultural employment share in today's rich economies declined by an average of almost 0.40 percentage points per annum, ranging from 0.19 percentage points in the UK (whose share was 22.7% in 1870) and 0.56 percentage points per annum in Japan (whose share was 72.6% in 1870) (Table 1).

Today, most developed economies have agricultural employment shares below 5%. Table 2 shows that the mean agricultural employment share in OECD countries was 7% in the 1980s, 5% in the 1990s, and 4% in the 2000s. The mean employment share of the Latin American economies exhibits a downward trend as well and was 17.1% during 2000–2013. The pace of this decline is slower in the

[5] We have undertaken a shift-share analysis for 1990-2011 and decomposed China's growth rate of labor productivity into that due to the sum of sectors' productivity growth rates (i.e., intra-sectoral productivity growth) and that due to structural trasformation (i.e., shift of workers from agriculture into industry and servcies). Somewhat surprisingly, results indicate that almost 80% of labor productiviy growth was due to the first component, that is, intra-sectoral productivity growth. Results are available upon request.

Table 1
Agricultural employment share in total employment in selected high-income economies, 1870 and 1979.

	Agricultural employment share in 1870 (%)	Agricultural employment share in 1979 (%)	Percentage point decline, 1870–1979 (per annum)
Australia	30.0	6.0	0.22
Austria	65.0	10.5	0.50
Belgium	43.0	2.7	0.37
Canada	53.0	5.0	0.44
Denmark	51.7	8.1	0.40
Finland	71.2	11.3	0.55
France	49.2	8.9	0.37
Germany	49.5	5.9	0.40
Italy	62.0	14.0	0.44
Japan	72.6	11.6	0.56
Netherlands	37.0	5.4	0.29
Norway	53.0	8.3	0.41
Sweden	53.9	5.9	0.44
Switzerland	49.8	7.3	0.39
UK	22.7	2.0	0.19
USA	50.0	3.1	0.43

Authors' calculations based on Table C5 of Maddison (1982).

Table 2
Agricultural employment shares in total employment, weighted by population (% of total employment).

	Asia		Latin American Countries		OECD		Sub-Saharan Africa	
	Mean	Obs	Mean	Obs	Mean	Obs	Mean	Obs
From 1980 to1989	60.7	76	21.6	97	6.98	191	44.7	11
From 1990 to 1999	52.6	99	17	159	5.09	235	68.4	29
From 2000 to 2013	45.0	131	17.1	200	3.92	308	41.2	72

Authors' calculations based on data from the World Development Indicators (accessed June 24, 2014).
Asian countries include Afghanistan, Bangladesh, Bhutan, Cambodia, China, Fiji, India, Indonesia, Kazakhstan, Kiribati, South Korea (*), Lao PDR, Marshall Islands, Micronesia Federal States, Myanmar, Nauru, Nepal, New, Zealand, Pakistan, Palau, Papua New Guinea, Philippines, Samoa, Solomon Islands, Sri Lanka, Tajikistan, Thailand, Timor-Leste, Turkmenistan, Tuvalu, Uzbekistan, Vanuatu and Vietnam. **Latin American countries** include Argentina, Belize, Bolivia, Brazil, Chile, Colombia, Costa Rica, Ecuador, El Salvador, Guatemala, Honduras, Mexico, Nicaragua, Panama, Paraguay, Peru, Uruguay and Venezuela. **OECD countries** are countries that became members before 1980. These include Australia, Austria, Belgium, Canada, Denmark, Finland, France, Germany, Greece, Iceland, Ireland, Italy, Japan, Luxembourg, Netherlands, New Zealand, Norway, Poland (*), Portugal, South Korea (*), Spain, Sweden, Switzerland, UK and US. **Sub-Saharan Africa** includes Angola, Benin, Botswana, Burkina, Faso, Burundi, Cameroon, Central, African, Republic, Chad, Comoros, Congo Dem Rep., Congo Rep., Cote d'Ivoire, Djibouti, Equatorial Guinea, Eritrea, Ethiopia, Gabon, Gambia, Ghana, Guinea, Guinea-Bissau, Kenya, Lesotho, Liberia, Madagascar, Malawi, Mali, Mauritania, Mauritius, Mozambique, Namibia, Niger, Nigeria, Reunion, Rwanda, Sao Tome and Principe, Senegal, Seychelles, Sierra Leone, Somalia, South Africa, Sudan, Swaziland, Tanzania, Togo, Uganda, Zambia and Zimbabwe.
(*) South Korea is included in Asia before 1996 but under OECD afterwards. Poland is included under OECD from 1996 onwards.

Asian countries, where the mean employment share in the last decade was still about 45%. This is similar to the average for the Sub-Saharan region during the same period.

Recently, some Asian countries have been observed to embark on a comparable pattern of labor moving out of agriculture (Holz, 2008). Aoki (2013) documents that the typical "Kuznets process", defined as the acceleration in per capita income growth as a result of the reduction in the share of agricultural employment, started to forcefully operate in China, Japan and South Korea during the second half of the last century. Table 3 shows the agricultural employment shares in China, South Korea and Taipei,China between 1962 and 2013. The percentage point declines during this 50-year period are much faster than those registered by the advanced economies between 1870 and 1979 (Table 1). It is worth noting that the shares of the Asian countries in 1962 were significantly higher than those of most advanced countries in 1870. The shares of South Korea and Taipei,China in 1975 were about the same as those observed in many of the advanced economies in 1870, while China's share in that year was about the same as those seen in Finland or Japan.

In 1962, Taipei,China had the smallest share of the three countries, but by 2013, South Korea had caught up, as a

Table 3
Agricultural employment shares in China, South Korea and Taipei,China (% of total employment).

	China	South Korea	Taipei,China
1962	82	69	50
1975	77	46	30
1990	60	18	13
2000	50	11	8
2013	31	6	5
Percentage point decline per annum	**1**	**1.23**	**0.88**

Authors' calculations based on data from ADB-Statistical Database System (accessed October 1, 2014). The share of Taipei,China in 1962 is obtained as the ratio of agricultural employment (taken from USDA-ERS) to total employment (taken from PWT 8.0). The share of South Korea in 1962 is taken from Fan-Yi (1994).

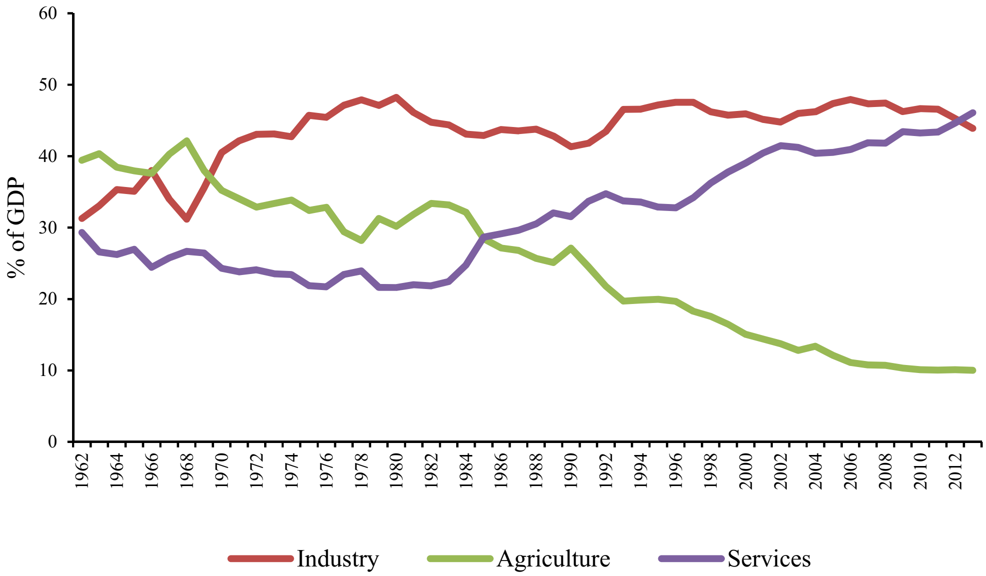

Fig. 3. Sector value added. Authors' calculations based on data from Comprehensive Economic, Industry and Corporate Data (accessed August 1, 2014). All three sectors are gross value added as % of GDP. Industry refers to the secondary sector: manufacturing, construction, mining and quarrying, and utilities.

result of the faster decline in the share, 1.23 percentage points per annum. Between 1962 and 2013, China's agricultural employment share declined from 82% to 31%.[6] This corresponds to a decrease of 51 percentage points, which translates into a 1 percentage point decline per year. While the decrease in the share was slow during the 1960s, the reduction during the 1970s, 1980s and 1990s increased to about 1 percentage point per annum, and it increased to about 2 percentage points per year during the last decade, a very fast pace by historical standards. It is worth noting that China's agricultural employment share in 1975 was much higher than in Korea and in Taipei,China; and that in 2013 it was still about the same as in Taipei,China in 1975. At the same time, between 1962 and 2013 the share of value added in agriculture declined from 39% to 10% (Fig. 3). This much smaller share indicates that labor productivity in agriculture is lower than the average for the economy as a whole. The cross-country evidence indicates that as labor moves out of this sector and income per capita increases, labor productivity across sectors tends to converge, and the differential is progressively reduced. This process, however, does not seem to have started in China yet (see Fig. 2).

3. Empirical strategy

Given the declining trend that characterizes China's employment share in agriculture since the 1960s and the historical experiences discussed in the introduction, the question is whether, as China develops, the share of employment in agriculture will or will not continue declining in the coming decades as fast as it did in the past—that is, at about 1 percentage point per annum.[7] This gives an idea of the expected speed of decline and it would be straightforward, by simple extrapolation, to generate a sensible estimate of how much smaller the share will be in the next few years. The objective of this paper, however, is to investigate the determinants of the declining trajectory of China's agricultural employment share. Specifically, we focus on the role played by changes in GDP per capita, the share of industrial (secondary sector) gross value added in GDP, the share in GDP of net foreign direct investment

[6] Rawski and Mead (1998) argue that Chinese official figures overestimate significantly China's employment in agriculture. According to their estimates, the over-count between 1979 and 1993 was well over 50 million each year, reaching over 100 million in the last years (Table 6, last two columns). We have checked these numbers with other China experts and concluded that the official figures, while not perfect, cannot be as incorrect as Rawski and Meade (1998) argue. Moreover, we have estimated that if the number of workers in agriculture in the 1990s were 100 million less than what official figures indicate, then the share of employment in agriculture was much lower in 1993, about 41-45%, as opposed to 56.5% (official figures). If we apply the same decline shown by the official figures for 1993-2003, about 25 percentage points, the share today would be 16-20%. This is very counterintuitive, especially when the share of employment in agriculture in countries like Indonesia, Philippines or Thailand is still slightly above 30%.

[7] There are other factors that can speed up the movement of labor out of agriculture in China. One such factor is its aging population. Banister et al. (2010a,b) document that between 1990 and 2005, young workers moved into industry and services, and that the age structure of the agricultural working population became older. In 2013, however, the agricultural employment share was still 31%, indicating that there is still room to improve inter-sectoral productivity. Another factor is land degradation and environmental pollution, which evidence suggests has affected yields (e.g. Rozelle et al., 1997). A third factor is the reforms and innovations the Chinese government intends to pursue to speed up agricultural mechanization. The "No. 1 Central Document" released in 2015 aims to deepen agricultural restructuring, boost farmers' income, accelerate the building of a new socialist countryside, deepen rural reforms, and improve agricultural and rural legal system (http://news.xinhuanet.com/english/china/2015-02/01/c_133962873.htm). Whether or not these factors will lead to a decline in agricultural employment larger than what our model strategy predicts is an empirical issue.

inflows (FDI), and the share in GDP of credit to the private sector.[8]

We use an error correction model (ECM) to analyze both the short- and long-run dynamics of the employment share in agriculture. We start from an Autoregressive Distributed Lag (ARDL) representation as follows (with variables in natural logarithms):

$$agriemp_t = c + \omega\, trend + \sum_{i=0}^{n} \alpha_i agriemp_{t-i} + \sum_{i=0}^{n} \beta_i gdppc_{t-i} + \sum_{i=0}^{n} \delta_i gdppcsq_{t-i} + \sum_{i=0}^{n} \phi_i indva_{t-i} + \sum_{i=0}^{n} \varphi_i fdi_{t-i} + \sum_{i=0}^{n} \eta_i credit_{t-i} + \varepsilon_t \quad (1)$$

where *agriemp* is the agricultural employment share, *gdppc* is income per capita, *indva* is industrial value added as a percentage of GDP, *fdi* is net FDI inflows as a percentage of GDP, *credit* is domestic credit to the private sector by banks as a percentage of GDP, and ε_t is a random disturbance term.[9] We also include income per capita squared (*gdppcsq*) to account for possible nonlinear effects of income per capita. The inclusion of a time trend is an empirical issue that will be discussed below.

As income per capita increases, it is expected that the agricultural employment share declines, a hypothesis consistent with the standard patterns of development and structural change. As mentioned, since the rate of decline associated with income per capita can change over time, the squared term is introduced in the model to capture possible nonlinearities. Likewise, a higher value added in industry as a share of GDP is expected to lead to a lower employment share as workers are drawn into industry. Higher foreign direct investment is also expected to lower the agricultural employment share. FDI facilitates technological transfers from advanced economies, which tend to foster the development of the more capital-intensive sectors in the long-term. As a result, FDI typically brings about faster capital accumulation, technological progress and productivity growth in industry and, via this channel, can boost the outflow of labor from agriculture. Finally, an increase in domestic credit is expected to decrease the employment share in agriculture because it is likely to encourage private investments into the more productive sectors.

[8] Other variables included in the initial search for the most appropriate model specification were: the real capital stock per worker, number of tertiary students to population ratio; arable land as a percentage of land area and value added in services as a percentage of GDP. However, they turned out to be statistically insignificant, and were therefore excluded from the model.

[9] Wei (1995) uses FDI as a proxy for China's open door policy. He documents that FDI was virtually nonexistent in the decades prior to the introduction of the open door policy and that China's accumulated FDI between 1979 and 1992 reached $34.5 billion. Jingwen et al. (1995) also argue that the Chinese economy grew rapidly after the introduction of the open door policy, a result of technological improvements and the rational utilization of resources.

While other methods are available to establish and analyze the possible cointegration among these variables, the ARDL strategy, apart from being easy to implement and interpret, can be used to model a mix of $I(0)$ and $I(1)$ series. This can be done through the bounds test procedure developed by Pesaran et al. (2001), which can be applied regardless of whether the variables are $I(0)$ or $I(1)$. Their procedure yields robust estimates in small samples and estimates of the long-run coefficients are super-consistent in small samples. The test for the existence of a significant long-run relationship is an F-test for the variables in lagged levels. If the (computed) F-statistic is smaller than the lower bound, the null hypothesis of no long-run relationship between the variables cannot be rejected. On the other hand, if it is bigger than the upper bound, then there exists a long-run relationship among the series. Finally, if the F-statistic falls within the range, the test is not conclusive.

Although ARDL estimates have a meaningful interpretation even when the series do not have the same order of integration, the bounds test is no longer valid when some of the series are $I(2)$ or of higher order of integration. Thus, as a preliminary step, we rely on the Dickey–Fuller generalized least squares (DFGLS) test to investigate the order of integration of the series under analysis. The computed DFGLS test statistics, shown in Table 4, indicate that the series are not $I(2)$ and hence the ARDL approach can be applied.

Before carrying out the estimation of the model, however, two additional issues must be dealt with. The first is the selection of the lag order for the variables in the model, which was carried out with a general-to-specific procedure, starting with a maximum lag order of 4 to take into account the length of the series available. The model specification selected as the most appropriate includes one lag of the dependent variable and two lags for the other regressors. The second issue relates to the inclusion or exclusion of a deterministic time trend. Regression estimates of the ARDL model with and without a deterministic trend were compared and the results indicated that the trend was not statistically significant. Moreover, excluding the trend from the model did not lead to relevant changes in the magnitude of the coefficients, or to changes in the signs and significance of the individual regressors.[10] Thus, the no-trend specification was chosen as the most appropriate.

Therefore, the model we estimate is the following $ARDL(1, 2\,; 5)$:

$$agriemp_t = c + \alpha_1 agriemp_{t-1} + \sum_{i=0}^{2} \beta_i gdppc_{t-i} + \sum_{i=0}^{2} \delta_i gdppcsq_{t-i} + \sum_{i=0}^{2} \phi_i indva_{t-i} + \sum_{i=0}^{2} \varphi_i fdi_{t-i} + \sum_{i=0}^{2} \eta_i credit_{t-i} + \varepsilon_t \quad (2)$$

[10] Results are not shown, but they are available from the authors upon request.

Table 4
Unit root tests (Dickey–Fuller generalized least squares).

	Log levels		First differenced		
	DFGLS test Statistic	Schwarz criterion lag	DFGLS test Statistic	Schwarz criterion lag	Order of integration
Without deterministic trend					
Agricultural employment share	0.29	1	−2.74[a]	2	$I(1)$
GDP per capita	−0.22	3	−2.55[a]	3	$I(1)$
Industry value added	−2.01	1	−2.82[a]	1	$I(1)$
FDI	−1.29	1	−3.97[a]	1	$I(1)$
Domestic credit	−0.14	1	−2.92[a]	1	$I(1)$
With deterministic trend					
Agricultural employment share	−1.28	1	−3.39[a]	2	$I(1)$
GDP per capita	−3.50[a]	3	−3.00[a]	3	$I(0)$
Industry value added	−2.34	1	−3.17[a]	1	$I(1)$
FDI	−2.15	1	−4.40[a]	1	$I(1)$
Domestic credit	−2.49	1	−4.22[a]	1	$I(1)$

[a] Null hypothesis of unit root is rejected at the 5% level.

where 1 is the number of lags of the dependent variable, 2 is the number of lags of the regressors, 5 is the number of regressors (other than the dependent variable), and the variables are as defined before.

For estimation purposes, and following Bårdsen (1989), Eq. (2) can be written in growth rates (denoted by Δ) as follows:

$$\begin{aligned}\Delta agriemp_t &= c + \beta_0\Delta gdppc_t + \beta_2\Delta gdppc_{t-1} + \delta_0\Delta gdppcsq_t + \delta_2\Delta gdppcsq_{t-1}\\ &+\phi_0\Delta indva_t + \phi_2\Delta indva_{t-1} + \varphi_0\Delta fdi_t + \varphi_2\Delta fdi_{t-1} + \eta_0\Delta credit_t + \eta_2\Delta credit_{t-1}\\ &+\alpha^+ agriemp_{t-1} + \beta^+ gdppc_{t-1} + \delta^+ gdppcsq_{t-1} + \phi^+ indva_{t-1} + \varphi^+ fdi_{t-1} + \eta^+ credit_{t-1} + \varepsilon_t\end{aligned} \tag{3}$$

where $\alpha^+=(\alpha_1-1)$; $\beta^+=\sum_{i=0}^{2}\beta_i$; $\delta^+=\sum_{i=0}^{2}\delta_i$; $\phi^+=\sum_{i=0}^{2}\phi_i$; $\varphi^+=\sum_{i=0}^{2}\varphi_i$ and $\eta^+=\sum_{i=0}^{2}\eta_i$.

The long-run multipliers are then given by:

$$\theta_{gdppc}=\frac{\beta^+}{-\alpha^+},\quad \theta_{gdppcsq}=\frac{\delta^+}{-\alpha^+},\quad \theta_{indva}=\frac{\phi^+}{-\alpha^+},\quad \theta_{fdi}=\frac{\varphi^+}{-\alpha^+}\quad\text{and}\quad \theta_{credit}=\frac{\eta^+}{-\alpha^+} \tag{4}$$

This parameterization embodies the ECM formulation, given by:

$$\begin{aligned}\Delta agriemp_t &= c + \beta_0\Delta gdppc_t + \beta_2\Delta gdppc_{t-1} + \delta_0\Delta gdppcsq_t + \delta_2\Delta gdppcsq_{t-1}\\ &+\phi_0\Delta indva_t + \phi_2\Delta indva_{t-1} + \varphi_0\Delta fdi_t + \varphi_2\Delta fdi_{t-1} + \eta_0\Delta credit_t + \eta_2\Delta credit_{t-1}\\ &+\alpha^+ ECT_{t-1} + \varepsilon_t\end{aligned} \tag{5}$$

where the speed of adjustment to the steady state is given by α^+ and dynamic stability requires $-1<\alpha^+<0$. The error correction term (ECT) is given by:

$$\begin{aligned}ECT_{t-1} &= agriemp_{t-1} - \theta_{gdppc} gdppc_{t-1} - \theta_{gdppcsq} gdppcsq_{t-1}\\ &-\theta_{indva} indva_{t-1} - \theta_{fdi} fdi_{t-1} - \theta_{credit} credit_{t-1}\end{aligned} \tag{6}$$

4. Estimation and discussion of the results

Eq. (3) was estimated by OLS and the results are presented in Table 5. Specifically, the table reports: the regression coefficients; the Durbin's alternative test for autocorrelation, which indicates that the null hypothesis of no autocorrelation cannot be rejected; Pesaran et al.'s (2001) cointegration test; the predictive-failure test, which indicates that the second period observations fall within the prediction confidence interval of the first period observations; and the long-run or steady-state solution derived from expression (4). The model's linear prediction of $\Delta agriemp_t$, as well as the actual series, are shown in Fig. 4.

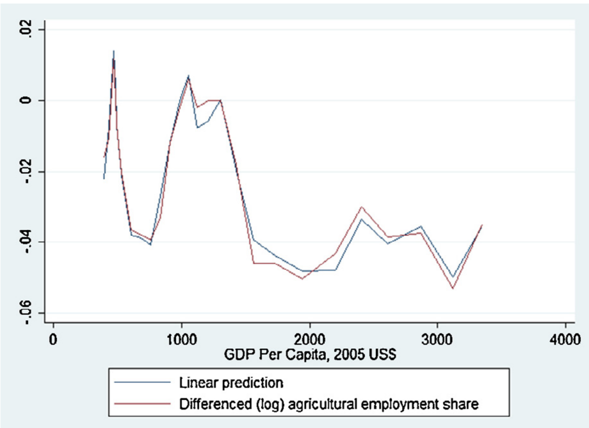

Fig. 4. Growth rate of agriculture's employment share: actual and predicted series.

Table 5
OLS estimates of Eq. (3), 1987–2012. Dependent variable is $\Delta agriemp$.

	Estimates	Standard error
$\Delta gdppc$	3.4108***	(0.8324)
$\Delta gdppc_{t-1}$	0.4326	(1.1754)
$\Delta gdppcsq$	−0.2324***	(0.0617)
$\Delta gdppcsq_{t-1}$	−0.0143	(0.0924)
$\Delta indva$	−0.4561***	(0.1184)
$\Delta indva_{t-1}$	−0.1458	(0.1359)
Δfdi	−0.0171	(0.0106)
Δfdi_{t-1}	0.0285**	(0.0092)
$\Delta credit$	−0.0305	(0.0436)
$\Delta credit_{t-1}$	0.0603**	(0.0264)
$agriemp_{t-1}$	−0.6448***	(0.1675)
$gdppc_{t-1}$	1.7096***	(0.3406)
$gdppcsq_{t-1}$	−0.1268***	(0.0250)
$indva_{t-1}$	−0.7628***	(0.2179)
fdi_{t-1}	−0.0433***	(0.0092)
$credit_{t-1}$	−0.0796	(0.0615)
constant	0.0813	(0.7047)
R^2	0.97	
No. observations	26	

Durbin's alternative test for serial autocorrelation: $\text{chi}^2 = 0.475$, $\text{prob} > \text{chi}^2 = 0.4906$
Cointegration test: $Ho: \alpha^+ = \beta^+ = \delta^+ = \phi^+ = \varphi^+ = \eta^+ = 0$, $F(6, 9) = 8.60$
Long-run equilibrium coefficients (based on the estimates above and Eq. (4)**):**

$$agriemp = \underset{(0.3856)}{2.6513 gdppc^{***}} \quad \underset{(0.0238)}{-0.1966 gdppcsq^{***}} \quad \underset{(0.1999)}{-1.1829 indva^{***}} \quad \underset{(0.0971)}{-0.1234 credit} \quad \underset{(0.0120)}{-0.0671 fdi^{***}} \quad \underset{(1.0707)}{+0.1261}$$

Computed F-statistic in the cointegration test is compared with the critical values in Table CI(iii) of Pesaran et al. (2001). Figures in parentheses under each long-run equilibrium value are the corresponding standard errors. Agricultural employment share in total employment and industrial value added share in GDP are taken from the Economic, Industry and Corporate Data database (accessed August 1, 2014). GDP per capita in constant 2005 US$, FDI as % of GDP and domestic credit to private sector as % of GDP are taken from the World Development Indicators (accessed June, 24 2014).
** Denotes significance at 5% level.
*** Denotes significance at 1% level.

To determine if a long-run relationship exists between the variables, we adopt Pesaran et al.'s (2001) bounds test procedure within the context of our ARDL model. As noted above, this is an F-test for the null hypothesis that $\alpha^+ = \beta^+ = \delta^+ = \phi^+ = \varphi^+ = \eta^+ = 0$. In other words, it is a test for the absence of a stationary long-run relationship among the variables embodied in the ECM. The resulting F-statistic based on the OLS estimates of Eq. (3) is 8.6. The relevant bands of critical values for a model with five regressors (excluding the lagged dependent variable), an unrestricted intercept and no deterministic trend are: 2.62–3.79 at the 5% level of significance, and 3.41–4.68 at the 1% level of significance. Since the computed F-statistic is above the critical band, the null hypothesis is rejected. There is, therefore, a long-run relationship among the share of employment in agriculture, income per capita, income per capita squared, industrial value added, FDI and domestic credit.[11]

Results indicate that a 1% increase in industrial value added leads to a decrease in the share of employment in agriculture by 0.60% in the short-run, while it leads to a long-run decrease in the share of 1.18%. The short-run effect of net FDI inflows is an increase in agriculture's employment share by a very small 0.01%, while it leads to a decrease in the share by 0.07% in the long-run. Credit to the private sector increases agriculture's employment by 0.03% in the short-run, while it leads to a decrease in the employment share by 0.12% in the long-run. The speed of adjustment toward the long-run equilibrium is relatively fast: 64.5% of the gap with the steady state is closed each year.

Finally, Fig. 5 shows the income elasticity of the agricultural employment share with respect to income per capita.[12] As hypothesized, the share declines as income per capita increases, although not at a constant rate (note that the long-run estimates of both income per capita and its square are significant). Results indicate that the income elasticity of the share is positive for very low income levels, and increases with income per capita up until it reaches

[11] We also used Johansen's cointegration test. Results are not identical to those discussed above but do support, at least partially, our analysis. Results suggest that there are at least two cointegrating vectors. The employment share cointegrating vector enters the employment share equation with a smaller adjustment coefficient than the estimated in Table 5; while it does not appear to enter the income per capita and industrial value added equations (i.e., the adjustment coefficients are zero, a necessary condition for these variables to be weakly exogenous in a conditional employment share equation). However, the adjustment coefficients of this vector in the domestic credit and FDI equations are implausibly large. The values of the adjustment coefficients of the other cointegrating vectors are extremely difficult to interpret (some of them have implausible values). Finally, if we impose the exactly identifying restriction and normalize the first cointegrating vector in the employment share regression with respect to the employment share, the values are very similar to those shown at the bottom of Table 6 (long-run equilibrium coefficients). Given these results, we concluded that modeling the agriculture's employment share conditioning on the other variables is a sensible strategy, assuming that these other variables are weakly exogenous for the parameters of the employment share equation.

[12] This is calculated as $elasticity = \theta_{gdppc} + \theta_{gdppcsq} * 2 * \ln gdppc$.

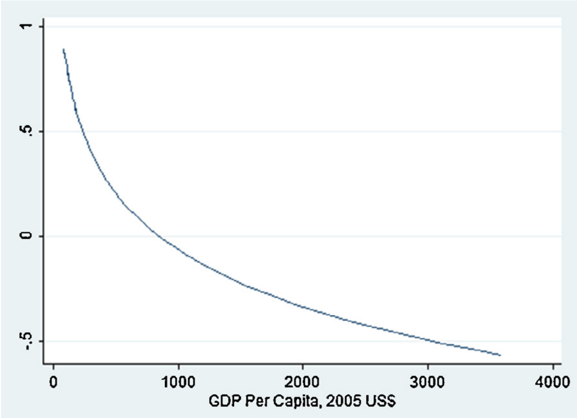

Fig. 5. Income elasticity of agricultural employment share.

$846—at this income level the elasticity becomes equal to zero. Beyond the $846 threshold the income elasticity of the agricultural employment share becomes negative, so that further increases in income per capita lead to (gradually smaller) decreases in the share.

5. Strong exogeneity analysis and forecasting

Engle et al. (1983) introduced three notions of exogeneity, namely, weak exogeneity for hypothesis testing, strong exogeneity for forecasting, and super exogeneity for policy analysis. These concepts denote properties of a variable with respect to the parameters of interest. Here we are interested in the concept of strong exogeneity. A variable z_t is said to be strongly exogenous with respect to another variable y_t (left hand-side variable in the conditional model) if z_t is weakly exogenous for the parameters of interest and if past values of y_t do not Granger-cause z_t. Therefore, testing for strong exogeneity consists of testing first for weak exogeneity, and then for Granger-causality.[13] Moreover, since our series are cointegrated, one or more terms on the right-hand side must be Granger-caused by the lagged error correction term, which is itself a function of the lagged elements on the right-hand side of the model (Granger, 1988).

To implement these tests, we follow Ericsson and Irons (1994) and Urbain (1993). While we are more interested in the long-run relationships between the variables under consideration, for completeness, we analyze both the short and long-run parameters in the model. Weak exogeneity requires: (i) the standard orthogonality condition and (ii) the absence of the cointegrating vector in the remaining equations. The two can be tested jointly by estimating unrestricted reduced ECMs for $\Delta gdppc$, $\Delta gdppcsq$, $\Delta indva$, Δfdi and $\Delta credit$ (i.e., the marginal models), to which we add the fitted residuals of the ECM in Table 5 and the one-period lagged error correction term.[14] Hypotheses (i) and (ii) can be verified by testing whether the last two additional terms are jointly equal to zero. Results are shown in Table 6.

The upper part of Table 6 shows the weak exogeneity tests, denoted *F*-weak. Except in the case of $\Delta gdppc$, the null hypothesis that the variables are weakly exogenous for the parameters of interest cannot be rejected. The tests for strong exogeneity (Granger causality), shown in the lower part of Table 6, denoted *F*-strong, indicate that none of the variables are Granger-caused by the error correction term; and that the null is rejected for the past values of the dependent variable only for $\Delta gdppc$ and $\Delta gdppcsq$. Overall, these results indicate that our conditional model (Eq. (3), shown in Table 5) can be used for forecasting.

Finally, we show in Table 7 the forecasts for China's agricultural employment share under different scenarios, designed to capture the speed of its decline. All scenarios assume that GDP per capita grows at 6.5% per annum from 2013 onward, with an initial GDP per capita (in 2013) of US$3583. Under scenario 1, industrial value added as a percentage of GDP, FDI as a percentage of GDP and domestic credit as a percentage of GDP are assumed to take their 2012 values of 45.27%, 3.59% and 133.69%, respectively. Results indicate that by 2020, the final year of the 13th Five-Year Plan, the employment share of agriculture in China will be 24%. Our model also implies that this share will be about 18% by 2025 and will fall down to 5% in 2044. Scenario 2 assumes that industrial value added, FDI and domestic credit grow during the forecast period at their 1985–2012 growth rates. Results are virtually identical to those in scenario 1. In scenario 3, industrial value added grows during the forecast period at its 1985–2012 growth rate, while the shares of FDI and domestic credit double. Under these circumstances, the employment share in 2020 (2025) will be 21% (16%), and it will reach 5% in 2042. In scenarios 4 and 5, we show what happens if industrial value added declines to 30% of GDP during the forecast period. In scenario 4, we further assume that the shares of FDI and credit to the private sector take on the same values as in scenario 2. In this case, the employment share in 2020 (2025) will be 38% (30%), and it will reach 5% in 2049. In scenario 5 we assume, as in scenario 3, that the shares of FDI and credit double. In this case, the employment share in 2020 (2025) will be 34% (26%), and it will reach 5% in 2048.

Based on these scenarios, it will take about 80 to 87 years (from 1962) for China's employment share to fall down at the level characteristic of an advanced economy today. This means that the pace of this process is likely to be faster in China than it was, on average, in the advanced economies in the past. Indeed, some of the scenarios suggest that the pace of decline of the agricultural employment share may continue being at about 1 percentage point per annum.

[13] A variable is said to be weakly exogenous for the parameters of interest if the latter are only functions of the parameters of interest in the conditional model, and if the parameters of the conditional and marginal models are variation-free (i.e., there are no cross-restrictions between conditional and marginal models). We already noted above that the employment share error correction term does not appear to enter the other equations (see footnote 6, where we refer to Johansen's cointegration test). Strong exogeneity also requires that past values of the left-hand side variable of the conditional equation (the employment share in our case) do not Granger-cause the other variables.

[14] Strictly speaking, the residuals we add are those from equation (5), that is, equation (3) re-estimated imposing the error correction term.

Table 6
Statistics for weak and strong exogeneity tests $\Delta agriemp$.

Weak exogeneity test		**F-Weak**
Differenced *gdppc*	*Residual*	Ho: $ECT_{t-1} = residual = 0$
ECT_{t-1}	0.00	$F(2, 23) = 3.33$
0.27[**]		$\text{Prob} > F = 0.05$
Differenced *gdppcsq*	*Residual*	Ho: $ECT_{t-1} = residual = 0$
ECT_{t-1}	0.00	$F(2, 23) = 0.90$
2.33		$\text{Prob} > F = 0.42$
Differenced *indva*	*Residual*	Ho: $ECT_{t-1} = residual = 0$
ECT_{t-1}	0.00	$F(2, 23) = 0.01$
0.051		$\text{Prob} > F = 0.99$
Differenced *fdi*	*Residual*	Ho: $ECT_{t-1} = residual = 0$
ECT_{t-1}	0.00	$F(2, 23) = 0.01$
0.25		$\text{Prob} > F = 0.99$
Differenced *credit*	*Residual*	Ho: $ECT_{t-1} = residual = 0$
ECT_{t-1}	0.00	$F(2, 23) = 1.58$
−0.56[*]		$\text{Prob} > F = 0.23$
Strong exogeneity test	**F-strong**	
	Ho: Differenced $agriemp_{t-1}$ = Differenced $agriemp_{t-2}$	Ho: $ECT_{t-1} = 0$
Differenced *gdppc*	$F(1, 22) = 2.29$; $\text{Prob} > F = 0.10$	$\text{Prob} > \lvert t \rvert = 0.20$
Differenced *gdppcsq*	$F(1, 22) = 3.07$; $\text{Prob} > F = 0.04$	$\text{Prob} > \lvert t \rvert = 0.54$
Differenced *indva*	$F(1, 22) = 1.15$; $\text{Prob} > F = 0.30$	$\text{Prob} > \lvert t \rvert = 0.17$
Differenced *fdi*	$F(1, 22) = 1.20$; $\text{Prob} > F = 0.35$	$\text{Prob} > \lvert t \rvert = 0.28$
Differenced *credit*	$F(1, 22) = 2.26$; $\text{Prob} > F = 0.12$	$\text{Prob} > \lvert t \rvert = 0.55$

ECT is the error correction term calculated as: $ECT = agriemp - 2.6513 gdppc + 0.1966 gdppcsq + 1.1829 indva + 0.1234 credit + 0.0671 fdi$.
[*] Denotes significance at 10% level.
[**] Denotes significance at 5% level.

Table 7
Forecasts of China's agricultural employment share.

Scenario	Forecast period	Agricultural employment share (%)	Agricultural employment share will become 5% by
1. Industrial value added, FDI and domestic credit are equal to their 2012 values at 45.27%, 3.59%, and 133.69%, respectively.	2013–2020	24	2044
	2013–2025	18	
2. Industrial value added, FDI and domestic credit are equal to 45.36%, 3.85%, and 137.25%, respectively[a].	2013–2020	23	2044
	2013–2025	18	
3. Industrial value added is equal to 45.36%[a]. 2012 FDI and domestic credit values double.	2013–2020	21	2042
	2013–2025	16	
4. Industrial value added declines to 30%. FDI and domestic credit are equal to 3.85% and 137.25%, respectively[a].	2013–2020	38	2049
	2013–2025	30	
5. Industrial value added declines to 30%. FDI and domestic credit double.	2013–2020	34	2048
	2013–2025	26	

[a] Figures are based on the assumption that industrial value added as % of GDP, FDI as % of GDP and domestic credit as % of GDP grow during the forecast period at their 1985–2012 growth rates: 0.20%, 7.3% and 2.65%, respectively. All scenarios assume 6.5% GDP per capita growth per annum. Initial GDP per capita is US$3583 in 2013.

Despite the fast pace of decline in the share of agriculture, the exercise suggests that China can be expected to have another three decades during which it will benefit from structural transformation as a source of economic growth. In our view, China has not reached the Lewis Turning Point and the wage increases observed in urban areas are the result of market segmentation and constraints on rural-urban migration, as argued by Knight et al. (2011).

6. Conclusions

Given the low productivity of the labor employed in agriculture, one key to China's aspirations to become a high-income economy in the coming decades is the decline in the agricultural employment share, still 31% in 2013. This paper has analyzed the drivers of China's agricultural employment share and used them to forecast the share by the end of the 13th Five-Year Plan (2016–2020). We have also forecast the year the employment share will reach 5%, approximately the same as in advanced economies today.

We have used an ARDL model to estimate a regression of the employment share in agriculture conditional on income per capita and its square, and the shares of industrial value added, FDI and credit to the private sector in GDP. Results identify the factors that can bring down the agricultural employment share. Some of the variables included are proxies for the reforms outlined in the 12th (and possibly 13th) Five-Year Plans. In particular, the long-run effect of FDI indicates that the proposed intensification of an open-door policy will help China's structural transformation.

Results also indicate that domestic credit has the potential to contribute to the decline of agricultural employment. With the enhanced role of markets in resource allocation, financial markets stand to become more competitive and efficient investment decisions will alter the composition of sectoral employment in the process. Enhancing markets to better allocate resources, combined with genuine reforms to relax institutional rigidities such as the *hukou* system, will help increase economic efficiency and accelerate the country's structural transformation.

In addition, industrial value added and income per capita have the biggest long-run effects on the decline of the employment share. These results confirm that China's path to structural transformation follows well-known patterns of development.

Based on our model, it will take about 80–87 years (from 1962) for China to have an agricultural employment share similar to that in most advanced economies today, about 5%. This decline is faster than that experienced by the advanced economies in the past. China's rapid growth since economic reforms started in 1978 has no historical precedent, and its growth of at least 8% each year is the strongest driver that propelled labor away from agriculture. Nevertheless, our analysis leads to the conclusion that the PRC has not reached the Lewis Turning Point.

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References

Aoki, M., 2013. Historical sources of institutional trajectories in economic development: China, Japan and Korea compared. Socioecon. Rev. 11 (2), 233–263.

Bårdsen, G., 1989. Estimation of long-run coefficients in error correction models. Oxf. Bull. Econ. Stat. 51, 345–350.

Banister, J., Bloom, D., Rosenberg, L.,2010a. Population Aging and Economic Growth in China. In: Program on the Global Demography of Aging Working Paper Series Number 53. Harvard University, Massachusetts.

Banister, J., Bloom, D., Rosenberg, L., 2010b. Growth and structural changes in employment in transition China. J. Comp. Econ. 38, 71–81.

Cai, F., Wang, M., 2008. A counterfactual of unlimited surplus labour in rural China. China World Econ. 16, 51–65.

Das, M., N'Diaye, P., 2013. Chronicle of a decline foretold: has China reached the Lewis turning point? IMF Working Paper 13/26. Washington D.C.

Engle, R., Hendry, D., Richard, J., 1983. Exogeneity. Econometrica 51, 277–304.

Ericsson, N.R., Irons, J., 1994. Testing Exogeneity. Oxford University Press, New York.

Fan-Yi, W., 1994. Reconsidering export-led growth: evidence from firm performance, Taiwan, 1983–1987. In: Aberbach, J., Dollar, D., Sokoloff, K. (Eds.), The Role of the State in Taiwan Development. M.E. Sharpe Inc., New York.

Granger, C.W.J., 1988. Some recent developments in the concept of causality. J. Econom. 39, 199–211.

Golley, J., Meng, X., 2011. Has China run out of surplus labour? China Econ. Rev. 22 (4), 555–572.

Herrendorf, B., Schoellman, T., 2012. Why is measured labor productivity so low in agriculture? Manuscript. Arizona State University, Arizona.

Hongbin, Q., Xiaoping, M., 2013. From the horse's mouth. HSBC Global Research (15 November). Full Transcript of Premier Li Keqiang's speech delivered at the 16th National Congress of the All-China Federation of Trade Unions.

Holz, C., 2008. China's economic growth 1978–2025: what we know today about China's economic growth tomorrow. World Dev. 36 (10), 1665–1691.

Jingwen, L., Feihong, G., Yisheng, Z., 1995. Productivity and China's economic growth, 1953–1990. In: Tsui, K., Hsueh, T., Rawski, T. (Eds.), Productivity, efficiency and reform in China's economy. Hong Kong Institute of Asia-Pacific Studies. The Chinese University of Hong Kong, Hong Kong, pp. 19–54.

Knight, K., Deng, Q., Li, S., 2011. The puzzle of migrant labour shortage and rural labour surplus in China. China Econ. Rev. 22, 585–600.

Lewis, A., 1978. Growth and Fluctuations 1870–1913. Allen and Unwin, London.

Maddison, A., 1982. Phases of Capitalist Development. Oxford University Press, New York.

Minami, R., Ma, X., 2010. The turning point of Chinese economy: compared with Japanese experience. China Econ. J. 3 (2), 712–723.

Pesaran, M., Shin, Y., Smith, R., 2001. Bounds testing approaches to the analysis of level relationships. J. Appl. Econ. 16, 289–326.

Rawski, T., Mead, R.W., 1998. On the trail of China's phantom workers. World Dev. 26 (5), 767–781.

Rozelle, S., Veeck, G., Huang, J., 1997. The impact of environmental degradation on grain production in China, 1975–1990. Econ. Geogr. 73 (1), 44–66.

Syrquin, M., 2008. Structural change and development. In: Dutt, A., Ros, J. (Eds.), International Handbook of Development Economics., vol. 1. Edward Elgar, pp. 48–67.

Tang, A., Stone, B., 1980. Food Production in PRC (Research Report). International Food Policy Research Institute, Washington D.C.

Urbain, J., 1993. Exogeneity in Error Correction Models. Springer-Verlag, Berlin Heidleberg.

Wei, S., 1995. The open door policy and China. In: Ito, T., Krueger, O. (Eds.), Growth theories in light of the East Asian experience. University of Chicago Press, Chicago, IL, pp. 73–104.

Wong, L., 1987. Agricultural productivity in China and India: A comparative analysis. Economic Development Center Bulletin Number 87-3. Department of Economics, Minneapolis, University of Minnesota, Minnesota.

Yao, Y., Zhang, K., 2010. Has China passed the Lewis turning point? A structural estimation based on provincial data. China Econ. J. 3 (2), 155–162.

Zhang, X., Yang, J., Wang, S., 2011. China has reached the Lewis turning point. China Econ. Rev. 22, 542–554.