Aging and Sectoral Productivity Gap

Yucheng Xing

November 26, 2025

[Latest Version]
[Online Appendix]

Abstract

This paper studies how population aging affects service sector productivity through a labor selection channel. Economies with older populations exhibit larger service sectors than those with younger populations. Aging populations also tend to display a decline in the relative productivity of services compared with manufacturing. To examine this phenomenon, I develop a quantitative Roy model embedded in an overlapping-generations structure with non-homothetic preferences. Aging increases service demand and relaxes the sectoral selection threshold, drawing workers with weaker comparative advantage and lower absolute advantage into services – thus lowering average productivity. Calibrated to cross-country data from 2000–2017, the model matches service employment and value-added shares with correlations of 0.87 and 0.65, and produces a 0.37 correlation for productivity gaps. The results suggest that demographic change can modestly depress the service sector's aggregate productivity through the selection channel.

1 Introduction

Among the rich literature on structural transformation, Cravino et al. (2022) document that population aging has contributed to the rise of service economies in the United States. This naturally raises the question of whether similar patterns hold across countries. Does population aging universally stimulate service demand and expansion? If so, what are the implications – if any – for sectoral productivity levels? In this paper, I document that for many countries, productivity levels are higher in the service sector than in the manufacturing sector. In countries with larger service sectors, however, productivity levels in services fall, relative to manufacturing productivity. Thus, aging is negatively correlated with the service–manufacturing productivity ratio. Countries with older populations have larger service sectors, and their service sectors are relatively less productive than we observe in countries with younger populations. Figure 1 documents the relationship between country demographic profiles and the ratio of productivity between services and manufacturing. As is evident, in all four countries, population aging is associated with a decline in the ratio of service productivity to manufacturing productivity. (Baumol, 1967).

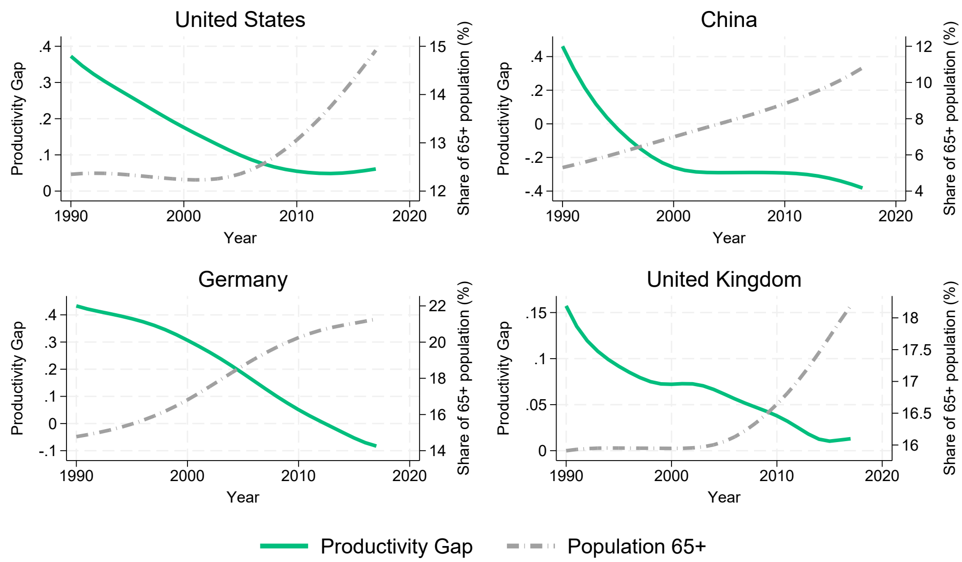


Figure 1: Cross-Country Comparison: Aging versus Productivity Gap

Note: The green solid line plots the service–manufacturing productivity gap for countries in the Panel over 1990–2017 (left y-axis), while the gray dashed line shows the share of population aged 65 and above over the same period (right y-axis). The productivity gap is calculated as service-sector productivity minus manufacturing productivity (PPP adjusted). For category definitions see Online Appendix, and the calculation method for productivity gap follows Gollin et al. (2014).

Although multiple interpretations of the data are possible, in this paper I draw on a framework from Lagakos and Waugh (2013) to understand the patterns of growth and sectoral productivity. This paper in turn makes use of Roy (1951)'s selection model. In this framework, as the service sector expands, it draws new workers from other industries through self-selection. Under some assumptions about the joint distribution of skills, these entrants possess lower sector-specific efficiency in services than incumbent workers. This compositional shift leads to a decline in measured productivity growth per worker, even though productivity per efficiency unit of labor remains constant. In contrast to the technology driven view of growth, Roy's framework emphasizes that such selection induced reallocation effects diminish over time as the scope for sectoral reallocation becomes exhausted.

In the model economy that I study, aging has two major long-run effects: it increases the demand for services, and it leads to an aging workforce. The first operates on the demand side, driving the expansion of the service sector, while the second operates on the supply side, creating incentives for automation (Acemoglu and Restrepo, 2022).

This paper contributes to a broader literature on the rise of service-based economies and the potential macroeconomic consequences of service-sector expansion (Duarte and Restuccia, 2010; Buera and Kaboski, 2012; Comin et al., 2021). Other work makes use of different mechanisms to explain the growth of services. For instance, Ngai and Pissarides (2007) rely on a model in which productivity growth exogenously differs between manufacturing and services. Under the assumption that services and manufactured goods are gross complements, faster productivity growth in manufacturing leads to a version of Baumol's cost disease, in which the service sector draws in productive resources (Ngai and Pissarides, 2007; Young, 2014; Duernecker et al., 2024). To be clear, the two mechanisms may be complementary. Some work (e.g., Shu (2025)) has tried to disentangle the relative importance of the selection mechanism and the differential productivity growth, but this can be challenging.

Building on these insights, this paper develops an overlapping-generations (OLG) selection model with non-homothetic PIGL (price-independent-generalized-logarithm) preferences and empirically tests its predictions using cross-country data, linking population aging to sluggish productivity growth in the service sector. To make demographics explicit and allow for dynamic analysis, we embed this selection mechanism in an OLG structure that links changes in age composition to heterogeneous preferences and labor supply. Following Gertler (1999), we model workers and retirees as transitioning across life stages with fixed probabilities in an economy with perfect annuity markets.

The mechanism is straightforward: as societies age, demand shifts toward services, raising their share and relative price. The higher relative price relaxes the selection threshold, drawing more workers into services. Because entry is based on comparative rather than absolute advantage, average service-sector productivity declines as composition shifts toward lower-ability workers. The model builds on the general-equilibrium Roy framework (Roy, 1951) of Lagakos and Waugh (2013) and extends it by incorporating PIGL preferences following Comin et al. (2021), Eckert and

Peters (2022), and Gollin et al. (2025). Across countries, economies differ only in their demographic structure and aggregate productivity, while the underlying skill distribution remains fixed over time.

Under the general-equilibrium Roy framework with PIGL preferences, the model yields two key propositions linking demographic aging to sectoral outcomes. First, as retirees have stronger preferences for service goods, population aging raises aggregate service demand and thus increases the relative price of services. Second, a higher relative price relaxes the self-selection threshold, drawing in workers with weaker comparative advantage in services and thereby lowering average service-sector productivity. Together, these results imply that aging economies experience higher service prices but slower service productivity - providing a theoretical foundation for the relatively lower productivity growth of the service sector observed across countries.

I calibrate separate PIGL parameters for workers and retirees using U.S. Consumer Expenditure Survey (CEX) data, finding that retirees allocate a larger asymptotic share of spending to services, which is consistent with the empirical evidence in Cravino et al. (2022). The skill distribution is calibrated using CPS data harmonized by CEPR: we choose the dispersion of skills to match observed wage dispersion and employ a Frank copula to capture the correlation of sector-specific skills.

Quantitatively, the static version of the model performs well in matching broad cross-country patterns in sectoral outcomes. Using cross-country data from 2000–2017, the benchmark calibration reproduces a substantial share of the observed variation in economies, achieving correlations of around 0.8 for employment shares and 0.6 for value-added shares between model-implied and actual data. The model's prediction for the productivity level displays a weaker correlation of about 0.3. The model captures how aging economies tend to allocate a larger fraction of employment and output to services, while also experiencing a widening productivity gap between services and manufacturing. However, because the benchmark framework abstracts from technology and capital accumulation, it underpredicts productivity levels in economies with strong sectoral technological shocks or policy driven demand shifts. These results confirm that demographic aging and non-homothetic demand jointly explain much of the observed cross-country heterogeneity in structural transformation.

The findings from my benchmark model are consistent with studies that employ parametric skill distributions, showing that productivity growth in an expanding sector tends to decline as new, less efficient workers enter (Lagakos and Waugh, 2013; Adão, 2015; Alvarez-Cuadrado et al., 2025). Results from the benchmark analysis show that aging alone has strong explanatory power for structural transformation and productivity-gap dynamics in the United States and other highly aged economies, but performs less well in many developing countries whose production structures differ markedly from advanced economies. My paper also complements recent research on demand-side drivers of service-sector productivity growth (Sen, 2020; Duernecker et al., 2024) by incorporating heterogeneous preferences and population dynamics, which allow the selection effect to be explicitly identified through demographic structure.

My benchmark model represents the service sector in an aggregate manner, without distinguishing among sub-sectors (Shu, 2025) or worker skill types (Adamopoulos et al., 2022; Buera et al., 2022; Ngai and Petrongolo, 2017). Moreover, it abstracts from potential cross-sector differences in automation and capital deepening (Acemoglu and Restrepo, 2019; Dauth et al., 2021), which likely leads the model to understate the dynamics of the service–manufacturing productivity gap. This abstraction limits the model's ability to capture within-sector heterogeneity and the role of high- and low-skill workers in shaping productivity outcomes. These limitations motivate an extension – included here in the Appendix – in which I introduce heterogeneous worker types and specify separate skill distributions for each, allowing the analysis to account for differential selection patterns and productivity effects across skill groups.

2 Related Literature

A large literature in macro-development documents sizable productivity gaps across sectors and highlights frictions in labor reallocation. Early work focuses on agriculture, showing that barriers to input adoption and mobility generate persistent agricultural productivity gaps (Restuccia et al., 2008; Adamopoulos and Restuccia, 2014; Gollin et al., 2014). Selection plays a central role: productivity differences partly reflect worker sorting across sectors, as shown by Gai et al. (2021); Cao et al. (2025) for China and Lagakos and Waugh (2013); Alvarez-Cuadrado et al. (2025) for the cross-country agricultural gap. These papers emphasize that misallocation and selection jointly shape sectoral productivity, providing a foundation for our focus on labor reallocation between services and manufacturing. Recent work turns to the service sector's rise and its distributional consequences. Leon-Ledesma and Moro (2020) link investment-specific technological change to service expansion, while Fang and Herrendorf (2021); Fan et al. (2023) show heterogeneous welfare effects of service-led growth in China and India. Service-sector growth also interacts with gender gaps: Ngai and Petrongolo (2017) show that expanding services increase female employment, and related Roy-model studies highlight frictions shaping sectoral entry (Lee, 2024; Cao et al., 2025). More broadly, sectoral reallocations contribute to aggregate productivity dynamics (Duarte and Restuccia, 2010), and micro evidence confirms selection into services based on comparative advantage (Shu, 2025). We contribute to this literature by showing how demographic shifts alter the composition of workers and reallocation patterns, generating service productivity declines.

Our second strand is demographic change. Classical overlapping-generations frameworks (Yaari, 1965; Blanchard, 1985; Aiyagari, 1994; Gertler, 1999) map changing age structure to savings, labor supply, and equilibrium outcomes. Empirical work documents multiple channels linking aging to growth: changing labor supply, capital deepening, and technology responses (Cutler et al., 1990; Eggertsson et al., 2019; Acemoglu and Restrepo, 2022). While some argue aging primarily affects labor supply, recent evidence highlights productivity effects as well. Aging alters managerial turnover and entrepreneurship (Liang et al., 2018), dampens competition through consumer inertia (Bornstein, 2025), and reduces regional GDP growth through slower employment and productivity growth (Maestas et al., 2023). We add to this literature by focusing on a specific mechanism: aging reshapes the skill and age composition of labor across sectors and reduces aggregate productivity through reduced sectoral productivity.

3 Motivating Facts

3.1 Cross Country Evidence

In the cross country analysis, we use country-level macro data to illustrate a descriptive relationship of aging on productivity gap of service and manufacturing sector. The data used are mainly drawn from the World Bank Global Productivity data, WDI and Penn World Table. The World Bank Productivity Project documents 9 sectoral and aggregated value added, employment and productivity statistics for 103 countries up to 2017. The classification of the production sectors follows a constructed category in Online Appendix. To make the productivity data comparable, we use 2010 international US dollar to obtain PPP adjusted value added and productivity for subsequent analysis. The aggregated sectoral productivity is calculated by

$$Prod^{s}_{i,t} = \frac{\sum_{j=g}^{G^s} Value^{g}_{i,t} / PPP^{2010}_{i,t}}{\sum_{j=g}^{G^s} Emp^{g}_{i,t}}, \quad s = \{\text{Service, Manufacturing}\},$$

where i is country, t is year and G is the classified groups.

The calculation of productivity gaps follows Gollin et al. (2014), is given by

$$prodgap_{i,t} = \frac{Prod^{S}_{i,t}}{Prod^{M}_{i,t}} - 1.$$

I construct a cross-country panel dataset that allows us to conduct descriptive regression analysis. By examining the two-dimensional data on aging levels and productivity gaps, we can easily observe their correlation. However, in a panel setting, cross-country heterogeneity makes it difficult to identify this relationship from simple correlations alone, since the level of calculated productivity level varies significantly across countries. The reduced form regression is given by

$$prodgap_{i,t} = \beta_0 + \beta_1 65share + X'_{i,t}\gamma + \mu_i + \lambda_t + \epsilon_{i,t}, \tag{1}$$

where $X_{i,t}$ is a vector of of covariates[1] which will control for country level heterogeneity in

[1] These covariates include: (1) Real GDP per capita, (2) share of government expenditure in GDP, (3) share of aggregate saving, (4) share of international trade; (5) person engaged in employment, (6) average annual hours worked

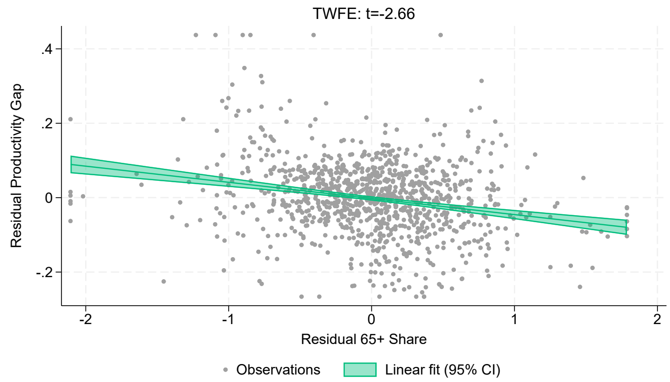
development level, standard errors are clustered at the country level. The estimated coefficient of -0.043 in Table 2 Panel (2a) suggests that a one percentage point increase in the share of population aged 65 and above is associated with a 0.043 reduction in the productivity gap. The calculated elasticity for aging is $\eta = -15.72\%$, which means that the partial effect of share of population aged 65 and above is economically significant.

I also want to re-examine whether aging will lead to the expansion of the service sector as one of the drivers of structural transformation as Cravino et al. (2022) have shown. The reason of the re-examination is that we want to use aging and the expansion of the service sector as one of the mechanisms to show the productivity shifts. I use the same covariates in (1) to control for country level heterogeneity, and standard errors are clustered at the country level. The reduced form is given by

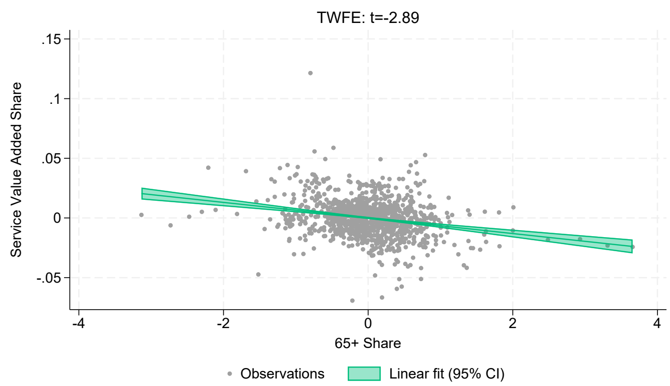
$$servshare_{i,t} = \beta_0 + \beta_1 65share + X'_{i,t}\gamma + \mu_i + \lambda_t + \epsilon_{i,t}, \tag{2}$$

where $servshare_{i,t}$ denotes the share of value added in the service sector relative to total value added or the share of employment in the service sector of country i at year t. Panel (2b) of figure 2 shows that, after controlling for two-way fixed effects, the coefficient on aging for the service value-added share remains statistically significant, but becomes negative. Panel (2c) further indicates that, under the same specification, aging's effect on the share of service employment is not statistically significant. Once fixed time effects are introduced, these estimates run counter to the empirical evidence documented in Cravino et al. (2022), who find that aging is associated with an expansion of the service sector. In short, the reduced-form evidence points to the need for structure: the model allows us to cleanly isolate the contribution of demographic change and trace its general-equilibrium implications for sectoral allocation and productivity.

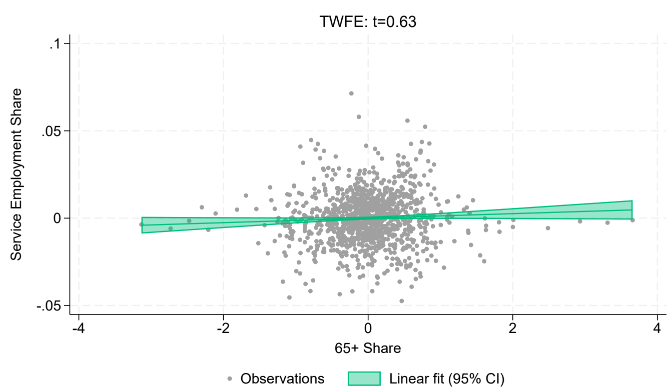
by persons engaged, (7) human capital index, (8) capital service, (9) Real capital stock at constant national prices, (10) share of labour compensation in GDP, (11) population. (1)-(4) are drawn from World Bank database and (5)-(11) are drawn from PWT.



(a) Productivity Gap



(b) Value Added Share



(c) Employment Share

Figure 2: Partial Correlation of Aging on Variables

Notes: Each gray dot in the plots is a country-year observation. On the y-axis is the residual of a regression of the service-manufacturing productivity gap (Panel a), Value-Added share of service (Panel b), and employment share of service (bottom Panel) on real GDP per capita, and other variables represent economic development level.

3.2 Consumer Expenditure Evidence

In this section, we use consumer-level microdata to support a key assumption of the theoretical model-that older individuals have a stronger preference for services. The analysis draws on Public-Use Microdata (PUMD) from the Interview Survey of the Bureau of Labor Statistics' (BLS) Consumer Expenditure Survey (CEX). This survey spans more than 40 years, from 1982 to 2023, during which approximately 10,000 addresses are contacted each quarter. It provides detailed Panel data on expenditures across more than 350 categories of goods and services, along with rich demographic information (the most recent release being PUMD 2023). This dataset has been widely used in studies of structural transformation and consumer behavior, including Boppart (2014), Aguiar and Bils (2015), Comin et al. (2021), Cravino et al. (2022), and among others. The main survey files used in this section are: (1) FMLI, which contains consumer-unit-level summary expenditures, income, characteristics, and weights; (2) MTBI, which provides monthly expenditures; and (3) MEMI, which records member-level income.

To categorize consumption, we follow the classification of Aguiar and Bils (2015), who grouped the original 350 CES categories into 24 broad expenditure types, and Cravino et al. (2022), who further divided these broad types into goods and services. Family member records are aggregated to the consumer-unit (CU) level to construct age-structure bins and average age. We exclude households with zero or negative service expenditures and restrict the sample to urban households. I calculate sectoral expenditure shares for four periods: 1982-1991, 1992-1901, 2002-2011, and 2012-2023 using CEX data[2] Within services, housing expenditures represent a large share. However, we exclude housing in the subsequent analysis, since the rental value of owner-occupied housing is self-reported and may not be directly comparable to rent payments reported by renters in the CEX.

I conduct a regression of age dummies on the expenditure share of service, controlling for consumer units, income decile, and region, time effects to capture the relative prices differences and shifts across states and time, following the construction of Aguiar and Bils (2015) and Comin et al. (2021). The reduced form estimation is given by

$$\begin{aligned} expshare_{it} = \alpha + \sum_{a=1}^{12} \beta_a \mathbf{1}\{agegroup_i = a\} + \gamma_1 famsize_{it} + \gamma_2 earners_{it} \\ + \gamma_3 income_{it} + \gamma_4 totexp_{it} + \mu_i + \lambda_t + \varepsilon_{it}, \end{aligned} \tag{3}$$

where the age group $[30, 34)$ serves as the baseline; *famsize* denotes family-size dummies; *earners* denotes dummies for the number of earners in the family; *income* denotes income-quartile dummies; *totexp* controls for the total expenditure of the consumer unit; and we also include two-way fixed effects. Figure 3 plots the estimated coefficients and confidential interval bars. The results show a clear positive age gradient in the expenditure share on services: coefficients are

[2] The detailed classification is shown in Online Appendix.

close to zero for households younger than 40, increase to about 0.05-0.10 for those in their 50s, and rise further to around 0.15-0.20 for households in their 60s and 70s. The effect is strongest for the oldest group (80 and above), where the coefficient approaches 0.25. The pattern is remarkably consistent across decades, although the estimates in more recent periods tend to be slightly larger.

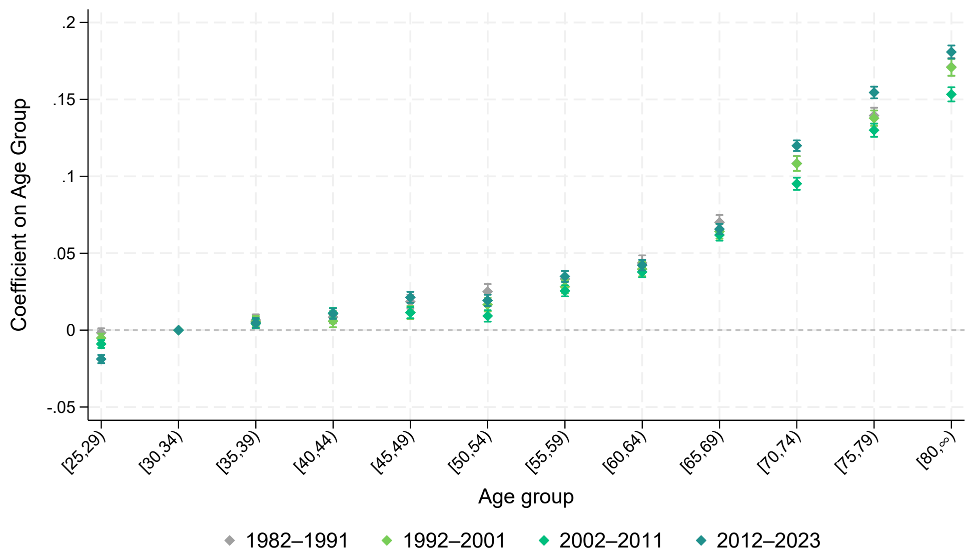


Figure 3: Coefficient Plot by Age Groups and Decades

Note: This figure displays the coefficients of age dummies resulting from estimating equation (3). Each dot represents the point estimate of the age dummies for a particular decade in the CES data. The omitted dummy is that of age group 25–30. The bands report the 95 percent confidence intervals based on standard errors clustered at the household level.

4 The Model

In this section, we develop a two-sector OLG-Roy model with workers and retirees evolving via constant transition probabilities and fair annuities market following the Yaari-Blanchard setting, which keeps aggregation and evolution process tractable and controllable. Production in services and manufacturing are simplified by using identical technologies with sectoral effective labor as the key input. Workers are heterogeneous in sector-specific skills, and will self-select themselves across sectors according to their relative advantage decided by their given skill level. The productivity gap between service and manufacturing is driven by aging from the following mechanism: the rising level of aging will rise the relative price for services and lower the relative threshold for workers to self-select into service sector and the process of self-selection is based on the comparative advantage of the worker. We follow Lagakos and Waugh (2013) and assume that a worker's comparative advantage is positively correlated with their absolute advantage. This implies that as a sector expands and labor reallocates, the marginal entrants may be less productive than the incumbents. In the benchmark model, sectoral labor reallocation is driven solely by the selection effect, that is, by workers sorting across sectors according to their comparative advantage in sector-specific skills.

4.1 Evolution of Population

Each individual is born a worker. Conditional on being a worker in the current period, the probability of remaining in one in the next period is ω. Conversely the probability of retiring is $1-\omega$. Conditional on being retired in the current period, the probability of surviving to the next is γ and, conversely, the probability of death next period is $1-\gamma$. The population grows at the net rate n. In particular each period $(1-\frac{\omega}{1+n})N_t$ new workers are born, which follows

$$N_t = (1+n)N_{t-1}.$$

The total work force at time t is N_t, and the number of retirees is $\left(\frac{1-\omega}{1+n-\gamma}\right)N_t$. The ratio of retirees to workers, ψ is

$$\psi \equiv \frac{1-\omega}{1+n-\gamma}$$

Here we assume perfect annuities market following Yaari (1965) and Blanchard (1985). The annuities market provides perfect insurance against this kind of risk. Under the arrangement each retiree effectively turns over his wealth to a mutual fund that invests the proceeds. The fraction γ of those that survive to the next period receive all the returns, while the fraction $1-\gamma$ who die receive nothing. Each surviving retiree receives a return that is proportionate to his initial contribution of wealth to the mutual fund. Thus, for example, if R is the gross return per dollar invested by the mutual fund, the gross return on wealth for a surviving retiree is R/γ.

4.2 Environment

Retiree's Problem

The retiree's utility are given by the following PIGL indirect utility function (Eckert and Peters, 2022; Gollin et al., 2025)

$$V(e_t^r, \mathbf{p}_{s,t}) = \frac{1}{\eta^r}\left(\frac{e_t^r}{\mathbf{p}_{s,t}^{\phi^r}}\right)^{\eta^r} - \nu^r \ln \mathbf{p}_{s,t}, \quad \eta^r, \phi^r \in (0,1),$$

where manufacturing goods' price is normalized to 1 and $\mathbf{p}_{s,t}$ is service sector's relative price. η^r, ϕ^r, ν^r are consumer type specific parameters, controlling for Engel elasticity, asymptotic share of service expenditure and taste shifter for relative price. Retiree maximize their life time utility subject to budget constraint

$$A^r_{t+1} = (R_t/\gamma)A^r_t - e^r_t.$$

We obtain the Euler equation

$$e^r_{t+1} = e^r_t \left[\frac{\mathbf{p}_{s,t+1}^{\phi^r \eta^r}}{\mathbf{p}_{s,t}^{\phi^r \eta^r}} \cdot \frac{\gamma}{\beta_r R_{t+1}} \right]^{1/(\eta^r - 1)}. \tag{4}$$

The expenditure share of services is given by Roy identity

$$\vartheta^r_s(e^r_t, \mathbf{p}_{s,t}) = \phi^r + \nu^r \left(\frac{\mathbf{p}_{s,t}^{\phi^r}}{e^r_t} \right)^{\eta^r}. \tag{5}$$

Worker's Problem

The workers are indexed by i, who differ in productivity, as explained below. Preferences are given by

$$V(e^w_{i,t}, \mathbf{p}_{s,t}) = \frac{1}{\eta^w} \left(\frac{e^w_{i,t}}{\mathbf{p}_{s,t}^{\phi^w}} \right)^{\eta^w} - \nu^w \ln \mathbf{p}_{s,t}, \quad \eta^w, \phi^w \in (0,1).$$

Each worker is endowed with one unit of time which she supplies inelastically to the labor market. Each worker is endowed with a vector of individual productivities, denoted $\{z^i_s, z^i_m\}$, which represent the efficiency of one unit of labor in sector s and m. Individual productivities are drawn from a distribution $G(z^i_s, z^i_m)$ with support on the positive reals. The endowed productivities will not change over a individual's life time. The budget constraint of worker i is

$$A^w_{i,t+1} = R_t A_{i,t} + W_{it} - e^w_{i,t}$$

Similarly we obtain the Euler equation and expenditure share of services

$$e^w_{i,t+1} = e^w_{i,t} \left[\frac{\mathbf{p}_{s,t+1}^{\phi^w \eta^w}}{\mathbf{p}_{s,t}^{\phi^w \eta^w}} \cdot \frac{\gamma}{\beta_w R_{t+1}} \right]^{1/(\eta^w - 1)} \tag{6}$$

and

$$\vartheta^w_s(e^w_{i,t}, \mathbf{p}_{s,t}) = \phi^w + \nu^w \left(\frac{\mathbf{p}_{s,t}^{\phi^w}}{e^w_{i,t}} \right)^{\eta^w}. \tag{7}$$

Production

In the production side, the market in both sectors has its own aggregate production function. To simplify the model we assume the technologies operated by the competitive entrepreneurs in both sectors are identical and freely available. The technologies are given by

$$\mathbf{Y}_{s,t} = X_t^s \cdot L_{s,t} \quad \text{and} \quad \mathbf{Y}_{m,t} = X_t^m \cdot L_{m,t},$$

where X_t is exogenous and captures the level of economy-specified technologies, and $L_{s,t}$ and $L_{m,t}$ represent the total number of effective labor units employed in the two sectors.

Let $\Omega_{s,t}$ $\Omega_{m,t}$ denote the sets of workers choosing to work in service and manufacture, the sector aggregated labor inputs $L_{s,t}$ and $L_{m,t}$ are defined as

$$L_{s,t} \equiv \int_{i \in \Omega_{s,t}} z_s^i dG_i \quad \text{and} \quad L_{m,t} \equiv \int_{i \in \Omega_{m,t}} z_m^i dG_i$$

which represents the sum of all individual productivity employed in two sectors. The total number of workers in each sector is defined as

$$N_{s,t} \equiv \int_{i \in \Omega_{s,t}} dG_i \quad \text{and} \quad N_{m,t} \equiv \int_{i \in \Omega_{m,t}} dG_i.$$

4.3 Optimization

An equilibrium of the economy consists of a relative service price $\mathbf{p}_{s,t}$, wages per efficiency unit of labor in each sector and allocations for all workers, where workers optimize and both labor markets and output markets clear. The measured labor productivity in the equilibrium is calculated by $Y_{s,t}/N_{s,t}$ and $Y_{m,t}/N_{m,t}$, which is the physical quantity of output produced per worker in each sector. Workers will first choose which sector to supply her labor, and maximize her utility subject to the budget constraint, and in competition markets, the wages per efficiency unit of labor are defined as

$$w_{s,t} = \mathbf{p}_{s,t} X_t \quad \text{and} \quad w_{m,t} = X_t.$$

Working in service sector is optimal for worker i if and only if

$$W_{s,t}^i \geq W_{m,t}^i \Rightarrow z_s^i \mathbf{p}_{s,t} X_t \geq z_m^i X_t.$$

Thus we obtain the simple cutoff rule (8). With sufficient high relative productivity in service sector, the worker will optimize her labor income by entering the service sector. With higher $\mathbf{p}_{s,t}$, the relative threshold for workers to self-select into service sector will decrease,

$$\frac{z_m^i}{z_s^i} \leq \mathbf{p}_{s,t}. \tag{8}$$

Using this cutoff rule, we will obtain the sets of employed workforce $\Omega_{s,t}$ and $\Omega_{m,t}$ as

$$\Omega_{s,t} = \left\{ i \left| \frac{z_m^i}{z_s^i} \leq \mathbf{p}_{s,t} \right.\right\}, \quad \Omega_{m,t} = \left\{ i \left| \frac{z_m^i}{z_s^i} > \mathbf{p}_{s,t} \right.\right\} \tag{9}$$

4.4 The Effect of Aging

Proposition 1: Consider a economy align with our assumption, if retiree have higher preference on services than workers, population aging will raise the relative price for service goods in equilibrium, i.e. $\partial \mathbf{p}_{s,t} / \partial \psi > 0$**.**[3]

By our assumption, retirees have a higher subsistence requirement for service goods, , population aging (i.e. a increase in ψ) increases aggregate service good consumption . If the supply of goods is relative inelastic, this rising demand exerts upward pressure on the relative price, potentially explaining structural changes in sectoral prices overtime. From the market clearing condition $Y_s = XL_s,\ Y_m = XL_m$, thus at equilibrium, we define

$$D(p_s, \psi) = \frac{C_s(p_s, \psi)}{C_m(p_s, \psi)} - \frac{L_s(p_s)}{L_m(p_s)} = 0.$$

By using implicit function theorem,

$$\frac{dp_s}{d\psi} = -\frac{D_\psi}{D_p} > 0, \quad \text{iff} \quad \vartheta_s^r > \vartheta_s^w,$$

and population aging will raise the relative price for service goods in equilibrium if and only if the expenditure share of service of the retiree is higher than the worker's.

Proposition 2: Consider two identical economies that differ only in aging level ψ**. Let** $E\left[z_s | \frac{z_m}{z_s} \leq \mathbf{p}_{s,t}\right]$ **be monotone decreasing in** $\mathbf{p}_{s,t}$ **. In equilibrium, economy with higher aging level will lead to lower service sector productivity, i.e. if** $\psi^\alpha > \psi^\beta$**, then** $\frac{Y_{s,t}^\alpha}{N_{s,t}^\alpha} < \frac{Y_{s,t}^\beta}{N_{s,t}^\beta}$ **.**

Intuitively, as the level of aging increases, by our assumption, the economy's aggregated demand for service goods will increase as a result, so the relative price of service goods in equilibrium will also increase as a response. Consequently, the relative wage in the service sector induces more workers to enter service sector. However, the result relies on a key assumption that the relative advantage of a worker is positively related to its absolute advantage.

In **Proposition 1**, an economy with a higher level of aging will lead to a higher relative price of service goods. From the cutoff rule (8), a higher relative price of service goods will lead to a lower threshold for workers to self-select into the service sector. Consequently, the average individual

[3] Proof in Online Appendix

productivity in the service sector, $E\left[z_s|\frac{z_m}{z_s} \leq \mathbf{p}_{s,t}\right]$, is decreasing $\mathbf{p}_{s,t}$. So, as ψ increases, the level of aging increases leading to higher $\mathbf{p}_{s,t}$, the new threshold for self-selection will lead to a more convenient condition for workers to have comparative advantage when working in the service sector. Thus, we will have

$$\text{if} \quad \psi^{\alpha} > \psi^{\beta}, \quad \text{then} \quad \frac{Y_{s,t}^{\alpha}}{N_{s,t}^{\alpha}} < \frac{Y_{s,t}^{\beta}}{N_{s,t}^{\beta}}.$$

4.5 Skill Distribution

In this section, we will discuss and construct a appropriate skill joint distribution $G(z_s, z_m)$ for our baseline model. To make **Proposition 2** hold, we must have $E\left[z_s|\frac{z_m}{z_s} \leq \mathbf{p}_{s,t}\right]$ monotonically decrease in $\mathbf{p}_{s,t}$. This property on the conditional expectation can be addressed by imposing correlation between the sector specific skills. In the quantitative analysis of Lagakos and Waugh (2013), skills are positively correlated, and the worker who is relatively more productive is also relatively more productive in the other sector. This imposed correlation allows flexibility in matching the data. However, as shown in Shu (2025) and Alvarez-Cuadrado et al. (2025), the micro-level selection pattern suggests that the correlation between service and manufacturing skills may not be positive. We follow the construction of Shu (2025) to qualitatively assess what is the sufficient assumption to support **Proposition 2**.

Assume skills are independently drawn from a Fréchet distribution, the comparative advantage of workers is given by

$$\kappa(q) = \kappa \ln \frac{q}{1-q}, \tag{10}$$

where q is the percentile of the worker's comparative advantage. The absolute advantage of the worker is given by

$$\alpha(q) = \bar{\alpha} + \alpha \ln q. \tag{11}$$

And the sector specific skills are now a composite of comparative and absolute advantage given its percentile. We let the skills of service to be the combination of comparative and absolute advantages since in our sample, most countries start with positive service-manufacturing productivity gap.

$$\ln z_s(q) = \alpha(q) + \kappa(q), \quad \text{and} \quad \ln z_m(q) = \alpha(q).$$

If $\alpha > 0$, then we will have

$$\ln z_s(q) = \bar{\alpha} + (\alpha + \kappa) \ln q - \kappa \ln(1-q), \quad \ln z_m(q) = \bar{\alpha} + \alpha \ln q.$$

Since $\alpha > 0, \kappa > 0$, sorting is monotone

$$\ln z_m(q) - \ln z_s(q) = \kappa \ln \left(\frac{1-q}{q}\right) > 0,$$

in this case as q increases, a worker will have higher comparative advantage in manufacturing. Since a quartile of allocation cutoff, q_s exists when workers are indifferent between the service and manufacturing sector. From the cutoff rule (8), the indifference conditions pins down a q_s such that

$$\ln z_m(q_s) - \ln z_s(q_s) = \ln \mathbf{p}_{s,t}.$$

Solving for q_s, we obtain the cutoff percentile of comparative advantage.

$$q_s(\mathbf{p}_{s,t}) = \frac{1}{1+\mathbf{p}_{s,t}^{\frac{1}{\kappa}}}, \quad \frac{\partial q_s(\mathbf{p}_{s,t})}{\partial \mathbf{p}_{s,t}} < 0. \tag{12}$$

Following previous derivation, the conditional expectations are given by

$$E[\ln z_s | q \leq q_s] = \bar{\alpha} - \alpha + (\alpha + \kappa) \ln q_s + \kappa \frac{1-q_s}{q_s} \ln(1-q_s) \tag{13}$$

From equation (13), we have $\partial E[\ln z_s | q \leq q_s(\mathbf{p}_{s,t})] / \partial q_s(\mathbf{p}_{s,t}) > 0$. Thus the conditional expectations of service skill is monotone increasing in q_s. Combine with equation (12), the conditional expectation of skill level in the service sector $E[\ln z_s | q \leq q_s(\mathbf{p}_{s,t})]$ is monotone decreasing in $\mathbf{p}_{s,t}$. As a conclusion, to ensure **Proposition 2** holds in our environment, it is sufficient that good workers need to stay good even after reallocation, i.e. $\alpha > 0$, $\kappa > 0$.

Dependent Skill Distribution

I follow the construction of Lagakos and Waugh (2013) by using joint Fréchet distribution. Compared to log-normal distributions, Fréchet distribution is more tractable in multi-sector selection problems and the extreme-value distribution allows for fat tails that align with real world skill distribution.

Let skills $\{z_s, z_m\}$ be drawn from a joint distribution

$$F(z_s, z_m) = C[F(z_s), F(z_m)],$$

where the marginal distributions are Fréchet distribution

$$F(z_s) = e^{-z_s^{-\theta_s}} \quad \text{and} \quad F(z_m) = e^{-z_m^{-\theta_m}},$$

and the marginal distributions are linked by a Frank copula

$$C[u,v] = -\frac{1}{\rho}\ln\left[1+\frac{(e^{-\rho u}-1)(e^{-\rho v}-1)}{e^{-\rho}-1}\right].$$

The key advantage is the ability to model both positive and negative dependence through the parameter ρ. $\rho > 0$ implies positive correlation and $\rho < 0$ implies negative correlation, and $\rho = 0$ implies independence. In the context of cross-sectional skills, this copula allows the model to incorporate different degrees and signs of the correlation between the skills of service and manufacturing while maintaining Fréchet marginal distributions.

5 Calibration Exercise

The parametrization in my model follows Table 1.

Table 1: Calibrated Parameters

Parameters	Definition	Value
θ_s	The dispersion level of worker's skill in service	2.638
θ_m	The dispersion level of worker's skill in manufacturing	3.505
ρ	The Frank Coupula correlation	3.762
ν^w	Worker's taste shifter	-0.03
ν^r	Retiree's taste shifter	-0.057
ϕ^w	Worker's asymptotic expenditure share of service	0.504
ϕ^r	Retiree's asymptotic expenditure share of services	0.656
η^w	Worker's Engel elasticity	0.86
η^r	Retiree's Engel elasticity	0.432

5.1 Individual Productivity

In order to recover the distribution of individual productivity draws, we use data from the U.S. Current Population Survey (CPS), harmonized by CEPR, to calibrate the moments that discipline our Fréchet distribution and Frank copula parameters. Our calibration sample spans the years 2003–2018, during which the CPS classifies employment sectors using the 2-digit NAICS 814 system. We group occupations into manufacturing and services following the classification in previous section[4], while excluding workers in agriculture, the armed forces, and those who report never having worked. To ensure consistency, we restrict the sample to individuals whose hourly wages exceed the federal minimum wage and who can be observed in consecutive survey years.

[4]The Classification of the Occupations from CPS is shown in Online Appendix

Wages are measured as salary income plus $0.66 \times$ business income and $0.44 \times$ farm income, with the income shares following Valentinyi and Herrendorf (2008).

To match the dispersion of wages (used as a proxy for underlying skills), we focus only on the non-transitory component of wage variation. For this reason, I restrict the CPS sample to workers observed in consecutive years, which allows us to separate uncorrelated transitory shocks from the total variance. I estimate a random-effects model to decompose log wages:

$$\ln wage_{i,t} = \mu + \underbrace{\alpha_i}_{\text{Random Effect}} + \epsilon_{i,t},$$

where $Var(\alpha_i)$ captures the variance of the non-transitory component. Using the calculated moments, the calibrated matched dispersion levels of the Fréchet distribution are $\theta_s = 2.638$ and $\theta_m = 3.505$ respectively. I use the difference in the P90–P50 wage gaps between sectors instead of the average wage ratio to identify the dependence parameter ρ in the Frank copula. A higher ρ implies that high-ability workers are more likely to cluster in one sector, raising the upper-tail inequality (P90–P50) in that sector relative to the other. Using the percentile gaps, the copula dependence matched is $\rho = 3.762$.

5.2 Individual Preferences

To calibrate the parameters of the PIGL utility function, we match the empirical expenditure shares of services across income bins and their overall mean to the corresponding model-implied moments. For retirees, the estimated parameters are $\hat{\phi^r} = 0.656$, $\hat{\nu^r} = -0.038$ and $\hat{\eta^r} = 0.423$; for workers, the estimated parameters are $\hat{\phi^w} = 0.504$, $\hat{\nu^w} = -0.006$ and $\hat{\eta^w} = 0.86$. Figure 4 plots the Engel curve given the calibrated parameters. The higher value of ϕ for retirees indicates a larger asymptotic share of services in their consumption, while a lower η suggests a more concave Engel curve, consistent with stronger but saturated service demand relative to workers. Individual's income is standardized in our model, so the estimated ν is around zero, so the deviations from asymptotic shares are weakly corrected. These values of ν is similar to Gollin et al. (2025), which uses the initial U.S. productivity gap as a target. The negative ν implies that services behave as luxuries, with the expenditure share converged to ϕ from below as income increases, consistent with Aguiar and Bils (2015).

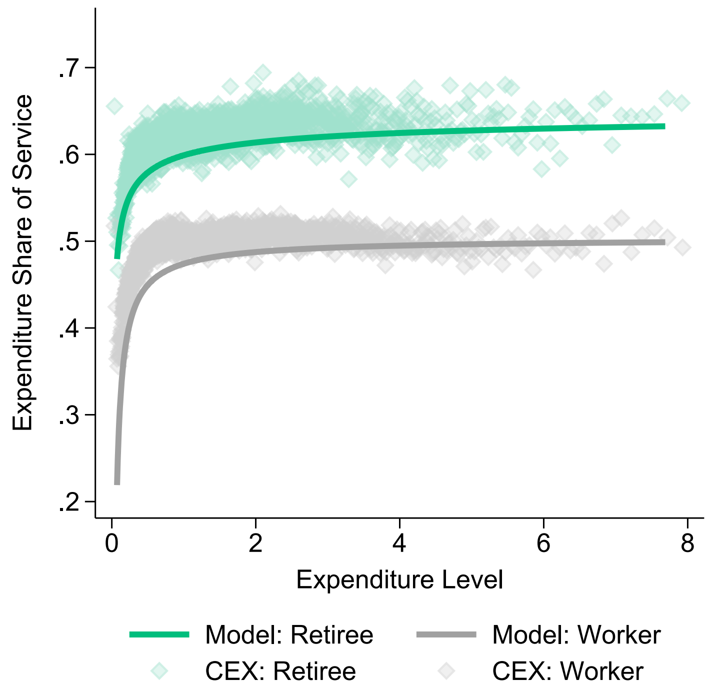


Figure 4: Engel Curves of Retiree and Worker

Notes: The y-axis is the expenditure share of service ϑ_s. This figure shows that retiree and worker's expenditure share of service as a function of expenditure level e. The observation from CEX data are clustered into 1000 bins, and individual's expenditure level is adjusted to match the simulated expenditure level

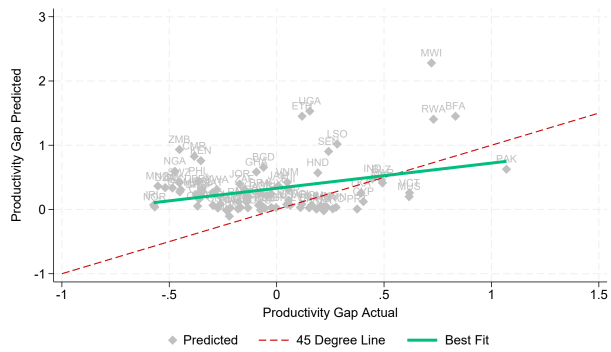
6 Quantitative Analysis for Static Economy

This section examines the comparative static equilibrium for both the United States and across countries. We evaluate how well the model's predictions align with the data, assess its explanatory power, and explore the main mechanisms underlying cross-country differences in productivity gaps.

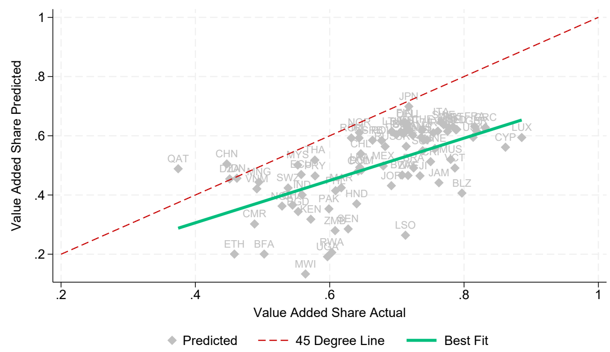
6.1 Benchmark Prediction

We first use our benchmark model to predict both the dynamics and levels of cross-country outcomes, including value-added shares and employment shares. Given the cross-country heterogeneity in economic characteristics and initial productivity gaps, we proxy the share of retirees ψ in our model using the old-age dependency ratio from the WDI database, and measure the aggregate level of technology by GDP per capita (inflation- and PPP-adjusted) from the Penn World Table. Figure 5 displays the model's predictions compared with actual data. We apply the non-targeted version of the model to all countries in our 2000–2017 sample. The red dashed line in each Panel represents the 45-degree line (perfect prediction), while the green solid line shows the linear best fit between predicted and observed data. The cross-country prediction in Panel (5a) yields a correlation of 0.327, suggesting that the model captures at least part of the variation in productivity levels. The benchmark model performs better in predicting the expansion of the service sector: Panels (5b) and (5c) show the predictions of the model for the value-added and employment shares of the service sector, with correlations of 0.648 and 0.873, respectively. These results indicate that, while the selection model accurately predicts labor allocation across sectors, it has a more limited ability to explain differences in output levels. One proposed reason is that the model does not explicitly incorporate sectoral differences in production technologies, so sectoral heterogeneity arises solely from differences in expected skill level of workers. Which leads to our extended model with high-and-low labor inputs and automation choice.

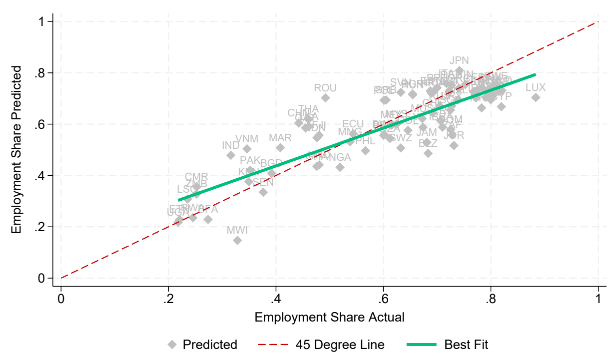
One of our benchmark model's highlights is that the prediction on labor allocation is accurate from 2000 to 2017, which means that the benchmark model successfully captures the relative wage shift and marginal rate of substitution between good and service when using United State's microdata as calibration targets. Another feature of the benchmark model is that although it correctly predicts a large proportion of variations between countries in value-added shares, it systematically underestimates the level by about 20–30%. This bias likely arises for two reasons. First, the model does not further disaggregate the service sector into its major sub-components, causing it to miss the rapid expansion of certain high-growth service sub-sectors. Second, many service outputs are used as intermediate inputs in production, so treating services purely as final consumption may lead the model to understate their overall demand and contribution to value added. Regarding productivity gaps, the model accurately matches the evolution of the service–manufacturing productivity gap from 2014 to 2017. This pattern suggests that, when using the United States as the benchmark frontier, the selection mechanism operates primarily in the modern period. In earlier decades, the rise of services appears to have been driven less by talent-based selection and more by sector-specific productivity improvements within services themselves.



(a) Productivity Gap



(b) Value-Added Share



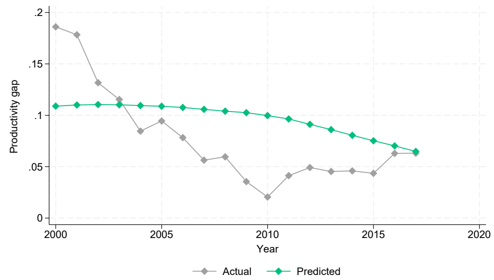
(c) Employment Share

Figure 5: Benchmark Model: Prediction vs Actual

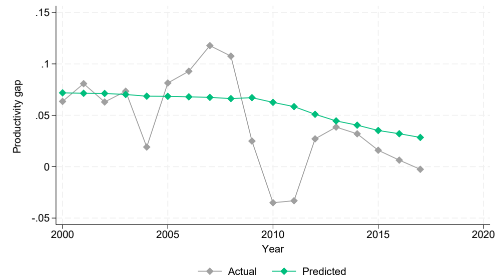
Notes: This figure compares the benchmark model predictions with the observed data. Panel (a) plots the predicted versus actual service–manufacturing productivity gap, Panel (b) reports the value-added share in services, and Panel (c) displays the employment share in services. The red dashed line represents the 45-degree line, indicating perfect prediction, while each gray dot denotes the model-predicted value (y-axis) against the observed outcome (x-axis). The green solid line shows the best-fitting linear regression line between predicted and actual values. The comparison is conducted in the last period for the model and the data.

Figure 6 compares the model's predictions with the actual data for several selected countries. In Panel (6a), the observed productivity gap in the United States exhibits much sharper movements: a pronounced compression in the early 2000s, a trough around 2010, and a partial rebound thereafter. These fluctuations reflect shocks that our demographically driven model abstracts from, such as sectoral TFP shocks, cyclical demand fluctuations, and policy-related factors. Similar underestimations occur in other economies that share similar demographic structures and income levels with the United States, suggesting that the impact of demographic selection alone is relatively modest. For countries with markedly different economic structures, our benchmark model may even fail to capture both the level and the trend of productivity gaps. In Panel (6e), for example, the model overestimates both the magnitude and dynamics of China's productivity gap, while in Panel (6f), it does not replicate the general trend in India's productivity. Figure 4 provides a potential explanation for these discrepancies: in low-income countries, the same amount of income growth has a much larger effect on the expenditure share of services than in high-income countries; and the Engel curves for countries like India and Chin should have different shapes from the one calibrated using U.S. microdata. Figure 6 raises an important question we seek to discuss: to what extent can our model account for the observed patterns? In most developed countries, our model successfully replicates the overall trend, although it tends to overestimate the level of the productivity gap in some cases. In contrast, for many developing countries where the opposite pattern often emerges, the expansion of the service sector appears to be closely associated with overall economic growth. As shown in Figure 6, the observed time-series data exhibit substantial cyclical volatility and measurement noise, making direct comparison with the model challenging. Moreover, most of the outliers correspond to developing countries, where data quality and consistency are often limited. This motivates our focus on the most recent years and cross-country comparisons, where data reliability is higher.

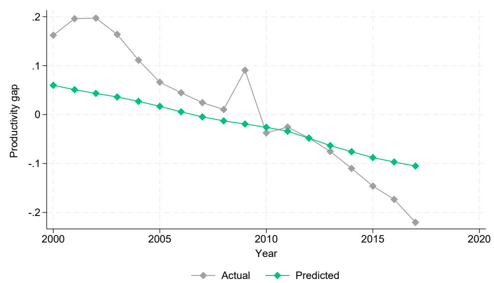
Figure 7 displays the model's predictions for the dynamics of the value-added share of services and the employment share of services. Panel (7a) shows that the model fits the United States well, but it underestimates the value-added share of services in the United Kingdom and overestimates it for Japan and Germany, where the value added share of service sector largely stagnated over the 2000–2017 period. Similarly, the model overestimates the sector expansion in China and India. Compared with the value-added share of services, the model's prediction of the employment share in Panel (7b) is more accurate, particularly for Japan and China. Moreover, combining Panels (7a) and (7b) shows that service-sector expansion in these countries does not necessarily translate into a simultaneous increase in the value-added share of services.



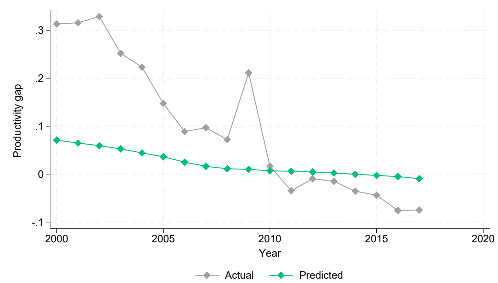
(a) United States



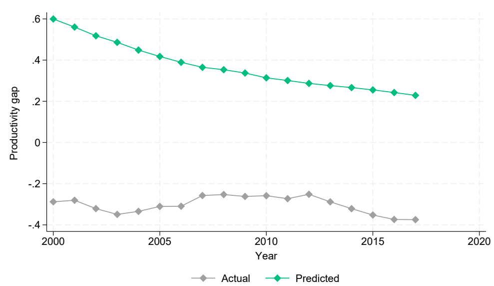
(b) United Kingdoms



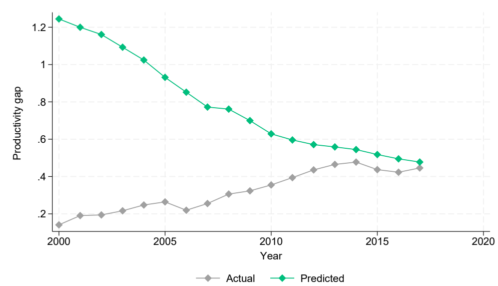
(c) Japan



(d) Germany



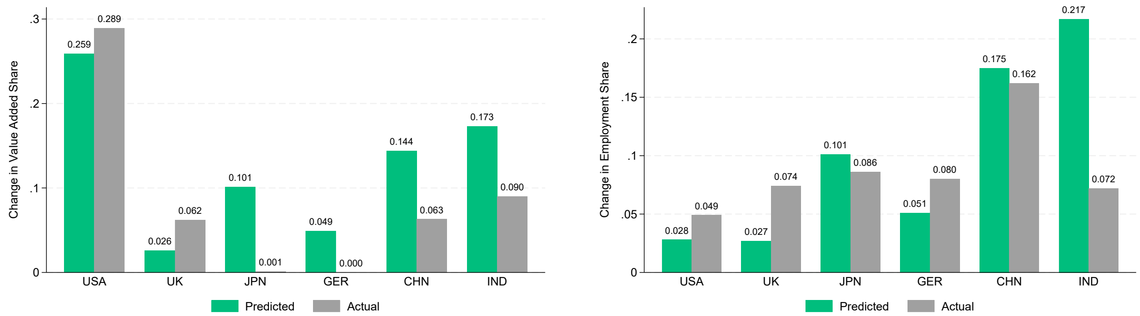
(e) China



(f) India

Figure 6: Benchmark Model: Selected Countries

Notes: This figure compares the model-predicted productivity gaps with the observed productivity gaps for selected countries from 2000 to 2017. Each gray dot connected by a line represents the realized productivity gap in a given country-year, while each green dot connected by a line represents the corresponding model-predicted value.



(a) Value-Added Share

(b) Employment Share

Figure 7: Benchmark Model: Selected Countries

6.2 The Impact of Aging

In our theoretical model, aging will shift the selection threshold from the demand side by increasing the relative price. Figure 8 displays the prediction of the model of the dynamics of productivity gaps within the country when aging is the only variable that is varied between countries. Figure 8 shows that the demand–sector expansion–selection channel only explains a modest portion of the cross-country variation. This result aligns with our expectations, since the deepening of aging is restricted compared to the growth of income or consumption. And the productivity decline caused by marginal new entrants is limited by the dispersion of skill distribution, since we simplify the role of machine and sector-specific technology change in the baseline model. However, quantitatively, aging alone still explains 35% of the actual within country dynamics of the productivity gap. But aging alone does not explain the level of productivity gaps. Panel (9a) shows that aging alone cannot explain the variations in cross country productivity level since the correlation is only 0.002, which aligns with our expectation since the level of the productivity is decided by the level of "technologies" term. The demographic shift accounts for more of the price/labor dynamics within a country, as shown in Panels (9c) and (9e). It also shows that aging will increase the selection effect on labor allocation.

These results present a fact about our model: when the demographic changes are limited, the income and price effects implemented by PIGL preferences are also limited, which leads to the modest scale of the model prediction. As demographics aging, and maintaining the expectation skill distribution is kept constant over time, the output per capita will certainly decline since the productive fraction is decreasing gradually. Panels (9c) and (9e) indicate that aging alone explains a substantial portion of the variation in both the value-added and employment shares of services across countries, and the correlations between model prediction and actual data are 0.626, 0.683 respectively. These results confirm that the aging mechanism in our model accurately captures labor reallocation across sectors through the demand–relative price–selection threshold channel, although aging alone tends to overestimate the employment share of services and underestimate the value-added share of services in many countries.

6.3 The Impact of Productivity Growth

In the context of Lagakos and Waugh (2013), cross-country productivity differences arise from a term on economy-wide efficiency that shifts the talent selection threshold, generating variation in sectoral productivity gaps. Figure 9 shows that feeding only productivity growth into our model yields a correlation of 0.376 between predicted and observed productivity gaps. The implications for value-added and employment shares are similar to the "aging-only" case, although the benchmark model delivers the closest fit overall. In our framework, productivity growth operates primarily through an income-driven demand channel, making the non-homothetic preference structure a key driver of the results. However, from Figures 4 and Figure 9, for countries whose income levels are far below those of the United States, an increase in total expenditure induces a much larger elasticity of the share of service expenditure. This strong income effect helps explain the overestimation of the productivity gap for developing countries in Figure 6, because income-driven demand shifts lead to a larger scale of labor reallocation compared to developed economies. Another implication is that cross-country differences in GDP per capita are far greater than differences in demographic structure. Consequently, the impact of aging is largely masked by the stronger income effects in countries with income levels well below that of the United States. This mismatch arises because the calibration relies on U.S. CEX data as the benchmark; in developing countries, the Engel curve for services will be flatter at the same expenditure level, and services may even behave as necessities (i.e., $\nu > 0$).

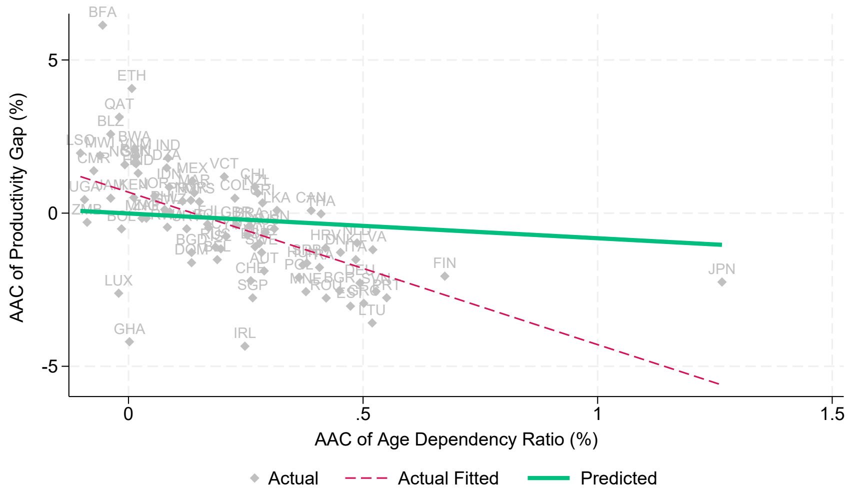
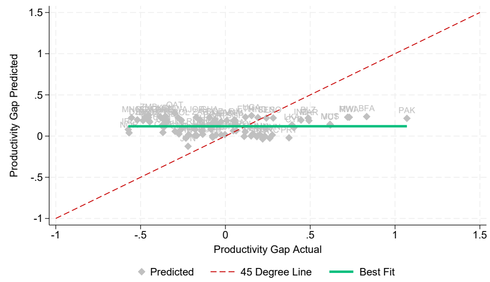
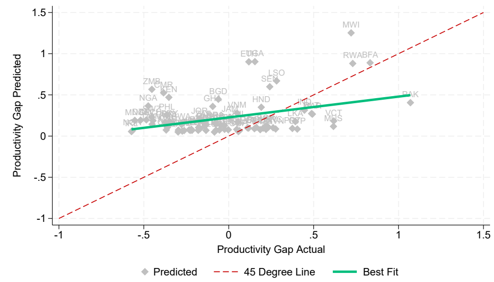


Figure 8: Aging Only: Within Country Dynamics

Notes: This figure displays the within-country dynamics of productivity gaps when aging is the only dependent variable in the model. The x-axis is the average annual change of age dependency ratio of the old and the y-axis in both panel is the average annual change of service-manufacturing productivity gap. Each dot in the plot is the actual dynamics of the country, and the red dashed-line is the fitted line on the actual data. The green solid line is the model's prediction.

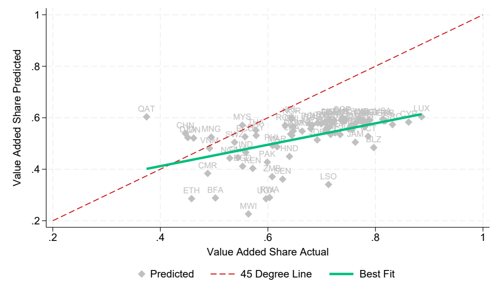


(a) Aging Only: Productivity Gap

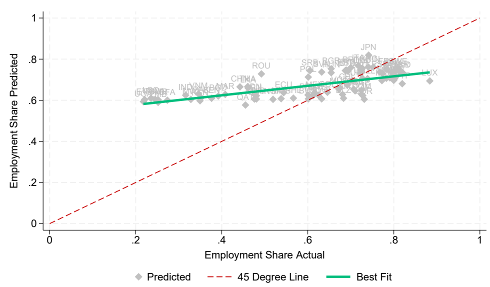


(b) GDPPC Only: Productivity Gap

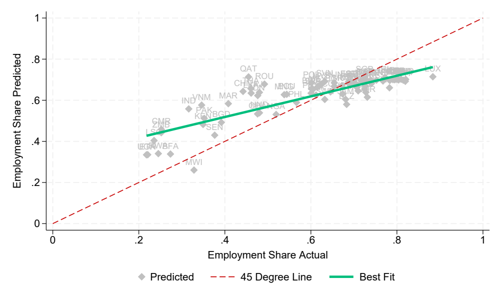
(c) Aging Only: Value-Added Share



(d) GDPPC Only: Value-Added Share



(e) Aging Only: Employment Share



(f) GDPPC Only: Employment Share

Figure 9: Aging & GDP Only: Prediction vs Actual

Notes: This figure compare the benchmark model—where cross-country differences arise solely from either demographic structure or GDP per capita—with the observed data. Panels (a), (c), and (e) present the comparison when demographic structure is the only driving factor, while Panels (b), (d), and (f) show the comparison when GDP per capita is the sole driver. The comparison is conducted in the last period for the model and the data.

7 Conclusion

This paper develops a quantitative framework to study how population aging affects service-sector productivity through a labor-reallocation channel. Motivated by the empirical fact that older economies exhibit both a larger service sector and lower measured service productivity relative to manufacturing, I build a model that embeds a Roy selection mechanism into an overlapping-generations structure with non-homothetic PIGL preferences. In this environment, demographic change shifts consumption demand towards services, raises relative service prices, relaxes the selection threshold, and reallocates workers with weaker comparative advantage into services, lowering average productivity.

A key contribution of the model is to separate the drivers of service expansion into two forces: productivity growth and population aging. Productivity growth operates through an income effect: higher income shifts spending toward services and expands the sector even in the absence of demographic change. Aging produces a similar expansion but via compositional forces: a larger retiree share strengthens service demand and draws marginal workers into the sector. Both forces contribute to increasing service shares, but only aging generates a decline in relative service-sector productivity through selection. Quantitatively, the benchmark aging model explains much of the variation in sectoral allocation patterns, matching employment shares with a correlation of roughly 0.87 and value-added shares with approximately 0.65. It also predicts the cross-country productivity gap with a correlation of around 0.37, performing nearly as well as a productivity-only specification but offering the best overall fit across outcomes. When demographic aging is the only driver, the prediction of the model still explains 35% of the actual within country productivity gap dynamics.

Taken together, the results suggest that population aging can amplify the dynamics of service expansion, expanding low-measured-productivity service activity, and slowing aggregate productivity growth through labor reallocation. As economies continue to age, understanding how the demographic structure interacts with skill distribution, technology adoption, and automation will be essential to evaluate future growth prospects and design policies to support efficient sectoral allocation.

Looking ahead, I plan to extend the analysis in three directions. First, I will compute a fully dynamic growth version of the model and study how technology shocks, tax changes, and retirement policy shifts affect productivity gaps over time, benchmarking the magnitude and direction of these effects against observed dynamics. Second, I will conduct counterfactual experiments including public provision of health services, delayed retirement, and labor market frictions to evaluate how institutional environments affect sectoral outcomes. Finally, I will develop an extended model with heterogeneous worker types and endogenous automation to amplify the selection effect and capture labor replacing technologies. Part of these developments will be presented in the Online Appendix.

References

Daron Acemoglu and Pascual Restrepo. Automation and new tasks: How technology displaces and reinstates labor. *Journal of economic perspectives*, 33(2):3–30, 2019.

Daron Acemoglu and Pascual Restrepo. Demographics and automation. *The Review of Economic Studies*, 89(1):1–44, 2022.

Tasso Adamopoulos and Diego Restuccia. The size distribution of farms and international productivity differences. *American Economic Review*, 104(6):1667–1697, 2014.

Tasso Adamopoulos, Loren Brandt, Jessica Leight, and Diego Restuccia. Misallocation, selection, and productivity: A quantitative analysis with panel data from china. *Econometrica*, 90(3): 1261–1282, 2022.

Rodrigo Adão. Worker heterogeneity, wage inequality, and international trade: Theory and evidence from brazil. *Unpublished paper, MIT*, 98, 2015.

Mark Aguiar and Mark Bils. Has consumption inequality mirrored income inequality? *American Economic Review*, 105(9):2725–2756, 2015.

S Rao Aiyagari. Uninsured idiosyncratic risk and aggregate saving. *The Quarterly Journal of Economics*, 109(3):659–684, 1994.

Francisco Alvarez-Cuadrado, Francesco Amodio, and Markus Poschke. Selection, absolute advantage, and the agricultural productivity gap. Technical report, 2025.

William J Baumol. Macroeconomics of unbalanced growth: the anatomy of urban crisis. *The American economic review*, 57(3):415–426, 1967.

Olivier J Blanchard. Debt, deficits, and finite horizons. *Journal of political economy*, 93(2):223–247, 1985.

Timo Boppart. Structural change and the kaldor facts in a growth model with relative price effects and non-gorman preferences. *Econometrica*, 82(6):2167–2196, 2014.

Gideon Bornstein. Entry and profits in an aging economy: The role of consumer inertia. Technical report, National Bureau of Economic Research, 2025.

Francisco J Buera and Joseph P Kaboski. The rise of the service economy. *American Economic Review*, 102(6):2540–2569, 2012.

Francisco J Buera, Joseph P Kaboski, Richard Rogerson, and Juan I Vizcaino. Skill-biased structural change. *The Review of Economic Studies*, 89(2):592–625, 2022.

Huoqing Cao, Chaoran Chen, and Xican Xi. Home production and gender gap in structural change. 2025.

Diego Comin, Danial Lashkari, and Martí Mestieri. Structural change with long-run income and price effects. *Econometrica*, 89(1):311–374, 2021.

Javier Cravino, Andrei Levchenko, and Marco Rojas. Population aging and structural transformation. *American Economic Journal: Macroeconomics*, 14(4):479–498, 2022.

David M Cutler, James M Poterba, Louise M Sheiner, Lawrence H Summers, and George A Akerlof. An aging society: opportunity or challenge? *Brookings papers on economic activity*, 1990(1):1–73, 1990.

Wolfgang Dauth, Sebastian Findeisen, Jens Suedekum, and Nicole Woessner. The adjustment of labor markets to robots. *Journal of the European Economic Association*, 19(6):3104–3153, 2021.

Margarida Duarte and Diego Restuccia. The role of the structural transformation in aggregate productivity. *The quarterly journal of economics*, 125(1):129–173, 2010.

Georg Duernecker, Berthold Herrendorf, and Akos Valentinyi. Structural change within the services sector and the future of cost disease. *Journal of the European Economic Association*, 22(1): 428–473, 2024.

Fabian Eckert and Michael Peters. Spatial structural change. Technical report, National Bureau of Economic Research, 2022.

Gauti B Eggertsson, Manuel Lancastre, and Lawrence H Summers. Aging, output per capita, and secular stagnation. *American Economic Review: Insights*, 1(3):325–342, 2019.

Tianyu Fan, Michael Peters, and Fabrizio Zilibotti. Growing like india—the unequal effects of service-led growth. *Econometrica*, 91(4):1457–1494, 2023.

Lei Fang and Berthold Herrendorf. High-skilled services and development in china. *Journal of Development Economics*, 151:102671, 2021.

Qingen Gai, Naijia Guo, Bingjing Li, Qinghua Shi, Xiaodong Zhu, et al. *Migration costs, sorting, and the agricultural productivity gap*. University of Toronto, Department of Economics Toronto, 2021.

Mark Gertler. Government debt and social security in a life-cycle economy. In *Carnegie-rochester conference series on public policy*, volume 50, pages 61–110. Elsevier, 1999.

Douglas Gollin, David Lagakos, and Michael E Waugh. The agricultural productivity gap. *The Quarterly Journal of Economics*, 129(2):939–993, 2014.

Douglas Gollin, David Lagakos, Xiao Ma, and Shraddha Mandi. The dynamics of agricultural productivity gaps: An open-economy perspective. Technical report, National Bureau of Economic Research, 2025.

David Lagakos and Michael E Waugh. Selection, agriculture, and cross-country productivity differences. *American Economic Review*, 103(2):948–980, 2013.

Munseob Lee. Allocation of female talent and cross-country productivity differences. *The Economic Journal*, 134(664):3333–3359, 2024.

Miguel Leon-Ledesma and Alessio Moro. The rise of services and balanced growth in theory and data. *American Economic Journal: Macroeconomics*, 12(4):109–146, 2020.

James Liang, Hui Wang, and Edward P Lazear. Demographics and entrepreneurship. *Journal of Political Economy*, 126(S1):S140–S196, 2018.

Nicole Maestas, Kathleen J Mullen, and David Powell. The effect of population aging on economic growth, the labor force, and productivity. *American Economic Journal: Macroeconomics*, 15(2): 306–332, 2023.

L Rachel Ngai and Barbara Petrongolo. Gender gaps and the rise of the service economy. *American Economic Journal: Macroeconomics*, 9(4):1–44, 2017.

L Rachel Ngai and Christopher A Pissarides. Structural change in a multisector model of growth. *American economic review*, 97(1):429–443, 2007.

Diego Restuccia, Dennis Tao Yang, and Xiaodong Zhu. Agriculture and aggregate productivity: A quantitative cross-country analysis. *Journal of monetary economics*, 55(2):234–250, 2008.

Andrew Donald Roy. Some thoughts on the distribution of earnings. *Oxford economic papers*, 3(2): 135–146, 1951.

Ali Sen. Structural change within the services sector, baumol's cost disease, and cross-country productivity differences. 2020.

Martin Shu. Selection, structural transformation, and the cost disease of services. *Available at SSRN 5395502*, 2025.

Valentinyi and Herrendorf. Measuring factor income shares at the sectoral level. *Review of Economic Dynamics*, 11(4):820–835, 2008.

Menahem E Yaari. Uncertain lifetime, life insurance, and the theory of the consumer. *The Review of Economic Studies*, 32(2):137–150, 1965.

Alwyn Young. Structural transformation, the mismeasurement of productivity growth, and the cost disease of services. *American Economic Review*, 104(11):3635–3667, 2014.