Structural Change and Aggregate Employment
Fluctuations in China

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First Complete Draft: December 2017. This Draft: October 2019.

Abstract

In developed countries, aggregate employment is strongly pro-cyclical 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 the aggregate employment fluctuations in China is the labour reallocation between the agricultural and non-agricultural sectors, and that income effect plays an important role in determining the labour reallocation dynamics in both the long-run and short-run. The short-run labour reallocation in China is further strengthened by some unique institutional features of the country.

JEL Classification: E24, E32, O41

Keywords: Structural Change, Income Effect, Labor Reallocation, Employment Fluctuations, China
1 Introduction

One salient feature of business cycles in developed countries is that the aggregate employment has a strong positive correlation with the aggregate output (procyclical) and is almost as volatile as the output. This is not the case in China. 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 carefully correct for some well-known measurement problems in the official employment series and using different detrending methods. In this paper, we argue that the key to understanding the aggregate employment fluctuations in China is the labour reallocation between the agricultural and non-agricultural sectors, and that income effect plays an important role in determining the labour reallocation dynamics in both the long-run and short-run. Our argument is motivated by the following three sets of empirical facts.

First, at sector level, the cyclical properties of employments in China are similar to those in developed countries. For both China and the OECD countries, the volatility of sector employment is close to the volatility of sector GDP for both agricultural and non-agricultural sectors, and employment is strongly procyclical in the non-agricultural sector, but acyclical in the agricultural sector.

Second, using data of 18 OECD countries, Da-Rocha and Restuccia (2006) show that countries with a high average share of employment in agriculture has low correlation of aggregate employment and output and low volatility of aggregate employment relative to output. We confirm this fact using a broader dataset of 40 countries from the Groningen Growth and Development Center (GGDC). Since the average share of employment in agriculture in China is much larger than those in developed countries, the labour reallocation between the two sectors could have an important dampening effect on aggregate employment fluctuations in China, but negligible effect in developed countries.

Third, using the cross-country data from the GGDC database, we document a new fact that the correlation between aggregate employment and output over business cycles is affected by not only the average share of employment in agriculture
over a period of time, but also the trend level of the share at each point of time. This dynamic effect of economic structure on aggregate employment fluctuations is particularly relevant for China, in which the share of employment in agriculture declines from 70% in 1978 to 26% in 2010. Therefore, any theory for explaining the aggregate employment fluctuations in China should be able to match the secular trend of labour reallocation out of agriculture.

Fourth, using the same cross-country data we document another new fact that the ratio of the employment in agriculture to the employment in non-agriculture is negatively correlated with per capita income over the business cycles. Boppart (2014) and Comin, Lashkari and Mestieri (2015) emphasize that income effect is important in understanding the secular trend of labour reallocation from agriculture to manufacturing and services. Our new fact shows the importance of income effect in determining labour reallocation between sectors even at the business cycle frequency.

Given these facts, we construct a two-sector growth model with non-homothetic CES preferences proposed by Comin, Lashkari, and Mestieri (2015). Fluctuations in this model is driven by productivity shocks in the two sectors. We calibrate the model so that it can account for the secular trend in labour reallocation from agriculture to non-agriculture in China. The calibration reveals that income effect is important in accounting for the long-run structural change in China. Without the income effect, the homothetic CES model could not match the rapid decline of the employment share in agriculture in China. We then examine the calibrated model’s implications for the labour market dynamics at the business cycle frequency. We find that our model can indeed account for the employment fluctuations at the sector level and in the aggregate for China. Furthermore, our model also does a reasonably good job in matching the structural change and aggregate employment fluctuations in a developed country like the US. In particular, our model implies a low employment-output correlation for China and, at the same time, a high employment-output correlation for the US.

The main contribution of our paper is documenting the importance of both structural change and income effect in understanding aggregate employment fluctuations and constructing a model with income effect that can account for both the structural
change in the long-run and employment fluctuations in the short run in China. As such, our paper is related to two strands of literature. First, the literature on structural change. See e.g., Caselli and Coleman (2001), Kongsamut, Rebelo and Xie (2001), Ngai and Pissarides (2007), Acemoglu and Guerrieri (2008), and Herrendorf, Rogerson and Valentinyi (2014) for an excellent survey. Most of the studies in this literature focus on understanding the sources of structural change in the long-run; our paper builds on this literature and studies the business cycle implications of structural change. We show in this paper that income effect is important for understanding aggregate employment fluctuations at the business cycle frequency. Our paper is also related to the literature on business cycles in China. Brandt and Zhu (2000) is one of the first papers studying business cycles in China during the reform period. Their focus, however, is on understanding the relationship between GDP growth and inflation over the business cycles in the 1980s and early 1990s. Chang et al. (2016) is a more recent study of business cycles in China, and their focus is on understanding the weak correlation between investment and consumption in China since the late 1990s. Neither of these studies examine the relationship between aggregate employment and output. He, Chong and Shi (2009) carry out an exercise of business cycle accounting for China in the spirit of Chari, Kehoe and McGrattan (2007). They find that most of the fluctuations in aggregate employment can only be accounted for by variations in an unobserved labour wedge, highlighting the inability of the standard one-sector business cycle models in accounting for the employment fluctuations in China. Our paper shows that a standard two-sector model with non-homothetic preferences can account for the aggregate employment fluctuations without introducing a time-varying labour wedge.

There are two studies that are closely related to our paper. Da-Rocha and Restuccia (2006) is the first paper that documents 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 labour reallocation in accounting for the cyclical behaviour of aggregate employment. To focus on the cyclical fluctuations, they assume that each country is fluctuating around a steady state with a constant employment share of agriculture.\(^1\) Since structural change -

\(^1\)Moro (2012) uses a similar method to examine the impact of reallocation from manufacturing
the secular decline of the agriculture’s share of employment - is a very prominent phenomenon in China during the period we study, and empirically the correlation between aggregate employment and output fluctuations is affected by the trend employment share of agriculture at each point of time, not just the average of the share over a period of time, we think it is important to have a unified model that can account for both the secular trend of structural change and the aggregate employment fluctuations around the trend. In an independent study, Storeslettern, Zhao and Zilibotti (2019) also use a two-sector model to account for both the structural change and aggregate employment fluctuations in China. Their model, however, is very different from ours. They emphasize capital deepening in the agricultural sector rather than income effect as the driving force for the labour reallocation between the agricultural and non-agricultural sectors. We think their study and ours are complementary.²

2 Data and Facts

Before presenting our model, we first discuss in detail the data and facts about the employment fluctuations in China and in other countries. For countries other than China, we directly use the annual sector-level data on real GDP and employment from the GGDC’s 10-Sector Database (Timmer, de Vries and de Vries (2015)), and aggregate the nine sectors outside agriculture into one non-agricultural sector.³ For China, the 10-Sector Database uses the official employment series from China’s National Bureau of Statistics (NBS) that are published in the annual China Statistical Yearbook. However, as pointed out by Brandt and Zhu (2010), there are two serious problems with the NBS’ employment series that need to be dealt with. We discuss next how we deal with these problems and construct revised annual employment series for China.

First, there is a discrete upward jump in total employment in 1990. This jump

²While their model can also generate lower relative volatility of employment and lower employment-output correlation than the standard one-sector business cycle models, the values from their calibrated model are still significantly higher than those in the Chinese data.

³Appendix A provides a list of the countries from the GGDC database.
is due to a change in the official definition of employment after 1990 census which broadened the coverage of the series. The NBS publishes the employment data using the new definition for the years since 1990, but still reports the employment data using the old definition for the years prior to 1990. Brandt and Zhu (2010) use the 1982 census data to adjust the employment data for the years before 1990 so that the entire employment series has a consistent coverage. The official and the revised employment series are plotted in the upper-left panel of Figure 1. The second problem of the NBS employment series is an overestimation of agricultural employment. Brandt and Zhu (2010) find that the official agricultural employment series can be closely approximated by the Total Rural Employment minus the Employment of the Township and Village Enterprises (TVEs). This series clearly overestimates agricultural employment because non-agricultural 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 Zhu (2010) and construct the agricultural employment series as the total rural employment minus rural employments in TVEs, private enterprises, and individual enterprises. The official and the revised agricultural employment series are plotted in the upper-right panel of Figure 1. Note that this revised agricultural employment series still has the same problem as the official total employment series for the years prior to 1990. To generate a consistent agricultural employment series for the entire period, for each year we first use the revised agricultural employment and the official total employment to calculate the share of employment in agriculture; 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 non-agricultural employment as the difference between the revised total employment and the revised agricultural employment. The lower panels of Figure 1 plots the revised agricultural and non-agricultural employments and the agriculture’s share of total employment using the revised data series.
Figure 1: Employment Data in China

- **Total Employment**: Shows the growth of total employment from 1980 to 2010, with two lines representing official and revised data.

- **Agriculture Employment**: Displays the employment data in the agriculture sector, differentiating between official and revised data, and further divided into rural and TVE categories.

- **Sector Employment**: Compares employment in agriculture and non-agriculture sectors, illustrating the share of agricultural employment over the years.

- **Agriculture Share of Employment**: Graphs the share of employment in agriculture, indicating a decline over time.
2.1 Employment Fluctuations at the Aggregate Level

Given the revised employment data for China, we now examine the cyclical properties of aggregate employment in China and compare them to the developed economies. Our annual data runs from 1978 to 2010. The data is detrended using hp-filter with a smoothing parameter of 100. All variables are in per capita term.

![Figure 2: Cyclical Fluctuations](image)

We first plot cyclical movements of the aggregate employment and output for China and the US in Figure 2. Two interesting facts of aggregate employment fluctuations are observed in China:

1. The magnitude of fluctuations in the aggregate employment is much lower than that of the aggregate output. This is in stark contrast with the US, where the aggregate employment fluctuates almost as much as the aggregate output.

2. Aggregate employment is acyclical in China, while it is strongly pro-cyclical in the US.

We then present the aggregate business cycle moments in China with those of the US and other OECD countries in Table 1. The statistics confirm our observation above. In China, the relative volatility of employment is only 0.11 and the correlation of the aggregate employment and output is close to zero, all of which are in
contrast with the established business cycle facts for the developed economies that has been documented in e.g., Cooley and Prescott (1995). In Appendix B, we also use alternative methods to detrend the data and show that the facts reported here are robust to alternative detrending methods.

Table 1: Aggregate Business Cycle Moments

<table>
<thead>
<tr>
<th></th>
<th>China</th>
<th>US</th>
<th>OECD average</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\sigma(L)/\sigma(Y)$</td>
<td>0.11</td>
<td>0.70</td>
<td>0.74</td>
</tr>
<tr>
<td>$\rho(L,Y)$</td>
<td>0.09</td>
<td>0.87</td>
<td>0.72</td>
</tr>
</tbody>
</table>

Note: $\sigma(x)$ is the standard deviation of variable $x$. $\rho(x,y)$ is the correlation of variable $x$ and $y$. $L$ and $Y$ are the aggregate employment and output. Variables are detrended using hp-filter with smoothing parameter of 100.

2.2 Sector-level Employment Fluctuations

The stark differences in the aggregate employment fluctuations between China and the developed countries conceal similarities at the sector level. Panel (A) and (B) in Table 2 present the cyclical properties of the employments in the non-agricultural ($na$) and agricultural ($a$) sectors, respectively. For both China and the OECD countries, the volatility of sector employment relative to the volatility of sector GDP is high in the agricultural and non-agricultural sectors, and employment is strongly pro-cyclical in the non-agricultural sector, but acyclical in the agricultural sector.

Some may argue that the low volatility of aggregate employment in China is due to the unique institutional constraints that limit the employment variability. While it is true that there could be strong employment rigidity in the state-owned enterprises, the labour market for the non-state sector in China is quite flexible, due to minimum regulations on hiring and firing workers by non-state firms. Since the non-state sector employment is usually the margin at which the aggregate employment adjusts over the business cycles, the institutional constraints on state-sector employment cannot explain the puzzle. Indeed, for the non-agricultural sector, which include the state-sector in China, the relative employment volatility in China is 0.75, which is actually higher than 0.71 in the US and close to the OECD average of 0.77.
Table 2: Sector Moments

<table>
<thead>
<tr>
<th></th>
<th>China</th>
<th>US</th>
<th>OECD Average</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>(A) Non-Agriculture Sector</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\sigma (L_{na}) / \sigma (Y_{na})$</td>
<td>0.75</td>
<td>0.71</td>
<td>0.77</td>
</tr>
<tr>
<td>$\rho (L_{na}, Y_{na})$</td>
<td>0.88</td>
<td>0.87</td>
<td>0.76</td>
</tr>
<tr>
<td><strong>(B) Agriculture Sector</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\sigma (L_{a}) / \sigma (Y_{a})$</td>
<td>0.70</td>
<td>0.33</td>
<td>0.66</td>
</tr>
<tr>
<td>$\rho (L_{a}, Y_{a})$</td>
<td>0.24</td>
<td>-0.05</td>
<td>0.08</td>
</tr>
</tbody>
</table>

Note: $\sigma (x)$ is the standard deviation of variable $x$. $\rho (x, y)$ is the correlation of variable $x$ and $y$. $L_{i}$ and $Y_{i}$ are the sector employment and output, where $i \in \{a, na\}$. Variables are detrended using hp-filter with smoothing parameter of 100.

2.3 Role of Structural Change

The difference between China and the OECD countries on the aggregate level reflects a more general phenomenon: the aggregate employment is less volatile and less correlated with output in countries with a larger average share of employment in agriculture. This fact is first documented in Da-Rocha and Restuccia (2006) using data from 18 OECD countries. We extend their finding in Figure 3 to a broader set of 40 countries using the GGDC dataset, which include high, middle, and low income countries. The complete list of countries are in Appendix A.
Figure 3: Aggregate Employment Fluctuations across Countries

Panel A

Panel B

Note: $L_a/L$ is the average share of employment in agriculture. Variables are detrended using hp-filter with smoothing parameter of 100. Dashed line represents simple regression of average agricultural employment shares against employment-output volatilities across countries. Solid dot indicates China.

Figure 3 shows that when a country has a higher average share of employment in agriculture, aggregate employment and output are less correlated. However, the share of employment in agriculture is not constant over time within a country. In fact, it generally declines due to structural change. This is important since the correlation between aggregate employment and output depends not only on the average share, but also on the trend of the share at each point of time. To show this, we regress aggregate employment on output across countries:

$$\log L^i_t = \beta_0 + \beta_1 \log Y^i_t + \beta_2 \log Y^i_t \times \overline{L}^i_a + \beta_3 \log Y^i_t \times (\overline{L}^i_{a,t} - \overline{L}^i_a) + \epsilon^i_t,$$

(1)

where $L^i_t$ and $Y^i_t$ are cyclical components of aggregate employment and output in country $i$ and year $t$, $\overline{L}^i_a$ is the average share of employment in agriculture in country $i$, $\overline{L}^i_{a,t}$ is the trend value of the share in country $i$ and year $t$. Table 3 reports the regression results. The coefficient on the interaction term $\log Y^i_t \times (\overline{L}^i_{a,t} - \overline{L}^i_a)$ (third row of column (1)) is negative and significant. It indicates that the trend agriculture
employment share is important in determining the correlation between aggregate employment and output, even after controlling for the average share of employment in agriculture.

Table 3: Structural Change and Aggregate Employment Fluctuations

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\log Y_t^i$</td>
<td>0.294***</td>
<td>0.291***</td>
</tr>
<tr>
<td></td>
<td>(0.020)</td>
<td>(0.020)</td>
</tr>
<tr>
<td>$\log Y_t^i \times \bar{l}_a$</td>
<td>-0.344***</td>
<td>-0.355***</td>
</tr>
<tr>
<td></td>
<td>(0.040)</td>
<td>(0.040)</td>
</tr>
<tr>
<td>$\log Y_t^i \times (\bar{l}_a - \bar{\bar{l}}_a)$</td>
<td>-0.275***</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.091)</td>
<td></td>
</tr>
<tr>
<td>Country Fixed Effect</td>
<td>Y</td>
<td>Y</td>
</tr>
<tr>
<td>Year Fixed Effect</td>
<td>Y</td>
<td>Y</td>
</tr>
<tr>
<td>Adj R-squared</td>
<td>0.194</td>
<td>0.192</td>
</tr>
<tr>
<td>Observations</td>
<td>1,929</td>
<td>1,929</td>
</tr>
</tbody>
</table>

Note: The dependent variable is the aggregate employment in country $i$, year $t$. Aggregate employment $L_t^i$ and output $Y_t^i$ are detrended using hp-filter with smoothing parameter of 100. Standard errors are reported in the parenthesis. *denotes significance at the 90% confidence level, **denotes significance at the 95% confidence level, *** denotes significance at the 99% confidence level.

Given the strong interaction of trend agricultural employment share and cyclical fluctuations of employment, it is important to have a model that can account for both the long-run structural change and short-run labour reallocation between sectors for countries like China, in which the share of employment in agriculture declines sharply from 1978 to 2010.

2.4 Labour Reallocation over Business Cycles

In order to investigate how labour is reallocated across sectors over the business cycles, we estimate the following cross-country regression on relative employment:

$$
\frac{\log L_{it}}{L_{nat}} = \beta_0 + \beta_1 \log Y_t^i + \beta_2 \log \frac{A_{it}}{A_{nat}} + \varepsilon_t,
$$

(2)
where $Y^i_t$ is cyclical component of GDP per capita, $L^i_{jt}$ and $A^i_{jt}$ are cyclical components of sector employment and labour productivity in country $i$ and year $t$, $j \in \{a, na\}$. In addition, we include controls for log sector net exports to account for the fact that trade may affect the relative demand of the goods in the two sectors, and therefore affects the relative employment of the two sectors. Column (1) and (2) in Table 4 reports the estimates with and without trade controls.

The negative and significant coefficient on the cyclical component of GDP per capita in the first row shows the important role of income on labour reallocation over the business cycles. Since the agricultural good has lower income elasticity than the non-agricultural good, higher income leads to lower relative demand for the agriculture good and therefore lower relative employment in agriculture. The negative coefficient on relative sector productivity in the second row reflects the substitution effect. Income and substitution effects over the long run is well documented in the structural change literature. For example, Comin, Lashkari and Mestieri (2015) emphasize the importance of income effect in understanding the structural change from agriculture to manufacturing and services. Here, we document the importance of the income effect on labour reallocation over the business cycles.

Table 4: Income Effect over the Business Cycle

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\log Y^i_t$</td>
<td>-0.403***</td>
<td>-0.415***</td>
</tr>
<tr>
<td></td>
<td>(0.026)</td>
<td>(0.026)</td>
</tr>
<tr>
<td>$\log \left( A^i_{at} / A^i_{nat} \right)$</td>
<td>-0.328***</td>
<td>-0.364***</td>
</tr>
<tr>
<td></td>
<td>(0.013)</td>
<td>(0.014)</td>
</tr>
<tr>
<td>Country Fixed Effect</td>
<td>Y</td>
<td>Y</td>
</tr>
<tr>
<td>Year Fixed Effect</td>
<td>Y</td>
<td>Y</td>
</tr>
<tr>
<td>Trade Controls</td>
<td>N</td>
<td>Y</td>
</tr>
<tr>
<td>Adj R-squared</td>
<td>0.329</td>
<td>0.352</td>
</tr>
<tr>
<td>Observations</td>
<td>1,929</td>
<td>1,807</td>
</tr>
</tbody>
</table>

Note: The dependent variable is the agriculture to non-agriculture employment ratio in country $i$, year $t$. Variables are detrended using hp-filter with smoothing parameter of 100. Column (2) controls for log sector net exports. Standard errors are reported in the parenthesis. * denotes significance at the 90% confidence level, ** denotes significance at the 95% confidence level, *** denotes significance at the 99% confidence level.
2.5 Uniqueness of China

Figure 4 plots the cross-country correlations between agriculture and non-agriculture employments against the average share of employment in agriculture, where China is highlighted by the solid dot. It can be seen that China has the lowest correlation among countries with similar average agricultural employment share, suggesting particularly strong labour reallocation over the business cycle in China. The strong labour reallocation across sectors dampens the aggregate employment fluctuations, hence China also has the lowest aggregate employment to output volatility, as shown in panel A of Figure 3.

Note: $L_a/L$ is the average share of employment in agriculture. Variables are detrended using hp-filter with smoothing parameter of 100. Dashed line represents simple regression of average agricultural employment shares against employment-output volatilities across countries. Solid dot indicates China.

Motivated by these stylized facts, we next present our two-sector model with non-homothetic preferences that we will use to quantitatively account for labour 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 non-agriculture, respectively. Each sector produces a consumption good with a linear technology using labour as the only input:

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

where \( Y_{it}, A_{it} \) and \( N_{it} \) are the output, labour 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, \( \sigma \) is a non-negative number representing the inverse of the Frisch labour supply elasticity, and \( B_t > 0 \) is a time-varying labour supply parameter that is used to capture the demographic factors (e.g., age structure and gender composition of the labour force) that affect average household’s labour supply decisions.\(^4\) Following Comin, Lashkari and Mestieri (2015), the composite consumption \( C_t \) is defined implicitly by the following equation:

\[
(\phi_a)\left(\frac{1}{\varepsilon} C_t^{\frac{1-\varepsilon}{\varepsilon}} C_{at}^{\frac{\varepsilon-1}{\varepsilon}} + (\phi_{na})\left(\frac{1}{\varepsilon} C_t^{\frac{1-\varepsilon}{\varepsilon}} C_{nat}^{\frac{\varepsilon-1}{\varepsilon}} \right) = 1,
\]

where \( \phi_a, \phi_{na}, \mu_a, \mu_{na} \) and \( \varepsilon \) are all positive constants. The parameter \( \phi_i \) represents the household’s preference weight on consumption good in sector \( i \) (\( \phi_a + \phi_{na} = 1 \)), \( \mu_i \) is a parameter that determines the income elasticity of consumption good \( i \) and \( \varepsilon \) is the elasticity of substitution between the two consumption goods. The implicit utility function is a generalization of the standard CES utility function by allowing for potentially different income elasticities for the two consumption goods. If \( \mu_a = \mu_{na} = 1 \), then the utility function is reduced to the standard CES utility function. If

\(^4\)Note that when \( B_t \) is a constant, our utility function is the same as the GHH utility function proposed by Greenwood, Hercowitz and Huffman (1988).
\( \mu_a < \mu_{na} \), the income elasticity is smaller for the agricultural good than for the non-agricultural 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 nor 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:

\[
c_{at} = A_{at} L_{at}, \quad (4)
\]

\[
c_{nat} = A_{nat} L_{nat}, \quad (5)
\]

\[
L_{at} + L_{nat} = L_t. \quad (6)
\]

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 the Appendix C, 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:

\[
c_{at} = \frac{\phi_a A_a^\epsilon C_t^{(1-\epsilon)\mu_a}}{\left( \phi_a A_a^\epsilon - 1 C_t^{(1-\epsilon)\mu_a} + \phi_{na} A_{nat}^\epsilon C_t^{(1-\epsilon)\mu_{na}} \right)^\frac{\epsilon}{\epsilon-1}}, \quad (7)
\]

\[
c_{nat} = \frac{\phi_{na} A_{nat}^\epsilon C_t^{(1-\epsilon)\mu_{na}}}{\left( \phi_a A_a^\epsilon - 1 C_t^{(1-\epsilon)\mu_a} + \phi_{na} A_{nat}^\epsilon C_t^{(1-\epsilon)\mu_{na}} \right)^\frac{\epsilon}{\epsilon-1}}, \quad (8)
\]

\[
L_t = \left[ \frac{\left( \phi_a A_a^\epsilon - 1 C_t^{(1-\epsilon)\mu_a} + \phi_{na} A_{nat}^\epsilon C_t^{(1-\epsilon)\mu_{na}} \right)^\frac{\epsilon}{\epsilon-1}}{B_t \left( \mu_a \phi_a A_a^\epsilon - 1 C_t^{(1-\epsilon)\mu_a - 1} + \mu_{na} \phi_{na} A_{nat}^\epsilon C_t^{(1-\epsilon)\mu_{na} - 1} \right)} \right] \frac{1}{\sigma}. \quad (9)
\]
3.2 Equilibrium Employment, Consumption and Output

From the goods market clearing conditions, (4), (5), (7), and (8), we have,

\[ L_{at} = \frac{\phi_a A_{at}^{e-1} C_t^{(1-e)\mu_a}}{\left(\phi_a A_{at}^{e-1} C_t^{(1-e)\mu_a} + \phi_n A_{nat}^{e-1} C_t^{(1-e)\mu_{nat}}\right)^{\frac{1}{\epsilon+1}}}, \]  

(10)

\[ L_{nat} = \frac{\phi_{nat} A_{nat}^{e-1} C_t^{(1-e)\mu_{nat}}}{\left(\phi_a A_{at}^{e-1} C_t^{(1-e)\mu_a} + \phi_n A_{nat}^{e-1} C_t^{(1-e)\mu_{nat}}\right)^{\frac{1}{\epsilon+1}}}. \]  

(11)

Hence the aggregate employment to population ratio is

\[ L_t = L_{at} + L_{nat} = \left(\frac{\phi_a A_{at}^{e-1} C_t^{(1-e)\mu_a} + \phi_n A_{nat}^{e-1} C_t^{(1-e)\mu_{nat}}}{\phi_a A_{at}^{e-1} C_t^{(1-e)\mu_a} + \phi_n A_{nat}^{e-1} C_t^{(1-e)\mu_{nat}}}\right)^{\frac{1}{1-\epsilon}}, \]  

(12)

and the share of employment in agriculture is

\[ l_{at} \equiv \frac{L_{at}}{L_t} = \frac{\phi_a A_{at}^{e-1} C_t^{(1-e)\mu_a}}{\phi_a A_{at}^{e-1} C_t^{(1-e)\mu_a} + \phi_n A_{nat}^{e-1} C_t^{(1-e)\mu_{nat}}}. \]  

(13)

Equation (13) can also be written as

\[ l_{at} \equiv \frac{L_{at}}{L_t} = \frac{\phi_a \left( \frac{A_{at}}{A_{nat}} \right)^{e-1} C_t^{(1-e)(\mu_a-\mu_{nat})}}{1 + \phi_a \left( \frac{A_{at}}{A_{nat}} \right)^{e-1} C_t^{(1-e)(\mu_a-\mu_{nat})}}, \]  

(14)

which shows that the agriculture’s share of employment is affected by two factors: the relative productivity of agriculture \( A_{at} / A_{nat} \) and the aggregate consumption per capita \( C_t \). The first factor represents the substitution effect and the second factor the income effect.
3.3 Solving the Equilibrium

Equation (12) and (9) can be combined to yield the following equation for the equilibrium value of the aggregate consumption $C_t$:

$$C_t = B_t \frac{\mu a \varphi a A_a^{1-\varepsilon} C(1-\varepsilon) \mu a + \mu na \varphi na A_{na}^{1-\varepsilon} C(1-\varepsilon) \mu na}{\varphi a A_a^{1-\varepsilon} C(1-\varepsilon) \mu a + \varphi na A_{na}^{1-\varepsilon} C(1-\varepsilon) \mu na}$$ \hspace{1cm} (15)

Equations (10), (11) and (15) can be used to solve for the equilibrium employment and output in the two sectors as follows. Given the preference parameters and the real labour productivities of the two sectors, $A_{at}$ and $A_{nat}$, equation (15) 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 in the two sectors are calculated as $Y_{at} = A_{at} L_{at}$ and $Y_{nat} = A_{nat} L_{nat}$, respectively. Finally, when the labour 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 $Y_t = Y_{at} + Y_{nat}$.

3.4 Employment Responses to Productivity Shocks

Before going into quantitative analysis, we first discuss analytically how do economic structure affect aggregate employment responses to productivity shocks and how does income effect affect the reallocation of labour between the two sectors.

From (12) and (15), we can derive the following equations about the response of aggregate consumption and employment to productivity shocks. The detailed derivations are shown in Appendix C.

$$d \ln C_t = \frac{[(\sigma + \varepsilon)(\mu a l_{at} + \mu na l_{nat}) + (1-\varepsilon)\mu a] A_{at} d \ln A_{at}}{[(\sigma + \varepsilon)(\mu a l_{at} + \mu na l_{nat})^2 + (1-\varepsilon)(\mu a^2 l_{at} + \mu na^2 l_{nat}) - (\mu a l_{at} + \mu na l_{nat})]} + \frac{[(\sigma + \varepsilon)(\mu a l_{at} + \mu na l_{nat}) + (1-\varepsilon)\mu na] A_{nat} d \ln A_{nat}}{[(\sigma + \varepsilon)(\mu a l_{at} + \mu na l_{nat})^2 + (1-\varepsilon)(\mu a^2 l_{at} + \mu na^2 l_{nat}) - (\mu a l_{at} + \mu na l_{nat})]}$$ \hspace{1cm} (16)

and

$$d \ln L_t = \frac{[(\mu a l_{at} + \mu na l_{nat}) - (1-\varepsilon)(\mu a - \mu na) l_{at}] A_{at} d \ln A_{at}}{[(\sigma + \varepsilon)(\mu a l_{at} + \mu na l_{nat})^2 + (1-\varepsilon)(\mu a^2 l_{at} + \mu na^2 l_{nat}) - (\mu a l_{at} + \mu na l_{nat})]} + \frac{[(\mu a l_{at} + \mu na l_{nat}) - (1-\varepsilon)(\mu a - \mu na) l_{at}] A_{nat} d \ln A_{nat}}{[(\sigma + \varepsilon)(\mu a l_{at} + \mu na l_{nat})^2 + (1-\varepsilon)(\mu a^2 l_{at} + \mu na^2 l_{nat}) - (\mu a l_{at} + \mu na l_{nat})]}$$ \hspace{1cm} (17)
In the special case of homothetic CES, i.e., \( \mu_a = \mu_{na} = 1 \), the above equations are reduced to
\[
d \ln C_t = (1 + \sigma^{-1}) (l_{a,t} d \ln A_{a,t} + l_{na,t} d \ln A_{na,t}) ,
\]
and
\[
d \ln L_t = \sigma^{-1} (l_{a,t} d \ln A_{a,t} + l_{na,t} d \ln A_{na,t}) .
\]
In this case, the responses of the 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 income effect would not be able to match the low employment-output correlation we observe in the data for China.

However, when \( \mu_{na} > \mu_a \), the responses of the 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 sector employment shares \( l_{a,t} \) and \( l_{na,t} \). This is consistent with the fact we presented in Table 3 of Section 2.3.

The volatility of the aggregate employment is also affected by the economic structure in the case of non-homothetic preferences. To see this clearly, consider the case of a sector neutral productivity shock, \( d \ln A_{at} = d \ln A_{nat} = dz \), then, from (16) and (17), we have
\[
d \ln L_t = \frac{\left[ (\mu_a l_{at} + \mu_{na} l_{nat}) - (1 - \varepsilon) (\mu_{na} - \mu_a)^2 l_{at} l_{nat} \right]}{(\sigma + \varepsilon) (\mu_a l_{at} + \mu_{na} l_{nat})^2 + (1 - \varepsilon) (\mu_a^2 l_{at} + \mu_{na}^2 l_{nat}) - (\mu_a l_{at} + \mu_{na} l_{nat})} dz .
\]
When \( \varepsilon < 1 \) and \( \mu_{na} > \mu_a \), the response of the 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 \( l_{nat} \).

Finally, to see the impact of income effect on the labour reallocation between the two sectors, we derive the following equation about the relative employment in
the two sectors from (10) and (11),

\[ \ln \left( \frac{L_{at}}{L_{nat}} \right) = \ln \left( \frac{\phi_a}{\phi_n} \right) - (1 - \varepsilon) \ln \left( \frac{A_{at}}{A_{nat}} \right) - (1 - \varepsilon)(\mu_{na} - \mu_a) \ln C_t \]  

(18)

If \( \varepsilon \) is less than one, the relative employment of agriculture is negatively related to the relative productivity of agriculture. Furthermore, if \( \mu_{na} > \mu_a \), then the relative employment of agriculture is also a decreasing function of the aggregate consumption. Since labour productivities in both sectors have positive impact on the aggregate consumption, they both have a negative effect on the relative employment of agriculture. Again, this is in line with the empirical fact we documented in Table 4 of Section 2.4.

4 Quantitative Analysis

We now examine quantitatively our model’s implications for structural change and aggregate employment fluctuations. We first assume that there is no productivity shocks so that the labour productivities in both sectors are at the respective trend values, and show that our calibrated model can quantitatively account for the secular decline of the agriculture’s share of employment in China. We then introduce productivity shocks into the model, and show that our calibrated model can also quantitatively account for the labour reallocation between the two sectors and the aggregate employment fluctuations around the trend at the business cycle frequency.

4.1 Structural Change: Labour Reallocation in the Long-run

We use the hp-filter to filter out the trends of the employment to population ratios in the two sectors and in the aggregate, and the labour productivities in the two sectors. Given the trend aggregate employment rate and trend labour productivities in the two sectors, we can see from equation (12) and (14) that both the trend of aggregate consumption and the trend of the agriculture’s share of employment are determined by the four implicit utility function parameters, \( \phi_a \), \( \varepsilon \), \( \mu_a \) and \( \mu_{na} \). Therefore we can use the trend data in China to calibrate these parameters. Since the agricul-
ture’s share of employment is invariant with respect to the scale of the two income elasticity parameters \( \mu_a \) and \( \mu_{na} \), we normalize the scale of the two parameters by setting \( \mu_a \) to 1. We discuss next our procedure of calibrating the remaining three parameters of the implicit utility function, \( \varphi_a \), \( \varepsilon \) and \( \mu_{na} \).

Let \( \bar{x}_t \) denote the hp-filtered trend component of any variable \( x_t \), and \( T = 33 \) the number of years of our sample. First, for any \( t = 1, \ldots, T \), and given the trend aggregate employment rate \( \bar{L}_t \) and trend labour productivities \( \bar{A}_{at} \) and \( \bar{A}_{nat} \) in the data, from equation (12), we can write the trend aggregate consumption \( \bar{C}_t(\varphi_a, \varepsilon, \mu_{na}) \) as an implicit function of the three parameters \((\varphi_a, \varepsilon, \mu_{na})\):

\[
\bar{L}_t = \left( \varphi_a \bar{A}_{at} \right)^{1-\varepsilon} \left( \bar{C}_t \right)^{1-\varepsilon} \left( \bar{A}_{nat} \right)^{1-\varepsilon} \left( \bar{C}_t \right)^{(1-\varepsilon)\mu_{na}}. \tag{19}
\]

Then, from (13), we can write the trend of the agriculture’s share of employment also as a function of \((\varphi_a, \varepsilon, \mu_{na})\),

\[
\bar{l}_{at}(\varphi_a, \varepsilon, \mu_{na}) = \frac{\varphi_a \left( \bar{A}_{at} / \bar{A}_{nat} \right)^{1-\varepsilon} \left( \bar{C}_t \right)^{(1-\varepsilon)\mu_{na}}}{1 + \frac{\varphi_a}{1-(1-\varphi_a) \frac{\bar{A}_{at}}{\bar{A}_{nat}} \left( \bar{C}_t \right)^{(1-\varepsilon)(1-\mu_{na})}}}.	ag{20}
\]

Finally, we choose the values of \((\varphi_a, \varepsilon, \mu_{na})\) to minimize the following loss function (i.e., non-linear least squares):

\[
\sum_{t=0}^{T} \left[ \bar{l}_{at}(\varphi_a, \varepsilon, \mu_{na}) - \bar{L}_at / \bar{L}_t \right]^2 \tag{21}
\]

where \( \bar{L}_at \) and \( \bar{L}_t \) are the employment trends from the data. This calibration yields the following results for China: \( \varphi_a = 0.3604 \), \( \varepsilon = 0.4751 \), and \( \mu_{na} = 5.0690 \). The calibrated value of the elasticity of substitution (\( \varepsilon \)) is less than one, implying that the substitution effect is such that the agriculture’s share of employment is negatively related to the agriculture’s relative productivity. This is consistent with the theoretical assumption of Ngai and Pissarides (2007) and the finding of Herrendorf,

\(^5\)See a proof in Appendix D.
Rogerson and Valentinyi (2014). The calibrated value of $\mu_{na}$ is significantly larger than one, implying that the income effect plays an important role for the decline of the agriculture’s share of employment. Figure 5 displays the trend of the agriculture’s share of employment from both the model and the data. The left panel shows that our calibrated model matches well the trend of the agriculture’s share of employment in China.

Our model also does a good job in accounting for the structural change in the US over the same time period. We keep the values of the two elasticity parameters, $\varepsilon$ and $\mu_{na}$, the same as the ones for China, but allow the value of $\phi_a$ to be different so that the average of the model-implied agriculture’s share of employment matches that in the US data. This yields a value of 0.0772 for $\phi_a$ in the US. The right panel of Figure 5 displays the trend of the agriculture’s share of employment from both the model and the data for the US. Similar to the case of China, our calibrated model also matches well the trend of the agriculture’s share of employment in the US. In other words, using the same income and substitution elasticities for both countries and country-specific preference weight $\phi_a$, our simple two-sector model with the non-homothetic CES utility function can quantitatively account for the structural changes in both China and the US. This result is consistent with the finding of Comin, Lashkari and Mestieri (2015) for a panel of countries which does not include China.

The income effect is crucial for our model’s ability in matching the speed of structural change in both economies. To illustrate this, we set $\mu_{na} = 1$, and re-calibrate the values of $\phi_a$ and $\varepsilon$ to minimize the same loss function in (21). The resulting value of $\varepsilon$ is 0, and the values of $\phi_a$ are 0.1663 for China and 0.0138 for the US. We plot the model implied trends of the agriculture’s share of employment for both China and the US in Figure 5, labeled as homothetic CES. The model with no income effect cannot match the speed of structural change in China nor in the US. This is consistent with the findings of Boppart (2014) for the US and Comin, Lashkari and Mestieri (2015) for other economies.

The difference in the values of $\phi_a$ does not necessarily mean that households in the two countries have different preferences. Rather, it may capture the potential differences in labour intensity of agricultural production, barriers to labour reallocation, and other factors that may influence the average share of employment in agriculture, but are abstracted from our model.
4.2 Labour Reallocation in the Short-run and Aggregate Employment Fluctuations

We now turn to the cyclical properties of our model when there are shocks to productivities in the two sectors. We set $\sigma = 0.6$ so that the Frisch elasticity of labour supply is 1.7, a value used by Greenwood, Hercowitz, and Huffman (1988) and many others in the business cycle literature. We summarize all the calibration results in Table 5.

Before presenting the quantitative results, we first discuss our strategies of dealing with the trend in the aggregate employment rate. In examining the structural change in the long-run, we have taken the trend of the aggregate employment rate $L_t$ as exogenous. Since our objective here is to investigate our model’s implication for aggregate employment fluctuations, we can no longer assume that the aggregate employment rate is exogenously given. Instead, we have to solve $L_t$ endogenously from the model, which implies that we need to solve the aggregate consumption $C_t$ from equation (15). We calibrate our model so that the model implied trend of the aggregate employment rate matches the trend in the data. Specifically, we choose the labour supply parameter $B_t$ to match the trend of aggregate employment using
Table 5: Benchmark Calibration

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Description</th>
<th>Target</th>
<th>China Value</th>
<th>US Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>( \varphi_a )</td>
<td>preference weight of agriculture</td>
<td>average of agriculture’s employment share</td>
<td>0.3604</td>
<td>0.0772</td>
</tr>
<tr>
<td>( \varepsilon )</td>
<td>elasticity of substitution between two goods</td>
<td>trend of agriculture’s employment share in China</td>
<td>0.4751</td>
<td>0.4751</td>
</tr>
<tr>
<td>( \mu_a )</td>
<td>income elasticity of agricultural good</td>
<td>normalization</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td>( \mu_{na} )</td>
<td>income elasticity of non-agricultural good</td>
<td>trend of agriculture’s employment share in China</td>
<td>5.0690</td>
<td>5.0690</td>
</tr>
<tr>
<td>( \sigma )</td>
<td>inverse of Frisch elasticity of labour supply</td>
<td>literature</td>
<td>0.6</td>
<td>0.6</td>
</tr>
</tbody>
</table>

the equation below:

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

where \( L_t, \bar{A}_{at} \) and \( \bar{A}_{nat} \) are the trends of the aggregate employment rate, the labour productivity in the agricultural and non-agricultural sectors, respectively, and \( \bar{C}_t \) is the trend aggregate consumption solved from equation (19).

We are now ready to simulate the model and compute the business cycle moments. Specifically, we take the actual labour productivities \( \{ A_{at} \}_{t=1,...,T} \) and \( \{ A_{nat} \}_{t=1,...,T} \) from the data, which include both the trend and the cyclical productivity shocks, to solve the sector-level and aggregate employment rates and GDP using the method described in Section 3.3. We then detrend the simulated variables from the model with hp-filter to retrieve the cyclical components and compute model-implied busi-
ness cycle moments. The benchmark results are presented in Table 6.

### 4.2.1 Benchmark Results

The first and second columns of Table 6 present the business cycle statistics calculated from the Chinese data and the simulated time series from the model, and the third and fourth columns present the corresponding results for the US. Panel A shows the relative standard deviations of the aggregate employment to output and the correlation between the aggregate employment and output, panel B the sector level correlations and relative standard deviations, and panel C the correlation between sector employment and the correlations of the agriculture employment ratio with relative labor productivities and aggregate income per capita.

**Results for China.** Overall, the model does a good job in matching both the aggregate and sector moments in the Chinese data. From panel A, we see that the model produces a relative aggregate employment volatility of 0.13, which is very close to 0.11 in the data. The model also generates an acyclical employment series, with its correlation with output close to zero. 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 non-agriculture employment is strongly pro-cyclical, as in the data. However, for the agricultural sector, employment is negatively correlated with output in the model and slightly positive in the data. The model-implied negative correlation between employment and output in the agricultural sector implies that the correlation between the agricultural employment and agricultural labour productivity is strongly negative. We explain below that this is due to a strong income effect. Panel C shows the labor reallocation between the two sectors. The correlation of employments in the two sectors is -0.83, which is the same as the data, indicating strong reallocation between the sectors. The last two rows in panel C document correlations of relative employment with relative labor productivity and income from the data. The negative correlations are in line with the cross-country regression result presented in Section 2.4. Our model can reproduce the negative correlations observed in the data: if the labor productivity in the agricultural sector increases, the relative price of the agricultural good falls. Given that the agricultural and non-agricultural goods are complements ($\varepsilon < 1$), substitu-
<table>
<thead>
<tr>
<th></th>
<th>China</th>
<th></th>
<th>US</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Data</td>
<td>Model</td>
<td>Data</td>
<td>Model</td>
</tr>
<tr>
<td>(A) Aggregate</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\sigma (L) / \sigma (Y)$</td>
<td>0.11</td>
<td>0.13</td>
<td>0.70</td>
<td>0.23</td>
</tr>
<tr>
<td>$\rho (L, Y)$</td>
<td>0.09</td>
<td>-0.03</td>
<td>0.87</td>
<td>0.87</td>
</tr>
<tr>
<td>(B) Within Sector</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\sigma (L_a) / \sigma (Y_a)$</td>
<td>0.70</td>
<td>0.82</td>
<td>0.33</td>
<td>1.08</td>
</tr>
<tr>
<td>$\sigma (L_{na}) / \sigma (Y_{na})$</td>
<td>0.75</td>
<td>0.54</td>
<td>0.71</td>
<td>0.24</td>
</tr>
<tr>
<td>$\rho (L_a, Y_a)$</td>
<td>0.24</td>
<td>-0.92</td>
<td>-0.05</td>
<td>-0.99</td>
</tr>
<tr>
<td>$\rho (L_{na}, Y_{na})$</td>
<td>0.88</td>
<td>0.83</td>
<td>0.87</td>
<td>0.86</td>
</tr>
<tr>
<td>(C) Cross Sector</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\rho (L_a, L_{na})$</td>
<td>-0.83</td>
<td>-0.83</td>
<td>-0.23</td>
<td>-0.28</td>
</tr>
<tr>
<td>$\rho (L_a / L_{na}, A_a / A_{na})$</td>
<td>-0.29</td>
<td>-0.86</td>
<td>-0.27</td>
<td>-0.99</td>
</tr>
<tr>
<td>$\rho (L_a / L_{na}, Y)$</td>
<td>-0.84</td>
<td>-0.76</td>
<td>-0.69</td>
<td>-0.22</td>
</tr>
</tbody>
</table>

Note: $\sigma (x)$ is the standard deviation of variable $x$. $\rho (x, y)$ is the correlation of variable $x$ and $y$. $L$ and $Y$ are aggregate employment rate and output per capita. $L_i$, $Y_i$ and $A_i$ are sector employment, output and labor productivity, where $i \in \{a, na\}$. Variables are detrended using hp-filter with smoothing parameter of 100.

Substitution effect leads to a fall of the agriculture employment. In addition, higher agricultural labor productivity also raises aggregate consumption. Given that $\mu_{na} > 1$, the income effect leads to the decline of agriculture employment. Thus, both the substitution and income effects lead to negative correlation between the agriculture employment and agriculture labor productivity, which explains why the model implies a very strong negative correlation of -0.92 between agriculture employment and output.

Results for the US. Our model also does a good job in replicating the US business cycle facts. In the aggregate, the model generate highly pro-cyclical aggregate employment. The model produces a relative employment volatility that is lower
than that in the data. This problem is common for standard real business cycle model, as pointed out by Cooley and Prescott (1995), that without additional labor market frictions these models have difficulty in generating sizable employment variations. Panel B and C illustrate the sector level correlations and labor reallocation across sectors, which are broadly consistent with the data. It is worth emphasizing that, as shown in panel C, the model is able to produce a negative correlation between sector employment and negative correlations of the agriculture employment ratio with relative labor productivities and aggregate income per capita.

In summary, despite being highly stylized, our model can match well the employment fluctuations in both China and the US at sector level and in the aggregate. Similar to the case for the long-run structural change, the key to the success of our model is the income effect generated by the non-homothetic preferences. Because the income elasticity of the agricultural good is less than that of the non-agricultural good, the income effect on the employments in the agricultural and non-agricultural sectors are in the opposite directions. When the agricultural sector is large, this income-effect-induced negative correlation between employments in the two sectors dampens the aggregate employment volatility and reduces the correlation between the aggregate employment and output. In the sensitivity analysis below, we will examine the quantitative implications of the two-sector model when the two consumption goods are aggregated by a standard homothetic CES utility function with no income effect, and we will show that the model cannot match the aggregate employment fluctuations in China.

4.2.2 Sensitivity Analysis

We first illustrate the importance of income effect by showing the results for the case of homothetic CES utility function, and then conduct some additional sensitivity analysis to show the robustness of our benchmark model.

Homothetic CES utility function. 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 Section 4.1 that without income effect the model cannot match the long-run structural change in the
data for either economy. We now investigate whether the model can account for the aggregate employment fluctuations in China if we follow the common practice in the business cycle literature to detrend the data and focus on the cyclical part. We follow the calibration strategy of Da-Rocha and Restuccia (2006) by choosing a country-specific value of $\phi_a$ to match the average of the agriculture’s share of employment in the data for each of the two economies, and choosing the value of $\varepsilon$ to match the ratio of the volatility of agricultural employment to that of non-agricultural employment in the US. Table 7 presents the business cycle statistics of the calibrated model without income effect.

For the case of China, the model performs poorly in the aggregate level, with a model-implied employment-output correlation of 1. This is not surprising from the analytical result we have in Section 3.4 that the model-implied aggregate employment and aggregate consumption are perfectly correlated. In this model with no investment, the aggregate output and the aggregate consumption are identical if the nominal GDP is deflated using the ideal price index. The real GDP (in the data and in our model) is slightly different because it is measured using the prices in a base year, but it is quantitatively very similar to the real GDP deflated using the ideal price index. So it is not surprising that the correlation of the aggregate employment and the measured real aggregate GDP in the model is also 1. Da-Rocha and Restuccia (2006) also use a CES utility function, but they were able to generate a low correlation between the aggregate employment and output because they introduced independent ex post shocks to the agricultural productivity (weather shocks). In the version of the model without ex post shocks, their model’s implied employment-output correlation is 0.95. It is slightly smaller than one because in their model there is investment so that output and consumption are not perfectly correlated. In contrast, our benchmark model with income effect can generate low employment-output correlation without introducing any ex post shocks.

The homothetic CES model without income effect also performs poorly at sector level. It generates a high correlation (0.99) between the agricultural employment and non-agricultural employment, which contradicts with the negative correlation in the data. Moreover, the model-implied correlation of relative agriculture employ-

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7See Table 9 on page 477 of Da-Rocha and Restuccia (2006).
ment and the relative labour productivity is positive (0.99) while the correlation in the data is negative (−0.29). Even for the US, the model also performs poorly at the sector level. Again, the correlation of the employments in the two sectors and the correlation of relative agriculture employment and the relative labour productivity and income are all positive in the model, but negative in the data.

Table 7: Comparison with Homothetic CES Utility Function

<table>
<thead>
<tr>
<th></th>
<th>China Data</th>
<th>China Model</th>
<th>Homothetic CES</th>
<th>US Data</th>
<th>US Model</th>
<th>Homothetic CES</th>
</tr>
</thead>
<tbody>
<tr>
<td>(A) Aggregate</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>(\sigma(L)/\sigma(Y))</td>
<td>0.11</td>
<td>0.13</td>
<td>0.62</td>
<td>0.70</td>
<td>0.23</td>
<td>0.64</td>
</tr>
<tr>
<td>(\rho(L,Y))</td>
<td>0.09</td>
<td>-0.03</td>
<td>1.00</td>
<td>0.87</td>
<td>0.87</td>
<td>1.00</td>
</tr>
<tr>
<td>(B) Within Sector</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>(\sigma(L_a)/\sigma(Y_a))</td>
<td>0.70</td>
<td>0.82</td>
<td>0.55</td>
<td>0.33</td>
<td>1.08</td>
<td>0.25</td>
</tr>
<tr>
<td>(\sigma(L_{na})/\sigma(Y_{na}))</td>
<td>0.75</td>
<td>0.54</td>
<td>0.73</td>
<td>0.71</td>
<td>0.24</td>
<td>0.63</td>
</tr>
<tr>
<td>(\rho(L_a,Y_a))</td>
<td>0.24</td>
<td>-0.92</td>
<td>0.99</td>
<td>-0.05</td>
<td>-0.99</td>
<td>0.90</td>
</tr>
<tr>
<td>(\rho(L_{na},Y_{na}))</td>
<td>0.88</td>
<td>0.83</td>
<td>0.96</td>
<td>0.87</td>
<td>0.86</td>
<td>1.00</td>
</tr>
<tr>
<td>(C) Cross Sector</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>(\rho(L_a,L_{na}))</td>
<td>-0.83</td>
<td>-0.83</td>
<td>0.99</td>
<td>-0.23</td>
<td>-0.28</td>
<td>0.70</td>
</tr>
<tr>
<td>(\rho(L_a/L_{na},A_a/A_{na}))</td>
<td>-0.29</td>
<td>-0.86</td>
<td>0.99</td>
<td>-0.27</td>
<td>-0.99</td>
<td>0.99</td>
</tr>
<tr>
<td>(\rho(L_a/L_{na},Y))</td>
<td>-0.84</td>
<td>-0.76</td>
<td>0.67</td>
<td>-0.69</td>
<td>-0.22</td>
<td>0.08</td>
</tr>
</tbody>
</table>

Note: \(\sigma(x)\) is the standard deviation of variable \(x\), \(\rho(x,y)\) is the correlation of variable \(x\) and \(y\). \(L\) and \(Y\) are aggregate employment and output. \(L_a, Y_a\) and \(A_i\) are sector employment, output and labor productivity, where \(i \in \{a, na\}\). Variables are detrended using hp-filter with smoothing parameter of 100.

We now conduct some additional sensitivity analysis to show the robustness of our benchmark model with income effect.

**Elasticity of labour supply.** The parameter \(\sigma\) governs the elasticity of labor supply, which affects directly the aggregate employment volatility. In line with the literature, we choose this parameter to be 0.6 in our benchmark calibration. We now
check the sensitivity of our model to this parameter by changing the value of $\sigma$. In column (3), (4), (8), (9) of Table 8, we report the simulation results for different values of $\sigma$ in China and the US. It can be seen that higher labor elasticity, or lower value of $\sigma$, implies higher aggregate employment volatility. Aggregate employment remains acyclic for China and pro-cyclical for the US under different values of $\sigma$. While there is some minor differences in the results across different value of $\sigma$, the properties of sector-level fluctuations and the labour reallocation between the two sectors of the benchmark model still hold.

**Stochastic shock process.** Our results are also robust to alternative specification of the shock process. In this section, instead of using the realized productivity shocks in the simulation, we assume that the cyclical fluctuations of sector labor productivity shocks follow a VAR(1) process. We estimate the VAR(1) process from the data and simulate the economy. To save space, the estimation details are reported in Appendix E. Column (5) and (10) of Table 8 show the business cycle moments for China and the US. Both the aggregate and sector level implications from the benchmark model hold for this alternative specification.

### 4.2.3 Unique Features of China

We noted in Section 2 that, comparing to other countries with the same share of agricultural employment, China stands out in two aspects in terms of employment fluctuations: It has the lowest employment volatility and the strongest reallocation between sectors, i.e the largest negative correlation between agriculture and non-agriculture employments. We think this is due to some unique institutional features of China that have direct effect on labour reallocation in the country.

China has a household registration system called hukou that separates rural residents from urban residents. Starting from 1978, the rural workers with agricultural hukou are allowed to work in the cities, but they are not entitled to the public services, such as education and medical care in the cities, that urban residents with non-agricultural hukou have. This implies that these migrant workers from rural area cannot expect to settle their family in the urban area. Hence they often go back to the rural area and work in agriculture when job opportunities are scarce in the
Table 8: Sensitivity Analysis - China and the US

<table>
<thead>
<tr>
<th></th>
<th>(1) China</th>
<th>(2) Benchmark</th>
<th>(3) $\sigma = 0.1$</th>
<th>(4) $\sigma = 2$</th>
<th>(5) VAR(1)</th>
<th>(6) US</th>
<th>(7) Benchmark</th>
<th>(8) $\sigma = 0.1$</th>
<th>(9) $\sigma = 2$</th>
<th>(10) VAR(1)</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>(A) Aggregate</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\sigma (L) / \sigma (Y)$</td>
<td>0.11</td>
<td>0.13</td>
<td>0.18</td>
<td>0.09</td>
<td>0.16</td>
<td></td>
<td>0.70</td>
<td>0.23</td>
<td>0.26</td>
<td>0.21</td>
</tr>
<tr>
<td>$\rho (L, Y)$</td>
<td>0.09</td>
<td>-0.03</td>
<td>0.02</td>
<td>-0.05</td>
<td>0.17</td>
<td></td>
<td>0.87</td>
<td>0.87</td>
<td>0.91</td>
<td>0.79</td>
</tr>
<tr>
<td><strong>(B) Within Sector</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
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<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\sigma (L_a) / \sigma (Y_a)$</td>
<td>0.70</td>
<td>0.82</td>
<td>0.88</td>
<td>0.76</td>
<td>0.84</td>
<td></td>
<td>0.33</td>
<td>1.08</td>
<td>1.08</td>
<td>1.08</td>
</tr>
<tr>
<td>$\sigma (L_{na}) / \sigma (Y_{na})$</td>
<td>0.75</td>
<td>0.54</td>
<td>0.51</td>
<td>0.58</td>
<td>0.50</td>
<td></td>
<td>0.71</td>
<td>0.24</td>
<td>0.27</td>
<td>0.22</td>
</tr>
<tr>
<td>$\rho (L_a, Y_a)$</td>
<td>0.24</td>
<td>-0.92</td>
<td>-0.90</td>
<td>-0.94</td>
<td>-0.90</td>
<td></td>
<td>-0.05</td>
<td>-0.99</td>
<td>-0.99</td>
<td>-0.99</td>
</tr>
<tr>
<td>$\rho (L_{na}, Y_{na})$</td>
<td>0.88</td>
<td>0.83</td>
<td>0.85</td>
<td>0.81</td>
<td>0.77</td>
<td></td>
<td>0.87</td>
<td>0.86</td>
<td>0.92</td>
<td>0.77</td>
</tr>
<tr>
<td><strong>(C) Cross Sector</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\rho (L_a, L_{na})$</td>
<td>-0.83</td>
<td>-0.83</td>
<td>-0.76</td>
<td>-0.87</td>
<td>-0.75</td>
<td></td>
<td>-0.23</td>
<td>-0.28</td>
<td>-0.20</td>
<td>-0.36</td>
</tr>
<tr>
<td>$\rho (L_a / L_{na}, A_a / A_{na})$</td>
<td>-0.29</td>
<td>-0.86</td>
<td>-0.85</td>
<td>-0.87</td>
<td>-0.84</td>
<td></td>
<td>-0.27</td>
<td>-0.99</td>
<td>-0.99</td>
<td>-0.99</td>
</tr>
<tr>
<td>$\rho (L_a / L_{na}, Y)$</td>
<td>-0.84</td>
<td>-0.76</td>
<td>-0.73</td>
<td>-0.79</td>
<td>-0.70</td>
<td></td>
<td>-0.69</td>
<td>-0.22</td>
<td>-0.21</td>
<td>-0.23</td>
</tr>
</tbody>
</table>

Note: $\sigma (x)$ is the standard deviation of variable $x$. $\rho (x, y)$ is the correlation of variable $x$ and $y$. $L$ and $Y$ are aggregate employment and output. $L_i, Y_i$ and $A_i$ are sector employment, output and labor productivity, where $i \in \{a, na\}$. Variables are detrended using hp-filter with smoothing parameter of 100.
cities. Every worker with agricultural hukou is also entitled with the right of land use back at home, so they can always go back home to work on their land.

We use the micro-level survey data from China to show that migrant workers indeed go back to work in agriculture when the economy slows down. The data on migration is from the National Fixed Point Survey of Agriculture conducted annually by China’s Ministry of Agriculture. This survey only starts to ask questions about rural migrant workers in 2003. Between 2004 and 2013, the percentage of migrant workers who went back to work in agriculture is around 9%. Figure 6 plots the real GDP growth rate and net out-migration rate (out-migration minus the return migration as a percentage of workers who worked in agriculture last year) for the period from 2004 to 2010. It is clear that the net out-migration rate is cyclical and positively correlated with GDP growth.

Figure 6: Migration and Output

In many other countries, however, rural workers migrate to cities with an expectation of staying in the cities. Therefore the reallocation is more like a long-term decision rather than a business cycle adjustment, and the employment adjustment at sector level would be more sticky. This may partially explains why our model without stickiness shows a higher negative correlation of employments between the two sectors than that in the US data. We capture the stickiness with a labour adjustment

---

8We thank Qingen Gai for sharing with us the data on migration.
Table 9: Counterfactual Labor Adjustment Cost

<table>
<thead>
<tr>
<th></th>
<th>Data</th>
<th>Benchmark</th>
<th>$\xi_a = 0.5$</th>
<th>$\xi_a = 1$</th>
<th>$\xi_a = 1.5$</th>
</tr>
</thead>
<tbody>
<tr>
<td>(A) Aggregate</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\sigma(L)/\sigma(Y)$</td>
<td>0.11</td>
<td>0.13</td>
<td>0.18</td>
<td>0.25</td>
<td>0.33</td>
</tr>
<tr>
<td>$\rho(L,Y)$</td>
<td>0.09</td>
<td>-0.03</td>
<td>-0.13</td>
<td>-0.15</td>
<td>-0.11</td>
</tr>
<tr>
<td>(B) Within Sector</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\sigma(L_a)/\sigma(Y_a)$</td>
<td>0.70</td>
<td>0.82</td>
<td>0.84</td>
<td>0.86</td>
<td>0.88</td>
</tr>
<tr>
<td>$\sigma(L_{na})/\sigma(Y_{na})$</td>
<td>0.75</td>
<td>0.54</td>
<td>0.48</td>
<td>0.42</td>
<td>0.35</td>
</tr>
<tr>
<td>$\rho(L_a,Y_a)$</td>
<td>0.24</td>
<td>-0.92</td>
<td>-0.92</td>
<td>-0.92</td>
<td>-0.92</td>
</tr>
<tr>
<td>$\rho(L_{na},Y_{na})$</td>
<td>0.88</td>
<td>0.83</td>
<td>0.82</td>
<td>0.82</td>
<td>0.83</td>
</tr>
<tr>
<td>(C) Cross Sector</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\rho(L_a,L_{na})$</td>
<td>-0.83</td>
<td>-0.83</td>
<td>-0.77</td>
<td>-0.67</td>
<td>-0.48</td>
</tr>
<tr>
<td>$\rho(L_a/L_{na},A_a/A_{na})$</td>
<td>-0.29</td>
<td>-0.86</td>
<td>-0.85</td>
<td>-0.84</td>
<td>-0.82</td>
</tr>
<tr>
<td>$\rho(L_a/L_{na},Y)$</td>
<td>-0.84</td>
<td>-0.76</td>
<td>-0.72</td>
<td>-0.68</td>
<td>-0.63</td>
</tr>
</tbody>
</table>

Note: $\sigma(x)$ is the standard deviation of variable $x$, $\rho(x,y)$ is the correlation of variable $x$ and $y$. $L$ and $Y$ are aggregate employment and output. $L_i$, $Y_i$ and $A_i$ are sector employment, output and labor productivity, where $i \in \{a, na\}$. Variables are detrended using hp-filter with smoothing parameter of 100.

cost to the agricultural employment’s deviation from its trend in the benchmark model

$$C_t = \frac{B_t}{1+\sigma} (L_{at} + L_{nat})^{1+\sigma} - \frac{\xi_a}{2} (L_{at} - \overline{L}_{at})^2,$$

where $\overline{L}_{at}$ is the trend of agriculture employment. We then perform counterfactual exercises by assuming different values of adjustment cost in China. Table 9 shows that with higher adjustment cost, the magnitude of the negative correlation of employments in the two sectors becomes smaller, and the volatility of aggregate employment relative to output becomes larger. This exercise suggests that the unusually strong labour reallocation and unusually low aggregate employment volatility in China are both due to the fact that most migrations in China are temporary, which itself is a result of China’s hukou system and land institution.
5 Conclusion

The cyclical behavior of aggregate employment differs significantly between China and the developed countries. This sharp difference at the aggregate level conceals similar behavior of cyclical properties of employments at 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 labour reallocation between sectors on the aggregate employment dynamics. We show both empirically and theoretically that income effect plays an important role in determining the labour reallocation dynamics in both the long-run and short-run. Using a simple two-sector growth model with productivity shocks and non-homothetic preferences, we can simultaneously account for the structural change in the long-run and the employment fluctuations in the short-run in China. In addition, we show that some unique institutional features in China result in particularly flexible labour reallocation in the short-run, which helps to explain why China’s aggregate employment volatility is low even among countries with similar average share of employment in agriculture.
References


Appendix

A Data Source

The data used in this paper is obtained from the GGDC’s 10-Sector Database (Timmer, de Vries and de Vries (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 countries are Argentina, Bolivia, Botswana, Chile, China, Colombia, Costa Rica, Denmark, Egypt, Spain, Ethiopia, France, United Kingdom, Ghana, Hong Kong, Indonesia, India, Italy, Japan, Kenya, South Korea, Mexico, Morocco, Mauritius, Malawi, Malaysia, Nigeria, Netherlands, Peru, Philippines, Senegal, Singapore, Sweden, Thailand, Taiwan, Tanzania, US, Venezuela, South Africa and Zambia. Among these, we have 12 OECD countries: Chile, Denmark, Spain, France, UK, Italy, Japan, South Korea, Mexico, Netherlands, Sweden and the US.

For countries other than China, we directly use data from the GGDC and aggregate the nine sectors outside agriculture into one non-agricultural sector. For China, the 10-Sector Database uses the official employment series from China’s National Bureau of Statistics (NBS) that are published in the annual China Statistical Yearbook. However, as pointed out by Brandt and Zhu (2010), there are two serious problems with the NBS’ employment series that need to be dealt with. Hence, we construct revised annual employment series for China as described in Section 2.

B Robustness of Facts

In Table 10 we show that our facts are robust to different filtering methods. In particular, we compute the business cycle moments from the Baxter-King filter, which defines business cycle as the cyclical components between 2 and 8 years. The business cycle moments from the Baxter-King filter are very close to those from the hp- filter.

C Derivation of Formulas

The FOCs of the social planner’s maximization problem with respect to $L_{at}$ and $L_{nat}$ are:

$$\frac{\partial C_t}{\partial c_{at}} C_t^{-1} A_{at} - B_t L_t^{\sigma} = 0 \quad (22)$$

$$\frac{\partial C_t}{\partial c_{nat}} C_t^{-1} A_{nat} - B_t L_t^{\sigma} = 0 \quad (23)$$

From equation (3), we have

$$\mu_a \left( \phi_a \right)^{\frac{1}{\varepsilon}} \epsilon_a^{\varepsilon-1} C_t^{\frac{1-\varepsilon}{\varepsilon}} \frac{\partial C_t}{\partial c_{at}} + \mu_{na} \left( \phi_{na} \right)^{\frac{1}{\varepsilon}} \epsilon_{nat}^{\varepsilon-1} C_t^{\frac{1-\varepsilon}{\varepsilon}} \frac{\partial C_t}{\partial c_{at}}$$

$$- \left( \phi_a \right)^{\frac{1}{\varepsilon}} \epsilon_a^{\varepsilon-1} C_t^{\frac{1-\varepsilon}{\varepsilon}} = 0,$$
Table 10: Robustness of Facts across Filters

<table>
<thead>
<tr>
<th></th>
<th>China</th>
<th>US</th>
<th>OECD Average</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>HP-Filter</td>
<td>Baxter-King Filter</td>
<td>HP-Filter</td>
</tr>
<tr>
<td>(A) Aggregate</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\sigma (L) / \sigma (Y)$</td>
<td>0.11</td>
<td>0.06</td>
<td>0.70</td>
</tr>
<tr>
<td>$\rho (L, Y)$</td>
<td>0.09</td>
<td>0.04</td>
<td>0.87</td>
</tr>
<tr>
<td>(B) Within Sector</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\sigma (L_{a}) / \sigma (Y_{a})$</td>
<td>0.70</td>
<td>0.52</td>
<td>0.33</td>
</tr>
<tr>
<td>$\sigma (L_{na}) / \sigma (Y_{na})$</td>
<td>0.75</td>
<td>0.71</td>
<td>0.71</td>
</tr>
<tr>
<td>$\rho (L_{a}, Y_{a})$</td>
<td>0.24</td>
<td>0.23</td>
<td>-0.05</td>
</tr>
<tr>
<td>$\rho (L_{na}, Y_{na})$</td>
<td>0.88</td>
<td>0.81</td>
<td>0.87</td>
</tr>
</tbody>
</table>

Note: $\sigma (x)$ is the standard deviation of variable $x$. $\rho (x, y)$ is the correlation of variable $x$ and $y$. $L$ and $Y$ are the aggregate employment and output. $L_i$ and $Y_i$ are the sector employment and output, where $i \in \{agriculture, non-agriculture\}$. 
we have the following:

From (29), then, we have

Thus, we have

where

which implies that

Thus, we have

\[
\frac{\partial C_t}{\partial c_{at}} = \left( \frac{\phi_a}{D_t} \right) \frac{\frac{\varepsilon - 1}{C_t} + \frac{\varepsilon - 1}{c_{nat} C_t} \mu_{nat}}{D_t},
\]

(24)

where

\[
D_t = \mu_a \left( \frac{\phi_a}{D_t} \right) \frac{\frac{\varepsilon - 1}{C_t} + \frac{\varepsilon - 1}{c_{nat} C_t} \mu_{nat}}{D_t},
\]

(26)

Substituting equations (24) and (25) into (22) and (23), respectively, and solving for \( c_{at} \) and \( c_{nat} \), we have the following:

\[
c_{at} = \phi_a \left( \frac{A_{at}}{D_t B_t L_t \sigma_{C_t}} \right)^\varepsilon (1 - \varepsilon) \mu_a,
\]

(27)

\[
c_{nat} = \phi_{nat} \left( \frac{A_{nat}}{D_t B_t L_t \sigma_{C_t}} \right)^\varepsilon (1 - \varepsilon) \mu_{nat}.
\]

(28)

Substituting these two equations into (3) we have

\[
\phi_a \left( \frac{A_{at}}{D_t B_t L_t \sigma_{C_t}} \right)^\varepsilon (1 - \varepsilon) \mu_a + \phi_{nat} \left( \frac{A_{nat}}{D_t B_t L_t \sigma_{C_t}} \right)^\varepsilon (1 - \varepsilon) \mu_{nat} = 1,
\]

which implies that

\[
(D_t B_t L_t \sigma_{C_t}) (1 - \varepsilon) (\phi_a A_{at}^{(1 - \varepsilon) \mu_a} + \phi_{nat} A_{nat}^{(1 - \varepsilon) \mu_{nat}}) = 1,
\]

(29)

Substituting (29) into (27) and (28) and solving for \( c_{at} \) and \( c_{nat} \) yield the solution in equations (7) and (8). Substituting (7) and (8) into (26) and simplifying yields the following:

\[
D_t = \frac{\mu_a \phi_a A_{at}^{(1 - \varepsilon) \mu_a - 1} + \mu_{nat} \phi_{nat} A_{nat}^{(1 - \varepsilon) \mu_{nat} - 1}}{\phi_a A_{at}^{(1 - \varepsilon) \mu_a} + \phi_{nat} A_{nat}^{(1 - \varepsilon) \mu_{nat}}}.
\]

From (29), then, we have

\[
L_t = \left[ \frac{1}{B_t} \left( \phi_a A_{at}^{(1 - \varepsilon) \mu_a + \phi_{nat} A_{nat}^{(1 - \varepsilon) \mu_{nat}}} \right) \right]^{\frac{1}{\sigma}}.
\]

(30)
We prove here that for any exogenously given \( L_t \), the solution of the agriculture’s share of employment from equation (12) and (14), \( l_{at}(\phi_a, \varepsilon, \mu_a, \mu_{na}) \) is invariant to the common scale of \((\mu_a, \mu_{na})\).
First, let \( C^*_t(\varphi, \epsilon, \mu_a, \mu_{na}) \) be the solution to equation (12) for the given \( L_t \). It can be shown that the solution is unique and the corresponding agriculture’s share of employment is

\[
l_{at}^* = \frac{\varphi_a \left( \frac{A_{at}}{A_{nat}} \right)^{\frac{\epsilon}{1-\varphi_a}} C^*_t(1-\epsilon)(\mu_a-\mu_{na})}{1 + \frac{\varphi_a}{1-\varphi_a} \left( \frac{A_{at}}{A_{nat}} \right)^{\frac{\epsilon}{1-\varphi_a}} C^*_t(1-\epsilon)(\mu_a-\mu_{na})}.
\]

(37)

Let \( \mu'_a = \eta \mu_a \) and \( \mu'_{na} = \eta \mu_{na} \) for an arbitrary positive constant \( \eta \). Equation (12) and (14) now become

\[
L_t = L_{at} + L_{nat} = \left( \varphi_a A_{at}^{1-\epsilon} C^*_t(1-\epsilon)\eta \mu_a + \varphi_{nat} A_{nat}^{1-\epsilon} C^*_t(1-\epsilon)\eta \mu_{na} \right)^{1\over 1-\epsilon},
\]

and

\[
l_{at}' = \frac{\varphi_a \left( \frac{A_{at}}{A_{nat}} \right)^{\frac{\epsilon}{1-\varphi_a}} C_t^{1-\epsilon}(1-\epsilon)\eta(\mu_a-\mu_{na})}{1 + \frac{\varphi_a}{1-\varphi_a} \left( \frac{A_{at}}{A_{nat}} \right)^{\frac{\epsilon}{1-\varphi_a}} C_t^{1-\epsilon}(1-\epsilon)\eta(\mu_a-\mu_{na})}.
\]

(38)

Let \( C'_t = C^*_t \). Then, we can rewrite the two equation as

\[
L_t = L_{at} + L_{nat} = \left( \varphi_a A_{at}^{1-\epsilon} C'_t(1-\epsilon)\mu_a + \varphi_{nat} A_{nat}^{1-\epsilon} C'_t(1-\epsilon)\mu_{na} \right)^{1\over 1-\epsilon},
\]

and

\[
l_{at}' = \frac{\varphi_a \left( \frac{A_{at}}{A_{nat}} \right)^{\frac{\epsilon}{1-\varphi_a}} C'_t(1-\epsilon)(\mu_a-\mu_{na})}{1 + \frac{\varphi_a}{1-\varphi_a} \left( \frac{A_{at}}{A_{nat}} \right)^{\frac{\epsilon}{1-\varphi_a}} C'_t(1-\epsilon)(\mu_a-\mu_{na})}.
\]

(39)

Since equation (38) has a unique solution, we have \( C'_t = C^*_t \). From (37) and (39), then, we know that \( l_{at}' = l_{at} \).

E Robustness

In this section, we describe in details the estimation of the labor productivities in Section 4.2.2. 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 \( A_t \) is the 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

\[
\rho = \begin{bmatrix}
0.38 & 0 \\
0 & 0.52
\end{bmatrix}
\]

and

\[
\Sigma = \begin{bmatrix}
0.024^2 & 0.355 \times 0.024 \times 0.043 \\
0.355 \times 0.024 \times 0.043 & 0.043^2
\end{bmatrix}.
\]


The estimated shock process for the US is

\[ \rho = \begin{bmatrix} 0.55 & 0 \\ 0 & 0.03 \end{bmatrix} \]

and

\[ \Sigma = \begin{bmatrix} 0.010^2 & 0.15 \times 0.010 \times 0.083 \\ 0.15 \times 0.010 \times 0.083 & 0.083^2 \end{bmatrix}. \]

We then simulate the shock process for 33 periods and add it back to the productivity trend. The model is then solved using the constructed productivity. We repeat the simulation for 3000 times and compute the average business cycle moments. Column (5) and (10) of Table 8 report the simulation results under this specification.