BARRIERS TO STRUCTURAL TRANSFORMATION IN THAILAND: THE ROLES OF HUMAN CAPITAL AND AGRICULTURAL PRODUCTIVITY

By

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ABSTRACT

There are potentially large gains to be realized in Thailand from facilitating the reallocation of workers from agriculture to other sectors, as indicated by the unusually high agricultural employment share and the large gap in sectoral labor productivity. I assess the potential effects of human capital and agricultural productivity by using a calibrated two-sector model with exogenous and heterogeneous levels of human capital to perform a counterfactual analysis. I estimate that increasing human capital leads to a reduction in agricultural employment and a higher aggregate output. Improvements in labor-augmenting technology in agriculture are found to draw more workers toward agriculture and increase aggregate output. However, the effect of labor-augmenting technical change on labor reallocation should be interpreted with caution as it is sensitive to the assumption about the openness of the economy.

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Table of Contents

List of Figures

List of Tables

1 Introduction

One of the main proximate reasons why poor countries are poor is that most workers in these countries are employed in the agricultural sector, which has significantly lower productivity than other sectors (Caselli, 2005; Restuccia, Yang and Zhu, 2008). 54.27% of workers in the least developed countries (LDCs) were employed in agriculture while producing only 18.80% of their nominal gross domestic product (GDP) in 2022, according to the data from the World Bank's World Development Indicators (WDI). Aggregate productivity and output would be substantially higher if they had successfully reallocated resources toward the more productive sectors.

"Structural transformation" or "structural change" usually refers to the transition of an economy from an agricultural-based economy to a manufacturing and, subsequently, service economy. Kuznets (1973) includes structural transformation as one of the six main features of modern economic growth. It was a common experience among high-income countries (Sen, 2019).

This issue is still relevant for many upper-middle-income countries, including Thailand. The case of Thailand is particularly interesting since the agricultural share of employment in Thailand is significantly higher than one would expect for an economy with its income level. In 2022, the agricultural employment share was 30.42% in Thailand, while agriculture only accounts for 8.8% of its nominal GDP. The agricultural employment share in Thailand was higher than those in countries with lower income, such as the Philippines (23.71%), Brazil (8.73%), South Africa (19.26%), or Botswana (17.64%), according to the WDI database.

In this study, I aim to shed light on this puzzle and to identify potential ways to promote sectoral reallocation. First, I analyze the data and review existing studies to obtain stylized facts about the structural transformation of the Thai economy. The results then guide the direction of the main empirical analysis of the paper. Specifically, I focus on the roles of human capital and agricultural productivity. This is because the educational attainment of the Thai population is relatively lower than in countries with similar income levels. Its agricultural productivity is also significantly lower than that of its peers as well.

To assess the potential effects of human capital and agricultural productivity, I conduct a counterfactual analysis using a model calibrated to the Thai economy. Specifically, I create a simple two-sector model with agents endowed with exogenous heterogeneous levels of human capital where human capital is more valued in non-agriculture. The parameters of the model are then calibrated such that the model can generate the observed patterns of the economy from 2001 to 2022. Lastly, I estimate the effects of increases in the level of human capital stock and agricultural productivity on agricultural employment and nominal GDP.

Traditionally, the literature has emphasized two main mechanisms of structural change. These are (i) greater income elasticities for non-agriculture goods and services, which implies greater relative demand for manufacturing goods and services as the economy grows, and (ii) a faster relative productivity growth in agriculture, which reduces the number of workers needed to produce food (Herrendorf, Rogerson and Valentinyi, 2014). More recently, researchers have also begun to examine the roles of the changes in the supply of different inputs (Acemoglu and Guerrieri, 2008; Caselli and Coleman, 2001; Porzio, Rossi and Santangelo, 2022).

For several decades, the conventional view has been that improvement in agricultural productivity is a key condition for successful industrialization as it allows workers to move toward other economic activities (Schultz, 1953; Rostow, 1960). However, this view has been challenged in more recent years. Previously, theoretical models were based on the assumption that the economy is a closed economy. However, in a small open economy, food can be imported and hence does not need to be produced locally. The production is then not determined by the local demand but by the economy's comparative advantage. Hence, according to this view, improving agricultural productivity would pull labor toward the agricultural sector (Matsuyama, 1992).

However, in most cases, the situation may not be well described by the binary in which the economy is either fully open or fully closed. Additionally, a country's border may be open, but the spatial frictions might render the rest of the country effectively closed (Gollin, 2023). Moreover, Bustos, Caprettini and Ponticelli (2016) show theoretically and empirically that an improvement in agricultural technology could lead to a reduction in agricultural employment even in a small open economy. The direction of the effect depends on the nature of the technical change and the elasticity of substitution between inputs. Hence, the impact of agricultural productivity depends on the context and time.

On human capital, Caselli and Coleman (2001) and Porzio, Rossi and Santangelo (2022) use overlapping generations models to illustrate the roles of human capital. In their models, workers need to acquire skills to work in non-agriculture (Caselli and Coleman, 2001), or their productivity and earnings in non-agriculture depend on their human capital level (Porzio, Rossi and Santangelo, 2022). They demonstrate empirically that the falling education or training costs explained the observed patterns of structural transformation and growth. I contribute to the literature by developing a relatively simpler model that can be easily applied to evaluate the potential effects of human capital formation policies on structural transformation.

Previous empirical work has suggested that the potential barriers in Thailand include government subsidies, lack of effective land reform, lack of investment in the modern sector, poor quality of schooling, and insufficient access to education (Lathapipat and Chucherd, 2013; Kanchoochat, 2023; Klyuev, 2015; Sen, 2018). However, these are mostly based on qualitative evidence or descriptive statistics. This paper is the first attempt to assess the effects of human capital on structural transformation in Thailand, which is the main contribution of this study.

There are a few empirical studies providing causal evidence on the obstacles to structural change in Thailand. Notable examples are Temsumrit and Sriket (2023) and Chankrajang (2012). Chankrajang (2012) estimates the effects of granting partial land right entitlement on sectoral labor reallocation using an instrumental variable strategy. She finds that the land right security led to a reallocation towards non-agriculture, and a quarter of the effect can be explained by an improvement in agricultural productivity. My paper takes a more structural approach to the question, which offers the ability to analyze the situation beyond historical events but possibly at the cost of internal validity.

Temsumrit and Sriket (2023) conducts a counterfactual analysis by changing Thailand's sectoral productivity growth rates to equal the growth rates in the Republic of Korea. One important difference between the approach in this study and the one from Temsumrit and Sriket (2023) is the assumption about the openness of the economy. While they assume that the Thai economy is a closed economy, I assume it is a small open economy. This has an important implication on the direction of the effects of sectoral productivity on agricultural employment, as explained previously. I believe that the assumption of a small open economy might be more realistic in the case of Thailand since exports account for 65.8% of its GDP in 2022 (World Bank, 2022).

I find that increasing human capital stock has considerable positive impacts on structural transformation and aggregate output. An increase in human capital by 5% leads to a 6.25% reduction in agricultural employment share and a 1% increase in the nominal GDP. On the other hand, an improvement in labor-augmenting technology in agriculture draws more labor into agriculture but still results in a higher aggregate output. A 5% increase in labor-augmenting technology results in a 3.22% higher employment share in agriculture and a 1.57% increase in GDP. However, the results on the effect of labor-augmenting productivity on sectoral employment should be interpreted with caution since it could be the case that the assumption of a small open economy does not hold. Nonetheless, it is still likely to increase the aggregate output.

The paper is structured as follows: In Section 2, I present stylized facts about Thailand's structural transformation process as well as findings from the existing empirical literature to motivate the model and the analysis. Section 3 describes the theoretical model. Section 4 explains data, calibration, and counterfactual analysis procedures. Section 5 presents the results. In Section 6, I discuss the findings, limitations, and further research that may be undertaken.

2 Stylized Facts of Structural Transformation of Thailand

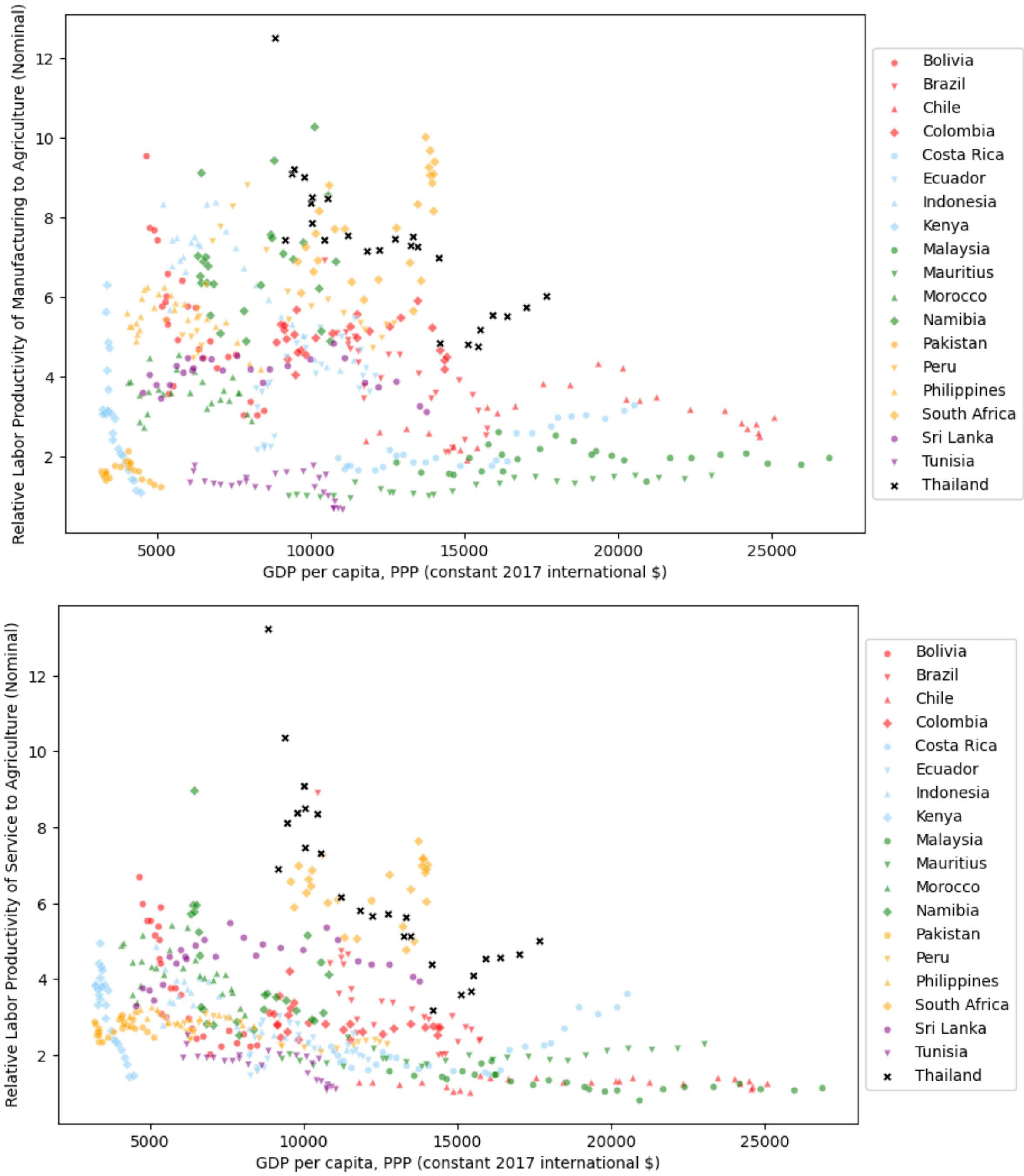
Thailand experienced an impressive growth episode from 1987 to 1996, with an average annual real GDP growth rate of 9.5% (Chuenchoksan and Nakornthab, 2008). During this time, aggregate labor productivity also doubled. Structural transformation played a key role in this economic boom. About half of the increase in labor productivity came from the movement of workers from agriculture to the manufacturing and service sectors (Lathapipat and Chucherd, 2013).

However, after the Asian Financial Crisis in 1997, it could not regain the same growth trajectory. Labor productivity grew by 27.0% from 2001 to 2006 and only 5.2% from 2006 to 2011. Structural change also stalled, contributing only 10% of the productivity growth from 2006 to 2011 (Lathapipat and Chucherd, 2013).

Although it is not surprising that structural transformation has played a smaller role in recent years, as a large fraction of workers had already moved away from agriculture, it is clear from the data that there are still substantial potential gains from sectoral reallocation. Figure 1 plots relative labor productivity in manufacturing and service sectors to agriculture against the real GDP per capita from 1993 to 2022. For Thailand, it can be seen that labor productivity in other sectors is still higher than in agriculture. Together with the fact that about 30% of employment is still in agriculture, these suggest that there are large potential productivity gains to be realized by facilitating a shift of workers from agriculture.

Another interesting fact or puzzle about Thailand's structural change is that its agricultural employment share has been unusually high, given its income level. This is clear from Figure 2, where I plot agricultural employment share against real GDP per capita from 1993 to 2022 of countries with similar income levels as Thailand in 1993. Thailand stands out as a clear outlier from the rest. One may expect the agricultural employment to be around 20% of total employment. This point is also made by Klyuev (2015).

Figure 1: GDP per capita and relative labor productivity of selected countries[1,2]

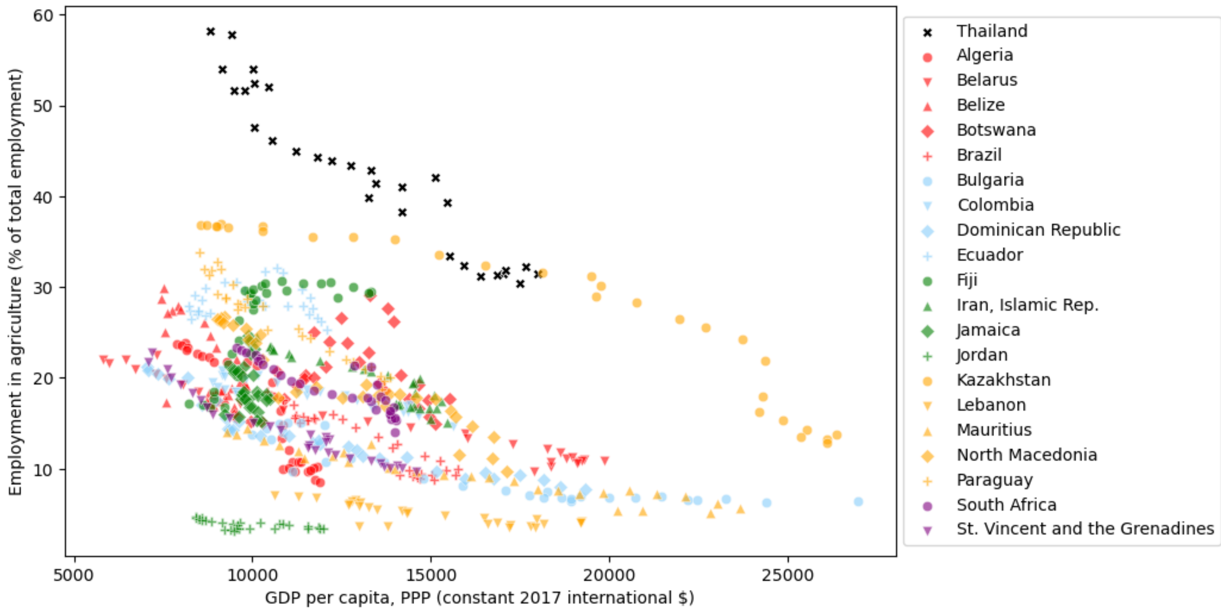


Source: Economic Transformation Database, World Development Indicators Database, and author's calculations

[1] 19 countries in the Economic Transformation dataset with the most similar level of real GDP per capita PPP as Thailand in 1993 are selected. Botswana is excluded because its data is drastically different from the others.

[2] Labor productivity of sector i is calculated as the nominal value added divided by employment in sector i. Relative labor productivity of sector i to agriculture is defined as the ratio between value added per worker in sector i to value added per worker in agriculture.

Figure 2: GDP per capita and agricultural employment share of selected countries[3]



Source: World Development Indicators Database

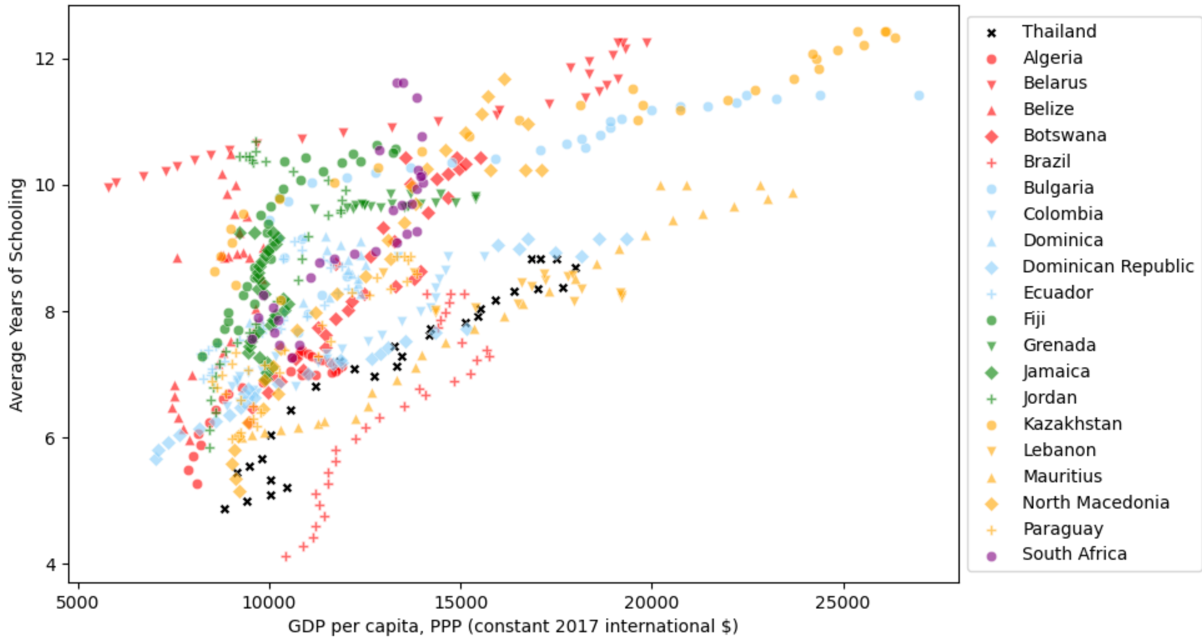
There could be many different underlying causes for this puzzle. One potential important barrier could be the large gap in productivity of the agricultural sector from the rest of the economy as shown in Figure 1. Additionally, agricultural productivity is surprisingly low in Thailand compared to its lower-income neighbors. The yield per harvested area for rice in Thailand, the staple crop in the region, was 47.60% lower than the yield in Vietnam, 24.52% lower than that in the Philippines, and 29.40 % lower than that in India in 2022 (Office of Agricultural Economics, 2023). This is a good starting point since the advance in agricultural productivity is conventionally viewed as a main driver of structural transformation (Herrendorf, Rogerson and Valentinyi, 2014; Rostow, 1960; Schultz, 1953).

Another potential major barrier to structural transformation is the relatively low level of human capital. Figure 3 shows that the mean years of schooling among the Thai population aged 25 years and older is lower than in many countries with similar income levels. Additionally, the low quality of education is also likely to be another contributing factor as Thai students usually rank on the lower end of the Programme for International Student Assessment (PISA) performance (Lathapipat and Chucherd, 2013; Klyuev, 2015). Human capital accumulation is

[3]Countries with real GDP per capita PPP 22.5% larger or smaller than Thailand in 1993 are selected.

important as non-agricultural production tends to be more skill-intensive or require different skills.

Figure 3: GDP per capita and mean years of schooling of selected countries[4]



Source: World Development Indicators Database, Human Development Report

Existing studies also suggest other factors that may be important obstacles to sectoral reallocation. One issue that is often raised is controversial agricultural price guarantees and subsidies that raise prices above market level (Klyuev, 2015; World Bank, 2020). The lack of effective land reform is also considered important as it is linked to incentives for investments of farmers (Sen, 2018). There's also empirical evidence that granting partial land rights to Thai farmers improves farm productivity and facilitates structural transformation (Chankrajang, 2012).

In summary, Thailand has had an unusually high agricultural employment share. Agricultural productivity is also significantly lower than that of the other sectors. These facts suggest that there are large potential gains from reallocating workers toward non-agriculture. The relatively low level of human capital and agricultural productivity will be the main focus of this study since the data suggests that these are some of the dimensions where Thailand differs from other countries. In the rest of this study, I assess the potential effects of increasing agricultural productivity and human capital.

[4]Countries with real GDP per capita PPP 22.5% larger or smaller than Thailand in 1993 are selected.

3 Model

The model in this paper is a two-sector model (agriculture and non-agriculture). The economy is inhabited by a continuum of mass one of workers which live infinitely. Each worker is endowed with different levels of human capital, with the average level among the population growing over time. Human capital is more valued in the non-agricultural sector. In particular, workers have identical productivity when working in agriculture, but their productivity scales with human capital in non-agriculture.

In each period, firms decide the amount of inputs they want to employ to maximize profit. Workers decide which sectors to supply their labor in. They supply their labor inelastically. I abstract from the costs of switching between sectors. My model can be viewed as a simplification and a modification of the model introduced in Porzio, Rossi and Santangelo (2022).

The economy is assumed to be a small open economy, which means that the prices of goods are exogenous. Inputs are immobile across countries. The labor market is characterized as a perfectly competitive market.

Workers—At time t, human capital of an individual can be expressed as

$$h(t, \varepsilon) = \bar{h}_t + \varepsilon, \tag{1}$$

where $\bar{h}_t$ is the average level of human capital of the workforce at time t. ε is a random variable assumed to follow a normal distribution with a mean of 0 and a standard deviation of σ. $\bar{h}_t$ is assumed to change exogenously, capturing the change in the costs or returns of human capital accumulation, such as an increase in education subsidy.

Production.— Non-agricultural production requires only labor input. Production of agricultural goods requires both land and labor. Land is exogenously determined and collectively owned by all workers. While the literature usually assumes a Cobb-Douglas production function, I choose to use a constant elasticity of substitution (CES) production instead, which allows factor-biased technical change. This is important, as shown in Bustos, Caprettini and Ponticelli (2016) because labor-augmenting technical improvements could reduce agricultural employment when land and labor are strong complements, even in the case of a small open economy.

An additional benefit of using a CES production function is that it is more consistent with empirical evidence on elasticity of substitution and patterns of factor income shares as summarized by Klump, McAdam and Willman (2012). The production functions of representative firms in the two sectors are given as

$$Y_{a,t} = [(Z_{l,t}L_{a,t})^{\frac{\mu-1}{\mu}} + (Z_{T,t}T_t)^{\frac{\mu-1}{\mu}}]^{\frac{\mu}{\mu-1}}, \tag{2}$$

$$Y_{m,t} = Z_{m,t}L_{m,t}. \tag{3}$$

$Y_{a,t}, Y_{m,t}$ denote the agricultural and non-agricultural output per capita respectively. $L_{a,t}$ is the share of agricultural employment in total employment. T_t is land per capita. $L_{m,t}$ denotes the total human capital employed in non-agriculture per capita. $Z_{l,t}$ is labor-augmenting technology, $Z_{T,t}$ is land-augmenting technology, $Z_{m,t}$ is productivity in non-agriculture. Lastly, μ denotes the elasticity of substitution between land and labor.

Let $\omega_t(\varepsilon)$ be the occupational choice function, which takes value 1 if individual (ε) works in agriculture at time t and 0 otherwise. Denoting the cumulative distribution function of ε as $F(\varepsilon)$, the labor inputs then can be expressed as:

$$L_{a,t} = \int \omega_t(\varepsilon)dF(\varepsilon),$$

$$L_{m,t} = \int h(t,\varepsilon)[1-\omega_t(\varepsilon)]dF(\varepsilon).$$

Differentiating Equation (2) with respect to $L_{a,t}$, one obtains the marginal product of labor in agriculture, which equals to

$$\begin{aligned} MPL_{a,t} &= Z_{l,t}^{\frac{\mu-1}{\mu}} L_{a,t}^{\frac{-1}{\mu}} [(Z_{l,t}L_{a,t})^{\frac{\mu-1}{\mu}} + (Z_{T,t}T_t)^{\frac{\mu-1}{\mu}}]^{\frac{1}{\mu-1}} \\ &= Z_{l,t}[1 + (\frac{Z_{T,t}T_t}{Z_{l,t}L_{a,t}})^{\frac{\mu-1}{\mu}}]^{\frac{1}{\mu-1}}. \end{aligned} \tag{4}$$

It can be seen from Equation (4) that an increase in land-augmenting productivity would increase the marginal product of labor. However, the effect of an increase in labor-augmenting productivity is ambiguous as it creates two opposing effects. While each worker is more productive, it also reduces the amount of land per unit of efficiency labor ($\frac{Z_{T,t}T_T}{Z_{l,t}L_{a,t}}$), which tends to lower the marginal product (Bustos, Caprettini and Ponticelli, 2016). Following their derivation, the derivative of the marginal product of labor with respect to labor-augmenting technology is

$$\frac{\partial MPL_{a,t}}{\partial Z_{l,t}} = \theta^{\frac{1}{\mu-1}}(L_{a,t}Z_{l,t})^{\frac{-1}{\mu}}\frac{\mu-1}{\mu}[1+\frac{1}{\mu-1}\theta^{-1}(L_{a,t}Z_{l,t})^{\frac{\mu-1}{\mu}}], \tag{5}$$

where $\theta = (Z_{l,t}L_{a,t})^{\frac{\mu-1}{\mu}} + (Z_{T,t}T_t)^{\frac{\mu-1}{\mu}}$. The product of the terms outside of the bracket is negative in the case where $\mu > 0$, i.e., land and labor are complements. Hence, in this case, $\frac{\partial MPL_{a,t}}{\partial Z_{l,t}} < 0$ if and only if the terms inside the bracket are greater than zero. As shown in Appendix A, this is true when $\mu < \frac{(Z_{T,t}T_t)^{\frac{\mu-1}{\mu}}}{(Z_{l,t}L_{a,t})^{\frac{\mu-1}{\mu}}+(Z_{T,t}T_t)^{\frac{\mu-1}{\mu}}}$, which is equal to the land income share if the land market is competitive.

Optimal Level of Inputs.—Firms choose the amount of labor inputs to maximize profits in each period. This results in:

$$\begin{aligned} w_{a,t} &= p_t Z_{l,t}^{\frac{\mu-1}{\mu}} L_{a,t}^{\frac{-1}{\mu}}[(Z_{l,t}L_{a,t})^{\frac{\mu-1}{\mu}} + (Z_{T,t}T_t)^{\frac{\mu-1}{\mu}}]^{\frac{1}{\mu-1}}, \\ &= p_t Z_{l,t}[1+(\frac{Z_{T,t}T_t}{Z_{l,t}L_{a,t}})^{\frac{\mu-1}{\mu}}]^{\frac{1}{\mu-1}}, \end{aligned} \tag{6}$$

$$w_{m,t} = Z_{m,t}, \tag{7}$$

where p_t is the relative price of agricultural goods. $w_{a,t}$ and $w_{m,t}$ denote the wage rate in agriculture and non-agriculture respectively.

Optimal Sectoral Choice.—The worker's sectoral choice problem in this model is a repeated static choice since there is no switching cost between sectors. Therefore, a worker with human capital $h(t,\varepsilon)$ works in non-agriculture at time t ($\omega_t(\varepsilon) = 0$) only if $w_{m,t}h(t,\varepsilon) \geq w_{a,t}$. From the definition of $h(t,\varepsilon)$, a worker works in non-agriculture if

$$\begin{aligned} w_{m,t}(\bar{h}_t+\varepsilon) &\geq w_{a,t} \\ \varepsilon &\geq \frac{w_{a,t}}{w_{m,t}} - \bar{h}_t \equiv \hat{\varepsilon}_t. \end{aligned}$$

Hence, the agricultural employment at time t is

$$L_{a,t} = F(\hat{\varepsilon}_t) \tag{8}$$

Equilibrium.—The economy is in equilibrium at time t when the wages $\{w_{a,t}, w_{m,t}\}$, sectoral allocation of inputs, and sectoral choice $\{L_{a,t}, L_{m,t}, \omega_t(\varepsilon)\}$ satisfy the profit maximization condition of firms, worker's optimal sectoral choice condition, and the input market clearing condition, for the given p_t, $\bar{h}_t$ and T_t.

4 Empirical Strategy

4.1 Data

The calibration process requires specifying and calculating the target moments to be matched. Values of exogenous variables are also needed to be determined. The FAOSTAT database contains data on agricultural land use. I use data from the labor force survey conducted by the National Statistical Office of Thailand (NSO) to compute agricultural employment, total employment, and average wages in each sector. The second dataset is the national account produced by the Office of the National Economic and Social Development Council (NESDC), which includes data on GDP. The last dataset is the Human Development Indices produced by the United Nations Development Programme (UNDP), which contains data on the average years of schooling among the population aged 25 years and older. I used the data from 2001 to 2022 for the calibration process.[5]

4.2 Calibration

For simplicity, I assume that technologies and the average human capital grow at constant rates. The growth rates of these exogenous variables are defined as follows:

$$
\begin{aligned}
g_p &\equiv \frac{\Delta p_t}{p_{t-1}} \\
g_{Z_l} &\equiv \frac{\Delta Z_{l,t}}{Z_{l,t-1}} \\
g_{Z_T} &\equiv \frac{\Delta Z_{T,t}}{Z_{T,t-1}} \\
g_{Z_m} &\equiv \frac{\Delta Z_{m,t}}{Z_{m,t-1}} \\
g_{\bar{h}} &\equiv \frac{\Delta \bar{h}_t}{\bar{h}_{t-1}}
\end{aligned}
$$

[5]There is no reliable data on wages before 2001. Upon my inspection, less than 1% of the sample in the labor force survey before 2001 have data on wages. Hence, I conduct the analysis using only the data from 2001 onwards.

The goal of the model calibration process is to select reasonable values of parameters such that the model can produce key features (moments) of the economy observed in the data. In this study, I calibrate the model to match the observed patterns of the Thai economy from 2001 to 2022.

Some parameter values are determined outside of the model. The initial level of productivity in non-agriculture and initial relative price are normalized to 1. Following Teignier (2018), g_p is set to equal the annualized growth rate of the ratio between the agricultural sector GDP deflator and the GDP deflator of the non-agricultural sector between 2001 and 2022. $g_{\bar{h}}$ is set to equal the annualized growth rate of the mean years of schooling among the population aged 25 years and older between the two periods. The value of μ is set to 0.5, taken from a meta-analysis conducted by Salhofer (2001). I also perform a sensitivity analysis to examine the robustness of the results across different values μ. The results from the sensitivity analysis are reported in Appendix C.

The remaining seven parameters are calibrated within the model. They are chosen to minimize the distance between the actual values and the simulated values of the seven target moments, taking μ, g_p, and $g_{\bar{h}}$ as given. Specifically, $Z_{l,2001}, g_{Z_l}, Z_{T,2001}, g_{Z_T}, g_{Z_m}, \bar{h}_{2001}$, and σ are chosen to match the ratio between the nominal GDP per total employment in 2001 and 2022, agricultural employment share, relative wage, and agricultural value-added share in nominal GDP in both 2001 and 2022. Appendix B provides more details on this process.

These seven parameters are jointly estimated, but it can be useful to think of them as being chosen to match particular moments in the data. In general, a parameter is pinned down by a moment that is especially affected by the value of that parameter. $Z_{T,2001}$ and g_{Z_T} are especially influential on relative wage as their effect on the marginal product of labor is clear. They are chosen to match the relative wage in both periods. $Z_{l,2001}$ and g_{Z_l} target the agricultural value-added shares as they do not only affect the amount of labor input used in agriculture but also the productivity of the agricultural labor. $\bar{h}_{2001}$ and σ are chosen to match agricultural employment shares. They are particularly influential on employment shares as they directly affect the cutoff threshold $\hat{\varepsilon}_t$ and the distribution of ε. Lastly, g_{Z_m} targets the ratio of the nominal GDP per total employment in 2001 to that of 2022. These are also supported by the results of a numerical exercise showing the sensitivity of target moments to changes in parameter values in Appendix D.

4.3 Counterfactual Analysis

After the parameters are calibrated, I perform a counterfactual analysis by asking what would happen if the levels of labor-augmenting productivity and human capital stock in 2022 were increased. Specifically, I increase both quantities by 5%, 10%, 15%, and 20%. In each scenario, the counterfactual agricultural employment share and the change in nominal GDP in 2022 (relative to the baseline case) are computed.

5 Results

5.1 Calibrated Model

The calibrated values of the parameters are reported in Table 1. The simulated moments are compared with the actual values in Table 2. It can be seen that the calibrated model performs reasonably well in reproducing the key features of the Thai economy. The model almost exactly matches all of the target moments in 2022. While the calibrated model performs somewhat poorer at matching the relative wage, this should not be a major concern. This is because the data on wages may be relatively less reliable as it is a sensitive topic, and the survey might not cover the upper tail of income distribution as well. Hence, it should receive less weight than other target moments.

Table 1: Calibrated parameter values

Parameter	Description	Value
Determined inside the model		
$Z_{l,2001}$	Level of labor-augmenting productivity in agriculture in 2001	0.2230
g_{Z_l}	Annual growth rate of $Z_{l,t}$	0.0362
$Z_{T,2001}$	Level of land-augmenting productivity in agriculture in 2001	1.0331
g_{Z_T}	Annual growth rate of $Z_{T,t}$	0.0322
g_{Z_m}	Annual growth rate of $Z_{m,t}$	0.0392
$\bar{h}_{2001}$	Average human capital level in 2001	0.4369
σ	Standard deviation of ε	0.5888
Determined Outside of the model		
μ	Elasticity of substitution between land and labor	0.5
$g_{\bar{h}}$	Annual growth rate of $\bar{h}_t$	0.0182
g_P	Annual growth rate of P_t	0.0205

Table 2: Actual and simulated values of the target moments

Target Moment	Actual	Simulated
Agricultural Employment Share 2001	0.4239	0.3582
Agricultural Employment Share 2022	0.3039	0.2951
Relative Wage 2001	0.3167	0.2860
Relative Wage 2022	0.4178	0.3466
Agricultural Value-added Share 2001	0.0860	0.0929
Agricultural Value-added Share 2022	0.0872	0.0928
GDP per capita 2022/ GDP per capita 2001	2.6667	2.6667

5.2 Impacts on Agricultural Employment and Aggregate Output

The calibrated parameters imply that $Z_{l,2022}$ and $\bar{h}_{2022}$ are equal to 0.4708 and 0.6382 in the baseline case, respectively. I increase these quantities by 5%, 10%, 15%, and 20%. I anticipated that both the improvement in labor-augmenting technology and the average human capital level would result in a reallocation of labor towards the non-agricultural sector and increase the GDP.

Theoretically, the effects of human capital improvement are clear. Since workers in non-agriculture are paid according to their human capital level, the increase in $\bar{h}_t$ would increase workers' relative incentive to work in non-agriculture. Thus, agricultural employment is expected to be lower. Aggregate output is expected to be higher due to both the reallocation effect and the higher level of human capital stock employed in non-agriculture.

However, the effects of the advance in labor-augmenting technology in agriculture are theoretically ambiguous. As explained in section 3, if $\frac{(Z_{T,2022}T_{2022})^{\frac{\mu-1}{\mu}}}{(Z_{l,2022}L_{a,2022})^{\frac{\mu-1}{\mu}}+(Z_{T,2022}T_{2022})^{\frac{\mu-1}{\mu}}} > \mu$, then the increase in labor-augmenting technology would reduce the agricultural employment share.

The results of the counterfactual analysis are reported in Table 3 and Table 4. Increasing the average human capital level by 20% reduces the agricultural employment share from 29.51% to 22.50%. This corresponds to a 23.75% reduction. In this scenario, nominal GDP is increased by 4.39%.

However, given the past record of the annualized $g_{\bar{h}}$ from 2001 to 2022, which was only

0.0182, the above scenario is unlikely to be achievable in the short or medium term. A more plausible scenario is where the average human capital increases by 5%. Even in this case, the impacts are still sizeable. Agricultural employment share drops by 6.24%, and nominal GDP increases by 1%.

The impact of the advances in labor-augmenting technology on agricultural employment is the opposite of what I had anticipated. The technological improvements induce workers to move from non-agriculture to agriculture. This is because the required condition does not hold at that point.[6] Hence, the improvements in labor-augmenting technology dampen the effect of human capital on agricultural employment. However, the nominal GDP still increases in every scenario where $Z_{l,2022}$ increases. For example, a 5% increase in labor-augmenting technology leads to a 3.22% higher employment share in agriculture but a 1.57% increase in aggregate output. This implies that the direct gain from higher within-sector productivity is larger than the loss from the labor reallocation toward agriculture. The positive impact on GDP is largest when both $Z_{l,2022}$ and $\bar{h}_{2022}$ increase.

The results from the sensitivity analysis, reported in Appendix C, show that the effects of increasing the average human capital level and labor-augmenting technology only marginally change when using different values of μ. The findings appear not to be sensitive to the assumption about the elasticity of substitution.

The effects of agricultural productivity on agricultural employment share beg the question of the appropriateness of the assumption of openness of the economy, which is the central assumption dictating the direction of the effect. It could really be the case that the small open economy assumption is realistic, and the required condition for negative effects does not hold. However, as I will argue below, the Thai economy might be better described as being somewhere in the middle between a small open and a closed economy.

McArthur and McCord (2017), using the instrumental variable approach, find that increases in staple yields reduce agricultural employment in most countries. However, they find the opposite effect in countries exporting more than 10% of their cereal production, which also includes Thailand. This empirical evidence is inconsistent with the closed economy case. On

[6] $\frac{(Z_{T,2022}T_{2022})^{\frac{\mu-1}{\mu}}}{(Z_{l,2022}L_{a,2022})^{\frac{\mu-1}{\mu}}+(Z_{T,2022}T_{2022})^{\frac{\mu-1}{\mu}}} = 0.000012$ in the baseline, which is well below μ.

the other hand, a large fraction of agricultural goods, such as rice, is still consumed locally.[7] Hence, the prices should also be somewhat influenced by the demand of Thai consumers.

Overall, increasing human capital can lead to a sizeable reduction in agricultural employment and a higher aggregate output. While the effect of improvement in labor-augmenting technology in agriculture on labor reallocation may be ambiguous, it can be expected to increase aggregate output nonetheless. Hence, promoting the adoption of farming technology and human capital accumulation seems to be the best course of action.

[7] According to the data from the FAOSTAT database, 34.52% of rice produced in Thailand was exported in 2022 (Food and Agriculture Organization of the United Nations, 2022)

Table 3: Agricultural employment share in each scenario

	Baseline $\bar{h}_{2022}$	Increases $\bar{h}_{2022}$ by 5%	Increases $\bar{h}_{2022}$ by 10%	Increases $\bar{h}_{2022}$ by 15%	Increases $\bar{h}_{2022}$ by 20%
Baseline $Z_{l,2022}$	0.2951	0.2767	0.2588	0.2416	0.2250
Increases $Z_{l,2022}$ by 5%	0.3046	0.2859	0.2677	0.2502	0.2333
Increases $Z_{l,2022}$ by 10%	0.3142	0.2952	0.2768	0.2590	0.2417
Increases $Z_{l,2022}$ by 15%	0.3239	0.3047	0.2860	0.2679	0.2503
Increases $Z_{l,2022}$ by 20%	0.3338	0.3143	0.2953	0.2769	0.2591

Table 4: Impact on Nominal GDP per total employment (%) in each scenario

	Baseline $\bar{h}_{2022}$	Increases $\bar{h}_{2022}$ by 5%	Increases $\bar{h}_{2022}$ by 10%	Increases $\bar{h}_{2022}$ by 15%	Increases $\bar{h}_{2022}$ by 20%
Baseline $Z_{l,2022}$	0.0000	0.9960	2.0574	3.1860	4.3833
Increases $Z_{l,2022}$ by 5%	1.5743	2.5086	3.5083	4.5754	5.7114
Increases $Z_{l,2022}$ by 10%	3.1947	4.0670	5.0046	6.0095	7.0835
Increases $Z_{l,2022}$ by 15%	4.8614	5.6715	6.5465	7.4888	8.5003
Increases $Z_{l,2022}$ by 20%	6.5749	7.3224	8.1347	9.0139	9.9622

6 Conclusion and Discussion

There are potentially large gains from facilitating labor reallocation from agriculture to non-agriculture in Thailand, as evidenced by the large gap in labor productivity and the large agricultural employment share. In this study, I investigate the potential impacts of increasing labor-augmenting productivity in agriculture and human capital stock on agricultural employment share and aggregate output. I build a simple two-sector model with exogenous and heterogeneous levels of human capital among workers, which is then calibrated to match the development path of the Thai economy. The calibrated model is used to perform a counterfactual analysis.

The effects of increasing the average human capital are as expected. Workers move to non-agriculture, and aggregate output increases. An increase in labor-augmenting technology draws more workers toward agriculture, which is not what I anticipated. Nonetheless, the aggregate output is higher, implying that the loss from reallocation is smaller than the gain from higher within-sector productivity. However, it may be the case that assuming the economy as a small open economy is not appropriate. I think the Thai economy is best characterized as being between a closed economy and a small open economy. This means that the actual direction of the effect of labor-augmenting technology on agricultural employment could be different from my estimation. Nonetheless, the impact on aggregate output can be expected to be positive.

There are some possible ways to improve the analysis, although at the cost of complexity. One may model openness using a more generalized approach, allowing for the economy to be completely closed, completely open, or between these two polar cases. Including a non-tradable sector and physical capital in the model may also be beneficial. Incorporating overlapping cohorts and frictions in switching between sectors would make the model more realistic and could result in more accurate predictions. Lastly, it is also interesting to model human capital endogenously. Among these, I expect that changing to endogenous human capital and generalized openness will have significant impacts on the results.

The decision of how much to invest in human capital is likely to depend on the path of relative wages. Hence, human capital will further propagate the effect of the increases in agricultural productivity on agricultural employment. For example, if the advancement in labor-augmenting technology increases the wage rate in agriculture, there would be less incentive to invest in human capital. This will result in a greater increase in agricultural employment than in the case where human capital is exogenous. However, the positive impact on GDP would be slightly lowered due to the larger loss from the reallocation channel.

When production is partly determined by demand within the economy, the effect of an increase in human capital would be greater due to a smaller relative demand for agricultural goods. An increase in human capital stock increases workers' income, which leads to higher consumption. Since the income elasticities of demand for non-agriculture goods are greater than that for agricultural goods, the relative demand for food will be lowered. The impact of an increase in labor-augmenting technology in agriculture is still ambiguous depending on the degree of openness, the land income share of agricultural output, and the elasticity of substitution between inputs in agriculture.

Nonetheless, the qualitative results on the effects on aggregate productivity and output are expected to remain the same. Improving human capital and labor-augmenting technology will still benefit the economy. The government can promote human capital accumulation by increasing subsidies to education, improving equity in the budget allocation to schools by taking into account the income levels and specific needs in each area, and changing the incentive system of teachers to be tied to student outcomes. One potential way to promote agricultural productivity is to improve access to irrigation since only 26% of agricultural households have access to irrigation and only 42% can access water resources (Attavanich et al., 2019). Further improving the land reform system could also be effective as it had already been shown to reallocate workers toward non-agriculture in Thailand (Chankrajang, 2012). Lastly, the government should also promote the adoption of modern machinery among agricultural households.

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Appendices

A. Derivations of the Effects of Labor-augmenting Technology on the Marginal Product of Labor

The marginal product of labor corresponding to the production function given by Equation (2) is

$$MPL_{a,t} = Z_{l,t}^{\frac{\mu-1}{\mu}} L_{a,t}^{\frac{-1}{\mu}} [(Z_{l,t}L_{a,t})^{\frac{\mu-1}{\mu}} + (Z_{T,t}T_t)^{\frac{\mu-1}{\mu}}]^{\frac{1}{\mu-1}}$$

Following the derivation in Bustos, Caprettini and Ponticelli (2016), let $\theta = (Z_{l,t}L_{a,t})^{\frac{\mu-1}{\mu}} + (Z_{T,t}T_t)^{\frac{\mu-1}{\mu}}$ to save space, the marginal product can then be expressed as

$$MPL_{a,t} = Z_{l,t}^{\frac{\mu-1}{\mu}} L_{a,t}^{\frac{\mu-1}{\mu}-1} \theta^{\frac{1}{\mu-1}}$$

The derivative of the marginal product with respect to labor-augmenting productivity is:

$$\begin{aligned}
\frac{\partial MPL_{a,t}}{\partial Z_{l,t}} &= L_{a,t}^{\frac{\mu-1}{\mu}-1}[\theta^{\frac{\mu-1}{\mu}-1}\frac{\mu-1}{\mu}Z_{l,t}^{-\frac{1}{\mu}} + Z_{l,t}^{\frac{\mu-1}{\mu}}\frac{1}{\mu-1}\theta^{\frac{\mu}{\mu-1}-2}\frac{\mu-1}{\mu}(Z_{l,t}L_{a,t})^{-\frac{1}{\mu}}L_{a,t}] \\
&= \theta^{\frac{\mu}{\mu-1}-1}L_{a,t}^{\frac{\mu}{\mu-1}-1}\frac{\mu-1}{\mu}[Z_{l,t}^{-\frac{1}{\mu}} + Z_{l,t}^{\frac{\mu-1}{\mu}}\frac{1}{\mu-1}\theta^{-1}(Z_{l,t}L_{a,t})^{-\frac{1}{\mu}}L_{a,t}] \\
&= \theta^{\frac{1}{\mu-1}}L_{a,t}^{-\frac{1}{\mu}}Z_{l,t}^{-\frac{1}{\mu}}\frac{\mu-1}{\mu}[1 + Z_{l,t}L_{a,t}\frac{1}{\mu-1}\theta^{-1}(Z_{l,t}L_{a,t})^{-\frac{1}{\mu}}] \\
&= \theta^{\frac{1}{\mu-1}}(Z_{l,t}L_{a,t})^{-\frac{1}{\mu}}\frac{\mu-1}{\mu}[1 + \frac{1}{\mu-1}\theta^{-1}(Z_{l,t}L_{a,t})^{\frac{\mu-1}{\mu}}].
\end{aligned} \tag{9}$$

In the case of $\mu > 0$, $\frac{\partial MPL_{a,t}}{\partial Z_{l,t}} < 0$ if and only if $1 + \frac{1}{\mu-1}\theta^{-1}(Z_{l,t}L_{a,t})^{\frac{\mu-1}{\mu}} > 0$ since the product of the terms outside of the bracket in Equation (9) is negative. Rearranging this condition, one can obtain the required condition for labor-augmenting technology to have a negative effect on the marginal product, which is

$$
\begin{aligned}
1+\frac{1}{\mu-1}\theta^{-1}(Z_{l,t}L_{a,t})^{\frac{\mu-1}{\mu}} &> 0 \\
\frac{1}{\mu-1}[(Z_{l,t}L_{a,t})^{\frac{\mu-1}{\mu}}+(Z_{T,t}T_t)^{\frac{\mu-1}{\mu}}]^{-1}(Z_{l,t}L_{a,t})^{\frac{\mu-1}{\mu}} &> -1 \\
[(Z_{l,t}L_{a,t})^{\frac{\mu-1}{\mu}}+(Z_{T,t}T_t)^{\frac{\mu-1}{\mu}}]^{-1}(Z_{l,t}L_{a,t})^{\frac{\mu-1}{\mu}} &< 1-\mu \\
\frac{(Z_{l,t}L_{a,t})^{\frac{\mu-1}{\mu}}}{(Z_{l,t}L_{a,t})^{\frac{\mu-1}{\mu}}+(Z_{T,t}T_t)^{\frac{\mu-1}{\mu}}}-1 &< -\mu \\
1-\frac{(Z_{l,t}L_{a,t})^{\frac{\mu-1}{\mu}}}{(Z_{l,t}L_{a,t})^{\frac{\mu-1}{\mu}}+(Z_{T,t}T_t)^{\frac{\mu-1}{\mu}}} &> \mu \\
\frac{(Z_{T,t}T_t)^{\frac{\mu-1}{\mu}}}{(Z_{l,t}L_{a,t})^{\frac{\mu-1}{\mu}}+(Z_{T,t}T_t)^{\frac{\mu-1}{\mu}}} &> \mu.
\end{aligned}
\tag{10}
$$

B. Details of the Calibration Procedures

The parameters are chosen to minimize the percentage differences squared. Specifically, the loss function used in this study is

$$\sum_{i=1}^{7} W_i [\frac{M_i(\Theta;\phi) - \hat{M}_i}{\hat{M}_i}]^2,$$

where $\hat{M}_i$ is the actual value of target moment i in the data, ϕ is parameters determined outside of the model, M_i is the simulated moment from using parameters Θ. W_i denotes the weight given to each target moment. Relative wage in each year receives a weight of 0.1. Each of the remaining moments receives a weight of 0.16. I give less weight to relative wage since it is not a typically used measure of structural transformation, and it may also be less reliable from issues in the survey data.

I use the downhill simplex method (Nelder-Mead) to identify the parameters, as suggested and described by Vanni et al. (2011). In practice, this is done by using *fminsearchbnd* optimization function in Matlab.

C. Sensitivity Analysis

The model is calibrated using different values of μ. The corresponding results of counterfactual experiments are reported in this section.

Table C.1: Agricultural employment share in each scenario, $\mu = 0.25$

	Baseline $\bar{h}_{2022}$	Increases $\bar{h}_{2022}$ by 5%	Increases $\bar{h}_{2022}$ by 10%	Increases $\bar{h}_{2022}$ by 15%	Increases $\bar{h}_{2022}$ by 20%
Baseline $Z_{l,2022}$	0.2951	0.2767	0.2588	0.2416	0.2250
Increases $Z_{l,2022}$ by 5%	0.3046	0.2859	0.2677	0.2502	0.2333
Increases $Z_{l,2022}$ by 10%	0.3142	0.2952	0.2768	0.2590	0.2417
Increases $Z_{l,2022}$ by 15%	0.3239	0.3047	0.2860	0.2679	0.2503
Increases $Z_{l,2022}$ by 20%	0.3338	0.3143	0.2953	0.2769	0.2591

Table C.2: Impact on Nominal GDP per total employment (%) in each scenario, $\mu = 0.25$

	Baseline $\bar{h}_{2022}$	Increases $\bar{h}_{2022}$ by 5%	Increases $\bar{h}_{2022}$ by 10%	Increases $\bar{h}_{2022}$ by 15%	Increases $\bar{h}_{2022}$ by 20%
Baseline $Z_{l,2022}$ 2001	0.0000	0.9959	2.0574	3.1860	4.3833
Increases $Z_{l,2022}$ by 5%	1.5743	2.5086	3.5083	4.5754	5.7113
Increases $Z_{l,2022}$ by 10%	3.1947	4.0670	5.0046	6.0095	7.0835
Increases $Z_{l,2022}$ by 15%	4.8615	5.6715	6.5465	7.4888	8.5002
Increases $Z_{l,2022}$ by 20%	6.5750	7.3225	8.1347	9.0139	9.9622

Table C.3: Agricultural employment share in each scenario, $\mu = 0.35$

	Baseline $\bar{h}_{2022}$	Increases $\bar{h}_{2022}$ by 5%	Increases $\bar{h}_{2022}$ by 10%	Increases $\bar{h}_{2022}$ by 15%	Increases $\bar{h}_{2022}$ by 20%
Baseline $Z_{l,2022}$	0.2951	0.2767	0.2588	0.2416	0.2250
Increases $Z_{l,2022}$ by 5%	0.3046	0.2859	0.2677	0.2502	0.2333
Increases $Z_{l,2022}$ by 10%	0.3142	0.2952	0.2768	0.2590	0.2417
Increases $Z_{l,2022}$ by 15%	0.3239	0.3047	0.2860	0.2679	0.2503
Increases $Z_{l,2022}$ by 20%	0.3338	0.3143	0.2953	0.2769	0.2591

Table C.4: Impact on Nominal GDP per total employment (%) in each scenario, $\mu = 0.35$

	Baseline $\bar{h}_{2022}$	Increases $\bar{h}_{2022}$ by 5%	Increases $\bar{h}_{2022}$ by 10%	Increases $\bar{h}_{2022}$ by 15%	Increases $\bar{h}_{2022}$ by 20%
Baseline $Z_{l,2022}$	0.0000	0.9959	2.0574	3.1860	4.3832
Increases $Z_{l,2022}$ by 5%	1.5743	2.5086	3.5083	4.5754	5.7113
Increases $Z_{l,2022}$ by 10%	3.1947	4.0670	5.0046	6.0095	7.0834
Increases $Z_{l,2022}$ by 15%	4.8616	5.6715	6.5466	7.4888	8.5002
Increases $Z_{l,2022}$ by 20%	6.5751	7.3226	8.1348	9.0139	9.9622

Table C.5: Agricultural employment share in each scenario, $\mu = 0.65$

	Baseline $\bar{h}_{2022}$	Increases $\bar{h}_{2022}$ by 5%	Increases $\bar{h}_{2022}$ by 10%	Increases $\bar{h}_{2022}$ by 15%	Increases $\bar{h}_{2022}$ by 20%
Baseline $Z_{l,2022}$	0.2951	0.2767	0.2588	0.2416	0.2250
Increases $Z_{l,2022}$ by 5%	0.3045	0.2858	0.2677	0.2502	0.2333
Increases $Z_{l,2022}$ by 10%	0.3141	0.2952	0.2768	0.2589	0.2417
Increases $Z_{l,2022}$ by 15%	0.3239	0.3046	0.2859	0.2678	0.2503
Increases $Z_{l,2022}$ by 20%	0.3337	0.3142	0.2953	0.2768	0.2590

Table C.6: Impact on Nominal GDP per total employment (%) in each scenario, $\mu = 0.65$

	Baseline $\bar{h}_{2022}$	Increases $\bar{h}_{2022}$ by 5%	Increases $\bar{h}_{2022}$ by 10%	Increases $\bar{h}_{2022}$ by 15%	Increases $\bar{h}_{2022}$ by 20%
Baseline $Z_{l,2022}$	0.0000	0.9972	2.0598	3.1894	4.3877
Increases $Z_{l,2022}$ by 5%	1.5724	2.5081	3.5092	4.5775	5.7146
Increases $Z_{l,2022}$ by 10%	3.1906	4.0645	5.0036	6.0099	7.0853
Increases $Z_{l,2022}$ by 15%	4.8549	5.6668	6.5435	7.4874	8.5004
Increases $Z_{l,2022}$ by 20%	6.5656	7.3152	8.1294	9.0104	9.9605

Table C.7: Agricultural employment share in each scenario, $\mu = 0.75$

	Baseline $\bar{h}_{2022}$	Increases $\bar{h}_{2022}$ by 5%	Increases $\bar{h}_{2022}$ by 10%	Increases $\bar{h}_{2022}$ by 15%	Increases $\bar{h}_{2022}$ by 20%
Baseline $Z_{l,2022}$	0.2944	0.2761	0.2584	0.2413	0.2248
Increases $Z_{l,2022}$ by 5%	0.3037	0.2851	0.2671	0.2497	0.2329
Increases $Z_{l,2022}$ by 10%	0.3131	0.2942	0.2760	0.2583	0.2412
Increases $Z_{l,2022}$ by 15%	0.3226	0.3035	0.2850	0.2670	0.2496
Increases $Z_{l,2022}$ by 20%	0.3322	0.3129	0.2941	0.2758	0.2581

Table C.8: Impact on Nominal GDP per total employment (%) in each scenario, $\mu = 0.75$

	Baseline $\bar{h}_{2022}$	Increases $\bar{h}_{2022}$ by 5%	Increases $\bar{h}_{2022}$ by 10%	Increases $\bar{h}_{2022}$ by 15%	Increases $\bar{h}_{2022}$ by 20%
Baseline $Z_{l,2022}$	0.0000	1.0138	2.0922	3.2367	4.4488
Increases $Z_{l,2022}$ by 5%	1.5470	2.5015	3.5205	4.6057	5.7588
Increases $Z_{l,2022}$ by 10%	3.1365	4.0316	4.9909	6.0164	7.1098
Increases $Z_{l,2022}$ by 15%	4.7688	5.6042	6.5035	7.4690	8.5024
Increases $Z_{l,2022}$ by 20%	6.4438	7.2195	8.0588	8.9639	9.9368

D. Sensitivity of Target Moments to Parameters

To examine the sensitivity of target moments to parameter values, I vary each parameter's value one-by-one. The value is increased and decreased by 1%, 2%, 3%, and 4% from the calibrated value. For each parameter, the other parameters are fixed at their calibrated values. I compute and report the corresponding percentage change in the target moments from the baseline simulated values.

Table D.1: Sensitivity with respect to $Z_{l,2001}$

	-4%	-3%	-2%	-1%	Calibrated Value	+1%	+2%	+3%	+4%
Agricultural Employment Share 2001	-1.5750	-1.1821	-0.7886	-0.3946	0.0000	0.3951	0.7908	1.1870	1.5837
Relative Wage 2001	-3.4103	-2.5534	-1.6994	-0.8482	0.0000	0.8453	1.6878	2.5274	3.3641
Agricultural Value-added Share 2001	-4.4948	-3.3733	-2.2503	-1.1258	0.0000	1.1272	2.2556	3.3854	4.5163
Agricultural Employment Share 2022	-2.5362	-1.9050	-1.2719	-0.6369	0.0000	0.6388	1.2794	1.9219	2.5662
Relative Wage 2022	-3.3511	-2.5083	-1.6689	-0.8328	0.0000	0.8295	1.6556	2.4784	3.2979
Agricultural Value-added Share 2022	-5.2940	-3.9778	-2.6567	-1.3307	0.0000	1.3354	2.6754	4.0199	5.3689
GDP 2022/ GDP 2001	-0.1410	-0.1066	-0.0717	-0.0361	0.0000	0.0367	0.0740	0.1118	0.1502

Table D.2: Sensitivity with respect to g_{z_l}

	-4%	-3%	-2%	-1%	Calibrated Value	+1%	+2%	+3%	+4%
Agricultural Employment Share 2001	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Relative Wage 2001	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Agricultural Value-added Share 2001	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Agricultural Employment Share 2022	-1.3387	-1.0048	-0.6704	-0.3355	0.0000	0.3360	0.6725	1.0095	1.3470
Relative Wage 2022	-1.7572	-1.3165	-0.8768	-0.4379	0.0000	0.4370	0.8731	1.3082	1.7425
Agricultural Value-added Share 2022	-2.7962	-2.0991	-1.4007	-0.7010	0.0000	0.7023	1.4059	2.1108	2.8169
GDP 2022/ GDP 2001	-0.6376	-0.4789	-0.3198	-0.1602	0.0000	0.1607	0.3218	0.4835	0.6457

Table D.3: Sensitivity with respect to $Z_{T,2001}$

	-4%	-3%	-2%	-1%	Calibrated Value	+1%	+2%	+3%	+4%
Agricultural Employment Share 2001	-0.000037	-0.000028	-0.000018	-0.000009	0.000000	0.000009	0.000018	0.000026	0.000034
Relative Wage 2001	-0.000080	-0.000059	-0.000039	-0.000019	0.000000	0.000019	0.000038	0.000056	0.000074
Agricultural Value-added Share 2001	-0.000063	-0.000047	-0.000031	-0.000015	0.000000	0.000015	0.000030	0.000044	0.000058
Agricultural Employment Share 2022	-0.000061	-0.000046	-0.000030	-0.000015	0.000000	0.000015	0.000029	0.000043	0.000057
Relative Wage 2022	-0.000080	-0.000059	-0.000039	-0.000019	0.000000	0.000019	0.000038	0.000056	0.000074
Agricultural Value-added Share 2022	-0.000085	-0.000063	-0.000041	-0.000020	0.000000	0.000020	0.000040	0.000059	0.000078
GDP 2022/ GDP 2001	-0.000004	-0.000003	-0.000002	-0.000001	0.000000	0.000001	0.000002	0.000003	0.000004

Table D.4: Sensitivity with respect to g_{z_T}

	-4%	-3%	-2%	-1%	Calibrated Value	+1%	+2%	+3%	+4%
Agricultural Employment Share 2001	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
Relative Wage 2001	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
Agricultural Value-added Share 2001	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
Agricultural Employment Share 2022	-0.000029	-0.000022	-0.000014	-0.000007	0.000000	0.000007	0.000014	0.000021	0.000028
Relative Wage 2022	-0.000038	-0.000028	-0.000019	-0.000009	0.000000	0.000009	0.000018	0.000027	0.000036
Agricultural Value-added Share 2022	-0.000040	-0.000030	-0.000020	-0.000010	0.000000	0.000010	0.000019	0.000029	0.000039
GDP 2022/ GDP 2001	-0.000012	-0.000009	-0.000006	-0.000003	0.000000	0.000003	0.000006	0.000009	0.000011

Table D.5: Sensitivity with respect to $\bar{h}_{2001}$

	-4%	-3%	-2%	-1%	Calibrated Value	+1%	+2%	+3%	+4%
Agricultural Employment Share 2001	3.1112	2.3304	1.5516	0.7748	0.0000	-0.7727	-1.5432	-2.3116	-3.0778
Relative Wage 2001	1.0380	0.7782	0.5186	0.2592	0.0000	-0.2590	-0.5178	-0.7763	-1.0346
Agricultural Value-added Share 2001	3.7790	2.8285	1.8818	0.9390	0.0000	-0.9351	-1.8662	-2.7932	-3.7162
Agricultural Employment Share 2022	5.1283	3.8355	2.5498	1.2713	0.0000	-1.2639	-2.5202	-3.7690	-5.0100
Relative Wage 2022	1.4071	1.0547	0.7028	0.3512	0.0000	-0.3507	-0.7011	-1.0509	-1.4003
Agricultural Value-added Share 2022	5.9599	4.4543	2.9590	1.4742	0.0000	-1.4634	-2.9159	-4.3573	-5.7876
GDP 2022/ GDP 2001	-0.1422	-0.1084	-0.0735	-0.0373	0.0000	0.0385	0.0782	0.1191	0.1612

Table D.6: Sensitivity with respect to σ

	-4%	-3%	-2%	-1%	Calibrated Value	+1%	+2%	+3%	+4%
Agricultural Employment Share 2001	-1.5742	-1.1693	-0.7721	-0.3824	0.0000	0.3754	0.7438	1.1056	1.4608
Relative Wage 2001	2.4167	1.8021	1.1945	0.5938	0.0000	-0.5871	-1.1676	-1.7416	-2.3092
Agricultural Value-added Share 2001	0.7291	0.5545	0.3746	0.1897	0.0000	-0.1941	-0.3924	-0.5947	-0.8008
Agricultural Employment Share 2022	-2.6078	-1.9388	-1.2813	-0.6351	0.0000	0.6244	1.2382	1.8418	2.4354
Relative Wage 2022	1.9673	1.4691	0.9752	0.4855	0.0000	-0.4813	-0.9585	-1.4316	-1.9006
Agricultural Value-added Share 2022	-0.6281	-0.4522	-0.2892	-0.1386	0.0000	0.1271	0.2430	0.3482	0.4430
GDP 2022/ GDP 2001	0.3013	0.2248	0.1491	0.0742	0.0000	-0.0735	-0.1462	-0.2183	-0.2897

Table D.7: Sensitivity with respect to g_{z_m}

	-4%	-3%	-2%	-1%	Calibrated Value	+1%	+2%	+3%	+4%
Agricultural Employment Share 2001	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Relative Wage 2001	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Agricultural Value-added Share 2001	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Agricultural Employment Share 2022	1.4512	1.0814	0.7163	0.3559	0.0000	-0.3514	-0.6983	-1.0409	-1.3793
Relative Wage 2022	1.8762	1.4009	0.9297	0.4628	0.0000	-0.4587	-0.9134	-1.3641	-1.8108
Agricultural Value-added Share 2022	3.0349	2.2611	1.4975	0.7438	0.0000	-0.7342	-1.4590	-2.1744	-2.8807
GDP 2022/ GDP 2001	-1.5371	-1.1537	-0.7697	-0.3851	0.0000	0.3857	0.7719	1.1587	1.5460