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Macroeconomic Impacts of College Expansion on Structural Transformation and Energy Economy in China: A Heterogeneous Agent General Equilibrium Approach

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Abstract: In this study, we construct heterogeneous agent general equilibrium models to investigate the relative importance of labor endowment in driving structural transformation. We aim to explore the following question: beyond the demand-side and supply-side structural transformation driving forces extensively studied in the existing literature, does labor, as a crucial endowment, play a pivotal role in facilitating structural transformation and the energy economy? In contrast to the prevalent partial equilibrium analyses, our study employs a general equilibrium framework to conduct a policy evaluation of college expansion, a significant policy that has altered the labor endowment structure in China. Our approach begins with developing a multi-sector model that integrates a nested CES production function and incorporates workers with different skill levels to assess the macroeconomic impact of college expansion on structural transformation. We calibrate the base model to reflect labor allocations across sectors and skill levels using the simulated method of moments (SMM), ensuring that the model-generated data align closely with actual labor allocation data. Utilizing this calibrated model, we perform counterfactual experiments to assess the impact and relative importance of the college expansion policy. Our counterfactual analysis demonstrates that the policy has resulted in an average decrease of 7.7% in labor allocation in the agricultural sector, alongside an average increase of 8.9% in the industry sector and 28.7% in the services sector. These results highlight the significant, yet often overlooked, contribution of labor in endowment-driven structural transformation. Furthermore, we extend the base model by constructing an industry-level heterogeneous agent general equilibrium model, enabling us to pinpoint which industries have developed as a result of the college expansion policy and recalibrate it at the industry level. This approach allows us to analyze the impact of changes in labor endowment on the energy economy. Counterfactual experiments conducted show that the college expansion policy has prompted a labor shift from industries with low energy efficiency and high pollution to high-end services. This macroeconomic pattern of structural transformation suggests that the college expansion policy has facilitated a transition toward a low-carbon economy by reducing dependency on high energy-consuming industries and promoting high-end services.



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1. Introduction

Structural transformation, also known as structural change, refers to the reallocation of economic activities across sectors (Herrendorf et al., 2014) [1]. The study of structural transformation dates back to the late 1930s, with Fisher (1939) being the pioneer in proposing a classification standard for the three sectors of the economy [2], analyzing the economic activities of these sectors based on indicators such as the employment share, value-added

share, and expenditure share. The early patterns of structural transformation are summarized by the Kuznets facts, stating that in the long run, both the value-added and labor shares of the agricultural sector decline, while those of the industry sector stabilize and those of the services sector increase (Kuznets, 1973) [3].

With the expanded availability of new data, researchers have enriched the characteristics of structural transformation beyond the Kuznets facts. For example, Duarte and Restuccia (2010) examine the labor shares across sectors and find that the characteristics of labor reallocation diverge from the traditional Kuznets facts [4], notably revealing that the labor share of industry sector first rises and then declines in the long-run in many countries. Similar stylized facts have been noted in China, for instance, Chen et al. (2011) observe that alongside the agricultural sector's declining share of the labor force [5], the industry sector displays a hump-shaped pattern with labor share initially increasing before experiencing a declining trend. Concurrently, the services sector undergoes consistent and rapid growth.

In the process of structural transformation in China, we emphasize the significant role of a particular policy in facilitating labor reallocation across sectors: the college expansion policy. Its implementation is intimately linked to China's unique national conditions. Driven by various factors, the Chinese government opted to substantially increase college enrollment rates in 1999. Specially, due to reforms in state-owned enterprises and the market economy, a large-scale unemployed population emerged in the 1990s, including 21.15 million laid-off workers. This surge in unemployed individuals exerted significant pressure on the job market. Meanwhile, the Asian financial crisis halted the rapid development of the Asian economy and quickly spread to China, leading to deflation, insufficient domestic demand, and a worsened labor market.

Against the backdrop of state-owned enterprise reform and the Asian financial crisis, China initiated a significant expansion of college enrollment to postpone young people's entry into the labor market and foster human capital for industrial upgrading. In 1998, the Central Committee of the Communist Party of China introduced the "Action Scheme for Invigorating Education Towards the 21st Century", deciding to implement a large-scale college expansion policy in China. The Ministry of Education subsequently unveiled a college admission plan, targeting 1.3 million students in 1999 and marking a 20% increase from 1998. By June of the same year, the admission target had surged to 1.56 million, representing an unprecedented 48% enrollment increase for colleges within a single year. Meanwhile, fiscal expenditures on higher education also saw rapid increases. As a result, the scale of colleges rapidly expanded. Consequently, this policy significantly increased the share of college-educated workers within the labor market, thereby transforming labor skill endowment distribution and impacting the structural transformation.

In this study, our objective is to investigate the following question: beyond the well-documented demand-side and supply-side drivers of structural transformation, does labor, as a vital endowment, play a critical role in propelling the structural transformation and energy economy? To address this issue, we use the college expansion policy, which significantly altered China's labor endowment structure, as a focal point to analyze the following three key aspects. First, what influence has the college expansion policy exerted on structural transformation? We aim to conduct a policy evaluation of the college expansion on structural transformation from a heterogeneous agent general equilibrium perspective. We argue that the expansion of higher education reshapes labor skill endowment by increasing the supply of college-educated workers, which subsequently reduces their relative wages. As both industry and services sectors require more skilled labor for production, the prices of corresponding sectoral products decrease. Consumers, reacting to these lower prices, increase their purchases from the industry and services sectors, thereby driving labor flows and therefore facilitating structural transformation. Second, what is the significance of changes in labor skill endowment within endowment-driven structural transformation? While the existing literature often highlights the influence of shifts in capital endowments, it frequently overlooks the critical role of labor in endowment-driven structural transformation. Through counterfactual analyses of eliminating the influence of change in labor

skill endowment and capital endowment, we argue that the magnitude of the impact of college expansion on structural transformation is as important as that of changes in capital endowments, underscoring the significant role that shifts in labor skill endowments play in driving structural transformation. Third, will college expansion foster sustainable development in China? We aim to analyze the impact of college expansion policy at the industry level to identify which specific industries have been promoted or inhibited by this policy. We argue that college expansion policy holds significant potential to advance sustainable economic development by driving changes in workforce skills, prompting industrial shifts, and aligning a nation's human capital with the needs of a greener economy. Enhanced alignment of workforce capabilities with future-oriented industries is essential for sustaining long-term economic growth and effectively addressing current and future sustainability challenges.

The rest of this paper is organized as follows. Section 2 reviews the relevant literature and proposes key hypotheses to be validated. Section 3 presents the base multi-sector heterogeneous agent general equilibrium model, which is calibrated and utilized to evaluate the impact and relative importance of the college expansion policy in driving structural transformation. Section 4 constructs the industry-level extended model that elucidates the influence of the college expansion policy on sustainable development in China. Section 5 summarizes the innovations, limitations, and future research directions of our study. And Section 6 concludes the paper.

2. Literature Review and Hypotheses Proposition

In this section, we will conduct a comprehensive review of the literature that is closely related to our study. Our review focuses on three key areas: policy evaluation of college expansion, the driving forces behind structural transformation, and the connection between college expansion, structural transformation, and sustainable development. Based on our discussion and analysis of the existing literature, we propose corresponding hypotheses whose validity will be examined in our subsequent quantitative analysis.

2.1. Policy Evaluation of College Expansion

Our research intersects with the three distinct literature strands, the first of which focuses on the policy evaluation of college expansion in China. Most studies approach this topic from a microlabor economics perspective by examining its effect on individual education returns and employment status. For instance, using data from the Urban Household Income and Expenditure Survey (UHIES), Meng et al. (2013) analyze changes in labor income between 1988 and 2009 [6], finding that college expansion leads to a reduced growth rate in the education returns for high-skilled labor. Li et al. (2009) [7], through an analysis of Chinese college graduates' wages, conclude that the college expansion policy fails to enhance the rate of return on education and accelerate human capital accumulation among graduates. Li et al. (2014) argue that the influx of high-skilled labor resulting from the college expansion policy increases the unemployment rate of college graduates by 6% to 9% [8]. Xing et al. (2018) further differentiate between the short-term and medium-term effects of college expansion on unemployment rates [9], noting that while college expansion indeed increases unemployment rates among college graduates in the short term, this effect largely dissipates after five years.

Our approach, however, positions the policy evaluation of college expansion within a macroeconomic framework, exploring the influence of educational expansions on labor allocations. In this context, our research, along with that of Lee and Malin (2013) and Porzio et al. (2022) [10,11], assesses the impact of educational expansions on the distribution of the macro labor force. Lee and Malin (2013) estimate a structural partial equilibrium model with an endogenous choice of education attainment level [10]. Their results suggest that the change in labor endowment due to educational expansions can explain 11% of the growth in output per worker, of which about 82% is realized through structural transformation. Porzio et al. (2022) compiled a dataset [11], which covers educational

reforms and political events relevant to individual educational costs around the world, based on data from the Integrated Public Use Microdata Series (IPUMS). Using a two-sector general equilibrium with endogenous educational choices and this novel dataset, they find that changes in the endowment of skilled labor count induce structural transformation.

It is essential to highlight our study's divergence from theirs in several aspects. Primarily, using data spanning 69 countries, Porzio et al. (2022) assess the broad effects of educational expansions—or what they refer to as human capital growth—on structural transformation [11]. The broad effects actually originate from a conglomeration of policies that aim to improve the labor skill endowment distribution. In contrast, our research specifically examines the direct effect of college expansion policy on structural transformation. Moreover, while both Lee and Malin (2013) and Porzio et al. (2022) focus on the movement of labor between the agricultural and non-agricultural sectors [10,11], there are significant differences in labor allocations across the industry and service sectors, which are lumped together into the non-agricultural sectors in these studies. Therefore, we seek to distinguish the differential impacts of college expansion on the structural transformation in the industry and services sectors. Indeed, in Section 4, we construct an industry-level heterogeneous agent general equilibrium model, enabling our quantitative analysis to observe labor shifts from industry sectors with low energy efficiency to high-end services. Furthermore, both Lee and Malin (2013) and Porzio et al. (2022) incorporate endogenous educational choices [10,11]; however, this approach may not be entirely applicable to studying the impact of college expansion policy on structural transformation in China. The implementation of the college expansion policy has increased the proportion of college graduates. However, before obtaining a college degree, one needs to participate in a competitive exam, the National College Entrance Examination (Gaokao), to gain admission to college. This examination is a highly competitive standardized test that high school students should take before they become admitted to colleges. Even though the optimal educational attainment level for some individuals might be college, they could still end up being recognized only with a high school diploma if they fail the competitive exam. In other words, due to the presence of this competitive exam, the supply of certifications for college degrees is inevitably lower than the demand. Therefore, using models that involve endogenous educational decisions to analyze the outcomes of college expansion policy may lead to inaccuracies. To illustrate this more clearly, we present the college enrollment rates from 1978 to 2022 in China in Figure 1.

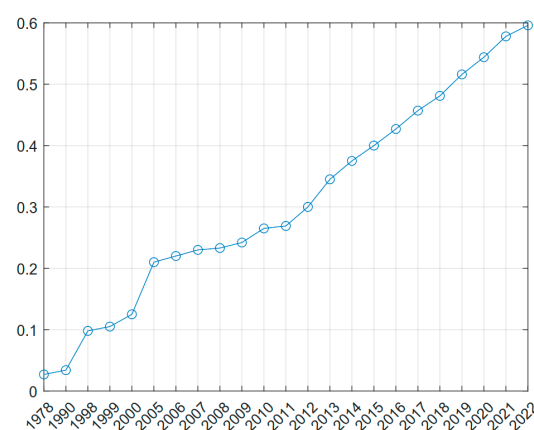


Figure 1. The college enrollment rates in China from 1978 to 2022. Source: Data compiled from the National Educational Development Statistics Bulletin (1998–2022), Ministry of Education of China.

This figure offers insights into two distinct aspects. On the one hand, since 1999, the college enrollment rate has experienced a substantial rise, increasing from 9.8% in 1998 to 59.6% by 2022. This demonstrates the effectiveness of the college expansion policy in augmenting the supply of high-skilled labor, thereby underscoring the importance of examining its influence on endowment-driven structural transformation. On the other

hand, despite the college expansion policy being in place for two decades, two-fifths of high school students still fail to secure college admission through the competitive National College Entrance Examination (Gaokao). Thus, we need to carefully consider the validity of incorporating endogenous educational decisions into our model. The data on college enrollment rates reveal that the supply of college degree certifications consistently falls short of the demand. Despite individuals making optimal decisions to become high-skilled laborers based on their circumstances, some of them may still be unable to gain college admission, thus entering the labor market as medium-skilled labor instead. Given these considerations, we suggest that endogenized educational decisions may not be appropriate for modeling the impact of the college expansion policy. Consequently, in our model, we consider the labor endowment for different skill levels as exogenously determined. This approach views the labor endowment as an equilibrium outcome, which is annually adjusted and influenced by the college expansion policy.

Based on the analysis above, we argue that college expansion policy alters the labor skill endowment distribution by increasing the proportion of high-skilled labor within the overall workforce, effectively reducing the cost of employing college-educated labor. On the one hand, since labor inputs are substitutes, firms show a marked preference for substituting medium-skilled and low-skilled labor with high-skilled labor. On the other hand, as both the industry and services sectors require more high-skilled labor in production compared to the agricultural sector, the prices of outputs in these sectors decrease more rapidly, prompting consumers to purchase more from them. As a result, the influx of labor predominantly flows into the services and industry sectors, thereby driving structural transformation. To validate the mechanism, we develop and calibrate a multi-sector model that incorporates labor with various skill levels to examine the impacts of the college expansion policy on structural transformation. Accordingly, we propose testing the following hypothesis through the following general equilibrium model:

Hypothesis 1 (H1). *The college expansion policy propels labor reallocation from the agricultural sector to the industry and services sectors.*

2.2. The Driving Forces behind Structural Transformation

The second strand of the literature delves into the driving forces propelling structural transformation. Structural transformation is categorized based on these driving forces into demand-side-driven, supply-side-driven, and endowment-driven structural transformation. First, the demand-side-driven structural transformation occurs either through non-homothetic preferences or ordered preferences. With non-homothetic preferences, sectors with different income elasticities of demand experience varying changes in consumption demand as income rises. Higher-income elasticity leads to an increased consumption share and a corresponding labor shift toward that sector. Conversely, sectors with lower income elasticity grow at a slower rate, triggering structural transformation (Echevarria, 1997; Laitner, 2000; Caselli and Coleman II, 2001; Kongsamut et al., 2001; Gollin et al., 2002; Gollin et al., 2007; Boppart 2014; Alder et al., 2022) [12–19]. Alternatively, ordered preferences suggest that individuals with higher incomes favor new products, leading to the emergence and growth of new sectors. Horizontal innovation and expanding product varieties drive labor toward these new sectors, thus facilitating structural transformation (Foellmi and Zweimüller, 2008; Buera and Kaboski, 2012b) [20,21].

Second, the supply-side-driven structural transformation is driven by changes in productivity and relative prices of products. Uneven growth of productivity among sectors will result in changes in relative prices of products, thus driving the process of structural transformation. Baumol (1967) is the first to highlight that sectoral relative productivity shifts alter relative product prices, thereby affecting labor allocation [22]. If the elasticity of substitution between sectoral outputs is less than 1, increased productivity in a sector lowers its product prices, raising equilibrium consumption levels and necessitating labor shifts toward less productive sectors to meet production needs. Conversely, if the elasticity

of substitution exceeds 1, consumers prefer cheaper products, shifting labor from less to more productive sectors (Ngai and Pissarides, 2007) [23]. This logic extends to open economies and trade introduces comparative advantages based on productivity differences across countries, influencing labor shifts between sectors depending on output substitution elasticity (Matsuyama, 2009; Uy et al., 2013; Matsuyama, 2019) [24–26].

The endowment-driven structural transformation focuses on labor reallocations driven by changes in production factors. Much research examines the impact of capital on structural transformation. Acemoglu and Guerrieri (2008) note that varying input intensities across sectors result in capital deepening, which alters input (capital and labor) prices and, consequently, output prices. This change affects product demand from different industries, driving structural transformation [27]. Ju et al. (2015) extend the Rybczynski Theorem, suggesting that capital accumulation accelerates growth in capital-intensive sectors in a two-input economy (capital and labor) [28]. Their endogenous growth model, featuring infinite industries, emphasizes that enhancing endowment structures, particularly through capital accumulation, is a new mechanism driving structural transformation. Alvarez-Cuadrado et al. (2017) argue that sectors with higher input substitution elasticity expand as they adapt better to rising labor wages due to capital accumulation [29].

While previous studies have predominantly focused on the role of capital in endowment-driven structural transformation, the impact of labor endowment has been somewhat overlooked. In this paper, we highlight the significant yet often underestimated role of labor endowment changes in driving structural transformation, paralleling the influence of capital. To evaluate the comparative importance of changes in labor skill endowment versus capital endowment, we will perform two counterfactual analyses using our calibrated model. These analyses will independently isolate the effects of changes in labor skill endowments and capital endowments, allowing us to gauge their relative contributions to structural transformation. Therefore, we propose testing the following hypothesis in our quantitative analysis:

Hypothesis 2 (H2). *Changes in labor skill endowments are critical in promoting structural transformation, which is as important as changes in capital endowments.*

2.3. College Expansion, Structural Transformation, and Energy Economy

The third strand of the literature related to our research focuses on energy economy and sustainable development, a concept widely acknowledged as integrating three core dimensions: environmental, economic, and social aspects (Giddings et al., 2002; Costanza et al., 2016; Scoones et al., 2020) [30–32]. The emphasis on the sustainability of the energy economy highlights the need for a shift in China's development model. While the rapid expansion of the industry sector has been a cornerstone of China's economic growth, it also poses severe challenges to achieving sustainable development. The prevailing growth pattern within the Chinese industrial sector is characterized by high labor intensity and considerable energy and resource consumption, leading to urgent environmental concerns (Lin and Xu, 2014) [33]. This growth pattern has precipitated significant increases in pollution and carbon emissions. The unchecked expansion of energy-intensive industries exacerbates inefficiencies in energy consumption, undermining efforts toward sustainable development (Jiang et al., 2014; Chen 2014; Herreras et al., 2014) [34–36].

The consequences of this expansive growth manifest in frequent smog and pollution incidents, severely compromising public health and impeding sustainable economic advancement (Lu et al., 2015; Xu and Lin, 2017) [37,38]. Moreover, enduring environmental issues such as acid rain and water eutrophication persistently impact daily life and hinder China's pursuit of sustainable development (Liu et al., 2016; Zhang et al., 2016) [39,40]. Therefore, it is imperative to promote structural transformation that accelerates the migration of labor away from industries associated with high levels of pollution. Such labor reallocation from energy-intensive industries ensures a more sustainable way of development and helps achieve the goals of green growth in China (Yu et al., 2018; Tian and Zhou,

2019) [41,42]. This structural transformation trend significantly enhances energy efficiency and facilitates a shift toward China's sustainable development (Schäfer, 2005; Li and Lin, 2017) [43,44].

We argue that college expansion plays a pivotal role in fostering sustainable development of the energy economy by facilitating labor shifts away from traditional pollution-heavy industries toward knowledge-intensive and innovative industries. This transformation is driven by a combination of economic innovation and broader societal changes that support a greener future. First, college expansion significantly increases the availability of high-skilled labor. These college-educated workers are well-versed in new technologies, making them essential for adapting to and promoting solutions that reduce carbon footprints and enhance resource efficiency (Lee and Heijden 2020; Hémous and Olsen, 2022; Ma, 2023) [45–47]. Their expertise drives innovation in sustainable practices, leading to advancements in energy efficiency, waste reduction, and eco-friendly solutions across industries (Jin et al., 2019; Xie et al., 2020; Alam et al., 2023) [48–50]. Beyond its direct economic impact, college expansion cultivates broader societal changes crucial for long-term sustainability. Colleges often offer programs and courses focused on environmental science and sustainability, which can elevate awareness and train professionals in fields critical to addressing environmental challenges (Arshad et al., 2020; Karpan et al., 2020; Menon and Suresh, 2020; Carducci et al., 2021) [51–54]. This leads to heightened public consciousness regarding environmental issues, fueling a greater demand for sustainable products and services. The combination of these factors leads to a shift toward a more sustainable development paradigm.

To examine whether the college expansion policy facilitates the low carbon economy in China, we develop an industry-level heterogeneous agent general equilibrium model, with which we will conduct a quantitative analysis of the impact of college expansion on industries. We aim to identify the industries that have experienced rapid growth or decline due to the college expansion policy. Based on the preceding analysis, we attempt to test the following hypothesis:

Hypothesis 3 (H3). *The college expansion policy restructures labor reallocation across industries, accelerating the transition toward a low-carbon economy in China.*

3. Model

In this section, we construct a heterogeneous agent general equilibrium model to demonstrate how the change in labor endowment drives the structural transformation in China. There are three sectors in this model, with labor being the only input in these sectors. We categorize labor into three types: workers with a college degree or higher are classified as high-skilled labor (denoted by H), those with a high school diploma are classified as medium-skilled labor (denoted by M), and low-skilled labor (denoted by L) refers to workers with a junior high school education or less. Even when considering heterogeneous agents with different educational attainment, researchers are often inclined to divide labor skill levels into only two categories for simplicity (e.g., Liao, 2020; Fang and Herrendorf, 2021) [55,56]. But we choose this three-level classification mainly for the reason beneath. Since this paper aims to study the impact of college expansion policy on structural transformation, a clear distinction between individuals with college or higher education and those with a high school or less education is essential. In addition, considering the significant difference in human capital levels between workers with a high school education and those with a junior high school education or less, it is necessary to further differentiate between the two education attainment levels.

3.1. Technology

There are three sectors producing agricultural goods, industrial goods and services in our model, and we index them by $i \in \{a, m, s\}$, respectively. Goods and services are produced using labor with constant returns to scale technologies:

$$Y_i = A_i \left\{ \alpha_i n_{iH}^{\frac{\varepsilon-1}{\varepsilon}} + (1 - \alpha_i) \left\{ \left[\beta_i n_{iM}^{\frac{\eta-1}{\eta}} + (1 - \beta_i) n_{iL}^{\frac{\eta-1}{\eta}} \right]^{\frac{\eta}{\eta-1}} \right\}^{\frac{\varepsilon-1}{\varepsilon}} \right\}^{\frac{\varepsilon}{\varepsilon-1}}, \quad (1)$$

where Y_i is the sectoral output; n_{iL} , n_{iM} , and n_{iH} are hours worked by the low-skilled, medium-skilled, and high-skilled laborers engaged in sector i ; A_i is the sector-specific productivity; $\alpha_i, \beta_i \in (0, 1)$ and capture the input intensity; and $\varepsilon, \eta \in [0, +\infty)$ are the elasticities of substitution between inputs. Similar to Ngai et al. (2019) and Buera et al. (2022) [57,58], labor is the only input in our model and thus A_i captures the influence of capital accumulation. This production function is a nested CES production function, which hierarchically combines multiple CES functions and allows for more complex substitution patterns between labor inputs. We adopt this production function because data from actual economic production reveal that all sectors employ labor at three skill levels, namely low-skilled labor, medium-skilled labor, and high-skilled labor. Thus, assuming that workers with different skill levels are perfect substitutes would lead sectors to hire only the type of least costly workers, which contradicts actual data. In our model, labor inputs are combined to produce outputs according to the CES production function, which implies that the marginal productivity of labor with any skill level approaches infinity when the amount of this kind of labor employed in production is sufficiently small. Therefore, corner solutions are eliminated, where firms in specific sectors employ only labor with a certain skill level. Since there are three skill levels in our model, we use nested CES functions to represent more flexible relationships between inputs than simple CES functions could. This setup helps illustrate the effects of labor-driven, rather than capital-driven structural transformation.

Firms employ labor and sell products to consumers in order to maximize profits.

$$\max_{\{n_{iL}, n_{iM}, n_{iH}\}} p_i Y_i - w_L n_{iL} - w_M n_{iM} - w_H n_{iH}, \quad (2)$$

where p_i is the price of output produced by sector i and w_L , w_M , and w_H refer to the wage paid to low-skilled, medium-skilled, and high-skilled laborers, respectively.

By solving the firms' profit maximization problems, we obtain first order conditions as follows:

$$\alpha_i p_i A_i \left(\frac{Y_i}{A_i} \right)^{\frac{1}{\varepsilon}} n_{iH}^{-\frac{1}{\varepsilon}} = w_H, \quad (3)$$

$$(1 - \alpha_i) \beta_i p_i A_i \left(\frac{Y_i}{A_i} \right)^{\frac{1}{\varepsilon}} \left[\beta_i n_{iM}^{\frac{\eta-1}{\eta}} + (1 - \beta_i) n_{iL}^{\frac{\eta-1}{\eta}} \right]^{\frac{\varepsilon-\eta}{\varepsilon(\eta-1)}} n_{iM}^{-\frac{1}{\eta}} = w_M, \quad (4)$$

$$(1 - \alpha_i)(1 - \beta_i) p_i A_i \left(\frac{Y_i}{A_i} \right)^{\frac{1}{\varepsilon}} \left[\beta_i n_{iM}^{\frac{\eta-1}{\eta}} + (1 - \beta_i) n_{iL}^{\frac{\eta-1}{\eta}} \right]^{\frac{\varepsilon-\eta}{\varepsilon(\eta-1)}} n_{iL}^{-\frac{1}{\eta}} = w_L. \quad (5)$$

3.2. Preference

The utility function for a consumer with skill level of $e \in \{L, M, H\}$ is given by

$$U_e = \left[\varphi_a^{\frac{1}{\gamma}} (c_{ae} - \bar{c}_a)^{\frac{\gamma-1}{\gamma}} + \varphi_m^{\frac{1}{\gamma}} c_{me}^{\frac{\gamma-1}{\gamma}} + \varphi_s^{\frac{1}{\gamma}} c_{se}^{\frac{\gamma-1}{\gamma}} \right]^{\frac{\gamma}{\gamma-1}}, \quad (6)$$

where c_{ae} , c_{me} , and c_{se} denote the consumption of agricultural goods and industrial goods and services, respectively; $\bar{c}_a > 0$ is the subsistence level for agricultural goods; $\varphi_a, \varphi_m, \varphi_s \in (0, 1)$ and satisfy that $\varphi_a + \varphi_m + \varphi_s = 1$; and γ is the elasticity of substitution between goods and services.

The budget constraint faced by a consumer with skill level of $e \in \{L, M, H\}$ is

$$p_a c_{ae} + p_m c_{me} + p_s c_{se} \leq w_e. \quad (7)$$

Consumers maximize their utility subject to the budget constraint and the optimality conditions are

$$\frac{c_{ae} - \bar{c}_a}{c_{me}} = \frac{\varphi_a}{\varphi_m} \left(\frac{p_a}{p_m} \right)^{-\gamma}, \quad (8)$$

$$\frac{c_{me}}{c_{se}} = \frac{\varphi_m}{\varphi_s} \left(\frac{p_m}{p_s} \right)^{-\gamma}. \quad (9)$$

Furthermore, the optimal consumption bundles of a consumer with a skill level of $e \in \{L, M, H\}$ are

$$c_{ae} = \frac{\varphi_a}{\varphi_a + \varphi_m \left(\frac{p_m}{p_a} \right)^{1-\gamma} + \varphi_s \left(\frac{p_s}{p_a} \right)^{1-\gamma}} \frac{w_e - p_a \bar{c}_a}{p_a} + \bar{c}_a, \quad (10)$$

$$c_{me} = \frac{\varphi_m}{\varphi_a \left(\frac{p_a}{p_m} \right)^{1-\gamma} + \varphi_m + \varphi_s \left(\frac{p_s}{p_m} \right)^{1-\gamma}} \frac{w_e - p_a \bar{c}_a}{p_m}, \quad (11)$$

$$c_{se} = \frac{\varphi_s}{\varphi_a \left(\frac{p_a}{p_s} \right)^{1-\gamma} + \varphi_m \left(\frac{p_m}{p_s} \right)^{1-\gamma} + \varphi_s} \frac{w_e - p_a \bar{c}_a}{p_s}. \quad (12)$$

3.3. Market Clearing Conditions and Equilibrium

We define n_e as the hours supplied by labor with a skill level of $e \in \{L, M, H\}$ and the total hours supplied by labor engaged in the economy is normalized to 1, i.e., $n_L + n_M + n_H = 1$.

The market clearing conditions for labor in the input market are

$$n_L = n_{aL} + n_{mL} + n_{sL}, \quad (13)$$

$$n_M = n_{aM} + n_{mM} + n_{sM}, \quad (14)$$

$$n_H = n_{aH} + n_{mH} + n_{sH}. \quad (15)$$

The market clearing condition for goods and services in the output market are

$$Y_a = n_L c_{aL} + n_M c_{aM} + n_H c_{aH}, \quad (16)$$

$$Y_m = n_L c_{mL} + n_M c_{mM} + n_H c_{mH}, \quad (17)$$

$$Y_s = n_L c_{sL} + n_M c_{sM} + n_H c_{sH}, \quad (18)$$

where the optimal consumption bundles have been defined by Equations (10)–(12).

The competitive equilibrium in our model is jointly defined by the output prices $\{p_i\}_{i=a,m,s}$, the labor wages $\{w_e\}_{e=L,M,H}$, the consumption bundles of agricultural goods and industrial goods and services $\{c_{ae}, c_{me}, c_{se}\}_{e=L,M,H}$, and the labor allocations $\{n_{ae}, n_{me}, n_{se}\}_{e=L,M,H}$. In total, there are 24 variables. By solving the optimization problems of consumers and firms, we obtain 18 first-order conditions. The market clearing conditions for goods and services help determine the equilibrium prices $\{p_i\}_{i=a,m,s}$, while the equilibrium wages $\{w_e\}_{e=L,M,H}$ can be determined by the labor market clearing conditions. Thus, the competitive equilibrium can be described by a nonlinear system comprising 24 equations for 24 variables.

3.4. Quantitative Analysis

In this subsection, we conduct the quantitative analysis of the heterogeneous agent general equilibrium model. First, we calibrate the model using data from the Socio-Economic Accounts (SEA) provided by the WIOD database [59]. Then, we evaluate the model performance by examining the discrepancies between the real data and the nontargeted moments generated by the calibrated model. Finally, we carry out a series of counterfactual experiments using the calibrated model. By analyzing the results of these experiments, we are able to quantitatively assess the impact of college expansion on structural transformation.

3.4.1. Data

Data required for calibration include sectoral labor participation of differently skilled workers and outputs. We use data from the SEA dataset provided by the WIOD database, which covers labor inputs and outputs for major countries worldwide. We chose the SEA dataset because official statistics from China rarely report labor inputs by industry and skill level. In contrast, the SEA dataset is comprehensive, offering detailed output and labor input data by skill level across industries. Additionally, although many micro surveys provide detailed information on individual educational attainment and employment, which enables aggregation to sectoral labor participation rates by skill, the corresponding output data (crucial for calibrating productivity parameters in our model) are not available. Therefore, we cannot use these micro survey data for calibration.

The SEA dataset has three versions in total. The 2012 and 2014 releases provide labor allocation series by skill level from 1995 to 2009. The 2016 release provides sectoral output data and total labor input data from 2010 to 2014 but it lacks data on labor inputs by skill level. Therefore, we need to use additional data to construct a labor allocation series by skill level for the period from 2010 to 2014. We will next explain how we use the SEA dataset, in conjunction with the *China Labor Statistical Yearbook*, to construct industry-level output and labor input series by skill level from 1995 to 2014 for calibrating our model.

For the data from 1995 to 2009, the SEA dataset does not directly provide industry-level working hours for labor by skill level. Instead, it provides data on labor working hours across 33 industries (indexed by 'H_EMP') and the share of working hours supplied by low-skilled, medium-skilled, and high-skilled labor (indexed by 'H_LS', 'H_MS', and 'H_HS', respectively) within each industry. By processing these data, we can obtain industry-level working hours for labor by skill level and classify them into three sectors: agriculture, industry, and services. Thus, the shares of working hours for labor with different skill levels across these three sectors can be determined. A similar method is applied to obtain industry output data from the SEA dataset.

For the data from 2010 to 2014, we refer to the *China Labor Statistical Yearbook* from 2010 to 2014, which provides the proportions of labor with different educational attainments in each industry. Although the official data do not report specific labor inputs by skill level for each industry, combining this with the SEA dataset allows us to calculate labor inputs by skill level for each industry. It is worth noting that the SEA dataset 2016 release categorizes industries more finely than the *China Labor Statistical Yearbook*. Specifically, the 2016 release includes data for 56 industries, while the yearbooks classify industries into 20 categories. Therefore, we need to aggregate the industries in the SEA dataset 2016 release to match the 20 categories in the yearbooks. For example, we combine "Financial service activities, except insurance and pension funding", "Insurance, reinsurance and pension funding, except compulsory social security", and "Activities auxiliary to financial services and insurance activities" into the "Financial intermediation" category of the yearbooks. This aggregation allows us to obtain output and total labor input data for 20 industry sectors as listed in the *China Labor Statistical Yearbook*. Using the proportions of labor with different educational attainments provided by the yearbooks, we can derive output and labor input data by skill level for these 20 industries. By further aggregating these 20 industries into agriculture, manufacturing, and services, we obtain output and labor input series by skill level for the three sectors from 2010 to 2014. Combining these data with

the corresponding data from 1995 to 2009 enables us to calibrate our model and analyze the impact of the college expansion policy on structural transformation from 1995 to 2014.

3.4.2. Calibration

The calibration strategy used here is similar to Rogerson (2008) [60]; our aim is to match the labor allocation (in terms of working hours) generated by the model with the real data in 1995 and 2009 using the simulated method of moments (SMM). Model parameters to be calibrated include preference parameters $\{\varphi_m, \varphi_s, \gamma, \bar{c}_a\}$, production parameters $\{\alpha_a, \beta_a, \alpha_m, \beta_m, \alpha_s, \beta_s, \varepsilon, \eta\}$, and productivity parameters $\{A_i(t)\}_{i \in \{a, m, s\}}$. We do not calibrate φ_a since $\varphi_a + \varphi_m + \varphi_s = 1$ holds and $\{\varphi_m, \varphi_s\}$ will be pinned down in our calibration.

Similar to Fang and Herrendorf (2021) [56], the TFP parameters $\{A_i(t)\}_{i \in \{a, m, s\}}$ are allowed to vary over time and match the labor productivity in real data, Y_i/n_i where $n_i = n_{iL} + n_{iM} + n_{iH}$ is the sectoral labor allocation. Parameters that are still unknown are jointly calibrated and we choose labor allocations in 1995 and 2009 as targets. It should be noted that while the labor allocation consists of 9 components, i.e., $\{n_{ae}, n_{me}, n_{se}\}_{e=L, M, H}$, only 6 observations each year will be useful to pin down values of model parameters, for the reason that the labor endowment is given for the specific skill level. For instance, since the supplied working hours of low-skilled labor n_L is given, if the model-generated n_{mL} and n_{sL} are close enough to the corresponding real data, then the model-generated n_{aL} will match real data automatically.

The calibration results are summarized in Table 1, where the moments and corresponding real data utilized for calibration are presented in the first two columns and the parameters along with their calibrated values are shown in the last two columns. In the third column, the values generated by our calibrated model indicate that the labor allocation for low-skilled and high-skilled workers is identical. As for the labor allocation of medium-skilled labor, there are only minimal differences, at most 0.002, between the real data and the model-generated data. The calibrated value of γ lying between (0,1) implies that outputs across sectors are gross complements and calibrated elasticities of substitution between labor with different skill levels exceed 1, which means that inputs are substitutes and are consistent with Fang and Herrendorf (2021) [56]. Other calibrated parameter values appear to be reasonable as well.

Table 1. Calibration results of the base model.

Moments	Data Values	Model Values	Relevant Parameter	Parameter Values
Initial period (1995) moments				
Share of low-skilled labor in industry	0.176	0.176	φ_m	0.262
Share of low-skilled labor in services	0.146	0.146	φ_s	0.704
Share of medium-skilled labor in industry	0.102	0.101	β_m	0.613
Share of medium-skilled labor in services	0.136	0.134	β_s	0.661
Share of high-skilled labor in industry	0.005	0.005	α_m	0.832
Share of high-skilled labor in services	0.018	0.018	α_s	0.913
Final period (2014) moments				
Share of low-skilled labor in industry	0.203	0.203	γ	0.931
Share of low-skilled labor in services	0.187	0.189	α_a	0.517
Share of medium-skilled labor in industry	0.159	0.159	$\bar{c}_a$	0.036
Share of medium-skilled labor in services	0.249	0.249	β_a	0.409
Share of high-skilled labor in industry	0.022	0.021	η	2.995
Share of high-skilled labor in services	0.071	0.071	ε	1.727

In econometric models, researchers aim to obtain asymptotically consistent estimators based on the assumptions of error terms. Statistical inference then determines the significance of the estimated coefficients, making econometric models a potent academic tool for testing research hypotheses. However, in macroeconomic studies, researchers often resort to calibration as a method to process real-world data. During calibration, researchers adjust model parameters to align the model-generated equilibrium results with known

economic outcomes, referred to as ‘moments’ in macroeconomics. Therefore, the most crucial criterion for calibration is that the general equilibrium model, based on specific parameter values, closely matches the model-generated data with actual data.

A common approach to test this match involves selecting certain moments and conducting a global search for parameter values that ensure the model-generated data corresponds with these selected moments, i.e., targeted moments. By comparing other important data moments—referred to as ‘nontargeted moments’ because they are not involved in parameter determination—with the model-generated data based on the calibrated parameters, we can evaluate the accuracy and quality of the calibration results. For instance, to investigate the goodness of fit of our calibrated model, we concentrate on a series of nontargeted moments. Given that the model is calibrated using only the labor allocation for the initial (1995) and final (2014) periods, the labor allocations from 1996–2013 are nontargeted and serve to illustrate the performance of our calibrated model. Table 2 summarizes the simulations of these nontargeted moments and their comparison with actual data.

Table 2. Simulations of nontargeted moments and comparison with actual data.

Moments	Low-Skilled Labor in Industry		Low-Skilled Labor in Services		Medium-Skilled Labor in Industry		Medium-Skilled Labor in Services		High-Skilled Labor in Industry		High-Skilled Labor in Services	
	Data Values	Model Values	Data Values	Model Values	Data Values	Model Values	Data Values	Model Values	Data Values	Model Values	Data Values	Model Values
1996	0.180	0.182	0.149	0.150	0.106	0.107	0.144	0.141	0.005	0.005	0.020	0.020
1997	0.179	0.184	0.144	0.151	0.110	0.111	0.147	0.145	0.006	0.006	0.021	0.021
1998	0.183	0.187	0.141	0.152	0.110	0.113	0.150	0.147	0.006	0.006	0.022	0.022
1999	0.173	0.186	0.134	0.150	0.113	0.115	0.150	0.149	0.006	0.006	0.024	0.024
2000	0.169	0.183	0.134	0.147	0.113	0.118	0.155	0.152	0.007	0.007	0.025	0.025
2001	0.172	0.181	0.151	0.145	0.109	0.120	0.163	0.154	0.006	0.007	0.027	0.027
2002	0.163	0.177	0.154	0.141	0.116	0.122	0.172	0.156	0.007	0.008	0.029	0.028
2003	0.167	0.177	0.150	0.143	0.114	0.123	0.177	0.160	0.008	0.009	0.033	0.032
2004	0.175	0.183	0.157	0.150	0.117	0.126	0.183	0.165	0.009	0.009	0.036	0.035
2005	0.172	0.187	0.161	0.155	0.126	0.130	0.185	0.173	0.010	0.011	0.042	0.041
2006	0.184	0.187	0.159	0.159	0.132	0.136	0.187	0.185	0.013	0.013	0.048	0.047
2007	0.187	0.191	0.165	0.168	0.136	0.137	0.192	0.193	0.012	0.013	0.047	0.046
2008	0.189	0.191	0.163	0.164	0.139	0.140	0.190	0.194	0.014	0.014	0.049	0.049
2009	0.192	0.192	0.168	0.169	0.141	0.144	0.201	0.202	0.014	0.014	0.051	0.050
2010	0.195	0.194	0.170	0.172	0.145	0.149	0.206	0.209	0.015	0.016	0.055	0.055
2011	0.194	0.193	0.174	0.177	0.143	0.148	0.212	0.218	0.016	0.016	0.058	0.059
2012	0.199	0.198	0.171	0.176	0.151	0.155	0.220	0.225	0.019	0.018	0.061	0.063
2013	0.202	0.201	0.182	0.186	0.153	0.156	0.234	0.237	0.020	0.020	0.067	0.068

The results in Table 2 indicate that the model-generated data align with the actual labor allocations quite well. The average prediction errors in absolute values are 1.89 points (for low-skilled labor in industry), 1.03 points (for low-skilled labor in services), 0.91 points (for medium-skilled labor in industry), 0.83 points (for medium-skilled labor in services), 0.05 points (for high-skilled labor in industry), and 0.07 points (for high-skilled labor in services), respectively. Even when considering relative prediction errors, the highest observed value remains below 10%. The discussions above indicate that our calibrated model performs well at prediction, thus validating its suitability for counterfactual analysis.

3.4.3. Counterfactual Analysis

In this subsection, we conduct two counterfactual experiments, based on the calibrated model, to demonstrate the impact of the college expansion policy on structural transformation in China and to highlight the role of labor in endowment-driven structural transformation.

The first counterfactual experiment conducted aims to remove the impact of the college expansion policy. To accomplish this, we reconstruct the labor endowment series under the assumption that the college expansion policy had not been implemented.

First, we calculate the hours worked by laborers with different skill levels using the SEA dataset. Next, we compute the growth rate of working hours for medium-skilled labor during the period from 1995 to 2002. This is because, starting in 2003, the first and subsequent high-skilled cohorts affected by the college expansion policy started to enter the labor market gradually, resulting in a decline in the growth rate of working hours for medium-skilled labor. In fact, the growth rate of working hours for medium-skilled labor from 1995 to 2002 was nearly twice as high as that of the period from 2003 to 2009. The decline is attributed to a segment within the high-skilled labor force that, under ordinary circumstances, would not have qualified for college admission and the chance to become high-skilled workers. Instead, they would have entered the market as medium-skilled labor. However, the implementation of the college expansion policy enabled them to become high-skilled labor. Then, we project that the working hours for medium-skilled labor would have continued to grow at the rate observed from 1995 to 2002 through the period from 2003 to 2009 to generate the counterfactual series of working hours for medium-skilled labor. Finally, since the college expansion policy has a negligible effect on low-skilled labor (defined as those with a junior high school education or less), its implementation does not alter the relevant data for low-skilled labor. Therefore, under the assumption that the total supply of working hours remains constant, we calculate the counterfactual series of working hours for high-skilled labor. We begin by calculating the growth rate of working hours for medium-skilled labor rather than high-skilled labor. This approach is selected because medium-skilled labor exactly corresponds to workers with a high school diploma, whereas high-skilled labor encompasses some graduates who do not directly relate to the college expansion policy. In order to achieve a more accurate assessment of the impact of college expansion on structural transformation, we decide to concentrate on the growth rate of working hours for medium-skilled labor and then conduct subsequent calculations. Using the counterfactual labor endowment series, we are able to figure out the labor allocations, which are shown in Figure 2.

The results indicate that the college expansion policy has released some labor from the agricultural sector into the non-agricultural sectors. This is because the implementation of the college expansion policy increases the supply of high-skilled labor, thus reducing the cost for firms to hire high-skilled workers. Given that labor inputs are substitutes, it must be recalled that the calibrated elasticities of substitution are greater than 1 and that sectors tend to employ more high-skilled labor in place of low-skilled and medium-skilled labor. Since the services sector requires a higher input of high-skilled labor ($\alpha_s > \alpha_m > \alpha_a$), there will be a greater influx of high-skilled workers into this sector. To observe this more clearly, we aggregate labor allocations at the skill level of the workers, yielding data on labor allocations across the three sectors, which are presented in Figure 3. It is evident that the implementation of the college expansion policy has, on average, reduced the working hours of agricultural sector labor by 7.7%, increased the working hours of industry sector labor by 8.9%, and significantly boosted the working hours of the services sector labor by 28.7%.

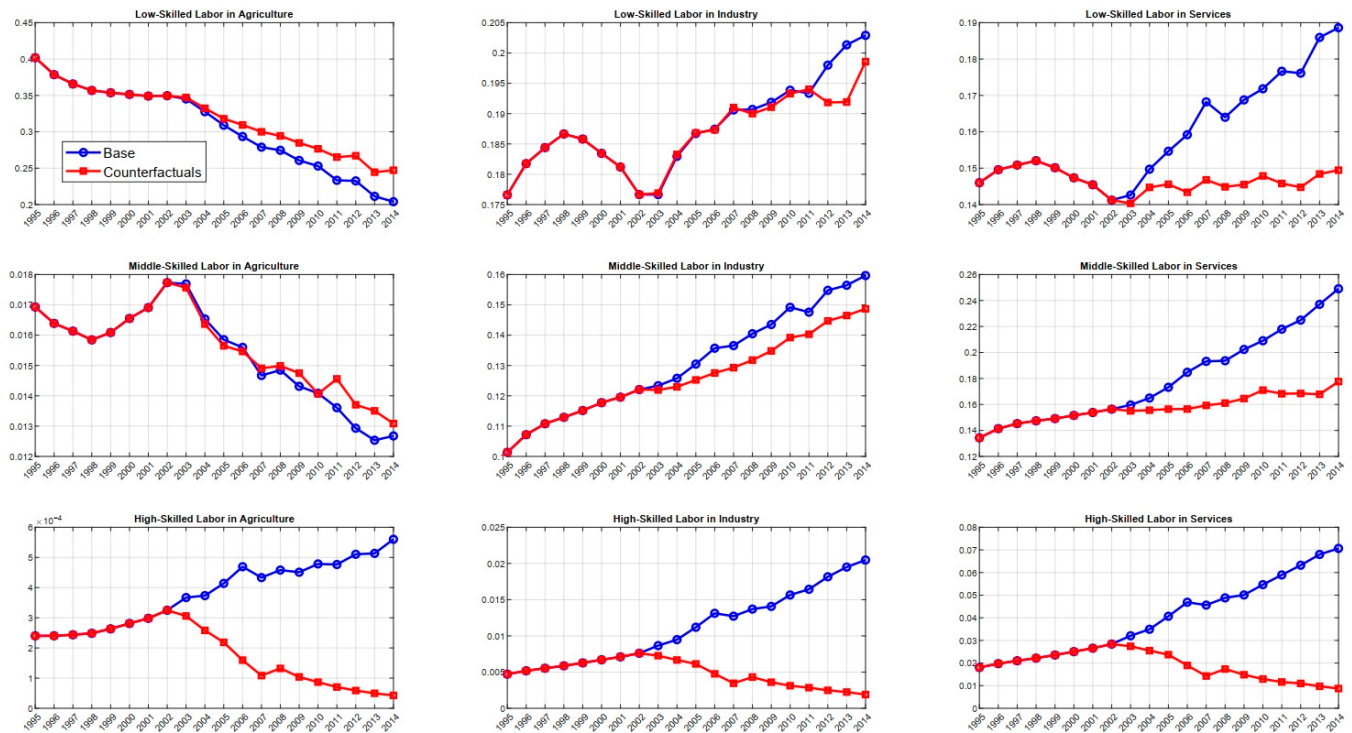


Figure 2. Labor allocations across sectors and skill levels by removing the impact of the college expansion policy.

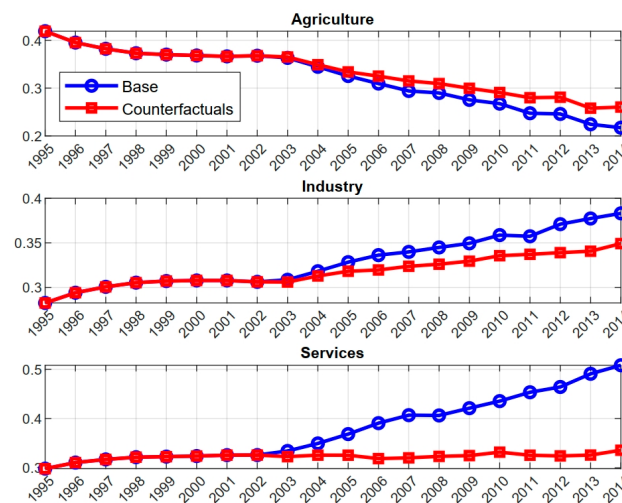


Figure 3. Labor allocations across sectors by removing the impact of the college expansion policy.

In our second counterfactual experiment, we explore the scenario of removing the influence of capital accumulation. Our model abstracts from capital, capturing capital accumulation through productivity parameters $\{A_i(t)\}_{i \in \{a,m,s\}}$, following Rogerson (2008), Ngai et al. (2019), and Garriga et al. (2021) [57,60,61]. To eliminate the effect of capital accumulation, we shut down the growth of $\{A_i(t)\}_{i \in \{a,m,s\}}$ starting from 2003, effectively fixing the productivity parameters at their 2002 levels for the period 2003 to 2009. The counterfactual experiment results are depicted in Figure 4.

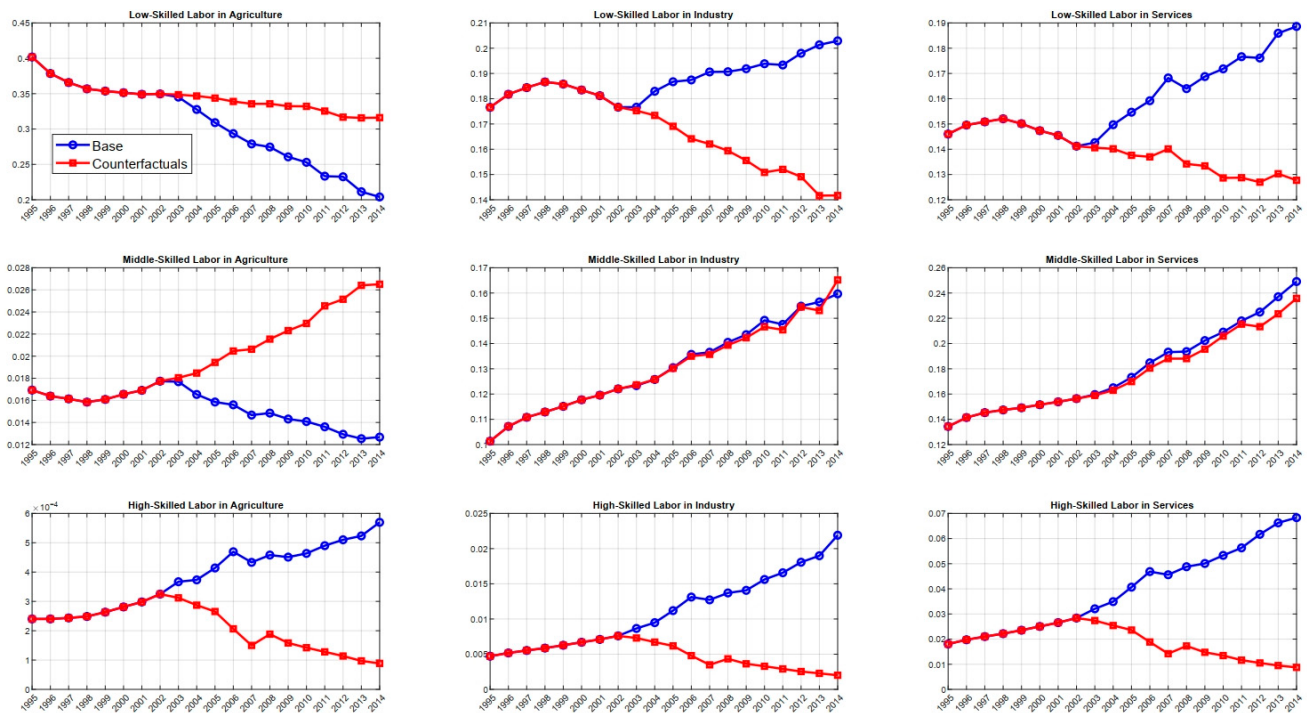


Figure 4. Labor allocations across sectors and skill levels by removing the impact of capital accumulation.

The results indicate that capital accumulation also facilitates the labor movement out of the agricultural sector. This occurs as technology progress, driven by capital accumulation, leads to changes in the relative prices of sectoral products. Given that productivity growth in the industry and services sectors outpaces that in the agricultural sector, the prices of their products decline more sharply. The subsequent increase in demand for industry goods and services prompts labor to shift from agricultural to non-agricultural sectors, thereby propelling structural transformation. To be more specific, we aggregate labor allocations at the skill level of the workers and present labor allocations across sectors in Figure 5. The capital accumulation has, on average, reduced the working hours of the agricultural sector labor by 20.4%, increased the working hours of industry sector labor by 14.8%, and markedly elevated the working hours of services sector labor by 21.3%.

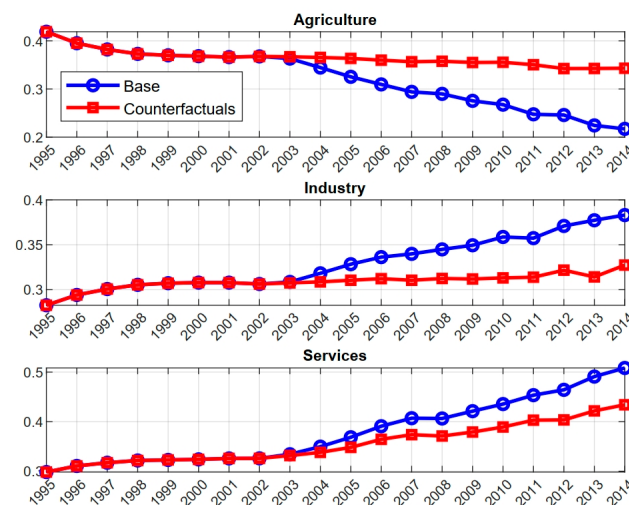


Figure 5. Labor allocations across sectors by removing the impact of capital accumulation.

3.5. Discussion

In this subsection, we discuss the results of our quantitative analysis and test the validity of the hypotheses proposed in Sections 2.1 and 2.2. Hypothesis 1 posits that the college expansion policy drives labor reallocation from the agricultural sector to the industry and services sectors. To test this hypothesis, we examine the counterfactual analysis outcomes detailed in Section 3.4.3. In Figure 3, the blue line marked as ‘Base’ in the legend represents equilibrium labor allocations with the college expansion policy in place, while the red line labeled ‘Counterfactuals’ depicts allocations in the counterfactual scenario where the impact of college expansion policy is eliminated. By comparing these scenarios, we gauge the policy’s impact on structural transformation. We find that the college expansion policy has brought about a significant restructuring of labor allocation patterns, with agricultural labor hours decreasing notably (−7.7%), industrial labor hours witnessing an increase (8.9%), and services sector labor hours undergoing a particularly striking surge (28.7%).

Before elucidating the mechanism of this structural transformation, we construct a simplified version of the base model in this section to illustrate the direct impact of college expansion on labor allocations across sectors. In this simple version, there are two types of skilled labor (low-skilled labor denoted by L and high-skilled labor denoted by H) and two sectors (agricultural sector indexed by a and non-agricultural sector indexed by n) with different labor intensities in the economy. Both goods are produced using labor with constant returns to scale technologies, as follows:

$$Y_i = A_i \left[\alpha_i n_{iH}^{\frac{\varepsilon-1}{\varepsilon}} + (1 - \alpha_i) n_{iL}^{\frac{\varepsilon-1}{\varepsilon}} \right]^{\frac{\varepsilon}{\varepsilon-1}}, \quad (19)$$

where Y_i is the sectoral output; n_{iL} and n_{iH} are workforce supplied by low-skilled and high-skilled laborers engaged in sector i ; A_i is the sector-specific productivity; α_i captures the input intensity; and ε is the elasticity of substitution between labor with different skill levels.

Firms employ labor and sell products to consumers in order to maximize profits.

$$\max_{\{n_{iL}, n_{iH}\}} p_i Y_i - w_L n_{iL} - w_H n_{iH}, \quad (20)$$

where p_i is the price of output produced by sector i and w_L and w_H represent the wage paid to low-skilled and high-skilled labor, respectively.

The utility function for a consumer with a skill level of $e \in \{L, H\}$ is given by

$$U_e = \left[\varphi_a^{\frac{1}{\gamma}} (c_{ae} - \bar{c}_a)^{\frac{\gamma-1}{\gamma}} + \varphi_n^{\frac{1}{\gamma}} c_{ne}^{\frac{\gamma-1}{\gamma}} \right]^{\frac{\gamma}{\gamma-1}}, \quad (21)$$

where c_{ae} and c_{se} stand for the consumption of agricultural and non-agricultural goods, respectively; $\bar{c}_a > 0$ is the subsistence level for agricultural goods; $\varphi_a, \varphi_n \in (0, 1)$ and satisfy that $\varphi_a + \varphi_n = 1$; and γ is the elasticity of substitution between agricultural and non-agricultural goods.

The budget constraint faced by a consumer with skill level of $e \in \{L, H\}$ is

$$p_a c_{ae} + p_n c_{ne} \leq w_e. \quad (22)$$

We define n_e as the hours supplied by labor with skill level of $e \in \{L, H\}$ and the total number of hours supplied by labor engaged in the economy is normalized to 1, i.e., $n_L + n_H = 1$.

The market-clearing conditions for labor in the input market are

$$n_L = n_{aL} + n_{nL}, \quad (23)$$

$$n_H = n_{aH} + n_{nH}. \quad (24)$$

The market clearing conditions for goods in the output market are

$$Y_a = n_L c_{aL} + n_H c_{aH}, \quad (25)$$

$$Y_n = n_L c_{nL} + n_H c_{nH}, \quad (26)$$

The competitive equilibrium in this simplified version is jointly determined by the output prices $\{p_i\}_{i=a,n}$, the labor wages $\{w_e\}_{e \in \{L,H\}}$, the consumption bundles of agricultural and non-agricultural goods $\{c_{ae}, c_{ne}\}_{e=L,H}$, and the labor allocations $\{n_{ae}, n_{ne}\}_{e=L,H}$. By analyzing the equilibrium labor allocations, we find that when the relative wage decline caused by an increase in high-skilled labor exceeds the threshold, both types of labor will flow toward the sector with higher labor intensive of high-skilled labor, as shown in the following proposition.

Proposition 1. *Both types of labor will flow toward the sector with higher labor intensive of high-skilled labor if and only if $\frac{d(w_H/w_L)}{dn_H} < -\Theta(n_H)$.*

Proof of Proposition 1. Please see Appendix A. $\square$

The content of Proposition 1 helps us understand the direct impact of changes in labor endowments on structural transformation from an economic perspective. As shown in the Appendix A, $\Theta(n_H) = \frac{n_H^2+1}{\varepsilon n_H n_L} \frac{w_H}{w_L}$, which implies that the greater the elasticity of substitution between different types of labor (ε), the smaller the absolute value of the threshold that determines the direction of labor transfer ($\Theta(n_H)$). Consequently, workers are more likely to move from sectors with lower skill intensities to the other. This is because, as the share of high-skilled workers increases in the economy, the relative wage of high-skilled labor compared to low-skilled labor will decrease. Therefore, firms can reduce the cost of producing each unit of output by employing more high-skilled labor. Firms in sectors with a higher intensity of high-skilled labor can benefit more significantly from this cost reduction. As a result, the relative price of product in this sector will decrease, leading consumers to purchase more products produced by this sector. The larger the elasticity of substitution ε , the greater the magnitude of structural transformation driven by labor substitution. When the elasticity of substitution ε reaches a certain level, labor will entirely shift from sectors with a higher intensity of low-skilled labor to those with a higher intensity of high-skilled labor.

The same economic logic can be applied to the analysis of our base model. The calibration results in Table 1 show that the calibrated elasticities of substitution between labor with different skill levels are greater than 1 ($\varepsilon > 1$ and $\eta > 1$), indicating that labor inputs a function as substitutes rather than complements. This substitutability, facilitated by the college expansion policy's enhancement of high-skilled labor supply and consequent reduction in their relative employment cost, enables firms to produce the same output at lower costs by substituting medium- and low-skilled labor with high-skilled labor. This dynamic leads to a significant influx of high-skilled labor across all economic sectors, as clearly observed in the three charts in the bottom row of Figure 2.

Additionally, since the demand for high-skilled labor across sectors is represented by $\{\alpha_i\}_{i=a,m,s}$ in the production functions, the calibrated values of $\{\alpha_i\}_{i=a,m,s}$ imply that the service sector exhibits the highest demand, followed by the industry sector, with the agricultural sector having the lowest ($\alpha_s > \alpha_m > \alpha_a$). The aforementioned cost reduction offers a significant advantage to sectors with higher demands for skilled labor, such as services and industry. The production functions, assuming constant returns to scale, dictate that firms earn zero profits, with output prices equating to the total production costs per unit. Therefore, the prices of outputs from sectors exhibiting higher demand for high-skilled labor in production decrease more rapidly. Consequently, this price reduction motivates

consumers to alter their spending patterns, increasingly favoring industrial goods and services, thereby driving structural transformation. From the analysis above, we confirm that Hypothesis 1 is validated.

We then proceed to test Hypothesis 2, which states that changes in labor skill endowments are as pivotal in promoting structural transformation as changes in capital endowments. To evaluate this, we compare the contributions of labor skill endowment and capital endowment in shaping structural transformation. In validating Hypothesis 1, we have already analyzed how changes in labor skill endowments, resulting from college expansion, affect structural transformation. We now focus on the result in another counterfactual scenario that removes the influence of changes in capital endowment on structural transformation. The findings, summarized in Figure 5, indicate that capital accumulation has led to a notable reduction in agricultural labor hours (−20.4%), an increase in industrial labor hours (14.8%), and an even larger increase in service sector labor hours (21.3%).

The underlying mechanism of Hypothesis 2 is that technological advancements, fueled by capital accumulation, induce shifts in relative sectoral product prices. As productivity growth in the industry and service sectors surpasses that of the agricultural sector, the prices of their products decline more rapidly. This price differential stimulates increased demand for industrial and service goods, prompting a labor shift from agricultural to non-agricultural sectors, thereby driving structural transformation. It is crucial to recognize that changes in productivity parameters are not solely attributable to capital accumulation. Therefore, the impact of capital accumulation on structural transformation identified in this counterfactual analysis represents the maximum possible effect. To summarize, even when compared to this upper-bound effect, changes in labor skill endowment play a significant role in driving structural transformation. This underscores the importance of acknowledging labor endowment shifts in analysis of endowment-driven structural transformation, thus affirming Hypothesis 2.

4. Extended Model Examining College Expansion and Sustainable Development

The SEA dataset provides detailed working hours data at the industry level, covering 33 industries, for labor with different skill levels, enabling us to conduct an in-depth analysis of the college expansion policy and sustainable development in China. The extensive information permits focusing on identifying the specific industries that have experienced expansion or decline due to the implementation of the college expansion policy. To achieve this, we construct an industry-level heterogeneous agent general equilibrium model, based on which we find that the college expansion policy contributes to sustainable development by facilitating structural transformation. This outcome stems from the policy's role in steering labor from industries with low energy efficiency toward high-end services. The dual effect of reducing reliance on high energy-consumption industries and enhancing high-end services underscores the environmental benefits and promotes sustainable development.

4.1. Technology

The SEA dataset encompasses working hours data for 33 industries: 1 in the agricultural sector, 17 in the industry sector, and 15 in the services sector. In other words, there are 33 industries involved in producing goods and services in our extended model and we index them by $i \in \{a, m_j, s_k\}$, where $\{m_j\}_{j=1,\dots,17}$ represents the j th industry that belongs to the industry sector and $\{s_k\}_{k=1,\dots,15}$ refers to the k th industry that belongs to the services sector. The production function at the industry level is defined as follows:

$$Y_i = A_i \left\{ \alpha_i n_{iH}^{\frac{\epsilon-1}{\epsilon}} + (1 - \alpha_i) \left\{ \left[\beta_i n_{iM}^{\frac{\eta-1}{\eta}} + (1 - \beta_i) n_{iL}^{\frac{\eta-1}{\eta}} \right]^{\frac{\eta}{\eta-1}} \right\}^{\frac{\epsilon-1}{\epsilon}} \right\}^{\frac{\epsilon}{\epsilon-1}}, \quad (27)$$

where Y_i represents the output at the industry level; n_{iL} , n_{iM} , and n_{iH} denote hours worked by low-skilled, medium-skilled, and high-skilled labor in industry i ; A_i is the industry-

specific productivity parameter; $\alpha_i, \beta_i \in (0, 1)$ capture the input intensities; and $\varepsilon, \eta \in (0, +\infty)$ are the elasticities of substitution between labor with different skill levels.

Firms determine the labor demand and aim to maximize profits, as follows:

$$\max_{\{n_{iL}, n_{iM}, n_{iH}\}} p_i Y_i - w_L n_{iL} - w_M n_{iM} - w_H n_{iH}, \quad (28)$$

where p_i is the price of output produced by industry $i \in \{a, m_j, s_k\}$ and w_L, w_M , and w_H denote the wage paid to low-skilled, medium-skilled, and high-skilled labor, respectively.

The first-order conditions of the profit maximization problem are identical to those in the base model, as follows:

$$\alpha_i p_i A_i \left(\frac{Y_i}{A_i} \right)^{\frac{1}{\varepsilon}} n_{iH}^{-\frac{1}{\varepsilon}} = w_H, \quad (29)$$

$$(1 - \alpha_i) \beta_i p_i A_i \left(\frac{Y_i}{A_i} \right)^{\frac{1}{\varepsilon}} \left[\beta_i n_{iM}^{\frac{\eta-1}{\eta}} + (1 - \beta_i) n_{iL}^{\frac{\eta-1}{\eta}} \right]^{\frac{\varepsilon-\eta}{\varepsilon(\eta-1)}} n_{iM}^{-\frac{1}{\eta}} = w_M, \quad (30)$$

$$(1 - \alpha_i)(1 - \beta_i) p_i A_i \left(\frac{Y_i}{A_i} \right)^{\frac{1}{\varepsilon}} \left[\beta_i n_{iM}^{\frac{\eta-1}{\eta}} + (1 - \beta_i) n_{iL}^{\frac{\eta-1}{\eta}} \right]^{\frac{\varepsilon-\eta}{\varepsilon(\eta-1)}} n_{iL}^{-\frac{1}{\eta}} = w_L. \quad (31)$$

4.2. Preference

The utility function for a consumer with a skill level of $e \in \{L, M, H\}$ diverges from Equation (6) in that it incorporates a more detailed classification of industries, expanding the range of varieties. The utility function in our extended model is specified as follows:

$$U_e = \left[\frac{1}{\varphi_a^\gamma} (c_{ae} - \bar{c}_a)^{\frac{\gamma-1}{\gamma}} + \sum_{j=1}^{17} \frac{\varphi_{m_j}^\gamma}{\varphi_a^\gamma} \frac{c_{m_j e}^{\gamma-1}}{c_{m_j e}^\gamma} + \sum_{k=1}^{15} \frac{\varphi_{s_k}^\gamma}{\varphi_a^\gamma} \frac{c_{s_k e}^{\gamma-1}}{c_{s_k e}^\gamma} \right]^{\frac{\gamma}{\gamma-1}}, \quad (32)$$

where c_{ae} , $c_{m_j e}$, and $c_{s_k e}$ represent the consumption of agricultural goods, products from the j th industry in the industry sector, and products from the k th industry in the services sector, respectively; $\bar{c}_a > 0$ is the subsistence level for agricultural goods; $\varphi_a, \varphi_{m_j}, \varphi_{s_k} \in (0, 1)$ satisfy that $\varphi_a + \sum_{j=1}^{17} \varphi_{m_j} + \sum_{k=1}^{15} \varphi_{s_k} = 1$; and γ remains the elasticity of substitution between outputs.

The budget constraint faced by a consumer with skill level of $e \in \{L, M, H\}$ is

$$p_a c_{ae} + \sum_{j=1}^{17} p_{m_j} c_{m_j e} + \sum_{k=1}^{15} p_{s_k} c_{s_k e} \leq w_e. \quad (33)$$

Consumers maximize their utility subject to the budget constraint, leading to the following optimal conditions:

$$\frac{c_{m_j e}}{c_{ae} - \bar{c}_a} = \frac{\varphi_{m_j}}{\varphi_a} \left(\frac{p_{m_j}}{p_a} \right)^{-\gamma}, \quad (34)$$

$$\frac{c_{s_k e}}{c_{ae} - \bar{c}_a} = \frac{\varphi_{s_k}}{\varphi_a} \left(\frac{p_{s_k}}{p_a} \right)^{-\gamma}. \quad (35)$$

Moreover, the optimal consumption bundles of a consumer with skill level of $e \in \{L, M, H\}$ are

$$c_{ae} = \frac{w_e + \left[\sum_{j=1}^{17} p_{m_j} \frac{\varphi_{m_j}}{\varphi_a} \left(\frac{p_{m_j}}{p_a} \right)^{-\gamma} + \sum_{k=1}^{15} p_{s_k} \frac{\varphi_{s_k}}{\varphi_a} \left(\frac{p_{s_k}}{p_a} \right)^{-\gamma} \right] \bar{c}_a}{p_a + \left[\sum_{j=1}^{17} p_{m_j} \frac{\varphi_{m_j}}{\varphi_a} \left(\frac{p_{m_j}}{p_a} \right)^{-\gamma} \right] + \left[\sum_{k=1}^{15} p_{s_k} \frac{\varphi_{s_k}}{\varphi_a} \left(\frac{p_{s_k}}{p_a} \right)^{-\gamma} \right]}, \quad (36)$$

$$c_{m_j e} = \frac{\frac{\varphi_{m_j}}{\varphi_a} \left(\frac{p_{m_j}}{p_a} \right)^{-\gamma}}{p_a + \left[\sum_{j=1}^{17} p_{m_j} \frac{\varphi_{m_j}}{\varphi_a} \left(\frac{p_{m_j}}{p_a} \right)^{-\gamma} \right] + \left[\sum_{k=1}^{15} p_{s_k} \frac{\varphi_{s_k}}{\varphi_a} \left(\frac{p_{s_k}}{p_a} \right)^{-\gamma} \right]} (w_e - p_a \bar{c}_a), \quad (37)$$

$$c_{s_k e} = \frac{\frac{\varphi_{s_k}}{\varphi_a} \left(\frac{p_{s_k}}{p_a} \right)^{-\gamma}}{p_a + \left[\sum_{j=1}^{17} p_{m_j} \frac{\varphi_{m_j}}{\varphi_a} \left(\frac{p_{m_j}}{p_a} \right)^{-\gamma} \right] + \left[\sum_{k=1}^{15} p_{s_k} \frac{\varphi_{s_k}}{\varphi_a} \left(\frac{p_{s_k}}{p_a} \right)^{-\gamma} \right]} (w_e - p_a \bar{c}_a). \quad (38)$$

4.3. Market Clearing Conditions and Equilibrium

The market clearing conditions for labor in the input market are

$$n_L = n_{aL} + \sum_{j=1}^{17} n_{m_j L} + \sum_{k=1}^{15} n_{s_k L}, \quad (39)$$

$$n_M = n_{aM} + \sum_{j=1}^{17} n_{m_j M} + \sum_{k=1}^{15} n_{s_k M}, \quad (40)$$

$$n_H = n_{aH} + \sum_{j=1}^{17} n_{m_j H} + \sum_{k=1}^{15} n_{s_k H}, \quad (41)$$

where n_e is the hours supplied by labor with a skill level of $e \in \{L, M, H\}$ and the total hours supplied by labor participating in the economy is still normalized to 1, namely $n_L + n_M + n_H = 1$.

The market clearing conditions for goods and services in the output market are

$$Y_i = n_L c_{iL} + n_M c_{iM} + n_H c_{iH}, \quad (42)$$

where the optimal consumption bundles have been determined by Equations (36)–(38) for any given $i \in \{a, m_j, s_k\}$.

The competitive equilibrium in our extended model is jointly defined by the output prices $\{p_i\}_{i=a, m_j, s_k}$, the labor wages $\{w_e\}_{e=L, M, H}$, the consumption bundles $\{c_{ie}\}_{i=a, m_j, s_k; e=L, M, H}$, and the labor allocations $\{n_{ie}\}_{i=a, m_j, s_k; e=L, M, H}$. In total, there are 234 variables. By solving the optimization problems of consumers and firms, we derive 198 first-order conditions. The 33 market clearing conditions for goods and services help determine the equilibrium prices $\{p_i\}_{i=a, m_j, s_k}$, while the equilibrium wages $\{w_e\}_{e=L, M, H}$ can be pinned down by three labor market clearing conditions. Thus, the competitive equilibrium in our extended model can be described by a nonlinear system consisting of 234 equations for 234 variables.

4.4. Quantitative Analysis of the Extended Model

The calibration of the extended model requires industry-level data on output and labor participation for workers of different skill levels. The SEA dataset directly provides output data for each industry (indexed by 'GO'). However, for industry-level labor working hours data across 33 industries, further calculations are necessary. Specifically, this dataset provides information on labor working hours for 33 distinct industries (indexed by 'H_EMP').

Additionally, it details the share of working hours supplied by low-skilled, medium-skilled, and high-skilled labor (indexed by ‘H_LS’, ‘H_MS’, and ‘H_HS’, respectively) within each specific industry. Utilizing this data, we can derive industry-level working hours for labor with different skill levels.

In this subsection, we calibrate the parameters in the extended model at the industry level. The SEA dataset lacks a more granular industry classification for the agricultural sector. In other words, the industry level category “Agriculture, hunting, forestry, and fishing” encompasses the agricultural sector itself. Consequently, when constructing our industry-level heterogeneous agent general equilibrium model, we cannot further divide the agricultural sector. Since the agricultural sector in the SEA dataset corresponds directly to the “Agriculture, hunting, forestry, and fishing” industry, we assume that the parameters A_a , α_a , and β_a in production function (1) and (27) are identical. Similarly, the preference parameters φ_a and $\bar{c}_a$ specified in Equations (6) and (32) are presumed to be exactly the same. Moreover, we posit that the elasticities of substitution between products and between inputs remain consistent with the base model. Parameters requiring calibration in the extended model are $\{\alpha_i, \beta_i, \varphi_i\}_{i \in \{m_j, s_k\}}$. Our calibration strategy for these parameters proceeds as follows:

Step 1. By Equations (29)–(31), the relative labor demands are defined as functions of relative wages.

$$\frac{n_{iL}}{n_{iM}} = \left(\frac{1 - \beta_i}{\beta_i} \frac{w_M}{w_L} \right)^\eta, \quad (43)$$

$$\frac{n_{iH}}{n_{iM}} = \left\{ \frac{1 - \alpha_i}{\alpha_i} \beta_i \left[\beta_i + (1 - \beta_i) \left(\frac{1 - \beta_i}{\beta_i} \frac{w_M}{w_L} \right)^{\eta-1} \right]^{\frac{\varepsilon - \eta}{\varepsilon(\eta-1)}} \frac{w_H}{w_M} \right\}^{-\varepsilon}. \quad (44)$$

Using Equations (43) and (44) and the labor allocation data $\{n_{aL}, n_{aM}, n_{aH}\}$ in the “Agriculture, hunting, forestry, and fishing” industry that is exactly that of the agricultural sector, we derive the relative wages w_M/w_L and w_H/w_M .

Step 2. By substituting the calculated relative wages and labor allocations into Equations (43) and (44) for industry $i \in \{m_j, s_k\}$, we formulate two equations involving the unknown variables α_i and β_i for each specified industry i . Solving this nonlinear system enables us to determine the values of $\{\alpha_i, \beta_i\}_{i \in \{m_j, s_k\}}$.

Step 3. The remaining parameters to be calibrated are $\{\varphi_i\}_{i \in \{m_j, s_k\}}$. Utilizing the determined $\{\alpha_i, \beta_i\}$ series for each industry $i \in \{a, m_j, s_k\}$, we calculate the industrial output Y_i using Equation (27). With w_L normalized to 1, we solve for the price p_i of products from industry i using Equation (31).

Step 4. From Equations (37) and (38), the industrial goods and services consumed by labor with skill level $e \in \{L, M, H\}$ can be expressed as functions of $\{\varphi_i\}_{i \in \{m_j, s_k\}}$.

Step 5. The market clearing conditions for the 32 types of industrial goods and services are presented in Equation (42). These equations involve outputs Y_i that have been figured out in Step 3, given skill endowments $\{n_L, n_M, n_H\}$, and consumptions of industrial goods and services that have been expressed as functions of $\{\varphi_i\}_{i \in \{m_j, s_k\}}$ in Step 4. Therefore, solving the nonlinear system consisting of 32 market clearing conditions uniquely determines the values of the 32 unknown parameters $\{\varphi_i\}_{i \in \{m_j, s_k\}}$.

Based on the calibrated extended model and the counterfactual skill endowments calculated in Section 3.4, we can determine the industry-level equilibrium labor allocations under the counterfactual scenario where the college expansion policy has not been implemented. By comparing these with actual labor allocations across industries, we can analyze the impact of the college expansion policy on the scale of industries. The results are summarized in Table 3, which details industries that experience a labor increase or decrease of more than 10% due to the college expansion policy. Due to constraints on space, Table 3 presents only those industries where the labor share change exceeds 10%. The results for other industries are summarized in Table A1, located in Appendix B.

Table 3. Industries with over 10% labor growth or decline due to college expansion.

Industries	Labor Share Change	Industry-Level Parameters		
		α_i	β_i	φ_i
Industries with Over 10% Labor Growth Due to College Expansion				
Education	39.1%	0.937	0.751	0.032
Post and Telecommunications	31.4%	0.913	0.726	0.026
Other Air Transport	28.5%	0.946	0.719	0.023
Renting of M&Eq and Other Business Activities	19.6%	0.926	0.662	0.025
Financial Intermediation	15.7%	0.875	0.831	0.027
Health and Social Work	13.9%	0.869	0.775	0.029
Industries with Over 10% Labor Decline Due to College Expansion				
Chemicals and Chemical	−15.7%	0.865	0.659	0.023
Pulp, Paper, Printing, and Publishing	−16.1%	0.817	0.625	0.020
Rubber and Plastics	−20.2%	0.821	0.573	0.022
Mining and Quarrying	−23.9%	0.813	0.602	0.029
Food, Beverages, and Tobacco	−29.1%	0.879	0.615	0.021
Basic Metals and Fabricated Metal	−31.3%	0.902	0.627	0.017

4.5. Discussion

An interesting observation from the results of the quantitative analysis in Section 4.4 is that industries witnessing significant expansion are primarily identified as high-end services, while those experiencing notable contraction are mainly industries characterized by low energy efficiency and high pollution. This implies that the college expansion policy has spurred the exodus of labor from less energy-efficient industries, with labor increasingly moving into high-end services. The observed structural transformation pattern is attributed to the effect of the college expansion policy in augmenting the supply of high-skilled labor. High-end services, in comparison to other industries, exhibit a generally higher demand for high-skilled labor, resulting in a disproportionate influx of the newly available high-skilled workforce in the labor market. While our paper does not explore endogenous growth models, insights from the relevant literature (e.g., Boucekkin et al., 2002; Docquier et al., 2007) suggest that an increase in the high-skilled labor force can drive technological progress [62,63], which subsequently leads to decreased prices of products in high-end services. This, in turn, elevates consumer demand for these products, thereby promoting the expansion of these industries.

The observed structural transformation pattern, characterized by labor shifts from industries with low energy efficiency to high-end services, emphasizes the significant role of college expansion policy in steering the economy toward a more sustainable development paradigm from two perspectives. Firstly, the expansion of high-end services plays a crucial role in advancing sustainable development. For instance, the growth of the financial industry facilitates the progression toward a green economy and sustainability (Yuan et al., 2019; Meng and Zhang, 2022) [64,65]. Similarly, advancements in digital services, such as telecommunications, encourage green innovation among enterprises, contributing to sustainable development (Fang et al., 2023) [66]. As Huo et al. (2021) note [67], renting and other business activities that involve low carbon emissions, are also typical eco-friendly industries beneficial to sustainability. Additionally, education and social work play a pivotal role in cultivating and spreading environmental awareness (Chawla and Cushing, 2007; Schmitz et al., 2012) [68,69]. It is evident that the expansion of high-end services promotes an eco-friendly economic transition and nurtures sustainable development.

Secondly, the shrinkage of industries with low energy efficiency promotes a transition toward sustainable development. Structural transformation is critical for an economy to transition from previous practices that are harmful to the environment (Lin and Xu 2014) [33]. Le et al. (2021) point out that low energy efficiency will hinder sustainable development at a national level [70]. Xie et al. (2021) also emphasize the significance of energy efficiency within industries for sustainable development [71]. Structural transformation from high energy-consuming industries toward high-end services not only improves resource utilization efficiency but also promotes the adoption of eco-friendly economic practices, thus paving the way for a new growth model consistent with sustainable development principles (Kaygusuz 2012; Zhou et al., 2013; Simkiv et al., 2021) [72–74].

It is noteworthy that the industries experiencing significant labor share declines align closely with those regarded as highly polluting. Despite the absence of an official definition of high-pollution industries in China, Gao et al. (2019) utilize information from the Carbon Emission Accounts and Datasets (CEAD) to measure pollution intensity based on industrial wastewater and emissions [75], identifying nine industries as highly polluting. While minor differences in industry names arise from different source databases, it is readily apparent that the industries undergoing significant labor reductions are mainly those classified as high-pollution in Gao et al. (2019) [75]. Specifically, in the CEAD database, the corresponding industries listed are Raw Chemical Materials and Chemical Products, Papermaking and Paper Products, Coal Mining and Washing Industry, Food Processing and Beverage Production, and Smelting and Pressing of Ferrous (Nonferrous) Metals. It is obvious that the implementation of the college expansion policy leads to the contraction of high-pollution industries. Therefore, this policy facilitates sustainable development by diminishing the scale of these high-pollution industries.

Hypothesis 3 posits that the college expansion policy reshapes labor reallocation across industries, thereby accelerating the transition toward a low-carbon economy in China. Utilizing more detailed industry-level data, we have examined the impact of the college expansion policy on the energy economy. We observe that college expansion facilitates labor reallocation from industries marked by low energy efficiency and high pollution toward high-end services. The dual effect of reducing reliance on high energy-consumption industries and enhancing high-end services underscores the environmental benefits and promotes sustainable development. Such trends in structural transformation undoubtedly favor the long-term sustainable development of the energy economy. By integrating the analysis from both perspectives above and considering the structural transformation patterns triggered by the college expansion policy, we are convinced that this policy has significantly propelled the low-carbon economy in China, thereby validating Hypothesis 3.

5. Research Innovations, Limitations, and Future Directions

This paper constructs heterogeneous agent general equilibrium models to investigate the macroeconomic impacts of labor endowment induced by college expansion in driving structural transformation and the energy economy. We evaluate the college expansion policy in China using a general equilibrium framework, focusing on its impact and relative importance on labor allocation across sectors. This section serves to summarize the innovations, limitations, and future research directions of our study.

5.1. Research Innovations and Limitations

This study introduces several innovative aspects that are different from existing research. Firstly, unlike the prevalent use of partial equilibrium analyses in the literature, we employ a heterogeneous agent general equilibrium framework. This approach allows for a more comprehensive evaluation of policy impacts, capturing the interdependencies across different sectors and providing a clearer picture of the broader economic effects of college expansion.

Secondly, our research places a strong emphasis on the role of labor endowment, which is often overlooked in favor of capital endowment in discussions of structural trans-

formation. By focusing on labor endowment, we offer new insights into how changes in the supply of skilled labor, particularly as a result of higher education expansion, contribute significantly to structural transformation and the energy economy. This perspective enriches the current understanding by highlighting the pivotal role of labor endowment in driving economic shifts.

Thirdly, we extend our analysis to an industry-level model, which allows for a more detailed examination of the college expansion policy's impacts on specific industries. This granular approach enables us to identify which industries benefit from an increased supply of educated labor and how this shift affects the energy economy. Our findings suggest that the policy has facilitated a labor transition from low-energy efficiency and high-pollution industries to high-end services, promoting a move toward a low-carbon economy. This industry-level analysis provides valuable insights for policymakers on how educational policies can be leveraged to support sustainable development and align workforce capabilities with the needs of a greener economy.

One limitation of our study is that the observation period extends only until 2014, which may not capture more recent developments. We acknowledge this limitation and have made efforts to extend the study period. The SEA dataset was selected to help conduct a quantitative analysis of our study due to its detailed industry-specific output and labor input data by skill level, which is rarely reported by the Chinese government. To extend the study period, we combine data from the *China Labor Statistical Yearbook* with the SEA dataset, allowing us to analyze the period from 1995 to 2014. Despite our efforts to construct a data series, 2014 remains the latest year for which we can obtain the necessary data for calibration. We appreciate the importance of extending the study period and will continue to update our analysis as more data become available in the future.

5.2. Future Research Directions

Integrating the analysis of equilibrium unemployment into the current framework presents a promising avenue for future research. Building on the work of Ljungqvist and Sargent (2008) [76], who utilize the search model to examine the critical role played by imperfect information and the labor market matching process in determining the unemployment rate, some macroeconomic studies have explored the issue of equilibrium unemployment. However, combining the search model with structural transformation poses challenges, as it requires the assumption that workers optimally select job vacancies across sectors, which significantly complicates the model and reduces its computational efficiency. Despite these difficulties, exploring this integration could provide valuable insights into how equilibrium unemployment interacts with change in labor endowment and structural transformation.

Another valuable research direction involves incorporating regional disparities into the assessment of college expansion policy. Firstly, colleges in China are unevenly distributed across different regions. Secondly, the attainment of higher education facilitates interregional labor migration. Such research is challenging, requiring data on the distribution of labor with different skill levels across sectors in various regions. Moreover, calibrating a large-scale general equilibrium model to accurately reflect real economic operations poses additional complexities. Nevertheless, constructing such a multi-regional heterogeneous agent general equilibrium model and conducting the corresponding quantitative analyses would enhance our understanding of variations in development structures across regions and provide valuable insights for policymakers aiming to support specific sectoral developments.

6. Conclusions

In this study, we explore an intriguing question: beyond the extensively studied demand-side and supply-side drivers, does labor, as a crucial endowment, significantly influence structural transformation and the energy economy? To tackle this inquiry, we focus on the college expansion policy, a policy that profoundly reshaped China's labor

endowment structure. We utilize the SEA dataset and the *China Labor Statistical Yearbook* to build heterogeneous agent general equilibrium models, providing a quantitative assessment of the macroeconomic effects of college expansion on structural transformation and the energy economy in China. While existing research predominantly explores the impacts of college expansion in China from a microeconomic standpoint, by focusing on shifts in the rate of return on education and employment outcomes post-policy implementation, there is a notable gap in macro-level analyses. Our study bridges this gap by linking college expansion to structural transformation and the energy economy, offering a comprehensive policy evaluation from a macroeconomic perspective.

We have developed a multi-sector model that includes workers with varying skill levels to investigate the macroeconomic effects of college expansion on labor distribution across sectors. Utilizing the simulated method of moments (SMM) for parameter calibration, we conducted several counterfactual experiments to explore the macroeconomic impact and relative significance of the college expansion policy. Our results reveal that the policy led to an average reduction of 7.7% in labor allocation in the agricultural sector while increasing labor allocation in the industry and services sectors by 8.9% and 28.7%, respectively.

Moreover, while the current literature on endowment-driven structural transformation emphasizes the role of capital accumulation, it often overlooks the substantial impact of labor, another critical endowment. This paper underscores the pivotal role of labor endowment changes in driving structural transformation. Our quantitative analysis, based on the calibrated general equilibrium model, compares the macroeconomic impacts of labor allocation changes due to the college expansion policy and capital accumulation. We demonstrate that labor is as vital as capital in endowment-driven structural transformation, thus enriching the discourse on the drivers of structural transformation.

Finally, we extend our base model to a heterogeneous agent general equilibrium model at the industry level. With detailed data from the SEA dataset and the *China Labor Statistical Yearbook*, we recalibrate the extended model to investigate the impact of the college expansion policy on labor distribution across industries. We observe a shift of labor from low energy efficiency and high pollution industries to high-end services, driven by the college expansion policy. This labor transition is expected to curb the growth of environmentally detrimental industries and reduce carbon emissions. By examining the policy's industry-level impacts, our study suggests that educational policy can foster a low-carbon economy through structural transformation, providing a novel perspective for policymakers aiming to develop sustainable energy policies.

For policymakers, to sustain the positive effects of college expansion on structural transformation and the energy economy, the following policy measures are recommended. Firstly, continuous investment in higher education is essential. Policymakers should prioritize funding for educational institutions, particularly in areas related to green technologies and sustainable practices. This will ensure a steady supply of skilled labor necessary for the growth of environmentally friendly industries.

Furthermore, strengthening industry–academia collaboration is crucial. By fostering partnerships between educational institutions and industries, the skills of graduates can be better aligned with the demands of the labor market. Initiatives such as internships, cooperative education programs, and joint research projects can facilitate the smooth transition of labor from traditional high-pollution industries to modern sustainable industries. Such collaborations can help bridge the gap between academic training and practical industry needs, ensuring that the workforce is adequately prepared for the evolving demands of a green economy.

Moreover, targeted support for industries undergoing transformation is vital. This includes providing resources for retraining programs and encouraging the adoption of green practices in industries transitioning to more sustainable models. By ensuring that both educational institutions and industries are well-supported, policymakers can foster an environment where labor market transitions contribute to broader economic and environmental goals, promoting a low-carbon economy and sustainable development.

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Appendix A

In this section, we will prove Proposition 1 to analyze the direct impact of college expansion on labor allocation across sectors.

By solving the profit maximization problem of a representative firm in sector i described by Equations (19) and (20), we can derive the following first-order condition:

$$w_L = p_i A_i \left(\frac{Y_i}{A_i} \right)^{\frac{1}{\varepsilon}} (1 - \alpha_i) n_{iL}^{-\frac{1}{\varepsilon}}, \quad (\text{A1})$$

$$w_H = p_i A_i \left(\frac{Y_i}{A_i} \right)^{\frac{1}{\varepsilon}} \alpha_i n_{iH}^{-\frac{1}{\varepsilon}}. \quad (\text{A2})$$

From these first-order conditions (A1) and (A2), we can derive the relative demand for labor in sector i :

$$\frac{n_{iL}}{n_{iH}} = \left(\frac{1 - \alpha_i}{\alpha_i} \frac{w_H}{w_L} \right)^{\varepsilon}. \quad (\text{A3})$$

By combining the labor market clearing conditions (23) and (24), we can solve for the equilibrium allocation of high-skilled labor between the agricultural and non-agricultural sectors:

$$n_{aH} = \frac{n_L / \left(\frac{1 - \alpha_n}{\alpha_n} \frac{w_H}{w_L} \right)^{\varepsilon} - n_H}{\left(\frac{1 - \alpha_a}{\alpha_a} \frac{w_H}{w_L} \right)^{\varepsilon} - 1}, \quad (\text{A4})$$

$$n_{nH} = \frac{n_L / \left(\frac{1 - \alpha_a}{\alpha_a} \frac{w_H}{w_L} \right)^{\varepsilon} - n_H}{\left(\frac{1 - \alpha_n}{\alpha_n} \frac{w_H}{w_L} \right)^{\varepsilon} - 1}. \quad (\text{A5})$$

From Equations (A4) and (A5) and $n_L + n_H = 1$, we can derive the relative share of high-skilled labor between the agricultural and non-agricultural sectors:

$$\frac{n_{aH}}{n_{nH}} = \frac{1 - \left[1 + \left(\frac{1 - \alpha_n}{\alpha_n} \frac{w_H}{w_L} \right)^{\varepsilon} \right] n_H}{\left[1 + \left(\frac{1 - \alpha_a}{\alpha_a} \frac{w_H}{w_L} \right)^{\varepsilon} \right] n_H - 1}. \quad (\text{A6})$$

By defining constants $\Omega_1 = \left(\frac{1 - \alpha_a}{\alpha_a} \right)^{\varepsilon}$ and $\Omega_2 = \left(\frac{1 - \alpha_n}{\alpha_n} \right)^{\varepsilon}$ and using the symbol w_{HL} instead of w_H / w_L for simplicity in notation, we can then write the relative share of high-

skilled labor between the agricultural and non-agricultural sectors as $\frac{n_{aH}}{n_{nH}} = \frac{1 - (1 + \Omega_2 w_{HL}^\varepsilon) n_H}{(1 + \Omega_1 w_{HL}^\varepsilon) n_H - 1}$. The derivative of this share with respect to n_H , i.e., $\frac{d(n_{aH}/n_{nH})}{dn_H}$ equals to

$$\frac{-\left[\left(1 + \Omega_2 \varepsilon w_{HL}^{\varepsilon-1} \frac{dw_{HL}}{dn_H}\right) n_H + (1 + \Omega_2 w_{HL}^\varepsilon)\right] \left[(1 + \Omega_1 w_{HL}^\varepsilon) n_H - 1\right]}{\left[(1 + \Omega_1 w_{HL}^\varepsilon) n_H - 1\right]^2} \cdot \frac{\left[1 - (1 + \Omega_2 w_{HL}^\varepsilon) n_H\right] \left[\left(1 + \Omega_1 \varepsilon w_{HL}^{\varepsilon-1} \frac{dw_{HL}}{dn_H}\right) n_H + (1 + \Omega_1 w_{HL}^\varepsilon)\right]}{\left[(1 + \Omega_1 w_{HL}^\varepsilon) n_H - 1\right]^2}. \quad (A7)$$

Define the numerator of the above expression as the function $-f$, then f can be expressed as

$$\left[\left(1 + \Omega_2 \varepsilon w_{HL}^{\varepsilon-1} \frac{dw_{HL}}{dn_H}\right) n_H + (1 + \Omega_2 w_{HL}^\varepsilon)\right] \left[(1 + \Omega_1 w_{HL}^\varepsilon) n_H - 1\right] + \left[1 - (1 + \Omega_2 w_{HL}^\varepsilon) n_H\right] \left[\left(1 + \Omega_1 \varepsilon w_{HL}^{\varepsilon-1} \frac{dw_{HL}}{dn_H}\right) n_H + (1 + \Omega_1 w_{HL}^\varepsilon)\right]. \quad (A8)$$

Thus, we know that the sign of $\frac{d(n_{aH}/n_{nH})}{dn_H}$ is necessarily opposite to the sign of f , i.e., $\text{sign}\left[\frac{d(n_{aH}/n_{nH})}{dn_H}\right] = -\text{sign}[f]$. Next, we simplify the function f to analyze its sign, as follows:

$$\begin{aligned} f &= (\Omega_2 - \Omega_1) w_{HL}^\varepsilon n_H^2 + (\Omega_2 - \Omega_1) w_{HL}^\varepsilon + (\Omega_2 - \Omega_1) \varepsilon w_{HL}^{\varepsilon-1} \frac{dw_{HL}}{dn_H} n_H (1 - n_H) \\ &= (\Omega_2 - \Omega_1) w_{HL}^\varepsilon n_H^2 + (\Omega_2 - \Omega_1) w_{HL}^\varepsilon + (\Omega_2 - \Omega_1) \varepsilon w_{HL}^{\varepsilon-1} \frac{dw_{HL}}{dn_H} n_H n_L \\ &= w_{HL}^\varepsilon (\Omega_2 - \Omega_1) \left(n_H^2 + 1 + \frac{\varepsilon}{w_{HL}} \frac{dw_{HL}}{dn_H} n_H n_L\right) \end{aligned} \quad (A9)$$

Since the non-agricultural sector is more intensive in high-skilled labor, we have $\alpha_n > \alpha_a$, and thus $\Omega_1 > \Omega_2$ by the definition of Ω_1 and Ω_2 . Therefore, $\text{sign}[f] = -\text{sign}\left[n_H^2 + 1 + \frac{\varepsilon}{w_{HL}} \frac{dw_{HL}}{dn_H} n_H n_L\right]$.

Since $\text{sign}\left[\frac{d(n_{aH}/n_{nH})}{dn_H}\right] = -\text{sign}[f]$, we know that the sign of $\frac{d(n_{aH}/n_{nH})}{dn_H}$ is always the same as $n_H^2 + 1 + \frac{\varepsilon}{w_{HL}} \frac{dw_{HL}}{dn_H} n_H n_L$. In the above derivations, we used the symbol w_{HL} instead of w_H/w_L to simplify the notation. Now, substituting w_H/w_L back into the expressions, we define $\Theta(n_H) = \frac{n_H^2 + 1}{\varepsilon n_H n_L} \frac{w_H}{w_L}$. Thus, we have

$$\frac{d(n_{aH}/n_{nH})}{dn_H} < 0 \Leftrightarrow f > 0 \Leftrightarrow \frac{d(w_H/w_L)}{dn_H} < -\Theta(n_H). \quad (A10)$$

Equation (A10) provides the necessary and sufficient condition for the direction of the high-skilled labor transfer between sectors. Next, we analyze the transfer of low-skilled labor between sectors. According to the relative labor demand in sector i given by Equation (A3), the allocation of high-skilled and low-skilled labor between sectors is as follows:

$$\frac{n_{aL}}{n_{nL}} = \left(\frac{1 - \alpha_a}{\alpha_a} \frac{\alpha_n}{1 - \alpha_n}\right)^\varepsilon \frac{n_{aH}}{n_{nH}}. \quad (A11)$$

Thus, for labor of all skill levels, the direction of structural transformation due to changes in labor endowments is always the same and $\frac{d(n_{aL}/n_{nL})}{dn_H} = \left(\frac{1 - \alpha_a}{\alpha_a} \frac{\alpha_n}{1 - \alpha_n}\right)^\varepsilon \frac{d(n_{aH}/n_{nH})}{dn_H}$.

In combination with Equation (A10), we obtain the necessary and sufficient condition for the transfer direction of low-skilled labor between sectors, as follows:

$$\frac{d(n_{aL}/n_{nL})}{dn_H} < 0 \Leftrightarrow f > 0 \Leftrightarrow \frac{d(w_H/w_L)}{dn_H} < -\Theta(n_H). \quad (A12)$$

By synthesizing the results from Equations (A10) and (A12), we establish the validity of Proposition 1.

Appendix B

Table A1. Calibrated parameters of other industries and labor changes due to college expansion.

Industries	Labor Share Change	Industry-Level Parameters		
		α_i	β_i	φ_i
Industries with Labor Growth Due to College Expansion				
Real Estate Activities	9.5%	0.835	0.712	0.029
Construction	9.1%	0.852	0.708	0.023
Public Admin and Defense; Compulsory Social Security	7.8%	0.813	0.653	0.028
Hotels and Restaurants	7.1%	0.792	0.689	0.035
Wholesale Trade and Commission Trade, Except for Motor Vehicles and Motorcycles	5.5%	0.809	0.611	0.016
Manufacturing Nec; Recycling	5.0%	0.829	0.595	0.019
Other Community, Social, and Personal Services	3.7%	0.803	0.630	0.022
Machinery, Nec	3.3%	0.785	0.676	0.017
Electrical and Optical Equipment	3.0%	0.827	0.581	0.015
Other Supporting and Auxiliary Transport Activities; Activities of Travel Agencies	2.1%	0.769	0.523	0.020
Industries with Labor Decline Due to College Expansion				
Other Inland Transport	−3.1%	0.713	0.552	0.017
Private Households with Employed Persons	−3.3%	0.705	0.578	0.025
Transport Equipment	−4.0%	0.621	0.603	0.018
Retail Trade and Except for Motor Vehicles and Motorcycles; Repair of Household Goods	−4.3%	0.574	0.517	0.026
Electricity, Gas, and Water Supply	−5.1%	0.539	0.676	0.031
Agriculture, Hunting, Forestry, and Fishing	−5.9%	0.517	0.409	0.034
Other Water Transport	−6.3%	0.579	0.519	0.033
Other Non-Metallic Mineral	−6.7%	0.593	0.536	0.027
Coke, Refined Petroleum, and Nuclear Fuel	−7.0%	0.591	0.545	0.023
Leather, Leather, and Footwear	−7.3%	0.674	0.603	0.029
Wood and of Wood and Cork	−8.2%	0.727	0.617	0.031

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