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STRUCTURAL CHANGE AND AGGREGATE EMPLOYMENT FLUCTUATIONS IN CHINA*

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In developed countries, aggregate employment is strongly procyclical and almost as volatile as output. In China, the correlation of aggregate employment and output is close to zero, and the volatility of aggregate employment is very low. We argue that the key to understanding aggregate employment fluctuations in China is labor reallocation between the agricultural and nonagricultural sectors, and that the income effect plays an important role in determining the labor reallocation dynamics in both the long run and short run.

1. INTRODUCTION

One salient feature of business cycles in developed countries is that aggregate employment has a strong positive correlation with aggregate output (i.e., is procyclical) and is almost as volatile as output. However, this is not the case in China, where the correlation of the cyclical components of aggregate employment and output is close to zero, and the volatility of aggregate employment is also very low. These puzzling facts about aggregate employment fluctuations in China are present even after we correct for well-known measurement problems in the official employment and GDP series, and they are robust to different detrending methods. In this article, we argue that the key to understanding aggregate employment fluctuations in China is labor reallocation between the agricultural and nonagricultural sectors, and that the income effect (i.e., the decline in the relative demand for agricultural goods with household income) plays an important role in the reallocation. Our argument is motivated by the following three sets of empirical facts.

First, at the sectoral level, the cyclical properties of employment in China are similar to those of developed countries. For both China and OECD countries, the volatility of sectoral employment relative to the volatility of sectoral GDP is high and employment is strongly procyclical in the nonagricultural sector. In the agricultural sector, the relative volatility of employment is actually higher in China than in OECD countries, and employment is acyclical in all the countries.

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Second, we show that disparities in aggregate moments between China and the developed countries are explained by the nations being in different stages of structural change. Using a panel data of 40 countries from the Groningen Growth and Development Center (GGDC), we find that the comovement of aggregate employment and output at any point in time is negatively related to the agricultural employment share at each point in time. Da-Rocha and Restuccia (2006) document that average agricultural employment share has a negative effect on the correlation between aggregate employment and output. However, we find that, even after controlling for the average share, the agricultural employment share at each point in time still matters. This dynamic effect of economic structure on aggregate employment fluctuations is particularly relevant for China, where agricultural employment share declined from 71% in 1978 to 27% in 2017. Therefore, any theory for explaining aggregate employment fluctuations in China should be able to match the secular trend of labor reallocation out of agriculture.

Third, and most importantly, we find that almost all countries in the GGDC data set have a ratio of agricultural employment to nonagricultural employment that is negatively correlated with per capita GDP over the business cycles. Boppart (2014) and Comin et al. (2020) emphasize that the income effect is important for understanding the secular trend of labor reallocation from agriculture to manufacturing and services. Our new fact suggests that the income effect is also important for determining labor reallocation between sectors at the business cycle frequency.

Given these facts, we construct a two-sector growth model with nonhomothetic Constant Elasticity of Substitution (CES) preferences recently used by Comin et al. (2020). In this model, the income effect plays an important role in labor allocation both in the long run and at the business cycle frequency. Using expenditure and price data of 40 countries and a panel regression that is derived from our model, we first show empirically the presence of a strong income effect. We then calibrate the parameters of our model so that it can account for China's secular trend in labor reallocation from agriculture to nonagriculture. The calibration reveals that the income effect is important in accounting for long-run structural change in China. Without the income effect, the model would not match the structural change in China in the long run. Finally, we examine the calibrated model's implications for labor market dynamics at the business cycle frequency. Fluctuations in this model are driven by productivity shocks in the two sectors. We find that our model can indeed account for China's employment fluctuations at the sector level and in aggregate. At the business cycle frequency, the income effect is also important for the model to match China's business cycle moments as, without the income effect, the model could generate neither the low correlation between aggregate employment and output nor the negative correlation between relative employment in agriculture and aggregate income in China. Our model also does a good job at matching the structural change and aggregate employment fluctuations in developed countries such as the United States. In particular, our model implies a low employment–output correlation for China and, at the same time, a high employment–output correlation for the United States.

Our article contributes to the literature by documenting the importance of the income effect for understanding aggregate employment fluctuations and constructing a model incorporating the income effect that can account for both long-run structural change and short-run employment fluctuations in China. As such, our article is related to two strands of literature. First, it is related to the literature on structural change; see, for example, Caselli and Coleman (2001), Kongsamut et al. (2001), Ngai and Pissarides (2007), Acemoglu and Guerrieri (2008), and Herrendorf et al. (2013). Most of the studies in this literature aim to understand the sources of structural change in the long run; our article builds on this literature and studies business cycle implications of the income effect to show that it is important for understanding aggregate employment fluctuations in the short run. Our article is also related to the literature on business cycles in China. Brandt and Zhu (2000) are one of the first to study business cycles in China during the reform period. Their focus, however, is on the relationship between GDP growth and inflation over the business cycles in the 1980s and early 1990s. More recently, Chang et al. (2016) focus on understanding the weak correlation between investment and consumption in China since the late 1990s. Neither of these studies examines the relationship between aggregate employment and output. He et al. (2009) carry out an exercise on business cycle accounting for China in the spirit of Chari et al. (2007). They find that most of the fluctuations in aggregate employment can be accounted for only by variations in an unobserved labor wedge, highlighting the inability of a standard one-sector business cycle model to account for China's employment fluctuations. Our article shows that a standard two-sector model with nonhomothetic CES preferences can account for aggregate employment fluctuations in China without introducing a time-varying labor wedge.

Two studies are closely related to our article. Da-Rocha and Restuccia (2006) are the first to document the low correlation between aggregate employment and output in countries with a large agricultural sector. They use a two-sector real business cycle model to examine the role of labor reallocation in accounting for the cyclical behavior of aggregate employment. In order to focus on cyclical fluctuations, they assume that each country is fluctuating around a steady state with a constant agricultural employment share.[1] Since structural change (i.e., the secular decline in agricultural employment share) is a very prominent phenomenon in China during our period of study, and since the correlation between aggregate employment and output fluctuations is affected by the agricultural employment share at each point of time, not just the average of the share over a period of time, it is important to have a unified model that can account for both the secular trend of structural change and employment fluctuations around the trend. We provide such a unified model in this article.

Another closely related paper is that by Storesletten et al. (2019) (hereafter referred to as SZZ), who also use a two-sector model to account for both structural change and aggregate employment fluctuations in China. Our article has four strengths. First, we show that the income effect is empirically important at the business cycle frequency for a large panel of countries and quantitatively important for accounting for aggregate employment fluctuations in China. In contrast, SZZ emphasize capital deepening within agriculture instead of the income effect as the driving force for labor reallocation between the two sectors. Note that, although SZZ also consider the income effect using a generalized Stone–Geary utility function, the income effect implied by the Stone–Geary utility function is very special in that it disappears in the long run. As shown by Comin et al. (2020), a model with a more general form of the income effect, that is, preferences represented by a nonhomothetic CES utility function, performs much better than the generalized Stone–Geary utility function in accounting for the secular trend of structural change across countries. In this article, we use the more general nonhomothetic CES utility function and show that it performs well in accounting for labor reallocation over the business cycles and aggregate employment fluctuations in China. Second, all important endogenous variables in our article, such as sectoral employment and output, have empirical counterparts that can be directly measured from available data. SZZ, however, assume that there are two subsectors within agriculture, that is, traditional agriculture and modern agriculture, that cannot be directly observed or identified in the data. Third, although SZZ assume an elasticity of substitution between agricultural and nonagricultural goods that is greater than one, we find in our estimation that this elasticity is less than one, which is consistent with the values used or estimated in the literature on structural change (e.g., Ngai and Pissarides, 2007; Acemoglu and Guerrieri, 2008; Herrendorf et al., 2013; Comin et al. 2020). An elasticity that is less than one implies that an exogenous increase in agricultural productivity

[1] Moro (2012) uses a similar method to examine the impact of reallocation from manufacturing to services on the GDP volatility in the United States.

would lead to a decline in agricultural employment share. This is precisely what happened in China at the end of 1970s and early 1980s, when an institutional reform, that is, the implementation of the household responsibility system, led to significant total factor productivity (TFP) growth (Lin, 1992) and faster labor productivity growth in agriculture. At the same time, agricultural employment share declined (Brandt et al. 2008). Finally, our model does a much better job at matching the moments in the Chinese data. Although SZZ's model can generate lower relative volatility of employment and lower employment–output correlation than a standard one-sector business cycle model, the values from their calibrated model are still significantly higher than those in the China data.

2. DATA AND FACTS

Before presenting our model, we first discuss the data and facts about the employment fluctuations in China and other countries.[2]

2.1. *Data.* For China, we use the official National Bureau of Statistics (NBS) data published in the latest China Statistical Yearbook, which can be accessed from NBS' website.[3] The annual data cover 40 years from 1978 to 2017. For countries other than China, we use annual sector-level data on real GDP and employment from the GGDC's 10-Sector Database (Timmer et al. 2015) and aggregate the nine sectors outside agriculture into one nonagricultural sector. To be consistent with the sample size of the China data, we use the latest 40 years available in the GGDC database.[4]

According to the official NBS China data, there is a discrete upward jump in total employment in 1990. Holz (2006) points out that this jump is due to a change in the official definition of employment after the 1990 census, which broadens the coverage of the series. Although NBS' published data use the new definition for the years since 1990, the old definition is still used for the years prior to 1990. We follow Brandt and Zhu (2010) in using the 1982 census data to adjust the employment data for the years before 1990 so that the entire employment series has consistent coverage. The official and revised versions of total employment are plotted in the left panel of Figure 1. We then apply the employment shares of agriculture and nonagriculture from the official NBS data to the revised total employment to generate the employment series for each sector before 1990. Figure 1 also shows the agricultural share of total employment in the right panel.[5]

Given the revised China employment data, we next present the facts on the cyclical properties of employment in China and compare them to those in developed countries. All data used are first normalized by population and then detrended using the HP filter with a smoothing parameter of 100.

2.2. *Facts.* We first document how China is different from developed countries in aggregate employment fluctuations but similar to these countries in employment fluctuations at the sector level. We then show that, across all countries, the correlation of aggregate employment and output is negatively related to agricultural employment share. Finally, we show that

[2] A more detailed discussion of data is given in Appendix A.1.

[3] http://data.stats.gov.cn/easyquery.htm?cn=C01

[4] All OECD countries in the GGDC database have at least 40 years of the data, but some developing countries in the database have less than 40 years of available data. For these countries, we use all years of available data. The Appendix includes a list of the countries that we study and the sample period for each country.

[5] Brandt and Zhu (2010) also point out some other problems in the official employment and GDP series. However, correcting these problems does not change the main facts we present in this article. In our main analysis, we use the official series (after correcting total employment) because it is available for 40 years from 1978 to 2017, which is longer than the revised series from 1978 to 2010. Moreover, the official series are also used by other papers in the literature such as Storesletten et al. (2019). We report the revised series between 1978 and 2010 and related quantitative analysis in Appendix A.8.

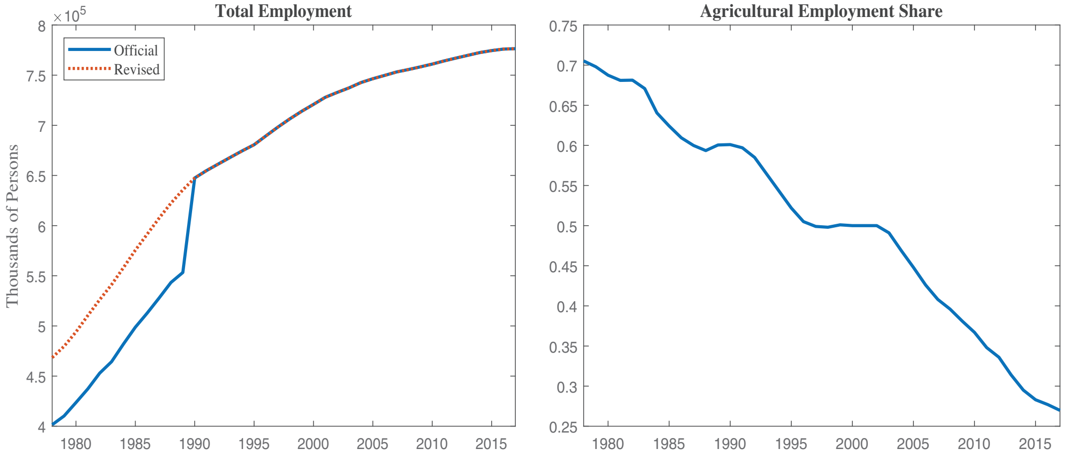

FIGURE 1

EMPLOYMENT DATA IN CHINA [COLOR FIGURE CAN BE VIEWED AT WILEYONLINELIBRARY.COM]

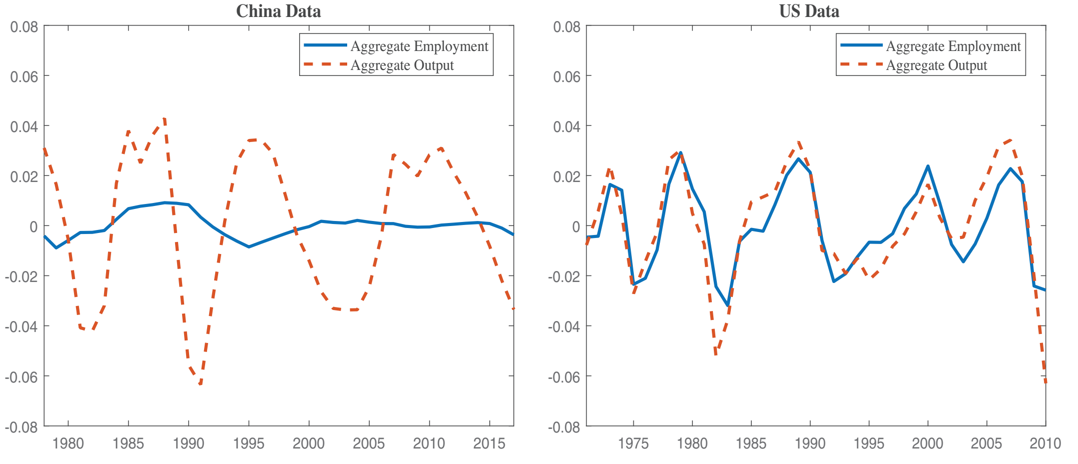

FIGURE 2

CYCLICAL FLUCTUATIONS [COLOR FIGURE CAN BE VIEWED AT WILEYONLINELIBRARY.COM]

the relative employment in agriculture is negatively correlated to GDP per capita over business cycles.

2.2.1. *Aggregate employment fluctuations.* Figure 2 plots the cyclical movements of aggregate employment and output for China and the United States. Two observations are clear from the plots:

(1) In China, the magnitude of fluctuations in aggregate employment is much lower than that of aggregate output. This finding is in stark contrast with the United States, where aggregate employment fluctuates almost as much as aggregate output.
(2) Aggregate employment is acyclical in China, whereas it is strongly procyclical in the United States.

Table 1 presents the aggregate business cycle moments in China, the United States, and other OECD countries. The statistics confirm our observations above. In China, the relative volatility of employment is only 0.15 and the correlation of aggregate employment and output

TABLE 1
AGGREGATE BUSINESS CYCLE MOMENTS

	China	United States	OECD Average
$\sigma(L)/\sigma(Y)$	0.15	0.75	0.69
$\rho(L, Y)$	−0.08	0.87	0.67

NOTE: $\sigma(.)$ represents standard deviation; $\rho(., .)$ represents correlation. L and Y are the aggregate employment and output, respectively, both normalized by population. Variables are detrended by the HP filter with a smoothing parameter of 100.

TABLE 2
SECTOR MOMENTS

	China	United States	OECD Average
(A) Nonagricultural sector			
$\sigma(L_{na})/\sigma(Y_{na})$	0.73	0.75	0.73
$\rho(L_{na}, Y_{na})$	0.83	0.87	0.72
(B) Agricultural sector			
$\sigma(L_a)/\sigma(Y_a)$	1.03	0.34	0.59
$\rho(L_a, Y_a)$	−0.39	−0.10	0.08

NOTE: $\sigma(.)$ represents standard deviation; $\rho(., .)$ represents correlation. L and Y are the aggregate employment and output, respectively, both normalized by population. Variables are detrended by the HP filter with a smoothing parameter of 100.

is close to zero, both of which are in contrast with the established business cycle facts for developed economies that have been documented in, for example, Cooley and Prescott (1995). In Appendix A.2, we use alternative methods to detrend the data and show that the facts reported here are robust to alternative detrending methods.

2.2.2. *Employment fluctuations at sector level.* The stark differences in the aggregate employment fluctuations between China and developed countries conceal the similarities at the sector level. Panels (A) and (B) in Table 2 present the cyclical properties of employment in the non-agricultural (*na*) and agricultural (*a*) sectors, respectively. For both China and the OECD countries, the volatility of sectoral employment relative to the volatility of sectoral GDP is high, and employment is strongly procyclical in the nonagricultural sector. The agricultural sector's relative volatility of employment is actually higher in China than in the OECD countries, and employment is acyclical in all the countries.

Some may argue that the low volatility of aggregate employment in China is due to unique institutional constraints that limit its employment variability. Although it is true that there could be strong employment rigidity in the state-owned enterprises, the labor market for the nonstate sector in China is quite flexible due to minimal regulations on hiring and firing workers by the nonstate firms. Since the nonstate sector's employment is usually the margin at which aggregate employment adjusts over business cycles, institutional constraints on state-sector employment cannot explain the puzzle. Indeed, for China's nonagricultural sector, which includes the state-sector, relative employment volatility is 0.73, which is the same as the OECD average and close to U.S. ratio value of 0.75.

2.2.3. *Role of structural change in employment fluctuations.* China's disparity with the developed countries on the aggregate-level reflects a more general phenomenon documented by Da-Rocha and Restuccia (2006) for 18 OECD countries: Aggregate employment is less volatile and less correlated with output in countries with a larger average share of agricultural employment. However, it is important to note that a country's agricultural employment share is not constant over time and, in fact, generally declines due to structural change. We now provide evidence that the degree of co-movement between aggregate employment and output

TABLE 3
STRUCTURAL CHANGE AND AGGREGATE EMPLOYMENT FLUCTUATIONS

Dependent Variable	$\log L_t^{cj}$ (1)	$\log L_t^{cj}$ (2)
$\log Y_t^{cj}$	0.434***	0.396***
	(0.094)	(0.111)
$\log Y_t^{cj} \times l_{a,avg}^j$		−0.997***
		(0.224)
$\log Y_t^{cj} \times (l_{at}^j - l_{a,avg}^j)$		−1.287***
		(0.367)
$\log Y_t^{cj} \times l_{at}^j$	−1.060***	
	(0.196)	
l_{at}^j	0.002	0.003
	(0.020)	(0.020)
Country fixed effects	Y	Y
Year fixed effects	Y	Y
R-squared	0.567	0.568
Observations	1,929	1,929

NOTE: The dependent variable is aggregate employment of country j in year t. Aggregate employment and output are detrended by the HP filter with a smoothing parameter of 100 to obtain their cyclic components, L_t^{cj} and Y_t^{cj}; $l_{a,avg}^j$ is average agricultural employment share of country j over the sample period; l_{at}^j is current agricultural employment share of country j in year t. Weighted least squares are weighted by countries' GDP. Robust standard errors are reported in parenthesis. *denotes significance at the 90% confidence level, **denotes significance at the 95% confidence level, and ***denotes significance at the 99% confidence level.

depends on the current agricultural employment share, not just the average agricultural employment share over a period of time.

In the baseline exercise, we run the following regression between aggregate employment and output using cross-country data from the GGDC:

$$(1) \qquad \log L_t^{cj} = \beta_1 \log Y_t^{cj} + \beta_2 \log Y_t^{cj} \times l_{at}^j + \beta_3 l_{at}^j + \nu^j + \xi_t + \epsilon_t^j,$$

where L_t^{cj} and Y_t^{cj} are cyclical components of aggregate employment and output (both normalized by population) of country j in year t, l_{at}^j is current agricultural employment share of country j in year t, and ν^j and ξ_t are country and year fixed effects. Column (1) of Table 3 reports the regression results, which shows a significant negative coefficient for the interaction term $\log Y_t^{cj} \times l_{a,t}^j$. The result indicates that the correlation between aggregate employment and output declines with the current agricultural employment share.

In order to illustrate that it is not just the average agriculture employment share that matters, we present an alternative regression specification in Equation (2) in which output interacts with average agricultural employment share ($l_{a,avg}^j$) and the difference between the current and average agricultural employment shares separately:

$$(2) \log L_t^{cj} = \beta_1 \log Y_t^{cj} + \beta_2 \log Y_t^{cj} \times l_{a,avg}^j + \beta_3 \log Y_t^{cj} \times \left(l_{at}^j - l_{a,avg}^j\right) + \beta_4 l_{at}^j + \nu^j + \xi_t + \epsilon_t^i.$$

Column (2) of Table 3 shows a negative coefficient for the interaction term of average agricultural employment share, which is consistent with the fact documented in Da-Rocha and Restuccia (2006). Moreover, the coefficient on the interaction term $\log Y_t^{cj} \times (l_{at}^j - l_{a,avg}^j)$ is also negative and significant, which suggests that current agricultural employment share is important for determining the correlation between aggregate employment and output, even after controlling for the average share. In both regressions, the coefficient on current agricultural employment share itself is insignificant.

TABLE 4
INCOME EFFECT OVER THE BUSINESS CYCLE

	China	United States	OECD Average	Non-OECD Average
$\rho(L_a/L_{na}, Y)$	−0.83	−0.68	−0.50	−0.33

NOTE: $\rho(.,.)$ represents correlation, L_i is the cyclic component of sector i employment, $i \in \{a, na\}$, and Y is the cyclic component of aggregate GDP per capita, both of which are obtained by using the HP filter with a smoothing parameter of 100.

Given the strong interaction between current agricultural employment share and the cyclic fluctuations of employment we document, it is important to have a model that can account for both long-run structural change and short-run labor reallocation between sectors for countries such as China, in which agricultural employment share declined sharply from 1978 to 2017.

2.2.4. *Role of the income effect in employment fluctuations.* It is well documented in the structural change literature that, in the long run, a country's agricultural employment share is negatively related to its income. For example, Comin et al. (2020) emphasize the importance of the income effect for understanding the structural change from agriculture to manufacturing and services. Table 4 reports the correlation between the cyclical components of the relative employment in agriculture (L_{at}/L_{nat}) and aggregate GDP per capita. The correlation is significantly negative for China, the United States, the other OECD countries, and non-OECD countries. The evidence suggests that the income effect may also be important for labor reallocation between the agricultural and nonagricultural sectors over business cycles.

In summary, we have documented that employment fluctuations at the sectoral level in China are similar to those in developed countries, that aggregate employment fluctuations are affected by economic structure and structural change, and that the reallocation of labor between the agricultural and nonagricultural sector is correlated with aggregate income. Motivated by these stylized facts, we next present our two-sector model with the income effect (nonhomothetic preferences), and we will use this model to quantitatively account for labor market dynamics in both the long run and short run in China.

3. THE MODEL

There are two sectors indexed by $i = a$ and na, representing agriculture and nonagriculture, respectively. Each sector produces a consumption good with a linear technology using labor as the only input:

$$Y_{it} = A_{it} N_{it}, \quad i = a, na,$$

where Y_{it}, A_{it}, and N_{it} are output, labor productivity, and employment in sector i, respectively. There is a stand-in representative household whose preferences over a composite consumption good C_t and working time L_t are represented by the following utility function:

$$U_t = C_t - \frac{B_t}{1+\sigma} L_t^{1+\sigma}.$$

Here, σ is a nonnegative number representing the inverse of the Frisch labor supply elasticity, and $B_t > 0$ is a time-varying labor supply parameter that is used to capture demographic factors (e.g., age structure and gender composition of the labor force) that affect average household labor supply decisions.[6]

[6] Note that, when B_t is a constant, our utility function is the same as the GHH utility function proposed by Greenwood et al. (1988).

Following Hanoch (1975) and Comin et al. (2020), composite consumption C_t is defined implicitly by the following equation:

$$(\varphi_a)^{\frac{1}{\varepsilon}} C_t^{\frac{(1-\varepsilon)\mu_a}{\varepsilon}} c_{at}^{\frac{\varepsilon-1}{\varepsilon}} + (\varphi_{na})^{\frac{1}{\varepsilon}} C_t^{\frac{(1-\varepsilon)\mu_{na}}{\varepsilon}} c_{nat}^{\frac{\varepsilon-1}{\varepsilon}} = 1, \tag{3}$$

where φ_a, φ_{na}, μ_a, μ_{na}, and ε are all positive constants. The parameter φ_i represents the household preference weight on consumption good in sector i ($\varphi_a + \varphi_{na} = 1$), μ_i is a parameter that determines the income elasticity of consumption good i, and ε is the elasticity of substitution between the two consumption goods. The implicit utility function is a generalization of the standard CES utility function that allows the two consumption goods to have different income elasticities. If $\mu_a = \mu_{na} = 1$, then the utility function is reduced to the standard CES utility function. If $\varepsilon < 1$ and $\mu_a < \mu_{na}$, then the income elasticity is smaller for the agricultural good than for the nonagricultural good, and therefore relative demand for the agricultural good declines with income.

3.1. *Social Planner's Problem.* Since we assume that there is no friction or externality in the economy, the competitive allocation is the same as the social optimal allocation, which is the solution to the following social planner's problem:

$$\max_{c_{at}, c_{nat}, L_{at}, L_{nat}, C_t} \left\{ N_t \left[C_t - \frac{B_t}{1+\sigma} L_t^{1+\sigma} \right] \right\}$$

subject to (3) and the following constraints:

$$c_{at} = A_{at} L_{at}, \tag{4}$$

$$c_{nat} = A_{nat} L_{nat}, \tag{5}$$

$$L_{at} + L_{nat} = L_t. \tag{6}$$

Here, N_t is the population size, and $L_{it} = N_{it}/N_t$ is the ratio of employment in sector i to total population ($i \in \{a, na\}$). In Appendix A.3, we show that the optimal consumption of the two goods, c_{at} and c_{nat}, and the aggregate employment rate L_t satisfy the following equations:

$$c_{at} = \frac{\varphi_a A_{at}^{\varepsilon} C_t^{(1-\varepsilon)\mu_a}}{\left(\varphi_a A_{at}^{\varepsilon-1} C_t^{(1-\varepsilon)\mu_a} + \varphi_{na} A_{nat}^{\varepsilon-1} C_t^{(1-\varepsilon)\mu_{na}}\right)^{\frac{\varepsilon}{\varepsilon-1}}}, \tag{7}$$

$$c_{nat} = \frac{\varphi_{na} A_{nat}^{\varepsilon} C_t^{(1-\varepsilon)\mu_{na}}}{\left(\varphi_a A_{at}^{\varepsilon-1} C_t^{(1-\varepsilon)\mu_a} + \varphi_{na} A_{nat}^{\varepsilon-1} C_t^{(1-\varepsilon)\mu_{na}}\right)^{\frac{\varepsilon}{\varepsilon-1}}}, \tag{8}$$

$$L_t = \left[\frac{\left(\varphi_a A_{at}^{\varepsilon-1} C_t^{(1-\varepsilon)\mu_a} + \varphi_{na} A_{nat}^{\varepsilon-1} C_t^{(1-\varepsilon)\mu_{na}}\right)^{\frac{\varepsilon}{\varepsilon-1}}}{B_t \left(\mu_a \varphi_a A_{at}^{\varepsilon-1} C_t^{(1-\varepsilon)\mu_a - 1} + \mu_{na} \varphi_{na} A_{nat}^{\varepsilon-1} C_t^{(1-\varepsilon)\mu_{na} - 1}\right)} \right]^{\frac{1}{\sigma}}. \tag{9}$$

3.2. *Equilibrium Employment, Consumption, and Output.* From the goods market clearing conditions, (4), (5), (7), and (8), we have,

$$L_{at} = \frac{\varphi_a A_{at}^{\varepsilon-1} C_t^{(1-\varepsilon)\mu_a}}{\left(\varphi_a A_{at}^{\varepsilon-1} C_t^{(1-\varepsilon)\mu_a} + \varphi_{na} A_{nat}^{\varepsilon-1} C_t^{(1-\varepsilon)\mu_{na}}\right)^{\frac{\varepsilon}{\varepsilon-1}}}, \tag{10}$$

$$L_{nat} = \frac{\varphi_{na} A_{nat}^{\varepsilon-1} C_t^{(1-\varepsilon)\mu_{na}}}{\left(\varphi_a A_{at}^{\varepsilon-1} C_t^{(1-\varepsilon)\mu_a} + \varphi_{na} A_{nat}^{\varepsilon-1} C_t^{(1-\varepsilon)\mu_{na}}\right)^{\frac{\varepsilon}{\varepsilon-1}}}. \tag{11}$$

Hence, aggregate employment rate is

$$L_t = L_{at} + L_{nat} = \left(\varphi_a A_{at}^{\varepsilon-1} C_t^{(1-\varepsilon)\mu_a} + \varphi_{na} A_{nat}^{\varepsilon-1} C_t^{(1-\varepsilon)\mu_{na}}\right)^{\frac{1}{1-\varepsilon}}, \tag{12}$$

and agricultural employment share is

$$l_{at} \equiv \frac{L_{at}}{L_t} = \frac{\frac{\varphi_a}{1-\varphi_a}\left(\frac{A_{at}}{A_{nat}}\right)^{\varepsilon-1} C_t^{(1-\varepsilon)(\mu_a-\mu_{na})}}{1 + \frac{\varphi_a}{1-\varphi_a}\left(\frac{A_{at}}{A_{nat}}\right)^{\varepsilon-1} C_t^{(1-\varepsilon)(\mu_a-\mu_{na})}}, \tag{13}$$

which is affected by two factors: relative productivity of agriculture A_{at}/A_{nat} and aggregate consumption per capita C_t. The first factor represents the substitution effect, and the second factor represents the income effect. In the special case of homothetic CES, when $\mu_a = \mu_{na}$, agricultural employment share is a function of relative productivity A_{at}/A_{nat} only, and the income effect is absent.

3.3. *Solving the Equilibrium.* Combining Equations (12) and (9) yields the following equation for the equilibrium value of aggregate consumption C_t:

$$C_t = B_t \frac{\mu_a \varphi_a A_{at}^{\varepsilon-1} C_t^{(1-\varepsilon)\mu_a} + \mu_{na}\varphi_{na} A_{nat}^{\varepsilon-1} C_t^{(1-\varepsilon)\mu_{na}}}{\left[\varphi_a A_{at}^{\varepsilon-1} C_t^{(1-\varepsilon)\mu_a} + \varphi_{na} A_{nat}^{\varepsilon-1} C_t^{(1-\varepsilon)\mu_{na}}\right]^{\frac{\sigma+\varepsilon}{\varepsilon-1}}}. \tag{14}$$

Given the preference parameters and labor productivity of the two sectors, A_{at} and A_{nat}, Equation (14) can be used to solve for C_t. Given C_t, Equations (10) and (11) can be used to solve for L_{at} and L_{nat}; GDP per capita is then calculated for the two sectors as $Y_{at} = A_{at}L_{at}$ and $Y_{nat} = A_{nat}L_{nat}$, respectively. Finally, when labor productivity levels are normalized so that the relative price of agriculture in some base year is 1, the aggregate real GDP per capita valued with base year prices is simply $Y_t = Y_{at} + Y_{nat}$.[7]

4. INCOME AND PRICE EFFECTS ON LABOR ALLOCATION

In this section, we discuss how labor allocation across the two sectors is affected by income and relative prices in our model, and we provide empirical evidence for these two effects.

[7] In the quantitative analysis, we use 2005 as the base year and Y_{at}, Y_{nat}, A_{at}, and A_{nat} are all valued using 2005 international prices from the GGDC Productivity Level Database.

From Equations (10) and (11), we can derive the following equation for relative employment:

$$\ln\left(\frac{L_{at}}{L_{nat}}\right) = \ln\left(\frac{\varphi_a}{\varphi_{na}}\right) - (1-\varepsilon)\ln\left(\frac{A_{at}}{A_{nat}}\right) - (1-\varepsilon)(\mu_{na}-\mu_a)\ln C_t. \tag{15}$$

Sectoral labor productivity affects relative employment through a substitution effect in the second term and an income effect in the third term. The value of the substitution elasticity, ε, and the relative magnitude of the two income elasticities, μ_a and μ_{na}, are important for determining how sectoral productivity affects relative employment. For example, if $\varepsilon < 1$, then the relative employment of agriculture is negatively related to the relative productivity of agriculture. Furthermore, if $\mu_{na} > \mu_a$ in addition to $\varepsilon < 1$, then the relative employment of agriculture is also a decreasing function of the aggregate consumption. Since labor productivities in both sectors have a positive impact on aggregate consumption, they both have a negative effect on the relative employment of agriculture through the income effect when $\varepsilon < 1$ and $\mu_{na} > \mu_a$.

Empirically, is ε less than one and μ_{na} greater than μ_a? We now use the panel data from the GGDC 10-Sector Database to answer this question. As indicated by Hanoch (1975) and Comin et al. (2020), substitution and income elasticities can be estimated using data on expenditures and prices. Let $E_t = p_{at}Y_{at} + p_{nat}Y_{nat}$ be the total expenditure per capita and $\omega_{it} = p_{it}Y_{it}/E_t$ be the sector i expenditure share, $i = a, na$. We prove in Appendix A.3 that the following equation holds:

$$\ln\left(\frac{\omega_{at}}{\omega_{nat}}\right) = \ln\left(\frac{\varphi_a}{\varphi_{na}}\right) + (1-\varepsilon)\ln\left(\frac{p_{at}}{p_{nat}}\right) + (1-\varepsilon)(\mu_a-\mu_{na})\ln C_t. \tag{16}$$

The last term of Equation (16) represents the income effect, which includes the aggregate consumption index C_t that is not directly observed. However, we also prove in Appendix A.3 that the following equation holds:

$$(1-\varepsilon)\ln C_t = \frac{1}{\mu_{na}}\left(-\ln\varphi_{na} + \ln\omega_{nat} + (1-\varepsilon)\ln\frac{E_t}{p_{nat}}\right).$$

Substituting it into Equation (16) yields the following:

$$\ln\left(\frac{\omega_{at}}{\omega_{nat}}\right) = \ln\left(\frac{\varphi_a}{\varphi_{na}^{\frac{\mu_a}{\mu_{na}}}}\right) + (1-\varepsilon)\ln\left(\frac{p_{at}}{p_{nat}}\right) + \left(\frac{\mu_a}{\mu_{na}} - 1\right)\left(\ln\omega_{nat} + (1-\varepsilon)\ln\frac{E_t}{p_{nat}}\right). \tag{17}$$

We can write the empirical counterpart of Equation (17) as

$$\ln\left(\frac{\omega_{at}^j}{\omega_{nat}^j}\right) = \beta_1\ln\left(\frac{p_{at}^j}{p_{nat}^j}\right) + \beta_2\ln\omega_{nat}^j + \beta_1\beta_2\ln\left(\frac{E_t^j}{p_{nat}^j}\right) + \nu_j + \zeta_{jt},$$

where $\beta_1 = 1-\varepsilon$, $\beta_2 = \mu_a/\mu_{na} - 1$, j is an index for country, ν_j represents country fixed effects,[8] and ζ_{jt} is the residual. The coefficient for the relative price term, β_1, measures the substitution effect. If $\beta_1 > 0$ (<0), the two goods are gross complements (gross substitutes). The coefficient for the real aggregate expenditure, $\beta_1\beta_2$, measures the income effect. If $\beta_1\beta_2 < 0$ (>0) the income effect is such that the relative demand for the agricultural good declines (increases) with aggregate income. Since the equation is log-linear in observables, it should

[8] Like Comin et al. (2020), we allow preference weights φ_a to vary by country but restrict the elasticities to be identical across countries.

TABLE 5
INCOME AND PRICE EFFECTS

Dependent Variable	$\log(\omega^j_{at}/\omega^j_{nat})$ Raw Data (1)	$\log(\omega^j_{at}/\omega^j_{nat})$ Trend Data (2)	$\log(\omega^j_{at}/\omega^j_{nat})$ Cyclic Data (3)	$\log(\omega^j_{at}/\omega^j_{nat})$ Raw Data (4)	$\log(\omega^j_{at}/\omega^j_{nat})$ Trend Data (5)	$\log(\omega^j_{at}/\omega^j_{nat})$ Cyclic Data (6)
$\log(p^j_{at}/p^j_{nat})$	0.960***	0.977***	0.864***	0.781***	0.776***	0.888***
	(0.054)	(0.058)	(0.049)	(0.049)	(0.010)	(0.097)
$\log(\omega^j_{nat})$	−0.808***	−0.792***	−0.937***	−0.992***	−1[9]	−0.884***
	(0.066)	(0.068)	(0.054)	(0.067)	.	(0.098)
$\log(E^j_t/p^j_{nat})$	−0.775***	−0.774***	−0.810***	−0.775***	−0.776***	−0.785***
	(0.025)	(0.025)	(0.029)	(0.014)	(0.010)	(0.085)
Implied value of						
ε	0.040	0.023	0.136	0.219	0.224	0.112
μ_a/μ_{na}	0.192	0.208	0.063	0.008	0.	0.116
Trade controls	N	N	N	Y	Y	Y
Country fixed effects	Y	Y	Y	Y	Y	Y
R-squared	0.984	0.982	0.864	0.991	0.994	0.813
Observations	1,929	1,929	1,929	1,682	1,682	1,682

NOTE: The dependent variable is the agriculture to nonagriculture expenditure ratio in country j, year t. Variables in column (1) are raw data. Variables in column (2) are the HP filtered trend levels. Variables in column (3) are the HP filtered cyclic components. Columns (4)–(6) are the corresponding regressions using domestic expenditures instead of value-added. Weighted least squares are weighted by countries' GDP. Robust standard errors are reported in parenthesis. *denotes significance at the 90% confidence level, **denotes significance at the 95% confidence level, and ***denotes significance at the 99% confidence level.

hold for the raw data, the HP filtered trend data, and the HP filtered cyclic data. Table 5 reports the results of our nonlinear least squares regression using the raw, trend, and cyclic data in columns (1), (2) and (3), respectively. Since Equation (17) should hold for domestic expenditures and since sectoral value-added $p_{it}Y_{it}$ may include the sector's net exports, we also make adjustments to the expenditure data by subtracting the sector's nominal net exports from the sectoral value-added and total nominal net exports from total value-added, respectively. The results of the regressions using the adjusted expenditure data are reported in columns (4)–(6).

In all the regressions reported in Table 5, the estimated value of β_1 is significantly positive and that of β_2 is significantly negative, which implies that $\varepsilon < 1$ and $\mu_a/\mu_{na} < 1$. Hence, the empirical evidence suggests that the elasticity of substitution between the agricultural and nonagricultural consumption good is less than one and that the income effect is such that the relative demand for the agricultural good declines with aggregate income. Since the estimation results are similar regardless of whether we use trend or cyclic data, we conclude that the income effect is important in both the long run and short run.

Although our regression results provide strong evidence for both $\varepsilon < 1$ and the income effect, we recognize that the estimated parameter values may be biased due to potential endogeneity problems as, according to our model, $\ln(\omega_{at}/\omega_{nat})$, $\ln \omega_{nat}$, and $\ln(E_t/p_{nat})$ are all endogenously determined by the sectoral labor productivities, A_{at} and A_{nat}. Therefore, in Section 6, we provide an alternative method that estimates these parameters structurally. The structural estimation in Section 6 also demonstrates that $\varepsilon < 1$ and $\mu_{na} > \mu_a$.

5. EMPLOYMENT RESPONSES TO PRODUCTIVITY SHOCKS

We now discuss how productivity shocks affect employment when $\varepsilon < 1$ and $\mu_{na} > \mu_a$. We first illustrate how the shares of sectoral employment affect the responses of aggregate

[9] The estimation imposes that $\mu_a/\mu_{na} \geq 0$ and the constraint binds.

consumption and employment to productivity shocks. We derive the following relationships from Equations (12) and (14). The detailed derivations are shown in Appendix A.3.

$$
\begin{aligned}
d\ln C_t = {} & \frac{[(\sigma+\varepsilon)(\mu_a l_{at}+\mu_{na} l_{nat})+(1-\varepsilon)\mu_a] l_{at}\, d\ln A_{at}}{(\sigma+\varepsilon)(\mu_a l_{at}+\mu_{na} l_{nat})^2+(1-\varepsilon)(\mu_a^2 l_{a,t}+\mu_{na}^2 l_{nat})-(\mu_a l_{at}+\mu_{na} l_{nat})} \\
& + \frac{[(\sigma+\varepsilon)(\mu_a l_{at}+\mu_{na} l_{nat})+(1-\varepsilon)\mu_{na}] l_{nat}\, d\ln A_{nat}}{(\sigma+\varepsilon)(\mu_a l_{at}+\mu_{na} l_{nat})^2+(1-\varepsilon)(\mu_a^2 l_{at}+\mu_{na}^2 l_{nat})-(\mu_a l_{at}+\mu_{na} l_{nat})},
\end{aligned}
\tag{18}
$$

and

$$
\begin{aligned}
d\ln L_t = {} & \frac{[(\mu_a l_{at}+\mu_{na} l_{nat})-(1-\varepsilon)(\mu_{na}-\mu_a)\mu_{na} l_{nat}] l_{at}\, d\ln A_{at}}{(\sigma+\varepsilon)(\mu_a l_{at}+\mu_{na} l_{nat})^2+(1-\varepsilon)(\mu_a^2 l_{at}+\mu_{na}^2 l_{nat})-(\mu_a l_{at}+\mu_{na} l_{nat})} \\
& + \frac{[(\mu_a l_{at}+\mu_{na} l_{nat})+(1-\varepsilon)(\mu_{na}-\mu_a)\mu_a l_{at}] l_{nat}\, d\ln A_{nat}}{(\sigma+\varepsilon)(\mu_a l_{at}+\mu_{na} l_{nat})^2+(1-\varepsilon)(\mu_a^2 l_{at}+\mu_{na}^2 l_{nat})-(\mu_a l_{at}+\mu_{na} l_{nat})}.
\end{aligned}
\tag{19}
$$

In the special case of homothetic CES, that is, $\mu_a = \mu_{na} = 1$, the above equations reduce to

$$d\ln C_t = (1+\sigma^{-1})(l_{at}\, d\ln A_{at} + l_{nat}\, d\ln A_{nat}),$$

and

$$d\ln L_t = \sigma^{-1}(l_{at}\, d\ln A_{at} + l_{nat}\, d\ln A_{nat}).$$

In this case, the responses of aggregate employment and aggregate consumption to productivity shocks are perfectly correlated. Since aggregate consumption and aggregate output are highly correlated, it implies that the responses of aggregate employment and aggregate output are also highly correlated. Therefore, the homothetic model without the income effect would not be able to match the low employment–output correlation that we observe in the China data.

However, when $\mu_{na} > \mu_a$, the responses of aggregate employment and aggregate consumption are no longer perfectly correlated. In fact, the responses of both aggregate variables depend on the economic structure at the time of the shock, which are the sectoral employment shares l_{at} and l_{nat}. This is consistent with the fact presented in Table 3 of Subsection 2.2.3.

Aggregate employment volatility is also affected by the economic structure in the case of nonhomothetic preferences. To see this clearly, consider the case of a sector-neutral productivity shock, $d\ln A_{at} = d\ln A_{nat} = dz_t$; then, from Equations (18) and (19), we have

$$d\ln L_t = \frac{\left[(\mu_a l_{at}+\mu_{na} l_{nat})-(1-\varepsilon)(\mu_{na}-\mu_a)^2 l_{at} l_{nat}\right]}{(\sigma+\varepsilon)(\mu_a l_{at}+\mu_{na} l_{nat})^2+(1-\varepsilon)(\mu_a^2 l_{at}+\mu_{na}^2 l_{nat})-(\mu_a l_{at}+\mu_{na} l_{nat})} dz_t.$$

When $\varepsilon < 1$ and $\mu_{na} > \mu_a$, the response of aggregate employment to the productivity shock is reduced by the term $(1-\varepsilon)(\mu_{na}-\mu_a)^2 l_{at} l_{nat}$, which again depends on the values of l_{at} and l_{nat}. Thus, the conditional variance of $d\ln L_t$ tends to be dampened when neither l_{at} nor l_{nat} is close to zero. The unconditional variance of $d\ln L_t$ is, of course, more complicated because employment shares are themselves endogenous variables affected by productivity shocks. In order to fully examine our model's implication for aggregate employment fluctuations, we next turn to quantitative analysis.

9. QUANTITATIVE ANALYSIS

We now quantitatively examine our model's implications for structural change and aggregate employment fluctuations. We first assume that there are no productivity shocks so that each sector's labor productivity is at its trend level, and we show that our calibrated model can quantitatively account for the secular decline in China's agricultural employment share. We then introduce productivity shocks into the same calibrated model and show that the model can also quantitatively account for labor reallocation between the two sectors and aggregate employment fluctuations around the trend at the business cycle frequency.

The data that we use for quantitative analysis are employment to population ratios and real GDP per capita of the agricultural and nonagricultural sectors for both China and the United States. Real GDP is valued at the 2005 international prices using price-level data from the GGDC Productivity Level Database. Labor productivity A_{it} is the ratio of real GDP to employment in sector i, $i = a, na$.

6.1. *Structural Change: Labor Reallocation in the Long Run.* We use the HP filter to filter out trends in sectoral employment to population ratios and in aggregate and sectoral labor productivities. Given the trends in aggregate employment rate and sectoral labor productivities, we can see from Equations (12) and (13) that the trends in both aggregate consumption and agricultural employment share are determined by the four implicit utility function parameters, φ_a, ε, μ_a, and μ_{na}. Therefore, we can use the China trend data to calibrate these parameters. Since agricultural employment share is invariant with respect to the scale of the two income elasticity parameters,[10] μ_a and μ_{na}, we normalize the scale of the two parameters by setting μ_a to 1. Next, we discuss our procedure for calibrating the remaining three parameters of the implicit utility function: φ_a, ε, and μ_{na}.

Let the HP filtered trend component of any variable be denoted by an upper bar, and let T be the number of years of our sample. First, for any $t = 1, \ldots, T$, and given the aggregate employment rate trend $\overline{L}_t$ and labor productivities trends $\overline{A}_{at}$ and $\overline{A}_{nat}$ in the data, we can solve from Equation (12) the aggregate consumption trend $\overline{C}_t$ by using the following equation:

$$\overline{L}_t = \left(\varphi_a\left(\overline{A}_{at}\right)^{\varepsilon-1}\left(\overline{C}_t\right)^{1-\varepsilon} + (1-\varphi_a)\left(\overline{A}_{nat}\right)^{\varepsilon-1}\left(\overline{C}_t\right)^{(1-\varepsilon)\mu_{na}}\right)^{\frac{1}{1-\varepsilon}}. \tag{20}$$

The solution defines aggregate consumption as an implicit function of the three parameters, $\overline{C}_t(\varphi_a, \varepsilon, \mu_{na})$. Then, from Equation (13), we can write the trend of the agricultural employment share as a function of $(\varphi_a, \varepsilon, \mu_{na})$,

$$\bar{l}_{at}(\varphi_a, \varepsilon, \mu_{na}) = \frac{\frac{\varphi_a}{1-\varphi_a}\left(\frac{\overline{A}_{at}}{\overline{A}_{nat}}\right)^{\varepsilon-1}\left(\overline{C}_t(\varphi_a, \varepsilon, \mu_{na})\right)^{(1-\varepsilon)(1-\mu_{na})}}{1 + \frac{\varphi_a}{1-\varphi_a}\left(\frac{\overline{A}_{at}}{\overline{A}_{nat}}\right)^{\varepsilon-1}\left(\overline{C}_t(\varphi_a, \varepsilon, \mu_{na})\right)^{(1-\varepsilon)(1-\mu_{na})}}. \tag{21}$$

Finally, we use the nonlinear least squares method to estimate the values of $(\varphi_a, \varepsilon, \mu_{na})$ by minimizing the following loss function:

$$\sum_{t=1}^{T}\left\{\left[\bar{l}_{at}(\varphi_a, \varepsilon, \mu_{na}) - \overline{L}_{at}/\overline{L}_t\right]^2\right\}, \tag{22}$$

where $\overline{L}_{at}$ and $\overline{L}_t$ are employment trends from the data. The estimation yields the following point estimates and their 95% confidence intervals for China: $\varphi_a = 0.350$ with a confidence interval of [0.319, 0.380], $\varepsilon = 0.197$ with a confidence interval of [0.086, 0.307], and $\mu_{na} = 3.678$

[10] See Appendix A.4 for the proof.

TABLE 6
BENCHMARK CALIBRATION

Parameter	Description	Target	China	United States
φ_a	Preference weight for agriculture	Average agricultural employment share	0.350 [0.319, 0.380]	0.116 [0.113, 0.119]
ε	Elasticity of substitution between two goods	Trend of China's agricultural employment share	0.197 [0.086, 0.307]	0.197 [0.086, 0.307]
μ_a	Income elasticity of agricultural good	Normalization	1	1
μ_{na}	Income elasticity of nonagricultural good	Trend of China's agricultural employment share	3.678 [3.019, 4.338]	3.678 [3.019, 4.338]
σ	Inverse Frisch elasticity of labor supply	Literature	0.6	0.6

NOTE: 95% confidence intervals are shown in square brackets.

with a confidence interval of [3.019, 4.338]. Table 6 summarizes the calibration results. The estimated value of substitution elasticity is less than one, implying that the substitution effect is such that the share of employment in agriculture is negatively related to agriculture's relative productivity. This result is consistent with the theoretical assumption of Ngai and Pissarides (2007) and the empirical finding of Herrendorf et al. (2013). The estimated value of μ_{na} is significantly larger than one, implying that the income effect plays an important role for the decline in agricultural employment share. Overall, our structural estimation results are consistent with the reduced-form regression results using expenditure and price data reported in Section 4.

Figure 3 displays the trend in agricultural employment share from the model and the data along with the trend of relative labor productivity $\overline{A}_{at}/\overline{A}_{nat}$ for both China and the United States. The top left panel shows that our calibrated model matches well the trend of China's agricultural employment share. For the United States, we keep the values of the two elasticity parameters, ε and μ_{na}, the same as those for China, but estimate φ_a to match the model-implied average agricultural employment share to that of U.S. data, which yields a value of 0.116 for φ_a in the United States.[11] The top right panel of Figure 3 shows that our calibrated model also matches well with United States' agricultural employment share trend. In summary, using the same income and substitution elasticities for both countries and country-specific preference weight φ_a, our simple two-sector model with nonhomothetic CES utility function can quantitatively account for structural changes in both China and the United States. This result is consistent with the finding of Comin et al. (2020) for a panel of countries that does not include China.

Note that the income effect is crucial to ensure that our model can match the speed of structural change in both economies. In order to illustrate this, we set $\mu_a = \mu_{na} = 1$ and recalibrate the values of φ_a and ε to minimize the same loss function in Equation (22). The resulting value of ε is 3.260, and the values of φ_a are 0.973 for China and 0.021 for the United States. We plot the model-implied trend of agricultural employment share for China and the United States in the upper panel of Figure 3, labeled as homothetic CES. For both China and the United States, the model without the income effect performs poorly in matching the observed structural change. As can be seen clearly from Equation (21), without the income effect, structural change would be purely driven by changes in relative labor productivity $\overline{A}_{at}/\overline{A}_{nat}$. If $\varepsilon > 1$, agricultural employment share is a strictly increasing function of the agricultural sector's relative labor productivity. However, for China, the relative productivity did not change monotonically over time; it increased between 1978 and 1983 (when an institutional reform

[11] Different values of φ_a does not necessarily imply that households in the two countries have different preferences. Rather, it may capture potential differences in labor intensity of agricultural production, barriers to labor reallocation, and other factors that may influence the average agricultural employment share but are abstracted from our model.

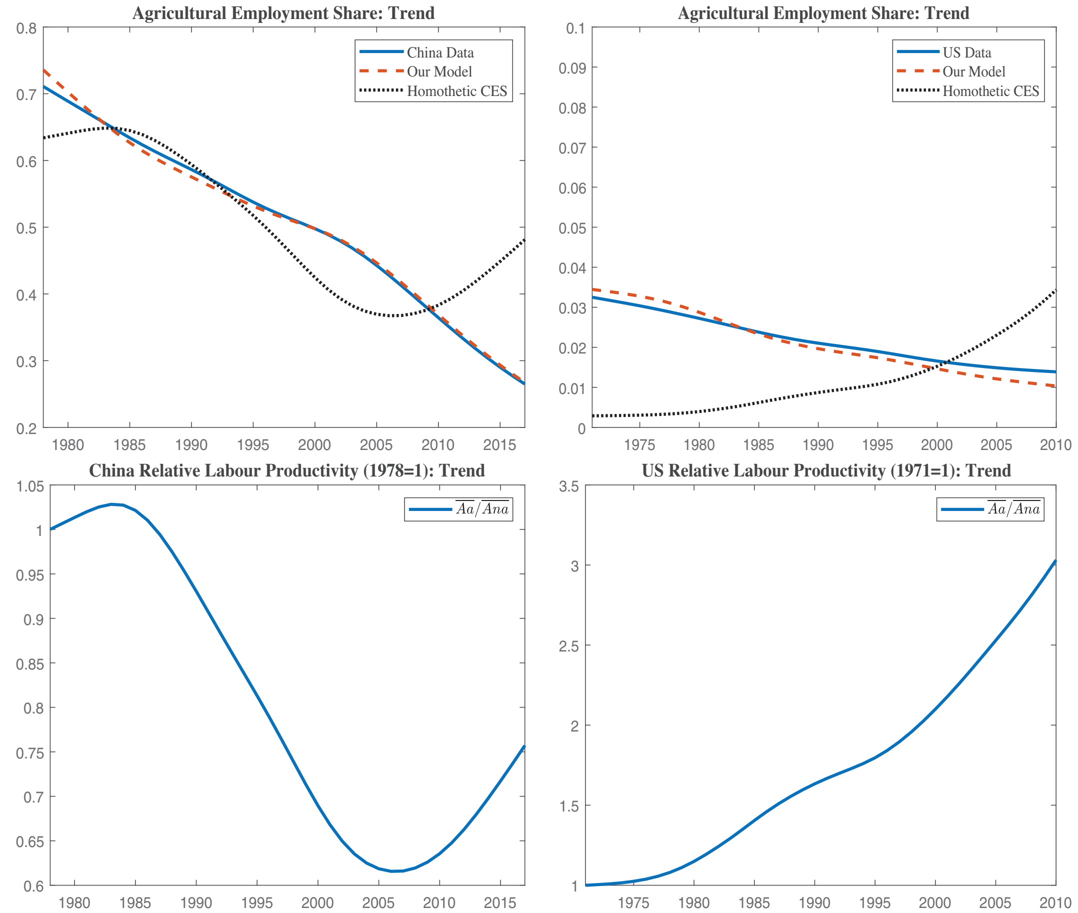

FIGURE 3

STRUCTURAL CHANGE: CHINA AND THE UNITED STATES [COLOR FIGURE CAN BE VIEWED AT WILEYONLINELIBRARY.COM]

in agriculture was carried out), decreased between 1983 and 2006, and then increased again after 2006 (when the nonagricultural sector's productivity growth slowed). Although the homothetic CES model can match the decline in China's agricultural employment share between 1983 and 2006, it cannot generate the decline in the share from 1978 to 1983 and subsequent increase after 2006 without the income effect. Since relative productivity in the United States has been growing during the sample period, $\varepsilon > 1$ also implies that agricultural employment share should increase instead of decrease.

6.2. *Labor Reallocation in the Short Run and Aggregate Employment Fluctuations.* We now turn to the cyclical properties of our model when there are shocks to sectoral productivity. We use the same values of φ_a, ε, and μ_{na} as those that are calibrated to match the long-run structural change in the data and reported in Table 6. For the value of σ, we choose 0.6 so that the Frisch elasticity of labor supply is 1.7, a value used by Greenwood et al. (1988) and many others in the business cycle literature. We show that our results are robust to alternative calibrations in Section 7.

Before presenting the quantitative results, we first discuss our strategy of dealing with the trend in the aggregate employment rate. As shown in Figure 4, due to the changes in demographic factors such as age structure, the trend of the aggregate employment rate is hump-shaped. Since the long-run trend of the aggregate employment rate is not the focus of

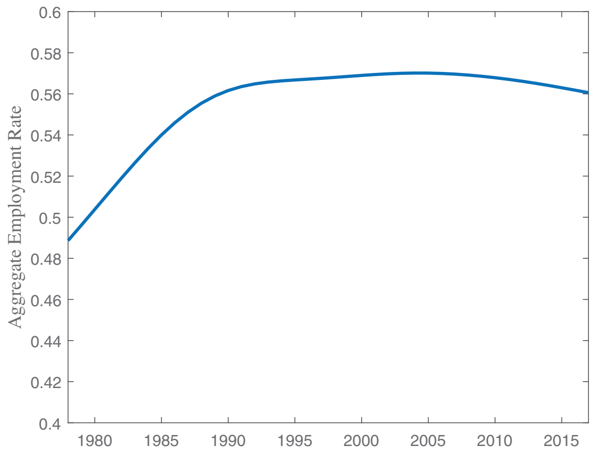

FIGURE 4

TREND OF AGGREGATE EMPLOYMENT RATE [COLOR FIGURE CAN BE VIEWED AT WILEYONLINELIBRARY.COM]

our article, we take it as given. Specifically, we choose the value of labor supply parameter B_t to match the trend of the aggregate employment rate using the equation below:

$$\overline{L}_t = \left[\frac{\left(\varphi_a\left(\overline{A}_{at}\right)^{\varepsilon-1}\left(\overline{C}_t\right)^{1-\varepsilon} + (1-\varphi_a)\left(\overline{A}_{nat}\right)^{\varepsilon-1}\left(\overline{C}_t\right)^{(1-\varepsilon)\mu_{na}}\right)^{\frac{\varepsilon}{\varepsilon-1}}}{B_t\left(\mu_a\varphi_a\left(\overline{A}_{at}\right)^{\varepsilon-1}\left(\overline{C}_t\right)^{-\varepsilon} + \mu_{na}(1-\varphi_a)\left(\overline{A}_{nat}\right)^{\varepsilon-1}\left(\overline{C}_t\right)^{(1-\varepsilon)\mu_{na}-1}\right)} \right]^{\frac{1}{\sigma}},$$

where $\overline{L}_t$, $\overline{A}_{at}$, and $\overline{A}_{nat}$ are the trends of the aggregate employment rate and labor productivity in agriculture and nonagriculture, respectively, and $\overline{C}_t$ is the aggregate consumption trend calculated using Equation (20).

We are now ready to simulate the model and compute the business cycle moments. Specifically, we take as input the actual labor productivities $\{A_{at}\}_{t=1,\ldots,T}$ and $\{A_{nat}\}_{t=1,\ldots,T}$ from the data, which include both the trend and the cyclical productivity shocks, and solve the sector-level and aggregate employment rates and GDP using the method described in Subsection 3.3. We then detrend the simulated variables from the model with the HP filter to retrieve the cyclic components and compute model-implied business cycle moments. The benchmark results are presented in Table 7.

6.2.1. *Benchmark results.* The first and second columns of Table 7 present the business cycle statistics calculated from the China data and the simulated time series from the model, and the third and fourth columns present the corresponding results for the United States. Panel A shows the relative standard deviations of the aggregate employment to output and the correlation between aggregate employment and output, Panel B shows sector-level correlations and relative standard deviations, Panel C shows the correlations of sectoral employment with aggregate output and employment, and Panel D shows the correlation between sectoral employment and the correlations of the agriculture's relative employment with relative labor productivity and aggregate income per capita.

Results for China. Overall, the model does a good job in matching both the aggregate and sectoral moments in the China data. From Panel A, we see that the model produces a relative aggregate employment volatility of 0.18, which is very close to 0.15 in the data. The model also generates an acyclical employment series that has a correlation with output close to zero.

TABLE 7
BENCHMARK RESULTS

	China		U.S.	
	Data	Model	Data	Model
(A)				
$\sigma(L)/\sigma(Y)$	0.15	0.18	0.75	0.24
$\rho(L, Y)$	−0.08	−0.02	0.87	0.89
(B)				
$\sigma(L_a)/\sigma(Y_a)$	1.03	1.67	0.34	3.75
$\sigma(L_{na})/\sigma(Y_{na})$	0.73	0.78	0.75	0.26
$\rho(L_a, Y_a)$	−0.39	−0.80	−0.10	−0.96
$\rho(L_{na}, Y_{na})$	0.83	0.81	0.87	0.88
(C)				
$\rho(L_a, Y)$	−0.73	−0.57	−0.27	−0.17
$\rho(L_{na}, Y)$	0.84	0.79	0.87	0.89
$\rho(L_a, L)$	0.35	0.75	−0.09	0.02
$\rho(L_{na}, L)$	0.15	−0.35	1.00	0.91
(D)				
$\rho(L_a, L_{na})$	−0.83	−0.82	−0.12	−0.38
$\rho(L_a/L_{na}, A_a/A_{na})$	−0.67	−0.91	−0.27	−0.99
$\rho(L_a/L_{na}, Y)$	−0.83	−0.72	−0.68	−0.22

NOTE: $\sigma(.)$ represents standard deviation; $\rho(.,.)$ represents correlation. L and Y are aggregate employment rate and output per capita. L_i, Y_i, and A_i are sectoral employment, output, and labor productivity, where $i \in \{a, na\}$. Variables are detrended using the HP filter with a smoothing parameter of 100.

From Panel B, we see that the model generates relative employment volatilities in the two sectors that are comparable to those in the data. The model-implied sector employment–output correlation is strongly positive for the nonagricultural sector and negative for the agricultural sector, as in the data. Panel C shows the correlations of sectoral employment with aggregate output and employment. Consistent with the data, agricultural employment in the model is strongly countercyclical, and nonagricultural employment in the model is strongly procyclical. The correlation of aggregate employment with agricultural employment is positive in both the data and the model. The correlation of the aggregate employment with nonagricultural employment, however, is negative in the model but slightly positive in the data. In Section 7, we will show that this correlation is affected by trade and investment demand and that introducing these factors into the model results in the model-implied correlation matching the data well. Finally, Panel D shows labor reallocation between the two sectors. The correlation of employment in the two sectors is −0.82 in the model and −0.83 in the data, indicating strong reallocation of labor between the two sectors. The last two rows in Panel D report correlations of relative employment with relative labor productivity and income. They are strongly negative in the model and data, suggesting that substitution and income effects are both important for labor reallocation over the business cycles in China.

Results for the United States. Our model also does a good job at replicating U.S. business cycle facts. In the aggregate, the model generates highly procyclical aggregate employment. The model produces a relative employment volatility that is lower than the data. This problem is common for standard real business cycle models, as pointed out by Cooley and Prescott (1995): Without additional labor market frictions, these models have difficulty generating sizable employment variations. Panels B and C report the within-sector employment–output correlations and the correlation of sectoral employment with aggregate output and employment from the model. These correlations are broadly consistent with the data. Panel D shows that the model can produce a negative correlation between sectoral employment and negative correlations of agriculture's relative employment with the relative labor productivity and aggregate income per capita, which are also in line with the U.S. data.

Because of $\varepsilon < 1$ and the income effect, our model implies that the agricultural labor productivity has a strong negative effect on agricultural employment. Although the correlation between employment and output in the agricultural sector and the correlation between the relative employment and the relative labor productivities across the two sectors are indeed negative in the data, as predicted by the model, for both China and the United States, the magnitude of the negative correlations are smaller than those implied by our model. We think this is likely due to the existence of ex post weather shocks that affect the measured agricultural output and labor productivity, but have no effect on agricultural employment because the employment decisions have been made before the ex post weather shocks.

In summary, despite being highly stylized, our model matches employment fluctuations in both China and the United States well, at both the sector level and in aggregate. Similar to the case for long-run structural change, the key to the success of our model is the income effect generated by the nonhomothetic preferences. Because the income elasticity of the agricultural good is less than that of the nonagricultural good, the income effect on employment in the agricultural and nonagricultural sectors are in opposite directions. When the agricultural sector is large, this income-effect–induced negative correlation between employment in the two sectors dampens aggregate employment volatility and reduces the correlation between aggregate employment and output.

In order to further illustrate the importance of the income effect, we next examine the quantitative implications of the two-sector model without the income effect when the two consumption goods are aggregated by a standard homothetic CES utility function. We will show that the model can account for neither the aggregate employment fluctuations nor the labor reallocation between the two sectors over business cycles in China.

6.2.2. *Comparison to homothetic CES model.* When $\mu_a = \mu_{na} = 1$, our model has the standard homothetic CES utility function, which is also the utility function used by Da-Rocha and Restuccia (2006). We have already shown in Subsection 6.1, that without the income effect, our calibration implies a value of 3.260 for ε, and the model cannot match the long-run structural change in the data for either China or the United States. We now investigate the cyclical implications of this homothetic model. The results are reported as CES 1 in Table 8. In addition, we also use an alternative calibration strategy as in Da-Rocha and Restuccia (2006), following the common practice in the business cycle literature by detrending the data and focusing on the cyclical moments in the calibration. We follow them by choosing a country-specific value of φ_a to match the average agricultural employment share in the data for each of the two economies, and setting the value of ε to 1.216 to match the ratio of the volatility of agricultural employment to that of nonagricultural employment in the United States. The model simulation results based on this alternative calibration are reported as CES 2 in Table 8.

In the case of China, the model performs poorly at the aggregate level for both calibrations, with a model-implied employment–output correlation of 1. This is in line with the analytical result of Section 5 in that there is perfect correlation between the model-implied aggregate employment and consumption. In this model with no investment, aggregate output and aggregate consumption are identical if nominal GDP is deflated using the ideal price index. Real GDP (both in the data and in our model) is slightly different because it is measured using base-year prices, but it is quantitatively very similar to real GDP deflated using the ideal price index. Therefore, it is not surprising that the correlation of aggregate employment and the measured real aggregate GDP in the model is also one. Da-Rocha and Restuccia (2006) are able to generate a low correlation between the aggregate employment and output with a CES utility function because they introduced independent ex post (weather) shocks to agricultural productivity. In the version of the model without ex post shocks, their model's implied employment–output correlation is 0.95.[12] The correlation is slightly smaller than one because there is investment in their model so that output and consumption are not

[12] See table 9 on page 477 of Da-Rocha and Restuccia (2006).

TABLE 8
COMPARISON WITH HOMOTHETIC CES UTILITY FUNCTION

	(1)	(2)	(3) China	(4)	(5)	(6)	(7) US	(8)
	Data	Our Model	Homothetic CES 1 $\varepsilon = 3.260$	Homothetic CES 2 $\varepsilon = 1.216$	Data	Our Model	Homothetic CES 1 $\varepsilon = 3.260$	Homothetic CES 2 $\varepsilon = 1.216$
(A)								
$\sigma(L)/\sigma(Y)$	0.15	0.18	0.62	0.62	0.75	0.24	0.63	0.63
$\rho(L, Y)$	−0.08	−0.02	1.00	1.00	0.87	0.89	1.00	1.00
(B)								
$\sigma(L_a)/\sigma(Y_a)$	1.03	1.67	0.63	0.53	0.34	3.75	0.69	0.25
$\sigma(L_{na})/\sigma(Y_{na})$	0.73	0.78	0.73	0.75	0.75	0.26	0.63	0.63
$\rho(L_a, Y_a)$	−0.39	−0.80	1.00	0.99	−0.10	−0.96	1.00	0.89
$\rho(L_{na}, Y_{na})$	0.83	0.81	0.99	0.93	0.87	0.88	1.00	1.00
(C)								
$\rho(L_a, L)$	0.35	0.75	1.00	1.00	−0.09	0.02	0.15	0.74
$\rho(L_{na}, L)$	0.15	−0.35	−0.42	0.99	1.00	0.91	0.98	1.00
$\rho(L_a, Y)$	−0.73	−0.57	1.00	1.00	−0.27	−0.17	0.14	0.74
$\rho(L_{na}, Y)$	0.84	0.79	−0.42	0.99	0.87	0.89	0.98	1.00
(D)								
$\rho(L_a, L_{na})$	−0.83	−0.82	−0.44	0.99	−0.12	−0.38	−0.06	0.72
$\rho(L_a/L_{na}, A_a/A_{na})$	−0.67	−0.91	0.97	0.97	−0.27	−0.99	0.99	0.99
$\rho(L_a/L_{na}, Y)$	−0.83	−0.72	0.88	0.69	−0.68	−0.22	0.05	0.07

NOTE: $\sigma(.)$ represents standard deviation; $\rho(.,.)$ represents correlation. L and Y are aggregate employment rate and output per capita. L_i, Y_i, and A_i are sectoral employment, output, and labor productivity, where $i \in \{a, na\}$. Variables are detrended using the HP filter with a smoothing parameter of 100.

perfectly correlated. In contrast, our benchmark model with the income effect can generate low employment–output correlation without introducing any ex post shocks.

The homothetic CES model without the income effect also performs poorly at the sectoral level. The model implies that agricultural employment is strongly procyclical, but it is countercyclical in China and acyclical in the United States. Moreover, the model implies that the relative employment of agriculture is positively correlated with both the relative labor productivity of agriculture and aggregate GDP per capita, which is contradictory to the data for both China and the United States.

6.2.3. *Variance decomposition.* In order to further examine our model's performance in accounting for China's business cycle fluctuations, we compare the variance decomposition of the output using both the data and model-simulated series. We run the following structural VAR for $(\triangle \ln A_{nat}, \triangle \ln A_{at}, \triangle \ln Y_t)'$,

$$\begin{pmatrix} \triangle \ln A_{nat} \\ \triangle \ln A_{at} \\ \triangle \ln Y_t \end{pmatrix} = C + \begin{bmatrix} f_{11} & f_{12} & 0 \\ f_{21} & f_{22} & 0 \\ f_{31} & f_{32} & f_{33} \end{bmatrix} \begin{pmatrix} \triangle \ln A_{nat-1} \\ \triangle \ln A_{at-1} \\ \triangle \ln Y_{t-1} \end{pmatrix} + \begin{bmatrix} a_{11} & 0 & 0 \\ a_{21} & a_{22} & 0 \\ a_{31} & a_{32} & a_{33} \end{bmatrix} \begin{pmatrix} \varepsilon_{nat} \\ \varepsilon_{at} \\ \varepsilon_{yt} \end{pmatrix},$$

where C is a 3×1 vector of the intercept term, and ε_t is a 3×1 vector of zero mean, serially uncorrelated shocks with a diagonal variance–covariance matrix. The structural identification restrictions that we impose here are as follows: (a) the labor productivities are exogenous and not affected by output shock ε_{yt}, and (b) the nonagricultural labor productivity shock, ε_{nat}, contemporaneously affects all three variables, whereas the agricultural productivity shock, ε_{at}, contemporaneously affects only agricultural labor productivity and output. Columns (1) and (2) in Table 9 show the percentage of variance of the k-step-ahead forecast error in $\triangle \ln Y_t$ due to nonagricultural and agricultural labor productivity shocks, respectively. In columns (3) and (4), we perform the same variance decomposition exercise using the simulated output

TABLE 9
VARIANCE DECOMPOSITION OF AGGREGATE OUTPUT

	Data		Model	
	(1)	(2)	(3)	(4)
Forecast Horizon	ε_{na}	ε_a	ε_{na}	ε_a
1	0.30	0.49	0.27	0.65
	[0.06, 0.54]	[0.26, 0.71]	[0.03, 0.51]	[0.42, 0.88]
2	0.22	0.56	0.21	0.69
	[−0.02, 0.45]	[0.32, 0.80]	[−0.02, 0.44]	[0.46, 0.92]
3	0.19	0.58	0.19	0.70
	[−0.04, 0.42]	[0.32, 0.84]	[−0.03, 0.41]	[0.47, 0.92]
4	0.18	0.59	0.19	0.69
	[−0.05, 0.40]	[0.31, 0.87]	[−0.03, 0.41]	[0.46, 0.92]

NOTE: ε_{na} denotes the nonagricultural labor productivity shock, ε_a denotes the agricultural labor productivity shock. 95% confidence intervals are shown in square brackets.

data from our model and find similar results to those using the actual output data. In both decompositions, the fraction of output variance accounted for by the nonagricultural labor productivity shock declines over time, whereas the fraction accounted for by the agricultural labor productivity shock increases over time. This result is consistent with our model's implication that the agricultural labor productivity has a larger impact on labor reallocation away from agriculture through both substitution and the income effect, and therefore has a more persistent impact on aggregate output through structural change. In contrast, the substitution and income effects of nonagricultural labor productivity on structural change work in opposite directions, and therefore, the overall impact of nonagricultural labor productivity on structural change is not as large as that of agricultural labor productivity. Note that, although the variance decomposition shows that the agricultural labor productivity shock contributes to a larger fraction of the variation in output than the nonagricultural labor productivity shock, this result is sensitive to the order of the recursive restrictions. In Appendix A.5, where we order the agricultural labor productivity shock first, the variance decomposition shows that nonagricultural productivity shock accounts for a larger portion of the variation in output. However, under the alternative ordering, it is still true that the fraction of output variance accounted for by the nonagricultural labor productivity shock declines over time, whereas the fraction accounted for by the agricultural labor productivity shock increases over time.

7. SENSITIVITY ANALYSIS

We now conduct several sensitivity analyses to show the robustness of our benchmark results.

7.1. *Model with Trade and Investment.* Since there is no international trade or capital investment in our benchmark model, we have so far equated consumption to output for both the agricultural and nonagricultural sectors. With international trade and investment in the data, however, consumption of the agricultural good should equal domestic agricultural output minus net export of the agricultural good, and the consumption of the nonagricultural good should equal domestic nonagricultural output minus net export of the nonagricultural good and investment. Instead of modeling trade and investment endogenously, we assume that the ratio of investment demand to nonagricultural output is exogenous and that, for $i = a, na$, the ratio of sector i's net export demand to its output is also exogenous. These ratios are calculated directly from the Penn World Table 9.1 and the GGDC 10-Sector Database. A detailed description of the model with trade and investment is given in Appendix A.6.

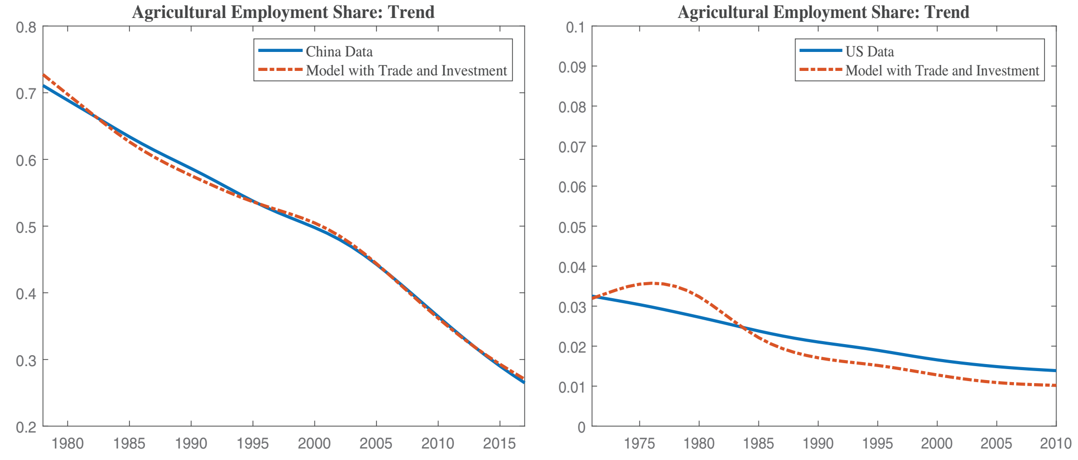

FIGURE 5

STRUCTURAL CHANGE: MODEL WITH TRADE AND INVESTMENT [COLOR FIGURE CAN BE VIEWED AT WILEYONLINELIBRARY.COM]

TABLE 10

SENSITIVITY ANALYSIS I: CHINA AND THE UNITED STATES

	China			U.S.		
	Data	Benchmark	Model with Trade and Investment	Data	Benchmark	Model with Trade and Investment
(A)						
$\sigma(L)/\sigma(Y)$	0.15	0.18	0.10	0.75	0.24	0.21
$\rho(L, Y)$	–0.08	–0.02	0.25	0.87	0.89	0.80
(B)						
$\sigma(L_a)/\sigma(Y_a)$	1.03	1.67	1.29	0.34	3.75	1.46
$\sigma(L_{na})/\sigma(Y_{na})$	0.73	0.78	0.77	0.75	0.26	0.34
$\rho(L_a, Y_a)$	–0.39	–0.80	–0.61	–0.10	–0.96	0.80
$\rho(L_{na}, Y_{na})$	0.83	0.81	0.88	0.87	0.88	0.81
(C)						
$\rho(L_a, L)$	0.35	0.75	0.21	–0.09	0.02	–0.17
$\rho(L_{na}, L)$	0.15	–0.35	0.17	1.00	0.91	0.61
$\rho(L_a, Y)$	–0.73	–0.57	–0.79	–0.27	–0.17	–0.51
$\rho(L_{na}, Y)$	0.84	0.79	0.89	0.87	0.89	0.77
(D)						
$\rho(L_a, L_{na})$	–0.83	–0.82	–0.86	–0.12	–0.38	–0.85
$\rho(L_a/L_{na}, A_a/A_{na})$	–0.67	–0.91	–0.70	–0.27	–0.99	–0.69
$\rho(L_a/L_{na}, Y)$	–0.83	–0.72	–0.88	–0.68	–0.22	–0.53

NOTE: $\sigma(.)$ represents standard deviation; $\rho(.,.)$ represents correlation. L and Y are aggregate employment rate and output per capita. L_i, Y_i, and A_i are sectoral employment, output, and labor productivity, where $i \in \{a, na\}$. Variables are detrended using the HP filter with a smoothing parameter of 100.

We calibrate this model using the China trend data and the same method as that for the benchmark model. The resulting values for ε and μ_{na} are 0.474 with a confidence interval of [0.389, 0.560] and 5.709 with a confidence interval of [4.130, 7.288], respectively. Figure 5 and Table 10 report the long-run and short-run properties of the model with trade and investment. The findings are largely consistent with the results from our benchmark model for both the structural change and business cycle fluctuations. Compared to the benchmark model, the model with trade and investment matches the correlations between aggregate employment and sectoral employment better for both China and the United States but generates a slightly higher correlation between aggregate employment and output in China.

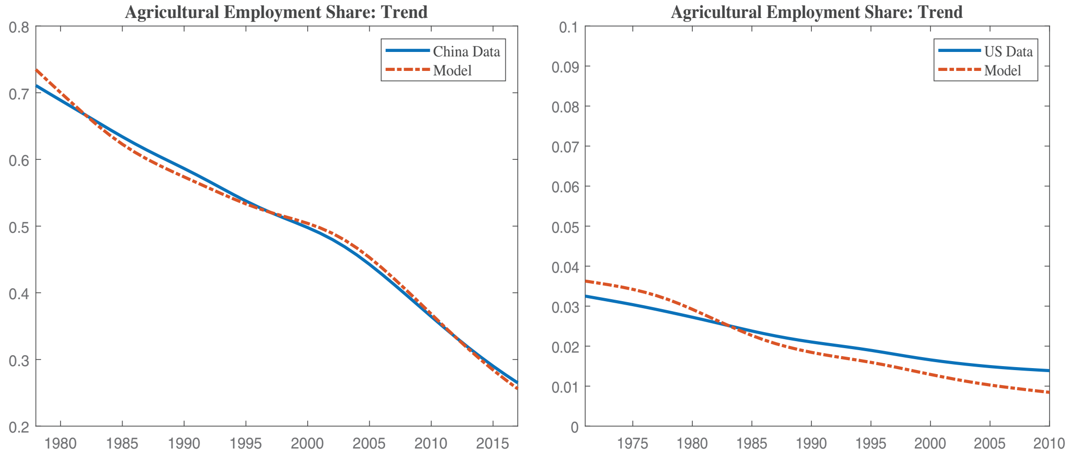

FIGURE 6

STRUCTURAL CHANGE: EXPENDITURE ESTIMATION [COLOR FIGURE CAN BE VIEWED AT WILEYONLINELIBRARY.COM]

7.2. *Expenditure Estimation.* Instead of choosing the values of the parameters φ_a, ε, and μ_{na} to fit the trend of China's agricultural employment share, we now use Equation (17) and the trends of China's expenditure and price data to estimate the value of ε and μ_{na} (with μ_a normalized to 1). The results are $\varepsilon = 0$,[13] and $\mu_{na} = 2.889$ with a confidence interval of [2.819, 2.958]. Given the estimated values of ε and μ_{na}, we then choose the value of φ_a so that the model-implied average agricultural employment share matches the data. This results in a value of 0.297 for φ_a. The model-implied structural change and cyclical moments are reported in Figure 6 and column (3) of Table 11. The model matches the data well except that the aggregate employment–output correlation is slightly higher at 0.24 under this calibration versus −0.02 in the benchmark case.

7.3. *Cross-Country Estimation.* In our benchmark calibration, we estimate the values of ε and μ_{na} to match the trend of China's agricultural employment share. We now use the same estimation method but with the GGDCcross-country data to estimate these two parameters. Specifically, given the aggregate employment rate trend $\overline{L}_t^j$, the agricultural employment share trend $\overline{L}_{at}^j/\overline{L}_t^j$, and the labor productivity trends $\overline{A}_{at}^j$ and $\overline{A}_{nat}^j$, for $j = 1, \ldots, N$, where N is the number of countries, we define $\overline{l}_{at}^j(\varphi_a^j, \varepsilon, \mu_{na})$ as follows:

$$\overline{l}_{at}^j(\varphi_a^j, \varepsilon, \mu_{na}) = \frac{\frac{\varphi_a^j}{1-\varphi_a}\left(\frac{\overline{A}_{at}^j}{\overline{A}_{nat}^j}\right)^{\varepsilon-1}\left(\overline{C}_t^j\right)^{(1-\varepsilon)(1-\mu_{na})}}{1+\frac{\varphi_a^j}{1-\varphi_a^j}\left(\frac{\overline{A}_{at}^j}{\overline{A}_{nat}^j}\right)^{\varepsilon-1}\left(\overline{C}_t^j\right)^{(1-\varepsilon)(1-\mu_{na})}}, \tag{23}$$

where $\overline{C}_t^j$ is the solution to the following equation:

$$\overline{L}_t^j = \left(\varphi_a^j\left(\overline{A}_{at}^j\right)^{\varepsilon-1}\left(\overline{C}_t^j\right)^{1-\varepsilon} + (1-\varphi_a^j)\left(\overline{A}_{nat}^j\right)^{\varepsilon-1}\left(\overline{C}_t^j\right)^{(1-\varepsilon)\mu_{na}}\right)^{\frac{1}{1-\varepsilon}}. \tag{24}$$

[13] The estimation imposes $\varepsilon \geq 0$. Given that the constraint binds, the confidence interval is not available.

TABLE 11
SENSITIVITY ANALYSIS II: CHINA AND THE UNITED STATES

	(1)	(2)	(3) China	(4)	(5)	(6)	(7) US	(8)
	Data	Benchmark Estimation	Expenditure Estimation	Cross-Country Estimation	Data	Benchmark Estimation	Expenditure Estimation	Cross-Country Estimation
(A)								
$\sigma(L)/\sigma(Y)$	0.15	0.18	0.17	0.23	0.75	0.24	0.27	0.23
$\rho(L, Y)$	−0.08	−0.02	0.24	−0.28	0.87	0.89	0.93	0.86
(B)								
$\sigma(L_a)/\sigma(Y_a)$	1.03	1.67	2.05	2.14	0.34	3.75	14.87	4.37
$\sigma(L_{na})/\sigma(Y_{na})$	0.73	0.78	0.84	0.80	0.75	0.26	0.29	0.25
$\rho(L_a, Y_a)$	−0.39	−0.80	−0.58	−0.82	−0.10	−0.96	−0.17	−0.97
$\rho(L_{na}, Y_{na})$	0.83	0.81	0.86	0.80	0.87	0.88	0.91	0.86
(C)								
$\rho(L_a, L)$	0.35	0.75	0.57	0.87	−0.09	0.02	0.02	0.05
$\rho(L_{na}, L)$	0.15	−0.35	−0.11	−0.55	1.00	0.91	0.90	0.89
$\rho(L_a, Y)$	−0.73	−0.57	−0.57	−0.59	−0.27	−0.17	−0.17	−0.18
$\rho(L_{na}, Y)$	0.84	0.79	0.84	0.76	0.87	0.89	0.91	0.86
(D)								
$\rho(L_a, L_{na})$	−0.83	−0.82	−0.81	−0.80	−0.12	−0.38	−0.40	−0.40
$\rho(L_a/L_{na}, A_a/A_{na})$	−0.67	−0.91	−0.92	−0.90	−0.27	−0.99	−0.99	−0.99
$\rho(L_a/L_{na}, Y)$	−0.83	−0.72	−0.75	−0.71	−0.68	−0.22	−0.21	−0.22

NOTE: $\sigma(.)$ represents standard deviation; $\rho(.,.)$ represents correlation. L and Y are aggregate employment rate and output per capita. L_i, Y_i, and A_i are sectoral employment, output, and labor productivity, where $i \in \{a, na\}$. Variables are detrended using the HP filter with a smoothing parameter of 100.

We choose $\varphi_a^1,\ldots,\varphi_a^N$, ε and μ_{na} to minimize the following loss function:

$$\sum_{j=1}^{N}\sum_{t=1}^{T}\left\{\left[\bar{l}_{at}^{j}(\varphi_a^j, \varepsilon, \mu_{na}) - \overline{L}_{at}^{j}/\overline{L}_{t}^{j}\right]^2\right\}.$$

The estimation gives $\varepsilon = 0.175$ with a confidence interval of $[0.143, 0.206]$ and $\mu_{na} = 4.319$ with a confidence interval of $[4.140, 4.499]$. These estimates of ε and μ_{na} are not too different from the values that we estimate using only the China data in Subsection 6.1. Using these estimated values from the cross-country data, Figure 7 plots the model-implied trend of agricultural employment share for China and the United States in comparison to the data. It can be seen that the model still does a good job at accounting for the structural change of both China and the United States. Column (4) of Table 11 presents the business cycle moments of the model simulation using the cross-country estimates of the parameters. Again, the model does a good job matching moments in the data.

7.4. *Elasticity of Labor Supply.* The parameter σ governs the elasticity of labor supply, which directly affects aggregate employment volatility. In line with the literature, we set this parameter to 0.6 in our benchmark calibration. We now check the sensitivity of our model to this parameter by changing the value of σ. Columns (3), (4), (8), and (9) of Table 12 report the simulation results for different values of σ in China and the United States. It can be seen that higher labor elasticity, that is, a lower value of σ, implies higher aggregate employment volatility. Aggregate employment remains acyclical for China and procyclical for the United States under different values of σ. Although there are some minor differences in the results for different values of σ, the properties of sector-level fluctuations and labor reallocation between the two sectors of the benchmark model still hold.

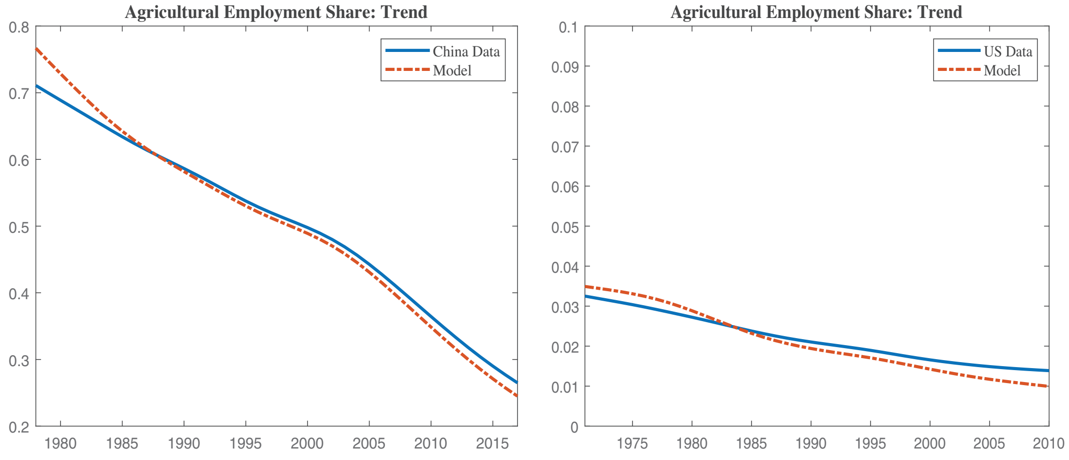

FIGURE 7

STRUCTURAL CHANGE: CROSS-COUNTRY ESTIMATION [COLOR FIGURE CAN BE VIEWED AT WILEYONLINELIBRARY.COM]

TABLE 12

SENSITIVITY ANALYSIS III: CHINA AND THE UNITED STATES

	(1)	(2)	(3) China	(4)	(5)	(6)	(7)	(8) US	(9)	(10)
	Data	Benchmark	$\sigma = 0.1$	$\sigma = 2$	VAR(1)	Data	Benchmark	$\sigma = 0.1$	$\sigma = 2$	VAR(1)
(A)										
$\sigma(L)/\sigma(Y)$	0.15	0.18	0.26	0.12	0.23	0.75	0.24	0.29	0.20	0.25
$\rho(L, Y)$	−0.08	−0.02	0.09	−0.09	0.29	0.87	0.89	0.94	0.80	0.81
(B)										
$\sigma(L_a)/\sigma(Y_a)$	1.03	1.67	1.80	1.55	1.80	0.34	3.75	3.75	3.76	3.79
$\sigma(L_{na})/\sigma(Y_{na})$	0.73	0.78	0.72	0.84	0.73	0.75	0.26	0.30	0.24	0.27
$\rho(L_a, Y_a)$	−0.39	−0.80	−0.72	−0.85	−0.65	−0.10	−0.96	−0.95	−0.97	−0.97
$\rho(L_{na}, Y_{na})$	0.83	0.81	0.81	0.81	0.73	0.87	0.88	0.95	0.76	0.84
(C)										
$\rho(L_a, L)$	0.35	0.75	0.79	0.62	0.63	−0.09	0.02	0.07	−0.04	0.05
$\rho(L_{na}, L)$	0.15	−0.35	−0.30	−0.25	0.02	1.00	0.91	0.94	0.87	0.91
$\rho(L_a, Y)$	−0.73	−0.57	−0.45	−0.66	−0.33	−0.27	−0.17	−0.14	−0.20	−0.19
$\rho(L_{na}, Y)$	0.84	0.79	0.80	0.80	0.69	0.87	0.89	0.95	0.77	0.84
(D)										
$\rho(L_a, L_{na})$	−0.83	−0.82	−0.75	−0.85	−0.61	−0.12	−0.38	−0.25	−0.51	−0.34
$\rho(L_a/L_{na}, A_a/A_{na})$	−0.67	−0.91	−0.89	−0.92	−0.87	−0.27	−0.99	−0.99	−0.99	−0.99
$\rho(L_a/L_{na}, Y)$	−0.83	−0.72	−0.66	−0.77	−0.57	−0.68	−0.22	−0.20	−0.24	−0.23

NOTE: $\sigma(.)$ represents standard deviation; $\rho(., .)$ represents correlation. L and Y are aggregate employment rate and output per capita. L_i, Y_i, and A_i are sectoral employment, output and labor productivity, where $i \in \{a, na\}$. Variables are detrended using the HP filter with a smoothing parameter of 100.

7.5. *Stochastic Shock Process.* Our results are also robust to alternative specifications of the shock process. Instead of using the realized productivity shocks in the simulation, we now assume that the cyclical fluctuations of sectoral labor productivity shocks follow a VAR(1) process. We estimate the VAR(1) process from the data and simulate the economy. We leave the estimation details to Appendix A.7. Columns (5) and (10) of Table 12 show business cycle moments for China and the United States. Both aggregate and sector-level implications from the benchmark model hold for this alternative specification.

In summary, we have conducted a series of sensitivity analyses in this section by examining a model with trade and investment, two alternative calibrations, alternative parameter values for labor supply elasticity, and an alternative productivity shock process. All sensitivity analyses yield results on structural change and employment fluctuation in China and the United States that are very similar to the results from our benchmark model.

8. CONCLUSION

The cyclical behavior of aggregate employment differs significantly between China and developed countries. This sharp difference at the aggregate level conceals similar behavior of the cyclical properties of employment at the sector level. We argue that the main difference between China and the developed countries is the size of the agricultural sector, which results in quantitatively different impacts of labor reallocation between sectors on the aggregate employment dynamics. We show both empirically and theoretically that the income effect plays an important role in determining the labor reallocation dynamics in both the long run and short run. Using a simple two-sector growth model with productivity shocks and nonhomothetic preferences, we can simultaneously account for the structural change in the long run and employment fluctuations in the short run in China.

APPENDIX A

A.1 *Data Source.* The data used in this article are obtained from the GGDC's 10-Sector Database (Timmer et al. 2015). This database reports annual sector-level data on real GDP (at constant 2005 national prices) and employment (persons engaged) for a wide coverage of regions, including sub-Saharan Africa, Middle East and North Africa, Asia, Latin America, North America, and Europe. The list of 40 countries are Argentina (1972–2011), Bolivia (1971–2010), Botswana (1971–2010), Chile (1972–2011), China (1978–2017), Colombia (1971–2010), Costa Rica (1972–2011), Denmark (1970–2009), Egypt (1973–2012), Spain (1970–2009), Ethiopia (1972–2011), France (1970–2009), United Kingdom (1970–2009), Ghana (1972–2011), Hong Kong (1974–2011), Indonesia (1973–2012), India (1971–2010), Italy (1970–2009), Japan (1972–2011), Kenya (1972–2011), South Korea (1971–2010), Mexico (1972–2011), Morocco (1973–2012), Mauritius (1972–2011), Malawi (1971–2010), Malaysia (1975–2011), Nigeria (1972–2011), Netherlands (1970–2009), Peru (1972–2011), Philippines (1973–2012), Senegal (1971–2010), Singapore (1972–2011), Sweden (1970–2009), Thailand (1973–2012), Taiwan (1973–2012), Tanzania (1972–2011), United States (1971–2010), Venezuela (1972–2011), South Africa (1972–2011), and Zambia (1971–2010). Among these, we have 12 OECD countries: Chile, Denmark, Spain, France, the United Kingdom, Italy, Japan, South Korea, Mexico, the Netherlands, Sweden, and the United States. The cross-country facts are computed based on the sample period in the parentheses. For our quantitative analysis of China and the United States, we convert real GDP in 2005 national prices to real GDP in 2005 international prices using the price level data from the GGDC Productivity Level Database.

For countries other than China, we use data directly from the GGDC and aggregate the nine sectors outside agriculture into one nonagricultural sector. For China, the 10-Sector Database uses the official employment series from China's NBS that are published in the annual China Statistical Yearbook. However, as pointed out by Holz (2006) and Brandt and Zhu (2010), there is a serious problem with the NBS' total employment series that needs to be dealt with. Hence, we revise the aggregate employment series for China by ensuring consistency in the definition of employment over time as described in Section 2. The cross-country regressions use the official NBS data (with revised aggregate employment) for China between 1978 and 2017 and the longest period possible for other countries from the GGDC database.

A.2 *Robustness of Facts.* Table A1 shows that our facts are robust to different filtering methods. In particular, we compute the business cycle moments from the Baxter–King filter, which extracts the business cycle components from a series with frequency band setting

TABLE A1
ROBUSTNESS OF FACTS ACROSS FILTERS

	China		United States		OECD Average	
	HP Filter	Baxter–King Filter	HP Filter	Baxter–King Filter	HP Filter	Baxter–King Filter
(A)						
$\sigma(L)/\sigma(Y)$	0.15	0.09	0.74	0.87	0.69	0.72
$\rho(L,Y)$	−0.08	−0.08	0.87	0.89	0.67	0.64
(B)						
$\sigma(L_a)/\sigma(Y_a)$	1.03	0.81	0.34	0.27	0.59	0.52
$\rho(L_a,Y_a)$	−0.39	−0.24	−0.10	0.00	0.08	0.15
$\sigma(L_{na})/\sigma(Y_{na})$	0.73	0.67	0.75	0.88	0.73	0.75
$\rho(L_{na},Y_{na})$	0.83	0.71	0.87	0.89	0.72	0.65

NOTE: $\sigma(.)$ represents standard deviation; $\rho(.,.)$ represents the correlation. L and Y are aggregate employment rate and output per capita. L_i andY_i are sectoral employment and output, where $i \in \{a, na\}$.

ranging from 2 years to 8 years. The business cycle moments from the Baxter–King filter are very close to those from the HP filter.

A.3 *Derivation of Formulas.* **Equations in Subsection** 3.1. The FOCs of the social planner's maximization problem with respect to L_{at} and L_{nat} are:

$$\frac{\partial C_t}{\partial c_{at}} C_t^{-1} A_{at} - B_t L_t^{\sigma} = 0, \tag{A.1}$$

$$\frac{\partial C_t}{\partial c_{nat}} C_t^{-1} A_{nat} - B_t L_t^{\sigma} = 0, \tag{A.2}$$

From (3), we have

$$\mu_a(\varphi_a)^{\frac{1}{\varepsilon}} c_{at}^{\frac{\varepsilon-1}{\varepsilon}} C_t^{\frac{(1-\varepsilon)\mu_a-\varepsilon}{\varepsilon}} \frac{\partial C_t}{\partial c_{at}} + \mu_{na}(\varphi_{na})^{\frac{1}{\varepsilon}} c_{nat}^{\frac{\varepsilon-1}{\varepsilon}} C_t^{\frac{(1-\varepsilon)\mu_{na}-\varepsilon}{\varepsilon}} \frac{\partial C_t}{\partial c_{at}} - (\varphi_a)^{\frac{1}{\varepsilon}} c_{at}^{-\frac{1}{\varepsilon}} C_t^{\frac{(1-\varepsilon)\mu_a}{\varepsilon}} = 0,$$

$$\mu_a(\varphi_a)^{\frac{1}{\varepsilon}} c_{at}^{\frac{\varepsilon-1}{\varepsilon}} C_t^{\frac{(1-\varepsilon)\mu_a-\varepsilon}{\varepsilon}} \frac{\partial C_t}{\partial c_{nat}} + \mu_{na}(\varphi_{na})^{\frac{1}{\varepsilon}} c_{nat}^{\frac{\varepsilon-1}{\varepsilon}} C_t^{\frac{(1-\varepsilon)\mu_{na}-\varepsilon}{\varepsilon}} \frac{\partial C_t}{\partial c_{nat}} - (\varphi_{na})^{\frac{1}{\varepsilon}} c_{nat}^{-\frac{1}{\varepsilon}} C_t^{\frac{(1-\varepsilon)\mu_{na}}{\varepsilon}} = 0.$$

Thus, we have

$$\frac{\partial C_t}{\partial c_{at}} = \frac{(\varphi_a)^{\frac{1}{\varepsilon}} c_{at}^{-\frac{1}{\varepsilon}} C_t^{\frac{(1-\varepsilon)\mu_a}{\varepsilon}}}{D_t}, \tag{A.3}$$

$$\frac{\partial C_t}{\partial c_{nat}} = \frac{(\varphi_{na})^{\frac{1}{\varepsilon}} c_{nat}^{-\frac{1}{\varepsilon}} C_t^{\frac{(1-\varepsilon)\mu_{na}}{\varepsilon}}}{D_t}, \tag{A.4}$$

where

$$D_t = \mu_a(\varphi_a)^{\frac{1}{\varepsilon}} c_{at}^{\frac{\varepsilon-1}{\varepsilon}} C_t^{\frac{(1-\varepsilon)\mu_a-\varepsilon}{\varepsilon}} + \mu_{na}(\varphi_{na})^{\frac{1}{\varepsilon}} c_{nat}^{\frac{\varepsilon-1}{\varepsilon}} C_t^{\frac{(1-\varepsilon)\mu_{na}-\varepsilon}{\varepsilon}}. \tag{A.5}$$

Substituting (A.3) and (A.4) into (A.1) and (A.2), respectively, and solving for c_{at} and c_{nat}, we have the following:

$$c_{at} = \varphi_a \left(\frac{A_{at}}{D_t B_t L_t^{\sigma} C_t} \right)^{\varepsilon} C_t^{(1-\varepsilon)\mu_a}, \tag{A.6}$$

$$c_{nat} = \varphi_{na} \left(\frac{A_{nat}}{D_t B_t L_t^{\sigma} C_t} \right)^{\varepsilon} C_t^{(1-\varepsilon)\mu_{na}}. \tag{A.7}$$

Substituting these two equations into (3) gives

$$\varphi_a \left(\frac{A_{at}}{D_t B_t L_t^{\sigma} C_t} \right)^{\varepsilon-1} C_t^{(1-\varepsilon)\mu_a} + \varphi_{na} \left(\frac{A_{nat}}{D_t B_t L_t^{\sigma} C_t} \right)^{\varepsilon-1} C_t^{(1-\varepsilon)\mu_{na}} = 1,$$

which implies that

$$(D_t B_t L_t^{\sigma} C_t)^{1-\varepsilon} \left(\varphi_a A_{at}^{\varepsilon-1} C_t^{(1-\varepsilon)\mu_a} + \varphi_{na} A_{nat}^{\varepsilon-1} C_t^{(1-\varepsilon)\mu_{na}} \right) = 1,$$

$$D_t B_t L_t^{\sigma} C_t = \left(\varphi_a A_{at}^{\varepsilon-1} C_t^{(1-\varepsilon)\mu_a} + \varphi_{na} A_{nat}^{\varepsilon-1} C_t^{(1-\varepsilon)\mu_{na}} \right)^{\frac{1}{\varepsilon-1}}. \tag{A.8}$$

Substituting (A.8) into (A.6) and (A.7) and solving for c_{at} and c_{nat} yields the solution in (7) and (8). Substituting (7) and (8) into (A.5) and simplifying yields the following:

$$D_t = \frac{\mu_a \varphi_a A_{at}^{\varepsilon-1} C_t^{(1-\varepsilon)\mu_a - 1} + \mu_{na} \varphi_{na} A_{nat}^{\varepsilon-1} C_t^{(1-\varepsilon)\mu_{na} - 1}}{\varphi_a A_{at}^{\varepsilon-1} C_t^{(1-\varepsilon)\mu_a} + \varphi_{na} A_{nat}^{\varepsilon-1} C_t^{(1-\varepsilon)\mu_{na}}}.$$

From (A.8), then, we have

$$L_t = \left[\frac{\left(\varphi_a A_{at}^{\varepsilon-1} C_t^{(1-\varepsilon)\mu_a} + \varphi_{na} A_{nat}^{\varepsilon-1} C_t^{(1-\varepsilon)\mu_{na}} \right)^{\frac{\varepsilon}{\varepsilon-1}}}{B_t \left(\mu_a \varphi_a A_{at}^{\varepsilon-1} C_t^{(1-\varepsilon)\mu_a - 1} + \mu_{na} \varphi_{na} A_{nat}^{\varepsilon-1} C_t^{(1-\varepsilon)\mu_{na} - 1} \right)} \right]^{\frac{1}{\sigma}}. \tag{A.9}$$

Equation (17) in Section 4. Given the total expenditure E_t, the household's problem is

$$\max_{c_{at}, c_{nat}} C_t(c_{at}, c_{nat})$$

subject to

$$p_{at} c_{at} + p_{nat} c_{nat} = E_t.$$

Similar to the derivation for the social planner's problem above, we can show that the expenditure on the sector i good, E_i, is given by the following equation:

$$E_{it} = p_{it} c_{it} = \frac{\varphi_i p_{it}^{1-\varepsilon} C_t^{(1-\varepsilon)\mu_i}}{\varphi_a p_{at}^{1-\varepsilon} C_t^{(1-\varepsilon)\mu_a} + \varphi_{na} p_{nat}^{1-\varepsilon} C_t^{(1-\varepsilon)\mu_{na}}} E_t, \; i = a, na.$$

From the definition of C_t, we have

$$\left(\varphi_a p_{at}^{1-\varepsilon} C_t^{(1-\varepsilon)\mu_a} + \varphi_{na} p_{nat}^{1-\varepsilon} C_t^{(1-\varepsilon)\mu_{na}}\right)\left(\frac{E_t}{\varphi_a p_{at}^{1-\varepsilon} C_t^{(1-\varepsilon)\mu_a} + \varphi_{na} p_{nat}^{1-\varepsilon} C_t^{(1-\varepsilon)\mu_{na}}}\right)^{\frac{\varepsilon-1}{\varepsilon}} = 1,$$

which implies that

$$\varphi_a p_{at}^{1-\varepsilon} C_t^{(1-\varepsilon)\mu_a} + \varphi_{na} p_{nat}^{1-\varepsilon} C_t^{(1-\varepsilon)\mu_{na}} = E_t^{1-\varepsilon}.$$

Therefore, we have

$$p_{it} c_{it} = \varphi_i p_{it}^{1-\varepsilon} C_t^{(1-\varepsilon)\mu_i} E_t^{\varepsilon}.$$

Solving for $C_t^{1-\varepsilon}$,

$$C_t^{1-\varepsilon} = \left(\varphi_i^{-1} p_{it}^{\varepsilon-1} \frac{E_{it}}{E_t^{\varepsilon}}\right)^{\frac{1}{\mu_i}} = \left(\varphi_i^{-1} \frac{E_{it}}{E_t} \frac{E_t^{1-\varepsilon}}{p_{it}^{1-\varepsilon}}\right)^{\frac{1}{\mu_i}}.$$

Therefore, we have

$$(1-\varepsilon)\ln C_t = \frac{1}{\mu_i}\left(-\ln\varphi_i + \ln\frac{E_{it}}{E_t} + (1-\varepsilon)\ln\frac{E_t}{p_{it}}\right).$$

From the equation for E_{it}, we have

$$\ln\frac{\omega_{at}}{\omega_{nat}} = \ln\frac{E_{at}}{E_{nat}} = \ln\frac{\varphi_a}{\varphi_{na}} + (1-\varepsilon)\ln\frac{p_{at}}{p_{nat}} + (1-\varepsilon)(\mu_a - \mu_{na})\ln C_t.$$

Combining the two equations, we have

$$\ln\frac{\omega_{at}}{\omega_{nat}} = \ln\left(\frac{\varphi_a}{\varphi_{na}}\varphi_i^{\frac{\mu_{na}-\mu_a}{\mu_i}}\right) + (1-\varepsilon)\ln\frac{p_{at}}{p_{nat}} - \left(\frac{\mu_{na}-\mu_a}{\mu_i}\right)\ln\omega_{it} - (1-\varepsilon)\left(\frac{\mu_{na}-\mu_a}{\mu_i}\right)\ln\frac{E_t}{p_{it}}.$$

Equation (17) is the case when $i = na$.

Equations in Section 5. Taking the natural logarithm of (14) and (12), we have

$$\begin{aligned}\ln C = \ln B &+ \frac{\sigma+\varepsilon}{1-\varepsilon}\ln\left[\varphi_a A_a^{\varepsilon-1} C^{(1-\varepsilon)\mu_a} + \varphi_{na} A_{na}^{\varepsilon-1} C^{(1-\varepsilon)\mu_{na}}\right] \\ &+ \ln\left[\mu_a\varphi_a A_a^{\varepsilon-1} C^{(1-\varepsilon)\mu_a} + \mu_{na}\varphi_{na} A_{na}^{\varepsilon-1} C^{(1-\varepsilon)\mu_{na}}\right],\end{aligned} \tag{A.10}$$

$$\ln L = \frac{1}{1-\varepsilon}\ln\left[\varphi_a A_a^{\varepsilon-1} C^{(1-\varepsilon)\mu_a} + \varphi_{na} A_{na}^{\varepsilon-1} C^{(1-\varepsilon)\mu_{na}}\right]. \tag{A.11}$$

Note that $dx^a = ax^{a-1}dx = ax^a d\ln x$ for any a. Differentiating (A.10) and (A.11) we have

$$
\begin{aligned}
d\ln C = &-\frac{(\sigma+\varepsilon)\varphi_a A_a^{\varepsilon-1}C^{(1-\varepsilon)\mu_a}d\ln A_a}{\varphi_a A_a^{\varepsilon-1}C^{(1-\varepsilon)\mu_a}+\varphi_{na}A_{na}^{\varepsilon-1}C^{(1-\varepsilon)\mu_{na}}}-\frac{(\sigma+\varepsilon)\varphi_{na}A_{na}^{\varepsilon-1}C^{(1-\varepsilon)\mu_{na}}d\ln A_{na}}{\varphi_a A_a^{\varepsilon-1}C^{(1-\varepsilon)\mu_a}+\varphi_{na}A_{na}^{\varepsilon-1}C^{(1-\varepsilon)\mu_{na}}}\\
&+\frac{(\sigma+\varepsilon)\left(\mu_a\varphi_a A_a^{\varepsilon-1}C^{(1-\varepsilon)\mu_a}+\mu_{na}\varphi_{na}A_{na}^{\varepsilon-1}C^{(1-\varepsilon)\mu_{na}}\right)d\ln C}{\varphi_a A_a^{\varepsilon-1}C^{(1-\varepsilon)\mu_a}+\varphi_{na}A_{na}^{\varepsilon-1}C^{(1-\varepsilon)\mu_{na}}}\\
&-\frac{(1-\varepsilon)\mu_a\varphi_a A_a^{\varepsilon-1}C^{(1-\varepsilon)\mu_a}d\ln A_a}{\mu_a\varphi_a A_a^{\varepsilon-1}C^{(1-\varepsilon)\mu_a}+\mu_{na}\varphi_{na}A_{na}^{\varepsilon-1}C^{(1-\varepsilon)\mu_{na}}}-\frac{(1-\varepsilon)\mu_{na}\varphi_{na}A_{na}^{\varepsilon-1}C^{(1-\varepsilon)\mu_{na}}d\ln A_{na}}{\mu_a\varphi_a A_a^{\varepsilon-1}C^{(1-\varepsilon)\mu_a}+\mu_{na}\varphi_{na}A_{na}^{\varepsilon-1}C^{(1-\varepsilon)\mu_{na}}}\\
&+\frac{(1-\varepsilon)\left(\mu_a^2\varphi_a A_a^{\varepsilon-1}C^{(1-\varepsilon)\mu_a}+\mu_{na}^2\varphi_{na}A_{na}^{\varepsilon-1}C^{(1-\varepsilon)\mu_{na}}\right)d\ln C}{\mu_a\varphi_a A_a^{\varepsilon-1}C^{(1-\varepsilon)\mu_a}+\mu_{na}\varphi_{na}A_{na}^{\varepsilon-1}C^{(1-\varepsilon)\mu_{na}}},
\end{aligned}
\tag{A.12}
$$

$$
\begin{aligned}
d\ln L = &-\frac{\varphi_a A_a^{\varepsilon-1}C^{(1-\varepsilon)\mu_a}d\ln A_a}{\varphi_a A_a^{\varepsilon-1}C^{(1-\varepsilon)\mu_a}+\varphi_{na}A_{na}^{\varepsilon-1}C^{(1-\varepsilon)\mu_{na}}}-\frac{\varphi_{na}A_{na}^{\varepsilon-1}C^{(1-\varepsilon)\mu_{na}}d\ln A_{na}}{\varphi_a A_a^{\varepsilon-1}C^{(1-\varepsilon)\mu_a}+\varphi_{na}A_{na}^{\varepsilon-1}C^{(1-\varepsilon)\mu_{na}}}\\
&+\frac{\left(\mu_a\varphi_a A_a^{\varepsilon-1}C^{(1-\varepsilon)\mu_a}+\mu_{na}\varphi_{na}A_{na}^{\varepsilon-1}C^{(1-\varepsilon)\mu_{na}}\right)d\ln C}{\varphi_a A_a^{\varepsilon-1}C^{(1-\varepsilon)\mu_a}+\varphi_{na}A_{na}^{\varepsilon-1}C^{(1-\varepsilon)\mu_{na}}}.
\end{aligned}
\tag{A.13}
$$

From (13), we can rewrite the equations above as

$$
\begin{aligned}
d\ln C = &-\left[(\sigma+\varepsilon)l_a+\tfrac{(1-\varepsilon)\mu_a l_a}{\mu_a l_a+\mu_{na}l_{na}}\right]d\ln A_a-\left[(\sigma+\varepsilon)l_{na}+\tfrac{(1-\varepsilon)\mu_{na}l_{na}}{\mu_a l_a+\mu_{na}l_{na}}\right]d\ln A_{na}\\
&+\left[(\sigma+\varepsilon)(\mu_a l_a+\mu_{na}l_{na})+\tfrac{(1-\varepsilon)\left(\mu_a^2 l_a+\mu_{na}^2 l_{na}\right)}{\mu_a l_a+\mu_{na}l_{na}}\right]d\ln C,
\end{aligned}
\tag{A.14}
$$

$$
\begin{aligned}
d\ln L = &-l_a d\ln A_a - l_{na}d\ln A_{na}\\
&+(\mu_a l_a+\mu_{na}l_{na})d\ln C.
\end{aligned}
\tag{A.15}
$$

Solving $d\ln C$ from (A.14) yields (18), and substituting (18) into (A.15) and simplifying yields (19).

A.4 *Invariance of Agricultural Employment Share to the Scale of μ_a and μ_{na}.* Here, we prove that, for any exogenously given L_t, the solution of agricultural employment share from Equations (12) and (13), $l_{at}(\varphi_a, \varepsilon, \mu_a, \mu_{na})$ is invariant to the common scale of (μ_a, μ_{na}). First, let $C_t^*(\varphi_a, \varepsilon, \mu_a, \mu_{na})$ be the solution to Equation (12) for the given L_t. It can be shown that the solution is unique and the corresponding agricultural employment share is

$$
l_{at}=\frac{\frac{\varphi_a}{1-\varphi_a}\left(\frac{A_{at}}{A_{nat}}\right)^{\varepsilon-1}C_t^{*(1-\varepsilon)(\mu_a-\mu_{na})}}{1+\frac{\varphi_a}{1-\varphi_a}\left(\frac{A_{at}}{A_{nat}}\right)^{\varepsilon-1}C_t^{*(1-\varepsilon)(\mu_a-\mu_{na})}}.
\tag{A.16}
$$

Let $\mu_a^{'}=\eta\mu_a$ and $\mu_{na}^{'}=\eta\mu_{na}$ for an arbitrary positive constant η. Equations (12) and (13) now become

$$
L_t = L_{at}+L_{nat}=\left(\varphi_a A_{at}^{\varepsilon-1}C_t^{(1-\varepsilon)\eta\mu_a}+\varphi_{na}A_{nat}^{\varepsilon-1}C_t^{(1-\varepsilon)\eta\mu_{na}}\right)^{\frac{1}{1-\varepsilon}}
$$

and

$$l'_{at} = \frac{\frac{\varphi_a}{1-\varphi_a}\left(\frac{A_{at}}{A_{nat}}\right)^{\varepsilon-1} C_t^{(1-\varepsilon)\eta(\mu_a-\mu_{na})}}{1+\frac{\varphi_a}{1-\varphi_a}\left(\frac{A_{at}}{A_{nat}}\right)^{\varepsilon-1} C_t^{(1-\varepsilon)\eta(\mu_a-\mu_{na})}}.$$

Let $C'_t = C_t^{\eta}$. Then, we can rewrite the two equations as

$$L_t = L_{at} + L_{nat} = \left(\varphi_a A_{at}^{\varepsilon-1} C_t^{'(1-\varepsilon)\mu_a} + \varphi_{na} A_{nat}^{\varepsilon-1} C_t^{'(1-\varepsilon)\mu_{na}}\right)^{\frac{1}{1-\varepsilon}} \tag{A.17}$$

and

$$l'_{at} = \frac{\frac{\varphi_a}{1-\varphi_a}\left(\frac{A_{at}}{A_{nat}}\right)^{\varepsilon-1} C_t^{'(1-\varepsilon)(\mu_a-\mu_{na})}}{1+\frac{\varphi_a}{1-\varphi_a}\left(\frac{A_{at}}{A_{nat}}\right)^{\varepsilon-1} C_t^{'(1-\varepsilon)(\mu_a-\mu_{na})}}. \tag{A.18}$$

Since Equation (A.17) has a unique solution, we have $C'_t = C_t^*$. Therefore, from Equations (A.16) and (A.18), we know that $l'_{at} = l_{at}$.

A.5 *Variance Decomposition.*

TABLE A2

VARIANCE DECOMPOSITION OF AGGREGATE OUTPUT: ALTERNATIVE ORDERING

	Data		Model	
	(1)	(2)	(3)	(4)
Forecast Horizon	ε_{na}	ε_a	ε_{na}	ε_a
1	0.62	0.17	0.64	0.27
	[0.41,0.83]	[−0.05,0.38]	[0.41,0.87]	[0.03,0.51]
2	0.52	0.26	0.56	0.34
	[0.27,0.78]	[−0.02,0.53]	[0.29,0.82]	[0.06,0.62]
3	0.48	0.29	0.53	0.36
	[0.20,0.76]	[−0.02,0.61]	[0.25,0.81]	[0.06,0.66]
4	0.46	0.31	0.52	0.36
	[0.16,0.75]	[−0.03,0.64]	[0.24,0.80]	[0.05,0.67]

NOTE: Columns (1) and (2) show the percentage of variance of the k-step-ahead forecast error in $\triangle \ln Y_t$ due to the non-agricultural labor productivity shock ε_{na}, and the agricultural labor productivity shock ε_a, respectively. In columns (3) and (4), we perform the same variance decomposition exercise using the simulated output data. 95% confidence intervals are shown in square brackets.

A.6 *Model with Trade and Investment.* In this section, we set up the model with exogenous investment and net exports. The social planner now solves the following problem:

$$\max_{c_{at},c_{nat},L_{at},L_{nat},C_t} \left\{ N_t\left[C_t - \frac{B_t}{1+\sigma} L_t^{1+\sigma}\right]\right\}$$

subject to (3) and the following constraints:

$$c_{at} + nx_{at} = A_{at} L_{at}, \tag{A.19}$$

$$c_{nat} + x_t + nx_{nat} = A_{nat} L_{nat}, \tag{A.20}$$

$$L_{at} + L_{nat} = L_t, \tag{A.21}$$

where x_t is investment, and nx_{it} is sector i's net export for $i = a, na$. We assume x_t, nx_{at}, and nx_{nat} are exogenously taken by the social planner. Therefore, the FOCs of the social planner's problem are the same as in the benchmark case and imply the following:

$$\frac{A_{at}}{A_{nat}} = \left(\frac{\varphi_{na}}{\varphi_a}\right)^{\frac{1}{\varepsilon}} C_t^{\frac{(1-\varepsilon)(\mu_{na}-\mu_a)}{\varepsilon}} \left(\frac{c_{nat}}{c_{at}}\right)^{-\frac{1}{\varepsilon}}, \tag{A.22}$$

$$\frac{B_t L_t^{\sigma}}{A_{at}} = \frac{\varphi_a^{\frac{1}{\varepsilon}} C_t^{\frac{(1-\varepsilon)\mu_a}{\varepsilon}-\lambda} c_{at}^{-\frac{1}{\varepsilon}}}{\left(\mu_a \varphi_a^{\frac{1}{\varepsilon}} C_t^{\frac{(1-\varepsilon)\mu_a}{\varepsilon}-1} c_{at}^{\frac{\varepsilon-1}{\varepsilon}} + \mu_{na} \varphi_{na}^{\frac{1}{\varepsilon}} C_t^{\frac{(1-\varepsilon)\mu_{na}}{\varepsilon}-1} c_{nat}^{\frac{\varepsilon-1}{\varepsilon}}\right)}. \tag{A.23}$$

We also assume that in equilibrium:

$$x_t = \tau_{xt} A_{nat} L_{nat},$$

$$nx_{it} = \tau_{nx_it} A_{it} L_{it},$$

where τ_{xt} and τ_{nx_it} are exogenous investment and net export wedges. These ratios are calculated directly from the Penn World Table 9.1 and the GGDC 10-Sector Database.[14]

Using Equations (A.22) and (A.23), together with (A.19), (A.20), (A.21), and (3), we can solve for $c_{at}, c_{nat}, C_t, L_{at}, L_{nat}$, and L_t.

A.7 *Alternative Shock Process.* In this section, we describe in detail the estimation of the stochastic shock process for labor productivities in Section 7. To be specific, we assume that the sectoral labor productivities follow the following vector autoregressive process

$$\begin{bmatrix} A_{nat} \\ A_{at} \end{bmatrix} = \rho \begin{bmatrix} A_{nat-1} \\ A_{at-1} \end{bmatrix} + \varepsilon_t,$$

where $\varepsilon_t \sim N(0, \Sigma)$ and A_{it} is cyclical labor productivity, $i \in \{a, na\}$. We assume that there is no cross persistence between A_{at} and A_{nat}. The estimated shock process for China is

$$\rho = \begin{bmatrix} 0.52 & 0 \\ 0 & 0.72 \end{bmatrix}$$

and

$$\sum = \begin{bmatrix} 0.016^2 & 0.055 \times 0.016 \times 0.026 \\ 0.055 \times 0.016 \times 0.026 & 0.026^2 \end{bmatrix}.$$

The estimated shock process for the United States is

$$\rho = \begin{bmatrix} 0.56 & 0 \\ 0 & 0.09 \end{bmatrix}$$

[14] The Penn World Table reports the share of net exports and investment in aggregate GDP. We convert them to shares in sectoral GDP by dividing the corresponding sector shares of aggregate GDP (in real terms valued at 2005 international prices) that we calculate from the GGDC 10-Sector Database. Since the shares in the Penn World Table 9.1 are valued at 2011 international prices, whereas the real sector GDP shares are valued at 2005 international prices, we implicitly assume here that the relative prices from the 2005 PPPs are approximately the same as the relative prices from the 2011 PPPs.

and

$$\sum = \begin{bmatrix} 0.010^2 & 0.15 \times 0.010 \times 0.079 \\ 0.15 \times 0.010 \times 0.079 & 0.079^2 \end{bmatrix}.$$

We then simulate the shock process for 40 periods and add it back to the productivity trend. The model is then solved using the constructed productivity. We repeat the simulation 3,000 times and compute the average business cycle moments. Columns (5) and (10) of Table 12 report the simulation results under this specification.

A.8 *Calibration and Simulation with Revised Data.* Brandt and Zhu (2010) argue that the NBS employment series overestimates employment in agriculture. They find that the official NBS agricultural employment series can be closely approximated by *Total Rural Employment* minus *Employment of the Township and Village Enterprises* (TVEs). This series overestimates agricultural employment because nonagricultural workers in rural private enterprises and rural individual enterprises (those that employ less than eight employees) are counted as agricultural workers. To better account for employment in agriculture, we follow Brandt and

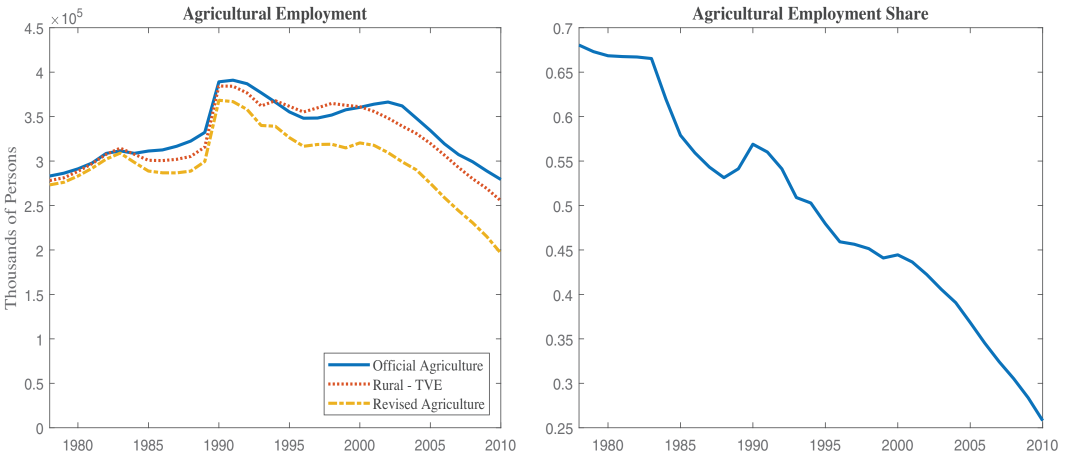

FIGURE A1

REVISED EMPLOYMENT DATA IN CHINA [COLOR FIGURE CAN BE VIEWED AT WILEYONLINELIBRARY.COM]

TABLE A3
CALIBRATION WITH REVISED DATA

Parameter	Description	Target	China	United States
φ_a	Preference weight for agriculture	Average agricultural employment share	0.360 [0.268,0.452]	0.0772 [0.0768,0.0777]
ε	Elasticity of substitution between two goods	Trend of China's agricultural employment share	0.475 [0.194,0.756]	0.475 [0.194,0.756]
μ_a	Income elasticity of agricultural good	Normalization	1	1
μ_{na}	Income elasticity of nonagricultural good	Trend of China's agricultural employment share	5.069 [−2.242,12.380]	5.069 [−2.242,12.380]
σ	Inverse Frisch elasticity of labor supply	Literature	0.6	0.6

NOTE: 95% confidence intervals are shown in square brackets.

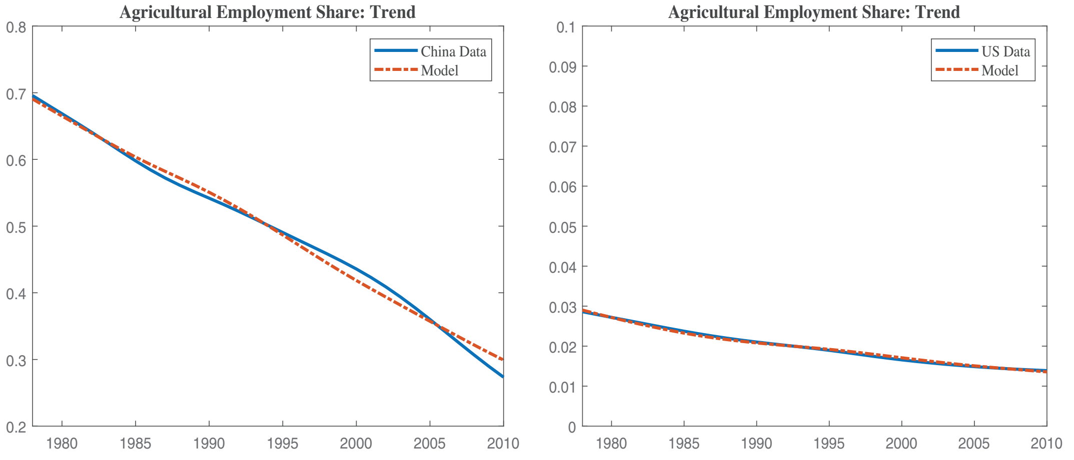

FIGURE A2

STRUCTURAL CHANGE: REVISED DATA [COLOR FIGURE CAN BE VIEWED AT WILEYONLINELIBRARY.COM]

TABLE A4
BENCHMARK SIMULATION: REVISED DATA

	China		U.S.	
	Data	Model	Data	Model
(A)				
$\sigma(L)/\sigma(Y)$	0.11	0.13	0.70	0.23
$\rho(L, Y)$	0.09	−0.03	0.87	0.87
(B)				
$\sigma(L_a)/\sigma(Y_a)$	0.70	0.82	0.33	1.08
$\sigma(L_{na})/\sigma(Y_{na})$	0.75	0.54	0.71	0.24
$\rho(L_a, Y_a)$	0.24	−0.92	−0.05	−0.99
$\rho(L_{na}, Y_{na})$	0.88	0.83	0.87	0.86
(C)				
$\rho(L_a, L)$	0.15	0.75	−0.20	0.00
$\rho(L_{na}, L)$	0.31	−0.34	1.00	0.96
$\rho(L_a, Y)$	−0.77	−0.60	−0.34	−0.15
$\rho(L_{na}, Y)$	0.83	0.86	0.87	0.87
(D)				
$\rho(L_a, L_{na})$	−0.83	−0.83	−0.23	−0.28
$\rho(L_a/L_{na}, A_a/A_{na})$	−0.29	−0.86	−0.27	−0.99
$\rho(L_a/L_{na}, Y)$	−0.84	−0.76	−0.69	−0.22

NOTE: $\sigma(.)$ represents standard deviation; $\rho(.,.)$ represents correlation. L and Y are aggregate employment rate and output per capita. L_i, Y_i, and A_i are sectoral employment, output, and labor productivity, where $i \in \{a, na\}$. Variables are detrended using the HP filter with a smoothing parameter of 100.

Zhu (2010) in constructing the agricultural employment series as total rural employment minus rural employment in TVEs, private enterprises, and individual enterprises. Unfortunately, the information needed for revising the employment series after 2010 is not readily available, hence our revised data series spans 33 years from 1978 to 2010. There has also been concerns about the official GDP deflators (see, e.g., Young, 2003, Brandt and Zhu, 2010, and Nakamura et al. 2016). In this section, we also follow Brandt and Zhu (2010) and construct alternative price deflators for both the agricultural and nonagricultural sectors.

The official and the revised agricultural employment series are plotted in the left panel of Figure A1. Note that this revised agricultural employment series still has the same problem as the NBS total employment series for the years prior to 1990. In order to generate a consistent agricultural employment series for the entire time period, we first use the revised agricultural employment and the official total employment to calculate the agricultural employment share (for each year); we then calculate the final revised agricultural employment as the product of the share and the revised total employment; and finally, we calculate the revised nonagricultural employment as the difference between the revised total employment and the revised agricultural employment. The right panel of Figure A1 plots the agriculture's share of total employment using the revised data series.

Given the revised data for GDP and the employment series, we estimate our nonhomothetic CES model and simulate the model-implied structural change and business cycle moments. The estimation results are reported in Table A3 and the simulation results in Figure A2 and Table A4. They show that our model matches well with the long-run structural change and short-run business cycle fluctuations in China.

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