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Demographic Structure and Comparative Advantages: Theory and Evidence

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We present a simple model to address how the demographic structure of a country determines trade patterns. A country with a higher ratio of youth in its workforce demonstrates more learning-by-doing capability and is associated with a faster productivity catch-up to a technology frontier country, thereby gaining comparative advantages in more industries and thus higher incomes. This theoretical prediction is supported by cross-country evidence obtained from a system GMM estimation. We find that the age group 25-44 has the largest influence on productivity catch-up. Moreover, a high quality of human capital among those who study abroad significantly facilitates productivity catch-up.

Key Words: Demographic structure; Productivity; Comparative advantage.
JEL Classification Numbers: J21, J24, O33, O47.

1. INTRODUCTION

Creativity is widely recognized as a key driving force of productivity; so is learning by doing. Much psychologic research indicates that scientific output varies over the life cycle: output first increases around the mid-20s, climaxes in the late 30s or early 40s, and undergoes a slow decline thereafter (e.g., Beard, 1874; Ruth and Birren, 1985; Jones et al., 2014; Lehman 1953; Simonton 1988). Jones et al. (2014) looked at Nobel Prize winners and the great technological innovators of the 20th century and found that the greatest scientific output typically peaks in middle age. This peak performance comes, on average, at an even younger age in the fields of mathematics and the physical sciences (e.g., Lehman, 1953; Zuckerman, 1977; Simonton, 1991). Moreover, the trend of decreasing creative thinking with age is consistently observed (e.g., Kim, 2011; Kim and Pierce, 2012), especially

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in the field of science. In light of the central role played by creativity in the economy, countries with an aging population might experience a decrease in creativity and a slowdown in learning capability as well, thereby suffering economically from lower productivity growth, which weakens its comparative advantages in many industry sectors.

As for the learning by doing, neuroscientists have found that most of our cognitive abilities, such as thinking quickly and recalling information, peak around the age of 20, while some cognitive abilities peak around the age of 40, and only then begin to decline slowly (e.g., Germine, et al., 2011; Hartshorne, 2008; Hartshorne and Germine, 2015).[1] Economic research also implicitly suggests that the young are more creative and more capable at learning new tasks. For example, many studies have highlighted the role of young firms, where young workers typically consist of a disproportionate share of the workforce, in resource allocation and cyclical shock, which contribute considerably to economic dynamism and growth (e.g., Decker et al. 2014; Haltiwanger et al. 2013; Haltiwanger 2012; Dent et al. 2016; Fort et al., 2013).[2] Conversely, the economic slowdown experienced by OECD countries since 2000 aligns with the aging workforce demographic during the same period,[3] despite the fact that enhancing productivity through various mechanisms remains a policy priority in most of these countries.[4]

Typically, a young worker, ceteris paribus, possessing greater creativity and learning capability, should inherently be more productive than an older counterpart, as an individual's capability of generating innovation that enhance productivity is expected to diminish with age (e.g., Michel and Pestieau, 2013). It is thus reasonable to argue that young people are generally not only more creative than their elderly counterparts but also possess a stronger ability for learning by doing. This perspective provides an insight into why, beyond various rational factors, population aging could be an underlying cause of the global productivity slowdown and the middle-income trap that affects many developing countries. Therefore, this paper

[1]Psychologists have also discovered that children absorb new information like sponges, they learn multiple skills at the same time and are committed to learning. In contrast, adults — especially the elderly — have lower expectations for learning, and efforts to solve these problems are minimal (e.g., Wu, 2019).

[2]Foster et al. (2001, 2006) found that the job reallocation triggered by young firms explains to a large degree intra-industry labor productivity growth in the United States.

[3]See Haltiwanger et al. (2011), Davis et al. (2012), Reedy and Strom (2012), Hyatt and Spletzer (2013), Decker et al. (2014), and Haltiwanger (2015) for observations on the recent economic slowdowns.

[4]Restricted access to credit markets impedes the effective reallocation of resources to innovation, thus hindering productivity growth (e.g., Cecchetti and Kharroubi, 2012; Redmond and Van Zandwhege, 2016). The quality of institutions is also an important factor contributing to the large difference in productivity among countries (Easterly, 2001). Addressing these obstacles to innovation remains a policy priority in many countries, with various mechanisms being proposed to overcome these challenges.

posits that a demographic structure with a higher proportion of youth could potentially exhibit faster productivity growth than one with a larger proportion of elderly individuals. Conversely, a country with an aging workforce may face a deceleration in productivity growth. This argument might help illuminate the notable observation that, despite a sustained slowdown in productivity growth among countries at the technological frontier, significant disparities in productivity growth rates persist between lagging and leading nations, particularly considering the potential for international technology transfer (Acemoglu et al., 2006).[5]

Some empirical studies support the above argument. For example, Cuaresma et al. (2016) found that aging has a negative effect on income convergence across European countries, because a higher dependency ratio lowers economic growth. However, reducing the educational attainment gap between Eastern European and Western European countries could lead to an accelerated pace of income convergence, implying that a demographic structure with more well-educated youth might facilitate productivity growth. Kitao (2014) found that labor productivity reaches its peak at age 50 and then decreases with age, so do both the elder workers' labor participation rate and work hours. This phenomenon of fewer working hours may be indicative of lower labor productivity among the elderly compared to younger individuals. Furthermore, Maestas et al. (2016) found that a 10 percent increase in the share of the population aged 60 and above decreases growth in GDP per capita by 5.5 percent, and this finding can be mostly explained by the aging population in the workforce in the U.S. over the period 1980-2010.

Although the importance of demographic structure has been empirically highlighted in the literature (e.g., Feyrer, 2007; Boulhol, 2009), theoretical discussions and sound interpretations are limited. This paper aims to shed light on the underlying divergence by investigating both theoretically and empirically why the demographic structure of a country plays a key role in its economic dynamism and its trade pattern. Our study first proposes a simple North-South model of trade. This model introduces demographic structure into the narrowing-moving-band framework of Krugman (1987), in which technology accumulation takes the form of learning by doing. In addition to Krugman's model, we presume that individuals are heterogeneous in age. In this model, the relatively "young" countries that have more youth in their workforce should, ceteris paribus, demonstrate more creativity and learning-by-doing capability than countries with aging populations, thus catching up faster with the technology frontiers in terms of productivity. Accordingly, this phenomenon results in a shift of comparative advantage to "young" countries in a way that is unfavorable to the

[5]Cuaresma et al. (2016) concluded that aging has a negative effect on income convergence across European countries. Feyrer (2007) and Boulhol (2009) also highlighted a similar observation.

aging-population country. Furthermore, we also show that the impacts of the change in demographic structure on trade pattern and relative income might be permanent. This is another novelty of our model.

The rest of this paper proceeds as follows. Section 2 sets up the model. Section 3 shows the equilibrium with an aging population. Section 4 illustrates the dynamics of specialization. Section 5 presents and discusses the empirical evidence. Section 6 concludes the paper.

2. THE MODEL

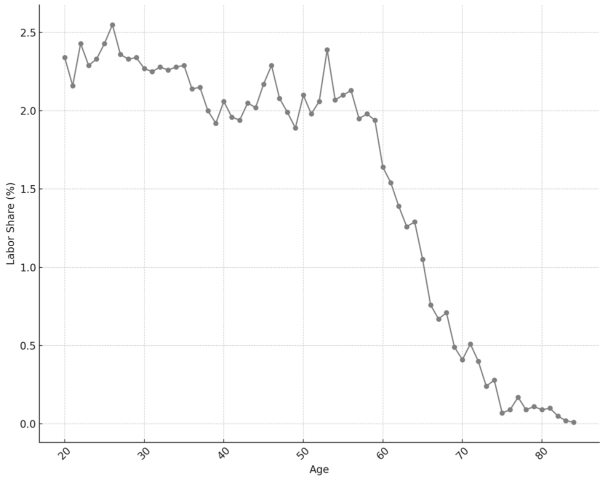
In a world of North and South, each country is clear in both labor and good markets. A constant share of income is assumed to be spent on non-traded goods. Each traded good receives a constant and equal share of expenditure. Suppose further that each country has an exogenously given labor force at any point in time: $L(t)$ for the North and $L^*(t)$ for the South, respectively. Both of these labor forces will be assumed to grow exponentially at the same rate.

In each country, there is a continuum of workers, and for the convenience of analysis, it is assumed that their ages follow a Pareto distribution, which is described as follows:

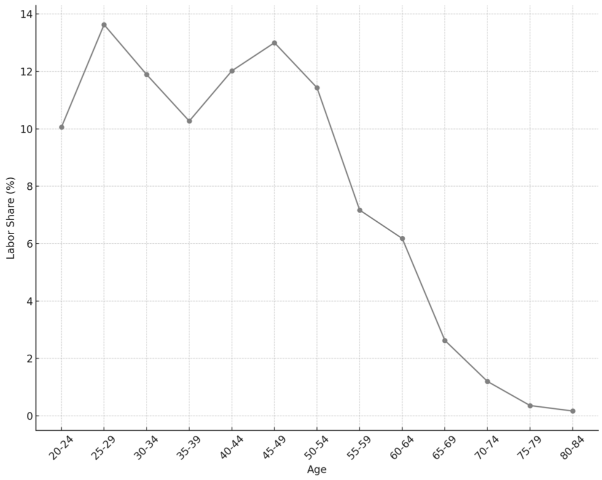
$$G(z) = 1 - \mu z^{-\theta} \text{ for } z \geq \mu^{1/\theta} > 0, \tag{1}$$

where $\theta > 1$ is a shape parameter. Here, we define an aging parameter μ in (1) and suppose $\mu'(g) < 0$, where g denotes the extent to which a country's labor force is aging. Applying the Pareto principle to demographic data suggests that a smaller segment of the population, such as the elderly, may disproportionately bear the wage costs in production, potentially diminishing the comparative advantage of firms in trade. For instance, Kitao (2014) shows that in the U.S., workers aged 50-64 experience a reduction to approximately 80% in both labor force participation rates and average work hours compared to the younger labor force aged 20-49. Furthermore, workers aged 65-85 exhibit a decline to about 13% in these same metrics. Conversely, according to the U.S. household income survey conducted in 2017 (Guzman, 2018, Table 3), the average income of households aged 45-64 was 2.3 times that of households under the age of 25. Moreover, the average income for households above the age of 65 was 1.3 times higher than that for those under 25. In contrast, younger workers, with their abundant creativity and entrepreneurial spirit, are more likely to generate externalities that enhance productivity, thus strengthening innovation and comparative advantage. Figure 1(a) illustrates the Probability Density Function (PDF) of the U.S. labor age distribution (ages 20 to 84) for the year 2016, while Figure 1(b) depicts that of China. The distributions show that a significant portion of the labor force is young, around age 20, with a smaller percentage being older, above age 60. This age structure of labor force indicates that the younger population constitutes a broad base of the demographic pyramid, with the numbers progressively decreasing for higher age groups, suggesting an approximation to a Pareto distribution.

FIG. 1.



(a). Distribution of Labor Supply by Age in China, 2016[6]



(b). Distribution of Labor Supply by Age in China, 2016[7]

Furthermore, upon comparison of Figure 1 (a) and (b), we observe country-specific demographic distributions: the 20-39 age group constitutes approximately 45.85% of China's labor force, compared to approximately 45.41% in the U.S. On the other hand, the age groups over 55 years old constitute approximately 17.71% of China's population (above age 15), compared to approximately 23.55% in the U.S. This signifies that China had a slightly younger labor force than the U.S. in 2016.

A country's technology stock is built up from the long-term accumulated experience of the country's labor force. When a country's workforce is composed of a larger share of young workers, the youthful demographic is linked to a heightened capacity for creating production externalities, such as through creativity or learning by doing. This contributes to the augmentation of the country's aggregate productivity. This view aligns with the findings of Cai and Stoyanov (2016), Gu and Stoyanov (2019), and Boucekkine et al. (2002) to some extent. Specifically, Cai and Stoyanov (2016) contend that demographic disparities form the basis of comparative advantages in international trade. Their findings suggest that as populations age, there's a shift towards specialization in industries that gain from age-enhancing skills, while sectors reliant on skills that diminish with age see a decline. On the other hand, Boucekkine et al. (2002) suggested that while increased life expectancy boosts per-capita growth at lower levels of longevity, the effect becomes negative beyond a threshold due to workforce aging.

Each firm employs its workforce randomly drawing from the Pareto distribution in (1). We assume that a firm's aggregate productivity is an aggregate of firm productivity and labor's production externalities. Suppose that there is only one firm in a sector since the firm has a comparative advantage and then dominates that sector. Then, with equation (1), the production function of a firm is given by

$$y_j = T_j \int_{i=0}^{\infty} l_j dG(i) = A_j l_j, \tag{2}$$

where l_j is a measure for workers hired by a firm j and T_j represents technology stock of sector j in a country. Here, $A_j = (\frac{\theta}{\theta-1})\mu(g)T_j$ represents the sectoral aggregate productivity of firm j in the sector j. The above argument suggests that population aging hampers labor productivity, as indicated by $\mu'(g) < 0$. To the contrary, Irmen (2021) contended that in

[6]This graph represents the distribution of effective labor by age, where effective labor is defined as the product of labor supply and the labor participation rate for each age group. The data of labor participation rate is from Panel Study of Income Dynamics (PSID).

[7]For convenience, we approximate the labor participation rate for China by using the average labor participation rates from the U.S. for each corresponding age group.

production settings where both labor and machines are essential inputs, population aging, by driving up equilibrium wages, incentivizes automation. This shift ultimately enhances labor productivity through increased automation in the long run. In our current model, which does not account for machines and automation, population aging, particularly from decreased fertility, does not lead to automation driven by rising wages. Instead, in this current model, this dynamic undermines a country's comparative advantage in trade by inflating labor costs without the productivity enhancements typically associated with automation.

In a way similar to Krugman's (1987) dynamic comparative advantage model, to feature an industry's learning curve, we suppose that technology development depends on an index of cumulative experiences:

$$T_j(t) = K_j(t)^{\varepsilon}, \quad 1 > \varepsilon > 0. \tag{3}$$

Krugman also suggested that international knowledge spillovers exist to some degree, such that both domestic production and foreign production enter into the index of experiences:

$$K_j(t) = \int_{-\infty}^{t} y_j(z) + \delta y_j^*(z) dz, \quad 0 \le \delta \le 1. \tag{4}$$

where the asterisk represents a foreign country and δ denotes a measure for the internationalization of learning.

3. EQUILIBRIUM

From (2) and (3), the relative sectoral productivity of a firm in the North to the firm in the South in sector j is:

$$\frac{A_j(t)}{A_j^*(t)} = \left(\frac{\mu}{\mu^*}\right)\left(\frac{K_j(t)}{K_j^*(t)}\right)^{\varepsilon}. \tag{5}$$

Taking a derivative of equation (4) with respect to time, we obtain

$$\dot{K}_j(t) = y_j(t) + \delta y_j^*(t) \text{ and } \dot{K}_j^*(t) = y_j^*(t) + \delta y_j(t).$$

The changes in the experience indices can therefore be written as

$$\frac{\dot{K}_j(t)}{K_j(t)} - \frac{\dot{K}_j^*(t)}{K_j^*(t)} = \frac{y_j(t) + \delta y_j^*(t)}{K_j(t)} - \frac{y_j^8(t) + \delta y_j(t)}{K_j^*(t)}. \tag{6}$$

In the long run, given that the aging parameters are exogenous, we have $\frac{\dot{(K)}_j(t)}{K_j(t)} = \frac{\dot{K}_j^*(t)}{K_j^*(t)}$ in the steady state, such that the growth of both technology and per capita income converge; otherwise, the income disparity might go to infinity. Thus, in the steady state, the left-hand side of (6) converges to zero, such that we can rewrite equation (6) with the help of equations (1) and (2) as

$$\frac{T_j(t)}{T_j^*(t)} = \left(\frac{\mu}{\mu^*}\right)^{\frac{1}{1/\varepsilon-1}} \left(\frac{l_j(t)}{l_j^*(t)}\right)^{\frac{1}{1/\varepsilon-1}} \left(\frac{1-\delta(T_j(t)/T_j^*(t))^{\frac{1}{\varepsilon}}}{1-\delta(T_j(t)/T_j^*(t))^{\frac{-1}{\varepsilon}}}\right)^{\frac{1}{1/\varepsilon-1}}. \quad (7)$$

It is easy to observe in (7) that a pair of firms' relative technology stock is positively related to their relative employment ($l_j(t)/l_j^*(t)$) and the relative aging of their workforce (μ/μ^*).[8]

This is a version of the Ricardian model, so we can rank the tradable sectors by their relative productivity $A_j(t)/A_j^*(t)$, in order of decreasing comparative advantage of the North over the South. There then exists a marginal sector in which two firms might coexist, say m, in equilibrium as

$$\frac{A_m(t)}{A_m^*(t)} = \frac{w(t)}{w^*(t)},$$

where $w(t)$ and $w^*(t)$ is the wage rate at time t of the North and South, respectively. Combining the above equation with (4) and (7), we obtain

$$\frac{w(t)}{w^*(t)} = \left(\frac{l_m}{l_m^*}\right)^{\frac{1}{1/\varepsilon-1}} \Psi_m\left(\frac{\mu}{\mu^*}\right), \quad (8)$$

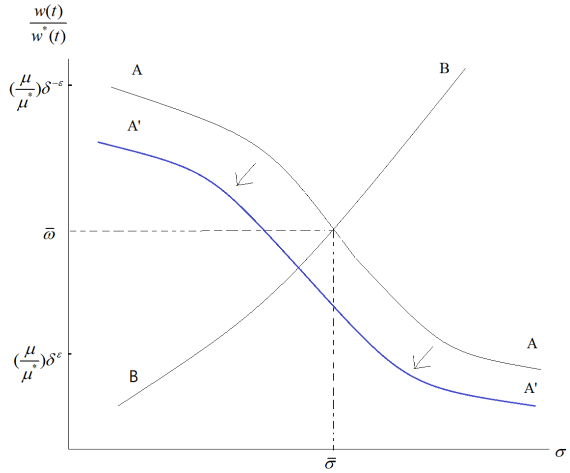
where $\Psi_m(\frac{\mu}{\mu^*}) = (\frac{\mu}{\mu^*})^{\frac{1/\varepsilon}{1/\varepsilon-1}} \left(\frac{1-\delta(T_j(t)/T_j^*(t))^{\varepsilon^{-1}}}{1-\delta(T_j(t)/T^*(t))^{-\varepsilon^{-1}}}\right)^{\frac{1}{1/\varepsilon-1}}$ is a function of μ/μ^* and l_m/l_m^* is the relative labor supply of home to foreign country in the marginal sector m. It is easy to observe from (8) that the $Psi_m(\mu/\mu^*)$ is increasing with μ/μ^*, indicating that a firm's relative productivity in a coexist sector increases with the firms' relative employment but decreases when its workforce is aging.

Define $\overline{\sigma}(t)$ as the share of tradable sectors in total tradable sectors that the North has a comparative advantage relative to the South at time t. As such, the North has a comparative advantage relative to the South over

[8] Let's suppose two lines from (7). The first line is $L_1 = T_j(t)/T_j^*(t)$, which increases with $T_j(t)/T_j^*(t)$. The second line is $L_2 = (\frac{\mu}{\mu^*})^{\frac{1}{1/\varepsilon-1}} (\frac{l_j(t)}{l_j^*(t)})^{\frac{1}{1/\varepsilon-1}} \left(\frac{1-\delta(T_j(t)/T_j^*(t))^{\varepsilon^{-1}}}{1-\delta(T_j(t)/T_j^*(t))^{-\varepsilon^{-1}}}\right)^{\frac{1}{1/\varepsilon-1}}$, which decreases with $T_j(t)/T_j^*(t)$. The two lines intersect on an equilibrium $T_j(t)/T_j^*(t)$. An increase in either μ/μ^* or $l_j(t)/l_j^*(t)$ will push the line l_2 upward, reaching a higher $T_j(t)/T_j^*(t)$ in a new equilibrium.

the sectors along $[0, \overline{\sigma}(t)]$ at time t. Then, we should observe $l_m > l_m^* \geq 0$ along $[0, \overline{\sigma}(t)]$ while $l_m^* > l_m \geq 0$ in the other sectors. Given that their relative productivity $A_j(t)/A_j^*(t)$ ranks in order of decreasing comparative advantage of the North over the South, and $A_m(t)/A_m^*(t)$ increases with l_m/l_m^*. This implies that the relative employment l_m/l_m^* should decrease with the share of tradable sectors $\overline{\sigma}(t)$. As such, $A_m(t)/A_m^*(t)$ should also decrease with $\overline{\sigma}(t)$. We can then illustrate equation (8) as a downward sloping curve as the AA curve in Figure 2, in which the thin line in black denotes a benchmark condition of $\mu = \mu^*$ in the first stage.

FIG. 2. Short-Run Equilibrium



The balance of payments equilibrium, as described by the standard framework of Dornbusch, Fischer and Samuelson (1977), is given by

$$\frac{w(t)}{w^*(t)} = \frac{\overline{\sigma}}{1 - \overline{\sigma}} \frac{L^*(t)}{L(t)}, \tag{9}$$

where the total labor supply is $L = \sum_j^s l_j$ and $L^* = \sum_j^{s^*} l_j^*$ for the North and the South, respectively. Here, s and s^* denote the number of sectors located in the North and the South, respectively. We can illustrate the equilibrium in (9) as an upward sloping curve as the BB curve in Figure 2, where $\omega = w(t)/w^*(t)$ denotes the relative wage of the North to the South. The AA and BB curves come across an equilibrium $(\overline{\sigma}, \overline{\omega})$ at a point of time as shown in Figure 2.

To illustrate how the demographic structure of a country determines its comparative advantages and income, we suppose that the North's labor force gradually ages more than the South such as $\mu < \mu^*$. Along time, we will have a new $A'A'$ curve in bold as in Figure 2, and the new equilibrium is $(\overline{\sigma}^*, \overline{\omega}^*)$, where $\overline{\omega}^* < \overline{\omega}$ and $\overline{\sigma}^* < \overline{\sigma}$. It implies that the range of sectors that the North has comparative advantages is contracting when its population is relatively aging (i.e., smaller μ/μ^*). This is the main implication in this model.

Figure 2 illustrates a short run equilibrium, which suggests a country that is endowed with a younger demographic, ceteris paribus, tends to acquire more sectors and achieve a higher relative wage than a country with an older demographic. As a result, the aging population in the North shrinks the sectors that the North has comparative advantages over the South, while those of the South expand. This argument is based on the perception that young people are relatively more efficient than older people in terms of productivity from learning-by-doing.

4. LEARNING BY DOING AND THE DYNAMIC OF SPECIALIZATION

As implied in (7), the relative productivity of firms in the two countries has an upper band as $(1/\delta)^\varepsilon$ and a lower band as $(\delta)^\varepsilon$. Then, with (4), the AA curve has an upper and lower band as $(\mu/mu^*)(1/\delta)^\varepsilon$ and $(\mu/mu^*)(\delta)^\varepsilon$, respectively. In the long-term dynamics of specialization, the learning-by-doing process, as addressed in Krugman's model, leads to an equilibrium as in Figure 3. Once a long-run equilibrium is reached, the sectors along $[0, \overline{\sigma}]$ are located in the North while the sectors along $[\overline{\sigma}, 1]$ are located in the South. The firms in the North will accumulate their productivity faster than the Southern firms in the sectors along $[0, \overline{\sigma}]$, but slower in the sectors along $[\overline{\sigma}, 1]$, such that the AA curve will come to have a "step" shape as shown in Figure 3.

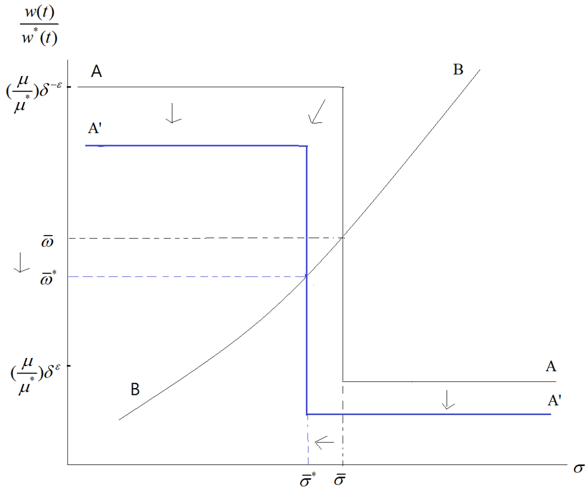
4.1. Aging Population and Relative Income

When the North's population is aging compared to the South, the new $A'A'$ curve intersects with the BB curve at a new equilibrium, making the Southern firms able to acquire comparative advantages in the sectors along $[\overline{\sigma}^*, \overline{\sigma}]$. Eventually, due to the learning-by-doing procedure, these Southern firms accumulate even more comparative advantages in these sectors until this band of sectors is completely relocated from the North to the South. As shown in Figure 3, it ends up that the "aging" North makes the South gain more market share and gain higher relative income afterwards.

4.2. Longer-run Impact of Aging Population

Next, suppose in the longer run that the labor force in the South is also aging, such that we have $\mu = mu^*$ again. Then, as shown in Figure 3, the $A'A'$ curve will shift upward back to the $A''A''$ curve, while the $A''A''$

FIG. 3. Long-Run Equilibrium



curve has the same upper and lower bands as the AA curve in Figure 3. However, these relocated sectors along $[\overline{\sigma}^*, \overline{\sigma}]$ will not return back to the North and the equilibrium still remains at $(\overline{\sigma}^*, \overline{\omega}^*)$. It is surprising that, as illustrated in Figure 4, even as the South's labor force later becomes as aging as the North, the North will not retrieve its market share. As a result, the North cannot regain its higher relative income and cannot restore its comparative advantages over those relocated sectors. The above analysis in our model suggests that a country with a "younger" demographic structure tends to acquire comparative advantages in more sectors and thus gains higher income, and these impacts could be permanent. This is the second implication of our model.

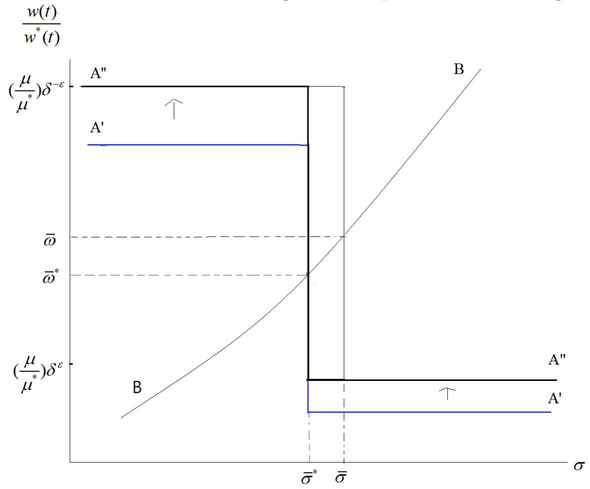
To summarize, the preceding analyses highlight the crucial role of aggregate productivity in determining competitive advantage within the international trade landscape. Importantly, it is emphasized that a country's aggregate productivity is significantly influenced by its demographic structure. Given equation (2), the total output of the North is given by

$$Y = \sum_{j}^{s} A_j l_j = \left(\frac{\theta}{\theta - 1}\right) \mu(g) \overline{T} L, \tag{10}$$

where $\overline{T} = \sum_j^s T_j(l_j/L)$ is defined to represent the aggregate technology stock of the North.[9] Note that a country's aggregate technology stock is positively related to the sectors that are located in the country, as in-

[9]With (2), we have $Y = \sum_j^s A_j L_j = L \sum_j^s (\frac{\theta}{\theta-1}) \mu(g) T_j (\frac{l_j}{L}) = (\frac{\theta}{\theta-1}) \mu(g) L \sum_j^s T_j (\frac{l_j}{L})$.

FIG. 4. Permanent Change in Comparative Advantage



dicated by $\overline{T}$ increases with s. Nevertheless, the number of sectors that can be located in a country is highly associated to the country's labor size and wage costs as well, as indicated by $s(L, w)$, reflecting the country's comparative advantage at the country level. It is then feasible to argue that, ceteris paribus, a country endowed with a larger labor size is supposed to acquire more sectors as indicated by $s_L(L, w) > 0$, but a country with higher wage costs tends to acquire fewer sectors as indicated by $s_w(L, w) < 0$. Consequently, we can reformulate equation (10) as $Y = aL$, where $a(L, w, g) = (\frac{\theta}{\theta-1})\mu(g)\overline{T}(L, w)$ represents the North's aggregate productivity, derived from summing its sectoral productivity. A country's aggregate productivity increases with its labor size (L) but decreases in response to higher wage rates (w), as indicated by $a_L(L, w, g) > 0$ and $a_w(L, w, g) < 0$, respectively. Most importantly, a country's aggregate productivity a is positively influenced by a younger demographic structure (lower g), as indicated by $a_g(L, w, g) < 0$. The following section will present an empirical analysis to substantiate this hypothesis.

5. EMPIRICAL EVIDENCE

Trade literature typically validates comparative advantage using bilateral trade data. For instance, Cai and Stoyanov (2016) and Gu and Stoyanov (2019) both establish a connection between population aging and the comparative advantage in trade. For instance, the findings of Cai and Stoyanov suggest a trend towards specialization in industries that benefit from age-enhancing skills, contrasted with a decline in sectors reliant on skills that wane with age. This paper, however, takes the influence of comparative advantage on trade patterns as given and focuses instead on how a country's demographic characteristics influence its aggregate productivity and thereby affect comparative advantage.

5.1. Empirical Specification and Data

Our model indicates that a lagging country (the South) can narrow its aggregate productivity gap with a frontier country (the North) by having a higher proportion of youth in its workforce. Narrowing the aggregate productivity gap naturally bolsters the catching-up country's comparative advantage in trade. To test our theoretical predictions, we specify the benchmark model as the following an autoregressive distributed lag model:

$$a_{i,t} = \beta_0+\beta_1 a_{i,t-1}+\beta_2\mu_{i,t}+\beta_3 L_{i,t-1}+\beta_4 r_{i,t}+\beta_5\varphi_{i,t}+\beta_6 w_{i,t-1}+u_i+v_i+\varepsilon_{i,t}, \tag{11}$$

where μ_i denotes a youth index of a country and the subscript i denotes country i. Here, $a_{i,t}$ define the productivity gap between country i and the technology frontier (i.e., the U.S.) at time t. As argued above, a country's technology gap relative to the frontier country ($a_{i,t}$) is narrowed when the country is relatively young, such that $a_{i,t}$ increases with μ_i when the country has a higher ratio of youth in its labor force. This model also suggests that a country's aggregate productivity increases with its labor size ($L_{i,t-1}$) but decreases in response to higher wage rates ($w_{i,t-1}$). The control variable $a_{i,t-1}$ denotes the technology gap of country i relative to the frontier country in the previous period and is included to test whether there is productivity convergence across countries. Using the U.S. as the reference country (i.e., the North), the productivity gap is measured by i country's total factor productivity (TFP) relative to that of the U.S. in year t. The information is drawn from the World Productivity Database (WPB) of the United Nations Industrial Development Organization.[10] Here, $L_{i,t-1}$ represents the population of the country relative to the U.S. The population information is obtained from the Census Bureau of the United States, and $w_{i,t-1}$ is per capita income in the initial period and it enters the equation in the form of a 2-year lag.

Term μ_i is the key variable of concern in the theoretical prediction, representing the ratio of youth demographics. As young talented people who engage in innovative activities are generally older than 20, we define youth as the age group between 20 and 39. To obtain robust evidence to support our prediction, we also define "youth" as being between the ages of

[10]The TFP is an international comparative indicator. When calculating the TFP, output and capital are measured by constant prices adjusted for purchasing power parity, labor input is adjusted for health and education to consider the labor quality.

20-44, 25-39, and 25-44. Estimates of youth variables are expected to be associated with a significantly positive coefficient.

In addition to the youth population, R&D is a key driver of productivity. We thus add research intensity (r_{it}), which is measured as the ratio of R&D expenditure to GDP, as a control variable. This information is drawn from the World Development Indicator (WDI) databank of the World Bank. Another control variable is educational level, especially the rate of students studying abroad in technology frontier countries (φ).[11] This variable is measured as the ratio of students to the population who have studied abroad in the U.S. in the past 10 years. We acquire information about students studying in the U.S. from various issues of the Open Doors Report published annually by the Institute of International Education (IIE). It also denotes international knowledge spillovers brought about by more educated talents who study abroad and who are expected to make a positive contribution to productivity catching-up. Finally, where u_t represents shocks to productivity common to all countries in a given year, v_y is a country-specific time-invariant component, and ε_{it} is a white-noise disturbance.

On estimating equation (11), OLS estimates are biased and inconsistent, because all covariates are likely to be correlated with the error term. We thus adopt the System Generalized Method of Moment (GMM) developed by Arellano and Bover (1995) and Blundell and Bond (1998) to conduct empirical estimations. This methodology provides consistent estimates by using appropriate instruments. The Hansen-Sargen test for over-identifying restrictions is also reported.

Constrained by the availability of information on the productivity gap relative to the U.S. and R&D intensity, we explore the predictions from the theory with a country-level panel data of 109 countries during the period 1996-2010. The data contain 17 European countries, 21 Asian countries, 22 North, Central, and South American countries, 46 African countries, and 3 Pacific island countries. Table 1 summarizes the variable definition, basic statistics, and data sources.

[11] In addition to those who major in STEM (Science, Technology, Engineering, and Mathematics), the contribution of non-STEM majors to technological innovation and catch-up is also crucial. For example, design and aesthetics, key components of product development, frequently originate from non-STEM disciplines. Breakthroughs often arise at the intersection of varied fields, underscoring the value of interdisciplinary collaboration. Effective deployment of technology also requires adept communication and management, areas where non-STEM majors particularly shine. As technology's reach becomes increasingly global, the ability to navigate cultural nuances and address worldwide challenges is more important than ever. Additionally, non-STEM majors are pivotal in developing and implementing governance policies for technology, with a focus on ethics, privacy, data protection, and equitable access, ensuring that technological advancement benefits society as a whole.

TABLE 1.

Variable definitions and basic statistics

Variable	Definition	Mean (S.D.)
a	TFP relative to the U.S.	0.4256 (0.2945)
μ_2039	Ratio of youth to workforce: measured by (age 20-39)/ (age 15-64).	0.5079 (0.0873)
μ_2044	Ratio of youth to workforce: measured by (age 20-44)/ (age 15-64).	0.6015 (0.971)
μ_2539	Ratio of youth to workforce: measured by (age 25-39)/ (age 15-64).	0.3591 (0.0577)
μ_2544	Ratio of youth to workforce: measured by (age 25-44)/ (age 15-64).	0.4527 (0.0729)
L	Population relative to the U.S.	0.1662 (0.5609)
r	R&D intensity: measured by R&D expenditure to GDP (%)	0.5769 (0.9105)
φ	Education: measured as the ratio of students studying in the U.S. in the past 10 years to the population.	0.0024 (0.0044)
w	Per capita income in the initial period, measured by 2-year lagged per capita income (US $1000)	9.1492 (14.640)

Note: The means and standard deviations are calculated by pooling data for the period 1996-2010. Some African countries lack R&D information. As they have quite limited expenditure on R&D, their miss value is replaced by a small number of 0.01.

5.2. Estimated Results

Table 2 reports the results for the estimation of equation (11). Before discussing the estimates, the lower panel shows that the Arellano-Bond test for zero auto-correlation in first-differenced errors is not significant. As for the Sargan test, the validity of the instrument set is not rejected at a conventionally significant level.

Our central covariates are, as expected, all associated with a significant coefficient. The variable of 1-year lag relative productivity to the U.S. (a_{t-1}) is significantly larger than 1, implying that, on average, the sampling countries did not catch up with the U.S. in terms of productivity. Instead, a widening productivity gap is witnessed that is consistent with studies on the issue of global productivity convergence (e.g., Bernard and Jones, 1996; Rodrik, 2013). This is caused by the small share of manufacturing employment in low-income countries and the slow pace of industrialization (Rodik, 2013).[12]

TABLE 2.

Empirical evidence on theoretical prediction: system GMM estimation

	(1)	(2)	(3)	(4)
a_{t-1}	1.0796^{***}	1.0767^{***}	1.0736^{***}	1.0679^{***}
	(0.0007)	(0.0007)	(0.0007)	(0.0007)
μ_2039	0.0626^{***}			
	(0.0071)			
μ_2044		0.0813^{***}		
		(0.0097)		
μ_2539			0.1950^{***}	
			(0.0099)	
μ_2544				0.2075^{***}
				(0.0129)
L	-0.0923^{***}	-0.0879^{***}	-0.1083^{***}	-0.1170^{***}
	(0.0108)	(0.0127)	(0.0106)	(0.0111)
r	0.0052^{***}	0.0069^{***}	0.0094^{***}	0.0099^{***}
	(0.0003)	(0.0003)	(0.0004)	(0.0004)
φ	5.0616^{***}	5.1142^{***}	4.9968^{***}	4.9632^{***}
	(0.0785)	(0.0920)	(0.1208)	(0.1054)
w_{t-1}	$-3.70e-5^{***}$	$-3.79e-5^{***}$	$-4.0e-5^{***}$	$-3.93e-5^{***}$
	$(1.29e-6)$	$(1.37e-6)$	$(1.04e-6)$	$(1.11e-6)$
Constant	-0.0625^{***}	-0.0794^{***}	-0.0970^{***}	-0.1173^{***}
	(0.0037)	(0.0055)	(0.0031)	(0.0052)
Year dummy	Yes	Yes	Yes	Yes
Country dummy	Yes	Yes	Yes	Yes
Arellano-Bond test	-1.1789	−1.1817	−1.1844	−1.1872
Sargan (p-value)	0.6187	0.5503	0.5289	0.5381
No. of countries	109	109	109	109
No. of Obs.	1,526	1,526	1,526	1,526

Note: The numbers in parentheses are standard errors. *** $p < 0.01$.

The youth variables, in terms of various measures, are positive and significant at the 1% level in all specifications, supporting our theoretical argument. Countries with a larger ratio of youth in their demographics demonstrate a faster productivity catch-up, ceteris paribus. Various estimates suggest a coefficient ranging between 0.0626 and 0.2075. Specifically,

[12]When focusing on OECD members or the EU, manufacturing sectors exhibit productivity convergence (e.g., Frantzen, 2004; Färe et al., 2006; Rodrik, 2013).

we find that the age group 25-44 has the largest influence on productivity catch-up.[13]

There is a number of non-competing explanations for the above finding. First, younger people are generally more efficient in terms of productivity improvement from learning-by-doing. Second, younger people are generally in better physical health than their elders, enabling them to spend more time in production. Third, for R&D personnel, the ages 25-44 might be the prime of their research life to carry out creative ideas and develop new technologies to break through the so-called infant industries. Interestingly, this finding is in line with the psychological research done by Zuckerman (1977), who examined Americans who won the Nobel Prize in science between 1901 and 1972, and found that the most outstanding work of these scientific laureates was accomplished, on average, at age 39.

The variable associated with R&D intensity indicates that a country with a higher R&D intensity exhibits a productivity catch-up. Columns (1)-(4) show that the estimated magnitude of the R&D intensity coefficient hovers between 0.0052 and 0.0099. This result shows that R&D intensity increases by 10% (e.g., R&D intensity increases from 2% to 12%), and that productivity relative to the U.S. is associated with an increase of 0.052% to 0.099%. Because it is hard for a developing country to sharply lift its R&D intensity, and the U.S. continues to have a moderate R&D intensity (2.734% in 2010), raising indigenous R&D alone is not an efficient strategy for developing countries to technologically catch up with a frontier country, although it is widely observed to help promote productivity. Thus, as claimed in Goedhuys et al. (2014), various sources of knowledge, such as better educated human capital, technology licenses, and imported machinery and equipment are also important for promoting productivity among firms in developing countries.

The estimate on the variable φ suggests a crucial finding that there is a strong effect of international knowledge spillover via studying abroad on productivity catch-up. It is worth noting that the measure of young talents studying abroad presents the largest influence on productivity catch-up. Various estimates demonstrate the associated coefficient hovering at 5, which suggests that if a country exhibits a 1% increase in this study abroad ratio, it is accompanied by a 5% increase in the ratio of productivity relative to the United States.

For non-technology frontier countries (the South), particularly developing countries, young talent enrolling in higher education in the U.S. can directly learn advanced technologies. The returning talent can contribute considerably to technological development for their mother countries. Even

[13] Feyrer (2007) found that changes in the proportion of workers between the ages of 40 and 49 seem to be associated with productivity growth.

though some of the brightest minds relocate to wealthier nations, they generally maintain close relations with their mother country and can thus help to upgrade its technology. Therefore, many governments implement incentives and subsidize policies to boost the income of returnees. Countries that have caught up quickly, such as China, Taiwan, and South Korea, saw a skyrocketing number of students studying abroad in the U.S., and had numerous returning talents in various disciplines.

TABLE 3.

Robustness checks

	(1)	(2)	(3)	(4)
a_{t-1}	1.0787^{***}	1.0800^{***}	1.0771^{***}	1.0727^{***}
	(0.0006)	(0.0007)	(0.0006)	(0.0007)
μ_2039/age 15+	0.0275^{***}			
	(0.0084)			
μ_2044/age 15+		0.0874^{***}		
		(0.0105)		
μ_2539/age 15+			0.1951^{***}	
			(0.0097)	
μ_2544/age 15+				0.2452^{***}
				(0.0151)
L	-0.0830^{***}	-0.0906^{***}	-0.1057^{***}	-0.1100^{***}
	(0.0104)	(0.0129)	(0.0105)	(0.0128)
r	0.0029^{***}	0.0062^{***}	0.0091^{***}	0.0106^{***}
	(0.0003)	(0.0003)	(0.0004)	(0.0005)
φ	4.8515^{***}	4.8917^{***}	4.7622^{***}	4.3809^{***}
	(0.0739)	(0.0937)	(0.1033)	(0.1264)
w_{t-1}	$-3.55e-5^{***}$	$-3.77e-5^{***}$	$-3.89e-5^{***}$	$-4.05e-5^{***}$
	$(1.25e-6)$	$(1.36e-6)$	$(1.48e-6)$	$(1.44e-6)$
Constant	-0.0429^{***}	-0.0791^{***}	-0.0923^{***}	-0.1248^{***}
	(0.0038)	(0.0052)	(0.0029)	(0.0055)
Year dummy	Yes	Yes	Yes	Yes
Country dummy	Yes	Yes	Yes	Yes
Arellano-Bond test	−1.1795	−1.1848	−1.1861	−1.1908
Sargan (p-value)	0.6180	0.5778	0.5015	0.6079
No. of countries	109	109	109	109
No. of Obs.	1,526	1,526	1,526	1,526

Note: The numbers in parentheses are standard errors. *** $p < 0.01$, ** $p < 0.05$.

To consolidate our theoretical predictions that a higher ratio of older people in the demographics is disadvantageous for technological catch-up, we reconstruct the measure for the key variable μ by including the group of the elderly who are older than 64 in the calculating base. That is, μ

is measured by the ratio of youth at (ages 20-39) in both the workforce (ages 15-34) and old (ages 65 and above), termed μ_2039/age 15+. Also, we define "youth" as being between the ages of 20-44, 25-39, and 25-44. Table 3 displays the estimated results.

We find that all youth variables continue to be associated with a significantly positive coefficient in all specifications, reconfirming our theoretical argument. The estimated magnitude of coefficients ranges between 0.0275 and 0.2452; this again suggests that the age group 25-44 has the largest influence on productivity catch-up which is consistent with the findings in Table 2.[14]

6. CONCLUSIONS

We have presented a simple model of trade to demonstrate that the income gap of developing countries relative to developed countries is attenuated when the latter has an aging population or when the former happens to have a higher ratio of youth in its demographics. In this paper, aging is suggested to play an important role in sustaining long-run growth in most countries, because it hinders productivity and generates a negative association with productivity catch-up. The root issue lies in the fact that young people are more efficient than old people in terms of improving productivity due to the externalities of learning by doing or creativity. Based on these theoretical predictions, after controlling R&D intensity and the ratio of students who study abroad, the cross-country finding obtained from the system GMM estimation provides supportive evidence. Specifically, countries with a higher proportion of youth in their demographics demonstrate a faster productivity catch-up, we find that the age group 25-44 has the largest influence on productivity catch-up.

Our study suggests some policy implications. For developed countries that experience this aging problem, a more open immigration policy may be considered. By attracting foreign young talent to attend higher education institutes of learning and encouraging them to live and work in the country, developed countries can lessen the aging problem and retain a sufficient source of young talent. The U.S. is one example of a country that typically retains technological leadership through this kind of policy. On the contrary, one feasible strategy to learn and absorb new knowledge for many developing countries is to encourage their young students to study abroad in advanced countries. More crucially, developing countries have to effectively attract returning talent to contribute to upgrading domestic technologies. A serious brain drain can hamper the productivity growth of

[14]If we use the total population as the denominator to calculate , the estimation results on the youth variables are similar.

developing countries that possess limited high-quality human capital. In sum, competition for recruiting young talent will become tougher in the international labor market.

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