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Will China's Demographic Transition Exacerbate Its Income Inequality?

A CGE Modeling with Top-down Microsimulation

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ABSTRACT

Demographic transition due to population aging is an emerging trend throughout the developing world, and it is especially acute in China, which has undergone demographic transition more rapidly than have most industrial economies. This paper quantifies the distributional effects in the context of demographic transition using an integrated recursive dynamic computable general equilibrium model with top-down behavioral microsimulation. The results of the poverty and inequality index indicate that population aging has a negative impact on the reduction of poverty while its impact is positive with regard to equality. In addition, elderly rural households are experiencing the most serious poverty, and their inequality problems compared with other household groups and within group inequality worsens with demographic transition. These findings not only advance the previous literature but also deserve particular attention from Chinese policy makers.

Keywords: demographic transition, poverty, inequality, CGE model

JEL codes: J11, D58, D63, D10

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1. INTRODUCTION

As the world's most populous country, China is experiencing an increasing number of young people and declining fertility, which boost economic productivity, and this is taken as a demographic dividend. China's abundance of cheap labor has made it internationally competitive in many low-cost, labor-intensive manufacturing sectors (Wang, Mayes, and Wan 2005). Scholars estimate that the demographic dividend accounts for one-fourth of China's economic growth since 1978 (Wang and Mason 2004; Cai 2009). Simultaneously, the standard of living in China has improved significantly, and poverty has been substantially reduced.

However, due to the combined influence of the strict implementation of the one-child policy and socioeconomic development, China has completed a demographic transition from the interim pattern (population with low death rate, high birth rate, and high growth rate) to the final pattern (population with low death rate, low birth rate, and low growth rate) within approximately 30 years, a short period of time when compared to the transitions of most developed countries (Cai and Wang 2010). According to the sixth national census in 2010, released by the National Bureau of Statistics, the proportion of the population older than 60 is 13.32 percent, and the population older than 65 accounted for more than 8.92 percent of the total population in China. China is positioned to undergo a period of rapid aging, with the proportion of the old population (older than 65 years old) reaching 16.52 percent by 2030. In addition, the total population is predicted to arrive at its highest point, which is 1.395 billion, in 2026, and the total labor force to decline by 2015 World Population Prospects (United Nations 2013). These projections imply that China's demographic dividend will soon be exhausted (Wang and Mason 2004) and will turn into a demographic deficit with important adverse economic consequences (Peng and Mai 2008). During the same period, the distribution of income in China has become much more unequal between rural and urban areas, coastal regions and inland regions, men and women, and different industry sectors. For example, in 1990, the income per capita for urban households was 1,516 yuan, which was 1.53 times that of rural households. However, this urban and rural inequality increased to 2.75 in 2014. The Gini coefficient was only 0.16 before China's reform and opening up policies were implemented in 1978. According to the National Bureau of Statistics' recent report, the Gini coefficient was 0.49 in 2008 and 0.47 in 2014, both of which crossed the international warning line, which implies that China's inequality is becoming dangerously severe. Is there any relationship between demographic transition and income distribution? What's the impact of population aging on poverty and inequality? Future inequality in the context of demographic transition in the middle- and long-run period will be a salient issue in the near future.

Due to the deterioration of income inequality that follows rapid economic growth and population aging, population transition with income distribution research became popular in the 1990s for developed countries. However, the general trend of such research is inconclusive as there is evidence supporting both a positive and a negative relationship. On one hand, some empirical research indicates that population aging worsens income inequality (Ohtake and Saito 1998; Deaton and Paxson 1994; Lan, Wei, and Wu 2014; Lin, Lahiri, and Hsu 2015). Deaton and Paxson (1995) analyze the relationship between population aging and inequality and conclude that population aging leads to greater inequality for both within-cohort inequality and between-cohort inequality. Their results fit the conditions of the Taiwanese economy and also predict increases in inequality in other fast-growing Asian countries. Followed by Deaton and Paxson (1995), Ohtake and Saito (1998) analyze how consumption inequality within a fixed cohort grows with age, using Japanese household microdata. Their results show that half of the rapid increase in economywide consumption inequality during the 1980s was caused by population aging. Miyazawa's (2006) analytical results reveal that the population's aging enlarges the inequality between different generations and inequality within a generation and finally expands total inequality. Lan, Wei, and Wu's (2014) empirical study uses a panel dataset from 76 countries and regions from 1970 and 2011 and finds that the population's aging does increase income inequality significantly. However, on the other hand, some studies find that aging may have a negligible effect on inequality (Jantti 1997; Bishop, Formby, and Smith 1997; Barrett, Crossley, and Worswick 2000; Schultz 1997) or even a positive effect on equality. Chu and Jiang (1997) examine the effects of age structure on family income using the Gini coefficient, and the results demonstrate that changes in Taiwan's demography reduced inequality in family earnings between 1980 and 1990. By applying the Overlapping Families Model, Lee and Mason (2003) find that population aging had little effect on income inequality. Morley (1981) expands Paglin's (1975) method, which decomposes inequality by age structure and finds that a younger age structure would widen income inequality while countries with serious population aging are less unequal. Goldstein and Lee (2016) try to find out the impact of different factors related to population aging on inequality and show that the changing age structure is found to have a small effect on aggregate inequality.

As the issue of population aging emerged at the beginning of the 21st century for developing countries, China was among the few developing countries that managed to transform into a society characterized by an aging population. These profound demographic changes, however, raise concern about the sustainability of China's economic growth (Cai 2009; Cai and Wang 2005). For example, scholars and Chinese government officials worry that the looming demographic challenge may undermine China's ability to grow rich before its population grows old (Jackson and Howe 2004; Cai and Lu 2013). There has been a great deal of theoretical and empirical research on the relationship between demographic transition and economic growth in China. Generally speaking, the literature indicates that population aging generates negative economywide effects that will slow economic growth. Peng and Fausten's (2006) simulation results show that the labor force decline caused by population aging will decelerate China's economic growth rate by 2 percentage points annually during the 2020s and by 3 percentage points annually during the 2040s. Cai and Lu (2013) estimate the average annual growth rate of potential output to be 7.2 percent during the 12th five-year plan period and 6.1 percent during the 13th five-year plan period.

However, there are only a few existing studies on the relationship between demographic transition and income distribution that focus on the developing world. Research on China's demographic transition and income distribution has begun to emerge in recent years, and the results regarding this relationship are still not clear. Some empirical research indicates that population aging will expand income inequality. Zhong (2011) investigates the relationship between population aging and income inequality in rural China by using five years' panel data from the China Health and Nutrition Survey and argues that a significant portion of the sharp increase of income inequality at the beginning of this decade can be attributed to demographic change. Dong, Wei, and Tang (2012) employ provincial-level panel data between 1996 and 2009 and confirm that population aging positively and significantly affects income inequality. But on the other hand, research finds that demographic transition accounts for only a tiny fraction of inequality. Cai, Chen, and Zhou (2010) analyze urban household survey data between 1992 and 2003 by employing a regression-based inequality decomposition and find that age has a negligible effect on inequality. Qu and Zhao (2008) investigate the relationship between inequality and population aging in rural China using the life cycle model with three years' rural household surveys from the China Household Income Project (CHIP). The results show that population aging plays only a small role in the inequality increase in rural China. Guo, Lu, and Jiang (2014) adopt the advanced decomposition method based on Ohtake and Saito (1998) by using the Urban Household Survey data from 1988 to 2009. Their research finds that the population aging effect explains only 16.33 percent of the total income inequality and this effect keeps decreasing. There are few other studies that have comprehensively analyzed the relationship between income distribution and problems associated with population aging in China.

The existing studies use mainly panel data and decompose inequality by age to simulate the contribution of aging on inequality. However, demographic transition is a long process; the economic and social impact of population aging has not yet totally emerged throughout China. The impact of any demographic change can be split into supply effects (consequences for labor and capital) and demand effects (consequences for public and private consumption, international trade, and domestic and foreign investment) (Poot 2008). A review of the literature indicates that demographic transition has economic and social impacts related to changes both in the supply of labor and in household consumption and investment demand. Subsequently, it tends to affect household income and expenditure via two channels: (1) the direct channel, which affects individual employment and wages, and (2) the indirect channel, which affects the sensitivity of commodities' supply and price due to productivity changes. Therefore, a computable general equilibrium (CGE) model, which is a type of economic model that uses economic data to estimate how an economy might react to changes in policy, technology, or other external factors, can be used to capture the macro impacts on factor price and household income in the context of demographic change. However, it is not enough to measure the micro-level impact using only a CGE model. The macro-micro modeling frameworks that integrate CGE models with microeconomic models have proved useful in capturing the effect of macroshocks to microdistribution.

This paper aims to examine the distributional effects of the demographic transition that is under way in China. The rest of the paper is organized as follows: Section 2 provides a methodological review and introduces the methodological framework for this study. Section 3 and Section 4 introduce the models and datasets. The macro model, micro model, and model linkages for this study will be set out in these two sections, and a detailed specification will be provided. Section 5 contains the empirical results on poverty and inequality, and finally, we present the conclusions of the paper and propose the policy implications arising from the results in the last section.

2. METHODOLOGY AND FRAMEWORK

In this section, we first introduce the recent developments in macro-micro modeling methodology and then describe the framework of this study.

Macro-micro Linkage Methodology

Dervis, de Melo, and Robinson (1982) and Gunning (1983) were the first to analyze income distribution by connecting a CGE model with microdata. After that, a series of various approaches were developed with different methods on the linkage between CGE models and micro–household data. These recent developments in macro-micro modeling frameworks have been proved to be helpful in capturing the impact of macro shocks to microdistribution.

As concluded by Debowicz (2012), there are mainly two channels that can link CGE models with microdata, including integrated links and layered links. Integrated links integrate the selected information about representative household groups into a macro-CGE model; they can be further divided into representative household integrated (RHI) (such as the studies in Dervis, de Melo, and Robinson 1982; Colatei and Round 2001; Agénor, Izquierdo, and Fofack 2001) and multihousehold integrated (MHI) (such as the studies in Decaluwé, Dumont, and Savard 1999; Cogneau and Robilliard 2000; Boccanfuso, Decaluwé, and Savard 2008). From the empirical research, the RHI link method can integrate the microdata into the macro model, and it works well when there is a small number of groups in the model. However, it does not allow researchers to take into account within-group changes in income distribution because the same groups in the macro model are assumed to be identified. The MHI link method can solve the problem of the RHI link method; however, it accounts for the majority of the micro–household data in the CGE model that makes the CGE model hard to converge when running such a large-scale CGE model (Chen and Ravallion 2004). What's more, it is difficult to balance the household income and expenditure account and to calibrate between micro–household data and macro data (Savard 2005; Boccanfuso, Decaluwé, and Savard 2008; Rutherford, Tarr, and Shepotylo 2005).

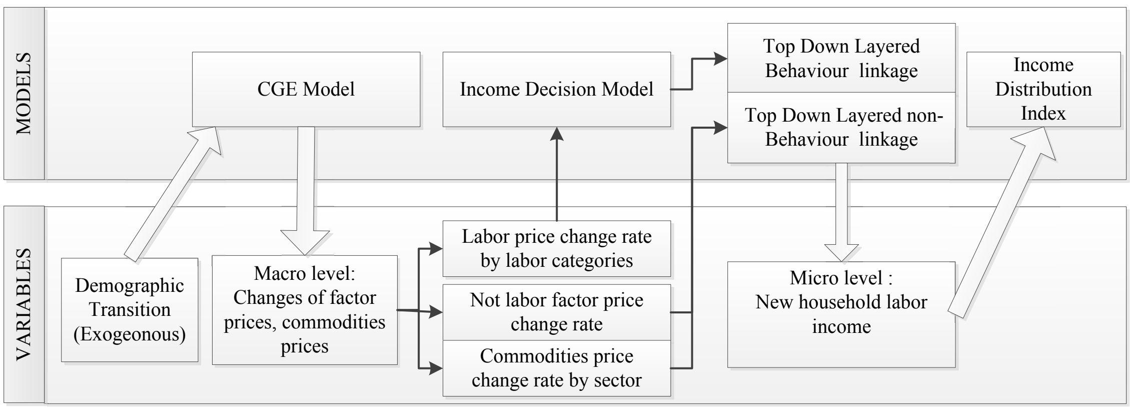
As such, the layered link method is more reasonable and popular. The layered link method involves connecting a separate micro model with a CGE model, and it can be further split into behavior-layered link and non-behavior-layered link. For the non-behavior-layering approaches, which assume that all the households in a group are affected in the same way by changes in the macro variables from the macro model, this can eliminate the within-group differences induced by individual heterogeneity. The behavior-layered link method connects a CGE model with a micro model that simulates the microbehavioral model separately. The behavior-layered link method can be further divided into top-down microsimulation and top-down (such as Bourguignon, Robilliard, and Robinson 2003; Debowicz 2012) and bottom-up microsimulation links (such as Savard 2005, 2010) due to the reflected difference. The former links the CGE model results to the microsimulation model, while the latter can further deliver the feedback from the microsimulation model back to the CGE model. However, the latter is much more difficult as the convergence cannot be guaranteed and needs to be confirmed at each stage.

Framework of This Study

Households receive income from factor endowments (labor income and capital) and transfers from the government. The CGE model is used to get the results of both the factor market price changes and the household income changes due to China's demographic transition. Therefore, the macro-micro linkage via household income or through the factor markets is helpful. Though the layered behavior link method seems better as described below, additional household behavior models are required for which not all data are suitable for these methods (Wang, Mi, and Liang 2015). Taking into consideration the tradeoff between the advantages and disadvantages of the micro-macro linkage method, data availability, and technical feasibility, we attempt both the behavior-layered link and the non-behavior-layered link approaches to connect the CGE model's macro results to microdata.

In our research, we first solve the dynamic CGE model with demographic transition to get the results on a vector of changes for commodity prices, labor price, nonlabor price, and government transfer. Then, (1) we link the household labor income, which is the majority part of the household income and remains at the individual level in this study, via the top-down behavior-layered link; (2) we link the nonlabor income changes, which are difficult to estimate via the micro–household regression model, through a top-down non-behavior-layered link; and (3) we deal with the micro level's household expenditure changes based on the consumption structure in each commodity sector and link the macro commodity price changes from the results of the CGE model via non-behavior-layered connection. Finally, we adopt poverty and inequality indexes to evaluate the distributional impact of the shock to the demographic transition with the results from the microsimulation model (Figure 2.1).

Figure 2.1 The framework of macro and micro models linkage



Source: Authors.
Note: CGE = computable general equilibrium.

3. MODELS AND DATASETS

In this section, we introduce the specification of the macro CGE model and micro model, respectively, as well as the setting of parameters and datasets.

The Specification of the CGE Model and Its Dataset

The dynamic CGE model adopted in this research is developed by the International Food Policy Research Institute and is an extension of the International Food Policy Research Institute's static standard model that was developed by Lofgren, Harris, and Robinson (2002). The model is a recursive dynamic model that is solved one period at a time, which indicates that the behavior of the model's institutions is based on adaptive expectations rather than on the forward-looking expectations that underlie intertemporal optimization models (Thurlow 2012). In this paper, we will briefly introduce the demographic-transition-related aspects of the model, such as labor factor, production function, household income and expenditure, and data settings.

The Definition of Factor Supply and Household Factor Income

Labor and capital factors are included as value added of factor input in our study. The demographic transition is expected to affect the size and structure of the labor supply. To consider demographic transition within the larger context of real economic development, four types of demographic changes are introduced for the basic scenario: population aging, gender shifts, urbanization, and human capital structure changes. Therefore, besides the population aging issue, labor is divided into regions and gender as well as rural-urban regions, with eight categories in all. Together with the capital factor, which is considered a factor value-added input in the sector production function, there are nine factor segments.

In this model, based on the producer's profit maximization principle, the value-added input is estimated by the constant elasticity of substitution (CES) function with different factor input ratio. The factor value-added input in sector *a* can be defined in the following CES function in equation 1:

$$QVA_a = \alpha_a^{va} \cdot \left(\sum_{f \in F} \delta_{f\,a}^{va} \cdot QF_{f\,a}{}^{-\rho_a^{va}} \right)^{-\frac{1}{\rho_a^{va}}}, \qquad (1)$$

where, α_a^{va} is the efficiency parameter in this CES function and $\delta_{f\,a}^{va}$ denotes the share parameter for factor f input in sector *a*. $QF_{f\,a}$ is the factor demand of *f* in the production activity, and ρ_a^{va} is the exponent in the CES function. It is the variant of factor elasticity substitution, which can be denoted as $\frac{1}{1+\rho}$.

Therefore, equation 1 can measure the value-added input changes in each sector *a* due to demographic transition. Consistent with the micro–household survey data and taking into consideration the household's work and consumption sectors, this model classifies production activities into 12 sectors in all, including (1) agriculture, forestry, animal husbandry, and fishery; (2) mining; (3) manufacture of foods, beverage, and tobacco; (4) manufacture of nondurable consumer goods; (5) other manufacture; (6) power, water, gas, and electricity processing industry; (7) construction; (8) transport, storage, post, and information; (9) wholesale, retail trades, and hotel; (10) financial intermediation; (11) real estate, leasing, and business services; and (12) other services. The parameters of factor elasticity substitution for the 12 sectors are based on Zhang, Wang and Chen (2014), who list 17 sectors in all. The efficiency parameter α_a^{va} can be taken as total factor productivity, which is enhanced with changes in human capital accumulation. In this paper, we assume that the increase of the ratio for the high-skilled labor force will improve sector total factor productivity. Finally, the total sector production for a sector is calculated using both the value-added input and the aggregate intermediate input, which is expressed by a Leontief function with a fixed share of disaggregated intermediate inputs.

Accordingly, the factor price is based on the optimal principle of cost minimization that the factor cost is subjected to equation 1 and calculated with the Lagrange method's first-order condition. Therefore, the price of factor f (eight types of labor factor and one capital factor) in sector *a* can be measured by equation 2, where the left side is the marginal cost of each factor and the right side can be taken as production marginal revenue. W_f is the average factor price, and $WFDIST_{fa}$ is the wage distortion parameter for factor f in sector *a.* It is set exogenously.

$$W_f \cdot \overline{WFDIST}_{fa} = PVA_a \cdot (1 - tva_a) \cdot QVA_a \cdot \left(\sum_{f \in F'} \delta^{va}_{f\,a} \cdot \left(\alpha^{vaf}_{f\,a} \cdot QF_{f\,a}\right)^{-\rho^{va}_a} \right)^{-1} \cdot \delta^{va}_{f\,a} \cdot \left(\alpha^{vaf}_{f\,a} \cdot QF_{f\,a}\right)^{-\rho^{va}_a - 1} . \quad (2)$$

The Definition of Household Income and Expenditure

The household is disaggregated into rural household and urban household in our model. Household income is from factor reward (labor factor and capital factor included) and transfers income from both government and nongovernment institutions. Equation 3 defines the total factor income for a household. It is the sum of all the factor income, which is the average factor price (WF_f) with wage distortion parameter times factor input (QF_{fa}). The demographic transition would influence the labor factor income, and therefore the total household income would be changed accordingly.

$$YF_f = \sum_{a \in A} WF_f \cdot \overline{WFDIST}_{f\,a} \cdot QF_{f\,a} . \quad (3)$$

The total household income for individual *i* is the sum of factor incomes (defined in equation 3), transfers from other nongovernment institutions, transfers from the government (indexed to the consumer price index [CPI]), and transfers from the rest of the world (indexed to the exchange rate). Equation 4 shows the household total income.

$$YI_i = \sum_{f \in F} YF_{i\,f} + \sum_{i' \in INSDNG'} TRII_{i\,i'} + trnsfr_{i\,gov} \cdot \overline{CPI} + trnsfr_{i\,row} \cdot EXR . \quad (4)$$

The transfers from domestic nongovernment institution *i'* to household *i* are paid as fixed shares of total institutional incomes net of direct taxes and savings. Equation 5 defines the transfer from institution *i'* to household *i. MPS* is the marginal saving propensity, *tins* is the direct tax rate, and $shii_{ii'}$ is the share of transfer rate.

$$TRII_{i\,i'} = shii_{i\,i'} \cdot (1 - MPS_{i'}) \cdot (1 - \overline{tins}_{i'}) \cdot YI_{i'} . \quad (5)$$

Finally, the total household disposable income is defined as the income that remains after direct taxes, savings, and transfers to other domestic nongovernment institutions. It is shown in equation 6.

$$EH_h = \left(1 - \sum_{i \in INSDNG} shii_{i\,h}\right) \cdot \left(1 - MPS_h\right) \cdot (1 - \overline{tins}_h) \cdot YI_h . \quad (6)$$

The household's commodities expenditure is calculated based on the linear expenditure system (LES) function (equation 7). The LES function is calculated by assuming that each household maximized a Stone-Geary utility function subject to a consumption expenditure constraint and captures its first-order conditions. There is a basic survival consumption for each commodity within a household in the LES function; it is measured by the share of this consumption (γ_{ch}^{m}) times the price of each commodity. Besides the basic consumption, there is an extra consumption for each commodity with the share of β_{ch}^{m}, which varies for different types of households. Therefore, the demographic transition will change the total consumption structure for all the commodities.

$$PQ_c \cdot QH_{c\,h} = PQ_c \cdot \gamma_{ch}^{m} + \beta_{ch}^{m} \cdot \left(EH_h - \sum_{c' \in C} PQ_{c'} \cdot \gamma_{c'h}^{m} \right). \tag{7}$$

The household consumption parameters include the commodity demand elasticity in each commodity sector and the basic consumption parameter γ_{ch}^{m}. For the commodity demand elasticity in the 12 sectors in our study, we adopt the calculation by Xie (2008), who employs both the Bayesian rules and generalized maximum entropy methods to estimate the substitution elasticity of 14 sectors based on the panel data throughout China's 31 provinces with household income and expenditure. Due to the difficulty of calculating the basic consumption parameter, previous research mainly uses the Frisch parameter to measure this parameter. Frisch's (1959) research finds that the value of the Frisch parameter for poor households is –10.0, whereas it is –0.7 for rich households. Based on these results and empirical experience, we set the Frisch parameter for rural and urban households at –2.5 and –2.0, respectively.

Besides affecting labor supply changes, the amount of population change will affect household consumption and expenditure. Therefore, it will significantly affect commodity sales, saving, and total investment changes. In our study, population growth is exogenously imposed in the model based on the United Nations' World Population Prospects (United Nations 2013) and extends over a time period from 2010 to 2030 to simulate population changes. Despite changes in household population, the model assumes the marginal rate of consumption for commodities to be unchanged, which implies that new consumers have the same preferences as existing consumers.

Specification of CGE Model's Database

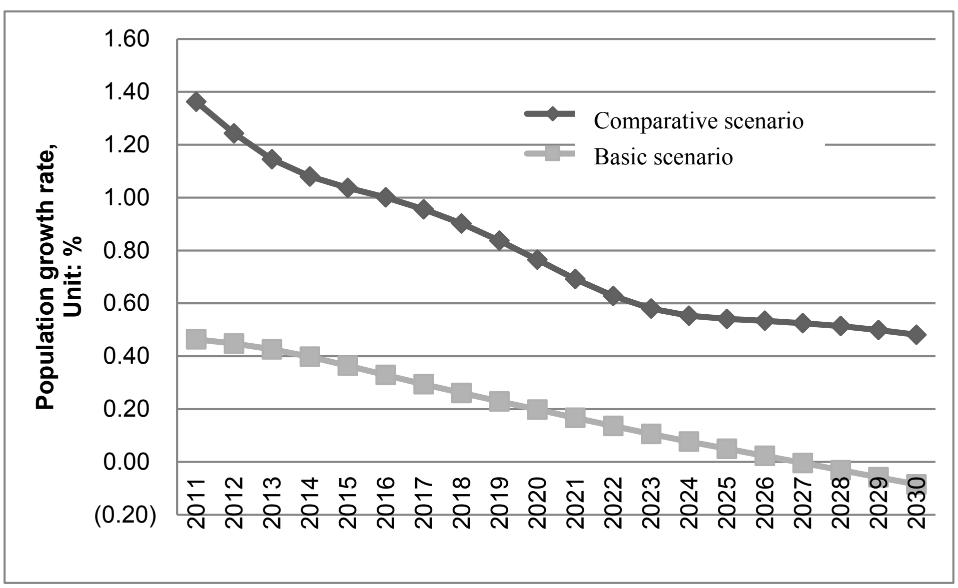
A social accounting matrix (SAM), which is a comprehensive and economywide data framework, serves as the database of the CGE model (Lofgren et al. 2002). SAM is built using the latest input-output (2010), which is an extension table of the input-output table for 2007; different kinds of yearbooks and the micro–household survey data are employed for SAM. There are 12 activities and commodities sectors, 8 segments of the labor force, and two types of households in SAM. To overcome the difficulty of collecting data for 8 types of labor factor inputs as value added on 12 sectors, we employ the household survey data with an econometrics model to calculate the ratio of the factor input distribution on 12 sectors. The wage difference between the 8 labor segments is estimated by a wage regression with region dummy, skill dummy, gender dummy, and their cross-variable dummy as well as other individual and household characteristics for independent variables. After getting the predicted slopes of these dummy variables, the marginal wage difference of the 8 types of the labor force can be calculated from the slopes. Then the wage differences for different labor forces are induced based on the average wages by sector, which can be collected from the China Stock Market and Accounting Research Database. Besides the parameters in CES and LES function that have been introduced in the previous sector, the elasticity in the constant elasticity transformation function and Armingtion function are mainly from Zhai and Hertel's (2005) results, which provides the elasticity of 53 sectors.

The Set of Simulation Scenarios

As mentioned before, to consider demographic transition within a context of real economic development, four types of demographic changes are introduced for the basic scenario. (1) First is population age structure change, which is the central focus of this paper. (2) Second is population gender structure change. The first two will be simulated based on World Population Prospects by the United Nations. (3) Third is human capital accumulation change. This is represented by the proportional changes for labor force with tertiary education to total labor force aging population. The share of the labor force with tertiary education was 19.52 percent and 2.63 percent, respectively, for rural and urban individuals in 2010, as reported by the China Statistics Yearbook (NBS 2011). On the basis of China's past growth rate for the share of the labor force with tertiary education as well as the current situation for developed countries, the simulation for the tertiary education share change is assumed to double for rural individuals and increase 1.5 times for urban individuals in 2030. (4) The population spatial change with urbanization. China has the largest urban population in the world, with 749 million urban dwellers in 2014, accounting for 54.77 percent of China's total population, and it is supposed to reach 68.7 percent by 2030 and 70.0 percent by 2033 (United Nations 2014). All four of these demographic transitions are linked to the labor factor supply and population changes within the periods of the CGE model's dynamic component.

A comparative scenario without population aging is used for comparing the base scenario to determine the real impact of population aging. In this scenario, the population age structure change from 2010 to 2030 follows the structure change from 1990 to 2010 and holds the other three demographic transitions constant. Figure 3.1 shows that the general trend of demographic transition for each of the two scenarios is similar, which shows that the population growth rate is slowing due to China's birth control policy since the 1970s. However, in the basic scenario, population growth becomes negative in 2027, and the average population growth rate is 0.189 percent from 2010 to 2030. While things are different in the comparative scenario without the population-aging problem, the population growth rate slows down but remains positive, and the average growth rate remains at 0.794 percent during the same period. Therefore, the results of the scenario can provide the absolute impact of population aging by comparing the base scenario with that which integrates population aging.

Figure 3.1 The population growth tendency for the two scenarios, 2011–2030



Source: World Population Project by the United Nations (2014) and China's Statistic yearbook by NBS (2014).

4. SPECIFICATION OF MICRO MODEL AND ITS DATASET

The Definition of the Micro Income Decision Model

Consistent with the macro model, micro–household income comprises labor income, capital income, government transfer income, and other incomes that cannot be classified into any one category. Both employed and self-employed wage income is classified as labor income that provides the majority of the income for households. The labor income is linked to the CGE results with a layered behavioral methodology that can reveal individual heterogeneity. Other nonlabor income, which cannot be estimated by an individual behavior function and may take only a small part of the income, is linked to the CGE results through a non-behavior-layering approach in which the income is changed with the same ratio within the same group segment according to the changes from the CGE model.

The labor income can be represented by function 8.

$$logW_i = a^s + b^s X_i + v_i, \tag{8}$$

where W_i is the nominal labor income of working individual i and dependent X_i variable denotes the vector of the characteristic of the individual, household, and regions. $a^s \; and \; b^s$ are the intercepts and slopes in the logarithm of the wage, respectively. v_i is the residual term that describes the effects of unobserved earning determinants and possibly measurement errors.

The total household income can be defined as equation 9. The nonlabor income and a household specific CPI are described in equation 10 and equation 11, respectively.

$$YH_h = \frac{1}{P_h}\left(\sum_{i \in h} W_{ih} IW_{ih} + Y_{0h}\right) \tag{9}$$

$$Y_{0h} = Capi_h + Trans_h + Other_h \; ; \tag{10}$$

$$P_h = \sum_{k=1}^{K} S_{hk} * p_k \; , \tag{11}$$

where YH_h is the total household income for the members within a household. It includes the household labor income and nonlabor income. For the labor income, IW_{ih} stands for a dummy variable, which denotes the individual work status (1 for work, 0 for not work). W_{ih} is the individual labor income that is calculated in equation 8. Therefore, the sum of the total labor income within a household is $\sum_{i \in h} W_{ih} IW_{ih}$. Nonlabor income ($Y_{0h}$), comprises the capital income, land income, transfer income, and other income, which are calculated at the household level and shown in equation 10. To compare the real household income changes as a result of the demographic transition shocks, household income is adjusted by a household-specific CPI (P_h), which is introduced in the household income function (equation 9) following Bourguignon, Robilliard, and Robinson's (2003) method.P_h is measured in equation 11, which can eliminate the effects caused by price differences in various households and in different years. Therefore, the adjusted household income is comparable within different years and households. S_{hk} is the observed budget shares of a household's consumption for commodity *k*, and p_k denotes the price of various consumption goods *k*.

Estimation of the Parameters for the Benchmark Simulation

The parameters of the labor income function are estimated for transmitting the CGE results to the microsimulation using a behavior method. Labor income is a nonlinear function of the observed characteristics of individuals, households, and regions. Consistent with the CGE model, this labor income function is defined independently across eight labor segments, which are classified by area (rural/urban), skill (with high education level), and gender (male/female). Therefore, eight separate regressions are run to estimate the parameters (a^s and b^s) of the labor income equation for each labor market segment. The subject of these regressions is the aging labor force, which may include the working-age population who do not participate in the workforce. To correct for the possibility of sample selection problems, we use the two-step Heckman procedure, which includes an inverse Mills ratio derived from a preprobit model that estimates the work status of the individual.

The Introduction of the Microdata

The household survey data we employ are from CHIP, which is carried out by the Institute of Economics, Chinese Academy of Social Sciences, with assistance from the National Bureau of Statistics. CHIP carried out the survey in 1995, 2002, and 2007. However, the question design for the income and expenditure sector in the 2002 survey is much more consistent with the requirements of our macro-CGE model. The micro-macro linkage requires that the sectors be consistent between the CGE model and microsimulation model. For example, the question design of the job sectors for the micro household in CHIP 2002 has 16 sectors, 25 sectors, and 18 sectors for urban household, migrant workers, and rural household, respectively, which is consistent with our CGE model's sector classification. After matching all the micro households' job sectors with the CGE models', 12 sectors are classified in our research. Only the 1995 and 2002 data were public when we started this study, and thus, the 2002 CHIP data are used for our research. To solve the problem that the income and consumption data in 2002 are too old, we updated the labor income data and household consumption data of 2002 to 2010 using an appropriate method that will be introduced in the following paragraph. The CHIP 2002 data were collected through a series of questionnaire-based interviews conducted in rural and urban areas and covered 22 provinces in China. There are a total of 6,835 urban households, 9,200 rural households, and 2,000 migrant households included in the survey, with a total number of 37,969 individuals. Because the sampling for migrants is based on the place of residence of migrants, migrants living in a dormitory or workplace (such as a construction site) are excluded in the sample (Zhao et al. 2010), and we merge the migrant households (which can be taken as low-skilled urban labor) with the urban households in our study.

To connect the CGE results with the base year 2010, we update the labor income data of 2002 to 2010 using a similar method for connecting CGE results with microdata. Different from the method of updating the micro income data according to the corresponding proportion from the macro data (such as is performed by Zhang, Wang, and Chen 2014), the advantage of this method is that it can sustain the individual heterogeneity for the wage changes to overcome the consistency of the within-group variance. Labor income is updated based on the sectors the individual worked for, and the macro data are collected from the China Stock Market and Accounting Research Database, which has the average wages in different sectors for both 2002 and 2010. Labor is classified by sectors, and each regression income model is done to estimate the parameters of different types of labor segments. Other income is updated to 2010 based on the proportion changes between 2002 and 2010 from the data collected in the China Statistics Yearbook. The dependent variables for the labor income regression function are the observed characteristics of the individual, household, and region, which include the individual's age, the individual's education year, the sector in which the individual works, the number of children and labor force in the household, whether the individual is the household head, and finally the region (east, middle, or west of China).

5. COMMUNICATION BETWEEN THE CGE MODEL AND MICROSIMULATION

As introduced in the previous section, the non-behavior-linkage approach conveniently links the micro–household income data by directly corresponding with the ratio from the CGE model's results. The following part of this section focuses more on the transmission channels from the CGE model's macro–labor factor price changes to the micro–labor income variation using the layered behavioral methodology in a top-down fashion, which can capture the distributional differences of both the within group and the between group by considering the individual's and household's heterogeneity.

After solving the dynamic CGE model for a period of 20 years from 2010 to 2030 in the context of demographic transition, new labor wage changes are generated in each of the periods. From the simulation of the dynamic CGE model, in the basic scenario, the simulation results show that the income difference between rural and urban households is decreasing. For example, the annual per capita income growth rate is 3.18 percent for urban households, while it is 10.08 percent for rural households. From the primary labor factor distribution, the results show that rural labor wages are growing faster than are those for urban labor, while low-skilled labor price growth is faster than that of high-skilled labor (Table 4.1). To determine the micro level's household income and expenditure changes due to demographic transition, we need to link the macro CGE models' results to the micro household for both the basic scenario and the comparative scenario. The following section focuses more on the transmission channels for the communication from the CGE model to the labor income model.

Table 4.1 The growth rate of labor wages, 2010–2030, in percentages

Labor type	Scenario	2010–2015	2015–2020	2020–2025	2025–2030	Annual
Urban skilled male	BASE	9.47	6.70	5.27	4.14	6.378
	NODE	11.62	9.97	8.84	7.60	9.499
Urban skilled female	BASE	9.31	6.67	5.26	4.13	6.324
	NODE	11.45	9.99	9.01	7.89	9.579
Urban unskilled male	BASE	9.83	7.19	5.89	5.10	6.989
	NODE	12.17	10.74	9.85	9.52	10.563
Urban unskilled female	BASE	9.45	6.91	5.74	5.04	6.771
	NODE	11.75	10.65	10.26	10.40	10.764
Rural skilled male	BASE	11.09	7.05	4.96	3.41	6.587
	NODE	13.57	10.07	7.77	5.84	9.274
Rural skilled female	BASE	12.14	7.22	4.59	2.59	6.576
	NODE	14.65	9.86	6.61	3.78	8.648
Rural unskilled male	BASE	11.32	7.17	5.10	3.70	6.785
	NODE	13.96	10.31	7.96	6.36	9.610
Rural unskilled female	BASE	12.59	7.88	5.53	3.79	7.396
	NODE	16.08	11.67	8.58	5.59	10.411

Source: Results from CGE model simulation by authors with GAMS.
Note: BASE = base scenario; NODE = comparative scenario.

The labor wage change in a specific simulation year is represented as $\widehat{W}_{r,s,g,p}$, ; here, r, s, g, and p denote the region, skill level, gender, and time period, respectively, and there are eight segments of the labor force in all as mentioned in the previous section. The microsimulation model is applied to generate the changes for the individual's labor income, consistent with the labor wage changes from the CGE model. Let us express the set of the original macro labor wage using equation 12, which is the consistency-adjusted microdata with the sample weights for each of the labor segments. The macro targets in a specific simulation period vector are indicated in equations 13 and 14.

$$f(x) = W_{r,g,s0}, \tag{12}$$

$$f^{*}(x) = W^{*}_{r,g,s,p}. \tag{13}$$

$$W^{*}_{r,g,s} = W_{r,g,s0} * (1 + \widehat{W}_{r,g,s,p}) \tag{14}$$

In equation 14, $\widehat{W}_{r,g,s}$ is taken as the percentage change from the base year of the macro simulation. The parameter changes are assumed to be neutral with respect to the individual characteristic. So only the intercepts of the labor income function are adjusted to generate a proportional change of all the income in each of the labor segments irrespective of individual characteristics. Then, consistent adjusting involves finding a row vector $x = a_{r,g,s}$ to be consistent with the $f^{*}(x)$ macro target vector. Following Bourguignon, Robilliard, and Robinson's (2003) and Debowicz's (2012) research, this problem can be solved using the Newton-Raphson method, which is a root-finding algorithm that uses the first few terms of the Taylor series of a function in the vicinity of a suspected root to find successively better approximations to the root of a real-value function. This requires a Jacobian matrix (equation 15) with all the possible combinations of partial derivatives of the element for the original macro labor wage, $f(x)$. A detailed discussion of the specification for this methodology can be found in Debowicz (2012).

$$\mathrm{J} = \begin{bmatrix} \frac{\partial \mathrm{W}_{\mathrm{u,s,m}}}{\partial \mathrm{a}_{\mathrm{u,s,m}}} & \cdots & \frac{\partial \mathrm{W}_{\mathrm{u,s,m}}}{\partial \mathrm{a}_{\mathrm{r,u,f}}} \\ \vdots & \ddots & \vdots \\ \frac{\partial \mathrm{W}_{\mathrm{r,u,f}}}{\partial \mathrm{a}_{\mathrm{u,s,m}}} & \cdots & \frac{\partial \mathrm{W}_{\mathrm{r,u,f}}}{\partial \mathrm{a}_{\mathrm{r,u,f}}} \end{bmatrix} \tag{15}$$

In addition, as the computation of a Jacobian matrix and the solution of a linear system in each iteration makes the Newtonian technique costly with two scenarios and spanning 20 years for the simulation periods, it would not be a good idea to simulate all 40 periods in a microsimulation model. To compare the income distribution associated with the demographic transition in a more practical manner, we choose 2010, 2015, 2020, 2025, and 2030 as the year points with two scenarios to quantify the trend of the distribution impact in our research instead.

In addition, the microdata are static cross-section data that can't reflect the demographic transition. Based on the ideas of Bussolo, De Hoyos, and Medvedev's (2008) study, we construct a new weight that can show the demographic characteristics and their tendency. In our study, the population is divided by 20 age groups and further split by regions. We calculate the new weight according to China's sixth nationwide population census as well as the United Nations' population projection.

6. MAIN RESULTS ON THE DISTRIBUTIVE EFFECTS

At this point, we are able to obtain the new micro–household income divided by specific household CPI. Both the Foster-Greer-Thorbecke (FGT) index and the Gini index are employed to estimate the changes in poverty and inequality. The scenarios with and without population aging are used to compare the impact of demographic transition so that we can get an idea of the relationship between population aging and income distribution. To study the distributional effect among different household age groups, we decompose the FGT index and Gini index into eight household groups that are classified by area and household head's age.

In this section, we briefly describe the FGT index and the Gini index first. Then, the results from the updated income from the microsimulation are introduced to the poverty and inequality index, and a general conclusion on the impact of demographic transition on income distribution is finally summarized.

Specification of the Poverty and Inequality Index

FGT Index and Its Decomposition

There are quite a lot of poverty measurement indexes, the most popular of which are the FGT index, the Watts index, and the Sen-Shorrocks-Thon poverty index. The FGT index proposed by Foster, Greer, and Thorbecke in 1984 is used in this research. The normalized FGT index is estimated in equation 16.

$$\hat{P}(z;\alpha) = \sum_{i=1}^{n} w_i[(z-y_i)/z)]^{\alpha}{}_{+} \Big/ \sum_{i=1}^{n} w_i \quad , \tag{16}$$

where w_i denotes total population when the sampling weight is taken into consideration, z is the poverty line, and y_i represents the household income per capita. The parameter α can be valued at 0, 1, and 2. When α = 0, FGT can measure the poverty incidence or heat-count, which is the ratio of poor people to total population. For α = 1, the poverty gap can be calculated, measuring the gap between income per capita for poverty and the poverty line. For α = 2, the severity of poverty can be calculated, measuring the equilibrium level of the poverty distribution. Both the poverty incidence and the poverty gap are measured in this paper.

The choice of poverty line is crucial when measuring poverty. We use both the World Bank's poverty line and China's official poverty standard for comparison. The World Bank's poverty line is US$1.25 per day based on the purchasing-power parity in 2005. China's official poverty line has been adjusted every year during the past decades, and it was set at 2,300 yuan per year in 2011, which is equal to US$1.80 per day based on the purchasing-power parity in 2005. It is worth noting that both urban and rural household incomes in different years are divided by a household-specific CPI (equation 11) so that we can use the same poverty line for both rural and urban households as well as for different simulated years.

The form of FGT decomposition can be represented as

$$\widehat{\mathrm{P}}(\mathrm{z};\alpha) = \textstyle\sum_{\mathrm{g}=1}^{\mathrm{G}} \widehat{\emptyset}\,(\mathrm{g})\widehat{\mathrm{P}}(\mathrm{z};\alpha;\mathrm{g}), \tag{17}$$

where G is the number of population subgroups. This can estimate the FGT index in each of the subgroups and measure the contribution of subgroups to total poverty as well. The relative contribution of each of the subgroups to total poverty can be expressed as

$$\widehat{\mathrm{P}}(\mathrm{z};\alpha;\mathrm{g}) = \widehat{\emptyset}(\mathrm{g})\widehat{\mathrm{P}}(\mathrm{z};\alpha;\mathrm{g})/\widehat{\mathrm{P}}(\mathrm{z};\alpha). \tag{18}$$

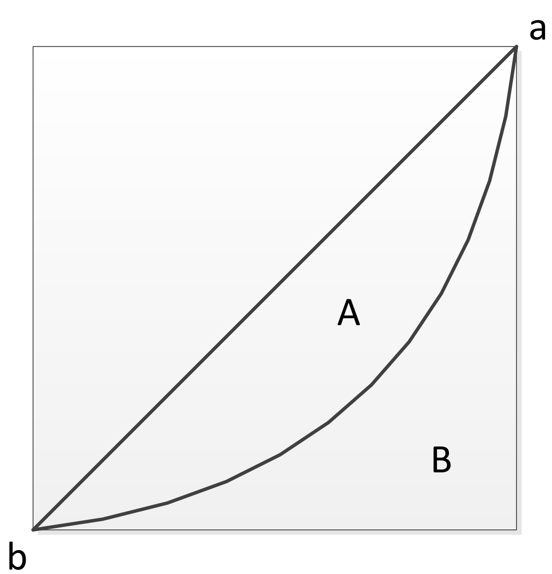
In this study, to estimate the demographic transition impact, the household groups are classified by household head's age, which can represent the age status for a household. If the household head's age is younger than 30, the household is classified as a young household; if 30 to 45, it is defined as an adult household; if 45 to 60, it is taken to be a senior household; and if older than 60, it is considered an old household. There are eight segments for households: rural-young, rural-adult, rural-senior, rural-old, urban-young, urban-adult, urban-senior, and urban-old.

Gini Coefficient and Its Decomposition

The Gini coefficient, which was developed by Gini (1912), is the most commonly used measure of inequality. This index is usually defined based on the Lorenz curve (Figure 5.1). In Figure 5.1, the straight line ab with 45 degrees represents perfect equality of income distribution curve while the curve ab represents the real income distribution curve, which is just the Lorenz curve. The area between these two curves is marked with "A," and the Lorenz curve with its right area is marked with "B." The Gini coefficient can then be calculated as

$$G = A / (A + B). \tag{19}$$

Figure 5.1 The Lorenz Curve



Source: Lorenz (1905).

The Gini coefficient ranges from 0 to 1. The smaller the Gini coefficient, the more equal is the society. The inequality 0.4 is internationally recognized as a warning line, and the inequality is dangerously large in a society if the Gini coefficient exceeds 0.4. The Gini index can be decomposed by population subgroups as follows:

$$I = \sum_{g=1}^{G} \emptyset_g \varphi_g I_g + \bar{I} + R, \tag{20}$$

where $\emptyset_g$ is the population share of group g to total population, ϕ_g denotes the income share of group g, $\sum_{g=1}^{G} \emptyset_g \varphi_g I_g$ indicates the between-group inequality, $\bar{I}$ is the within-group inequality, and R is the residual implied by group income overlap.

Both poverty's and inequality's effects on evolution in the context of demographic transition are presented in this section with FGT and the Gini index as well as their decomposition methods as mentioned before. Moreover, to quantify aging's impact on both poverty and inequality, the scenario of non–population aging across five time points is used for comparison with the basic demographic evolution scenario.

The Impact of Demographic Transition on Poverty and Inequality

From the simulation results, we obtain the following preliminary conclusions.

1. **Demographic transition will further reduce poverty in China; however, population aging itself has a negative impact on the reduction of poverty.**

Both the poverty incidence and the poverty gap associated with the two poverty lines are presented in Table 5.1. The poverty incidence and poverty gap are, respectively, 7.25 percent and 3.53 percent using the Chinese poverty line of 2,300 yuan per year in 2010. Generally speaking, in the context of basic demographic evolution and economic growth, poverty has been greatly reduced by 2015. For example, when using the 2,300 yuan poverty line, poverty incidence decreased from 7.25 percent in 2010 to 4.09 percent in 2015 and further dropped to 2.97 percent in 2020. However, poverty reduction after 2020 slowed to only a 0.95 percentage point reduction from 2020 to 2030. This is because poverty is a universally persistent problem. The government has to improve the well-developed social assistance system to address poverty. In a comparative scenario without population aging, poverty is estimated to decrease faster. For example, poverty incidence is estimated to decrease to 3.59 percent in 2015 and to drop further to 1.68 percent in 2030. This is due to the faster macroeconomic development because of the demographic dividend with the relative abundance of the labor force. In other words, the general demographic transition will reduce poverty while population aging itself opposes poverty reduction as it slows economic development.

Table 5.1 The Foster-Greer-Thorbecke index evolution in the context of two scenarios

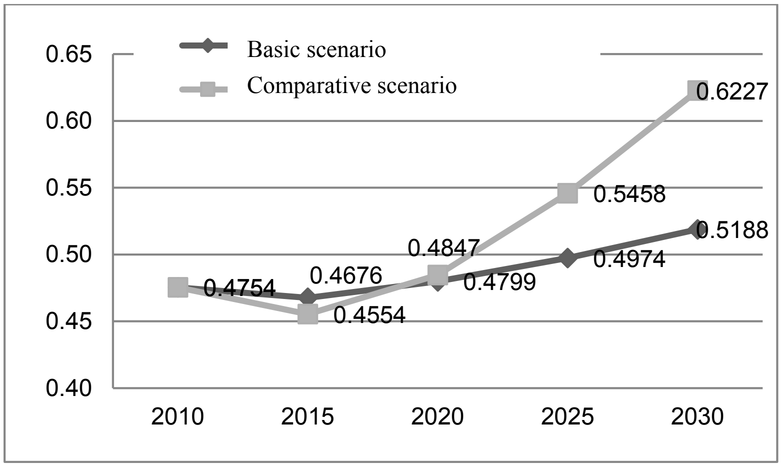
Scenario	Base scenario				Comparative scenario			
Poverty line	2,300 yuan per year		US$1.25 per day		2,300 yuan per year		US$1.25 per day	
Year	a = 0	a = 1	a = 0	a = 1	a = 0	a = 1	a = 0	a = 1
2010	0.0725	0.0353	0.0564	0.0298	0.0725	0.0353	0.0564	0.0298
2015	0.0409	0.0236	0.0347	0.0208	0.0359	0.0215	0.0302	0.0193
2020	0.0297	0.0192	0.0254	0.0176	0.0245	0.0170	0.0218	0.0158
2025	0.0247	0.0172	0.0219	0.0160	0.0198	0.0152	0.0180	0.0145
2030	0.0202	0.0150	0.0182	0.0143	0.0168	0.0136	0.0157	0.0131

Source: Results from CGE model simulation by authors with GAMS.
Note: Comparative scenario is the simulation without considering the population-aging issue.

2. **Inequality is increasing with China's demographic transition; however, population aging itself has a positive impact on equality.**

However, the story is somewhat different for inequality. Population aging is estimated to improve equality according to our research in China. From the results in Figure 5.2, we can see both that inequality decreases in 2015 and that it increases in the two scenarios. However, the change rate is different from the base scenario. The Gini coefficient is estimated to decrease from 0.475 in 2010 to 0.468 in 2015. This can be attributed to the fact that China's total labor force is predicted to drop from 2015. Compared with the non-population-aging scenario, inequality is much better in the basic demographic transition scenario. For example, the Gini coefficient increases to 0.4799 in 2020 and further increases to 0.5188 in 2030, but it is 0.4847 and 0.6227, respectively, in the scenarios of non–population aging. These indicate that though population aging has negative effects on economic growth and, as a result, is not good for poverty reduction, it may lead to improved equality of distribution. However, in the case of basic demographic transition, which includes four types of demographic change, inequality still increases. This may be due to other demographic transitions. Further research on different scenarios of various types of demographic change can involve studies to estimate the exact causes of inequality.

Figure 5.2 The Gini tendency for the two scenarios, 2010–2030



Source: Results from CGE model simulation by authors with GAMS.

3. **The rural-old group is the poorest group in China, while the young household group is better poised to escape poverty.**

To further understand the distributional impact on a specific household group, we decompose the FGT poverty index and Gini coefficient into different population groups by areas and age to estimate the poverty and inequality in each of the different household groups and their contribution.

From the results of the FGT poverty index decomposition in Table 5.2, we can see the following: First, all household-specific poverty is declining with the development of economic growth and demographic transition. Second, from the cross-section data, the general poverty of rural areas is much more serious than that of urban areas, and the old group is worse off than the young group. Among them, the rural-old household group is the group most seriously threatened by poverty. In 2010, for example, the FGT index for rural-old households was 19.65 percent, while it is only 0.10 percent for urban-adult households. The entire FGT index is greater than 10 percent in the rural household group, while the largest poverty incidence is only 1 percent for the urban group. This can be attributed to migration in rural China where the old population is left in rural areas while the working-aging population migrates to urban areas for work. Third, the relatively young household group can escape poverty much easier than can the old household group. For example, the rural young and adult household groups are estimated to experience a reduction in poverty incidence from 16.38 percent and 13.49 percent in 2010, respectively, to 2.61 percent and 3.76 percent in 2030, while the rural-old household group's poverty incidence remains greater than 11 percent in 2030. It is worth noting that the poverty incidence for the urban-old household group experiences a tiny increase during the whole period of our scenarios. Fourth, after considering the population share, the rural-senior group contributes the most to the total FGT poverty incidence with a relative contribution of 42.45 percent to the total population poverty incidence in 2010. But with the relatively faster reduction of poverty for this group as well as the decrease of the rural population due to urbanization and population aging, this group's contribution to poverty is decreasing, and it is estimated to contribute only 30.89 percent in 2030.

Table 5.2 The Foster-Greer-Thorbecke index decomposition by household subgroup, 2010–2030

Year	Index	The FGT index								
		Rural				Urban				
		Young	Adult	Senior	Old	Young	Adult	Senior	Old	Total
2010	FGT index	0.164	0.135	0.108	0.197	0.002	0.001	0.001	0.010	0.073
	Pop. share	0.014	0.197	0.286	0.061	0.036	0.201	0.166	0.038	1.000
	Ab. contrib.	0.002	0.027	0.031	0.012	0.000	0.000	0.000	0.000	0.073
	Rel. contrib.	0.033	0.366	0.425	0.166	0.001	0.003	0.002	0.005	1.000
2015	FGT index	0.083	0.080	0.059	0.134	0.000	0.001	0.001	0.011	0.041
	Pop. share	0.016	0.179	0.277	0.061	0.039	0.196	0.183	0.048	1.000
	Ab. contrib.	0.001	0.014	0.016	0.008	0.000	0.000	0.000	0.001	0.041
	Rel. contrib.	0.033	0.351	0.398	0.200	0.000	0.004	0.003	0.013	1.000
2020	FGT index	0.060	0.059	0.041	0.123	0.000	0.001	0.000	0.013	0.030
	Pop. share	0.014	0.163	0.263	0.061	0.038	0.204	0.203	0.054	1.000
	Ab. contrib.	0.001	0.010	0.011	0.008	0.000	0.000	0.000	0.001	0.030
	Rel. contrib.	0.028	0.325	0.365	0.251	0.000	0.007	0.002	0.023	1.000
2025	FGT index	0.045	0.046	0.034	0.116	0.000	0.001	0.000	0.013	0.025
	Pop. share	0.013	0.160	0.244	0.062	0.037	0.215	0.207	0.061	1.000
	Ab. contrib.	0.001	0.007	0.008	0.007	0.000	0.000	0.000	0.001	0.025
	Rel. contrib.	0.024	0.301	0.338	0.294	0.000	0.009	0.002	0.033	1.000
2030	FGT index	0.026	0.038	0.030	0.113	0.000	0.001	0.000	0.013	0.020
	Pop. share	0.011	0.143	0.209	0.063	0.038	0.237	0.220	0.079	1.000
	Ab. contrib.	0.000	0.005	0.006	0.007	0.000	0.000	0.000	0.001	0.020
	Rel. contrib.	0.014	0.266	0.309	0.351	0.000	0.011	0.000	0.049	1.000

Source: Results from CGE model simulation by authors with GAMS.
Note: Ab. contrib. = Absolute contribution; FGT = Foster-Greer-Thorbecke; Pop. = population. Rel. contrib. = Relative contribution.

4. Between-group inequality explains the majority of inequality, but its contribution keeps decreasing.

As for the inequality decomposition by household group in the context of demographic transition, we can get the following conclusions from the estimated results in Table 5.3. First, the between-groups inequality accounts for the majority of the Gini coefficient. For example, the between-groups inequality contributed 59.27 percent to the total population's inequality in 2010, and it continued to account for around half of the total inequality for the whole period's simulation. Second, inequality between groups keeps decreasing while the inequality within groups is increasing with the demographic change. For example, the absolute contribution of between-groups inequalities, regarded as a Gini coefficient, decreases from 0.2817 to 0.2431 in 2030. At the same time, the within-group inequality contributes 0.0680 to the total Gini coefficient, and this continues to increase and reaches 0.0840 in 2030. Third, the inequality for rural household groups is much more severe at the beginning, while urban households suffer higher inequality than do rural households with the development of demographic changes. This may be due to urbanization, which is defined as growth of the urban population in the base scenario. Fourth, among the eight household groups, both inequality and poverty pose the greatest threat to the rural-old group. For example, the Gini coefficient in 2010 is 0.4591 for the rural-old household group. It continues to grow and reaches 0.4943 in 2030.

Table 5.3 The Gini index decomposition by household subgroup, 2010–2030

	2010		2015		2020		2025		2030	
Subgroup	**Gini index**	**Ab. contrib.**	**Gini index**	**Ab. contrib.**	**Gini index**	**Ab. contrib.**	**Gini index**	**Ab. contrib.**	**Gini index**	**Ab. contrib.**
Rural-young	0.4073	0	0.4171	0.0001	0.4207	0.0000	0.4257	0.0000	0.4304	0.0000
Rural-adult	0.4481	0.0095	0.4477	0.0086	0.4511	0.0074	0.4588	0.0077	0.4665	0.0064
Rural-senior	0.4144	0.0182	0.4193	0.0189	0.4279	0.0183	0.4371	0.0169	0.4442	0.0129
Rural-old	**0.4591**	0.0007	**0.4609**	0.0008	**0.4758**	0.0009	**0.4858**	0.001	**0.4943**	0.001
Urban-young	0.3766	0.0010	0.4025	0.0010	0.4372	0.0009	0.4681	0.0008	0.4938	0.0007
Urban-adult	0.3587	**0.0234**	0.3798	0.0188	0.4102	0.0181	0.4396	0.018	0.4697	0.0196
Urban-senior	0.3362	0.0146	0.3737	**0.0208**	0.4242	**0.0293**	0.4617	**0.0332**	0.4937	**0.0382**
Urban-old	0.3127	0.0006	0.3531	0.0012	0.3932	0.0018	0.4091	0.0028	0.4157	0.0052
Within	—	0.0680	—	0.0702	—	0.0767	—	0.0804	—	0.0840
Between	—	0.2817	—	0.2530	—	0.2424	—	0.2390	—	0.2431
Overlap	—	0.1256	—	0.1443	—	0.1607	—	0.1780	—	0.1917
Population	0.4754	0.4754	0.4676	0.4676	0.4799	0.4799	0.4974	0.4974	0.5188	0.5188

Source: Results from CGE model simulation by authors with GAMS.

Note: Ab. Contrib. = Absolute contribution.

6. CONCLUSIONS

Demographic transitions influenced by population aging have been attracting increasing attention throughout China and are becoming recognized as an important issue in most developing countries. However, only sparse research has studied the relationship between income distribution and demographic transition. In this paper, we investigated the evolution of poverty and inequality in the context of demographic transition. An integrated recursive dynamic CGE model with a layered microsimulation model is used to measure the income changes in light of the shock of demographic changes, such as population aging, gender shifts, urbanization, and human capital structure changes that contribute to real economic development. A comparative scenario with demographic change simulations other than population aging is adopted to capture the real impact of population aging. With the two scenarios in hand, both the FGT index and the Gini coefficient are employed to estimate the poverty and inequality changes due to demographic transition.

From previous studies, we cannot find a conclusion about the relationship between population aging and inequality immediately. This paper's results show that a significant decrease in poverty and an increase in inequality are expected in the context of the multi-demographic transition. However, inequality is negative during population aging as there would be a sharp increase in income inequality with the comparative scenario, which excludes the population-aging transition. This is consistent with the macro results that the population-aging tendency would have a positive impact on reducing the rural-urban income gap and when the wage growth rate of the rural labor force and unskilled labor force is higher than that of the urban and skilled labor forces, respectively. This could be explained by China's high saving rate for rural populations. The social welfare system is not comprehensive, especially pension insurance for the rural population. This suggests that rural residents may be unable to get pensions from the government after retiring and that people expect to have to feed themselves as they get older. As a result, rural people have to work hard and start to save money for their retirement when they are young. In addition, most of the rural old people would still work the land even in their 70s. These factors may result in the decreasing rural-urban income gap with the population-aging issue. However, this result is inconsistent with some empirical research such as Zhong (2011) and Dong, Wei, and Tang (2012), which indicate that population aging would expand income inequality. However, such research mainly decomposes inequality by age and simulates the contribution of aging on inequality based on historical cross-section data or panel data, which is quite different with our study. In addition, our study shows that the process of poverty reduction is much slower when considering population. This is because the aging population has been shown to have a negative impact on economic growth from both theoretical and empirical studies in China (Peng and Fausten 2006; Cai and Lu 2013; Huang et al. 2014), which would slow down the poverty reduction process.

Furthermore, the reduction of poverty and inequality are important policy objectives for China as well as for other developing countries. This study on China's case indicates that the old population, especially the rural-old population, should be prioritized because both poverty and inequality are more serious among these groups than among other household groups. This is due to urban-biased economic policies (Lu and Chen 2004) on one hand and fast urbanization development on the other hand. Our research further shows that the urbanization process, which can be measured by urban population share in our scenario, may help to reduce poverty but not inequality. This is because China's policy makers focus too much on the quantity of urbanization, not the quality of urbanization. Although China has experienced rapid urbanization, 298 million people still did not have *Hukou*[1] in the urban areas in 2014 although they lived and worked in these areas. As a result, they cannot enjoy the same social welfare as do urban citizens, which leads to even worse income distribution. This suggests that relevant measures such as the improvement of the social pension insurance system, especially for China's rural areas where China's social insurance coverage is insufficient, as well as the enhancement of the educational system, social

[1] In China's household registration system the households are classified into urban household and rural household. In Chinese, it is often referred as Hukou.

security, and health insurance for migrant workers in urban areas may be helpful for reducing the inequality associated with the process of urbanization. Meanwhile, the local governments must put more effort into implementing urban-planning support systems such as public infrastructure, educational infrastructure, and the medical care system.

Further research on specific demographic structure changes (such as urbanization, human capital accumulation, and gender ratio shifts) with different scenarios can be studied to find out the specific demographic reason for poverty and inequality. Future studies also should focus on China's rural population and the related economic and social problems. As for methodological considerations, there are quite a lot of scholars attempting to link CGE models with micro models, and it is proving useful in analyzing the distributional impact of exogenous policy shocks. This is an area of great interest as approaches and techniques are still under development. This paper is a layered behavioral methodology in a top-down fashion that links the results from a CGE model to the microdata. However, poverty and inequality changes can in turn induce changes in the macro economy itself, and therefore a trial of a top-down and bottom-up linkage would be much better for connecting the macro model with the micro model. This may provide fertile areas of study for future research.

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