The Global Demographic Transition and Its Impact on Economic Power

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Abstract

This study deploys a multi-region, dynamic life-cycle, general equilibrium model to assess demography's impact, through the course of this century, on global development. Our model's 17 regions encompass more than 150 countries comprising 99% of the world's population. Output is produced with three labor skill groups and internationally-mobile capital, with each country deciding annually whether to adopt its frontier automation technology. Our model features region-specific fiscal policy, TFP growth, and idiosyncratic mortality. Agents live for 100 years, first as children, then as workers, and then as retirees. Work and saving decisions are governed by CES preferences. Lifespan is uncertain, but there are no annuities apart from state pensions. Hence, bequests, while significant, are unintended. Our fertility, mortality, and net immigration rates are region- and age-specific and align fully with the UN's projections. To illustrate demographics' power to impact the global transition, we simulate our model under the UN's markedly different demographic projections for 2017 and 2024. The 2024 forecast is particularly pessimistic about China's fertility prospects. Both projections produce very substantial global aging, a major global capital glut producing very low long-run real capital returns. The latest forecast entails 10% lower global GDP in 2100 and far higher payroll tax rates to fund old-age benefits. Most important, it entails a major change in the course of economic hegemony with China's 2100 global GDP share falling from 25.6% to 14.9% and the US share rising from 11.2% to 14.4%. Our results are sensitive. Should the US eliminate all future immigration, its 14.4% global 2100 GDP share would drop to 9.2%. And were global fertility to follow the UN's low variant, 2100 world output would be one third, not one tenth lower. The level and division of global output is also highly sensitive to the speed at which AI expands frontier technologies. Accelerated AU/AI (AAI) – 4x faster-than-recent growth in capital's share through 2050 – or Transformative AU/AI (TAI) – 10x faster capital-share growth – reinforce demographic forces, ensuring long-run US economic hegemony. Indeed, TAI combined with 2024 demographics implies US and Chinese 2100 global GDP shares of 25.3% and 16.9%, respectively. Intuitively, capital in our model flows to technology. And not withstanding its considerable technological catch up, the US retains, based on our calibration, a technological edge over China throughout the century.

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1 Introduction

The baby bust that followed the baby boom is giving way to the baby bummer. The UN's Global Fertility Rate (GFR) – annual births per woman – tells the story. In 1960, the GFR was 4.98. In 1980 it was 3.69. In 2000, it was 2.73. In 2020, it was 2.30. And in 2024, the latest forecast, it was 2.25 – less than half the 1960 rate. The worsening fertility picture has led to dramatic changes in the United Nation's demographic projections. The UN's 2024 forecast is the first *World Population Prospects*, since their debut in 1951, to predict an end to world population growth before 2100. The UN now foresees global population peaking at 10.3 billion in 2084 and then gradually declining.

Figure 1 shows how much the 2024 UN global population prediction differs from its 2017 prediction. The figure's dotted lines extend the UN's forecasts by assuming births stabilize in all countries starting in 2100. Even under this assumption, global population declines through at least 2150. Of course, nothing guarantees that any nation's births will stabilize, let alone grow. But if they don't, many countries will go extinct. Currently, more than half of the world's 237 countries and territories have fertility rates below 2.1, the ZPG (zero-population-growth) level needed for long-term population replacement.

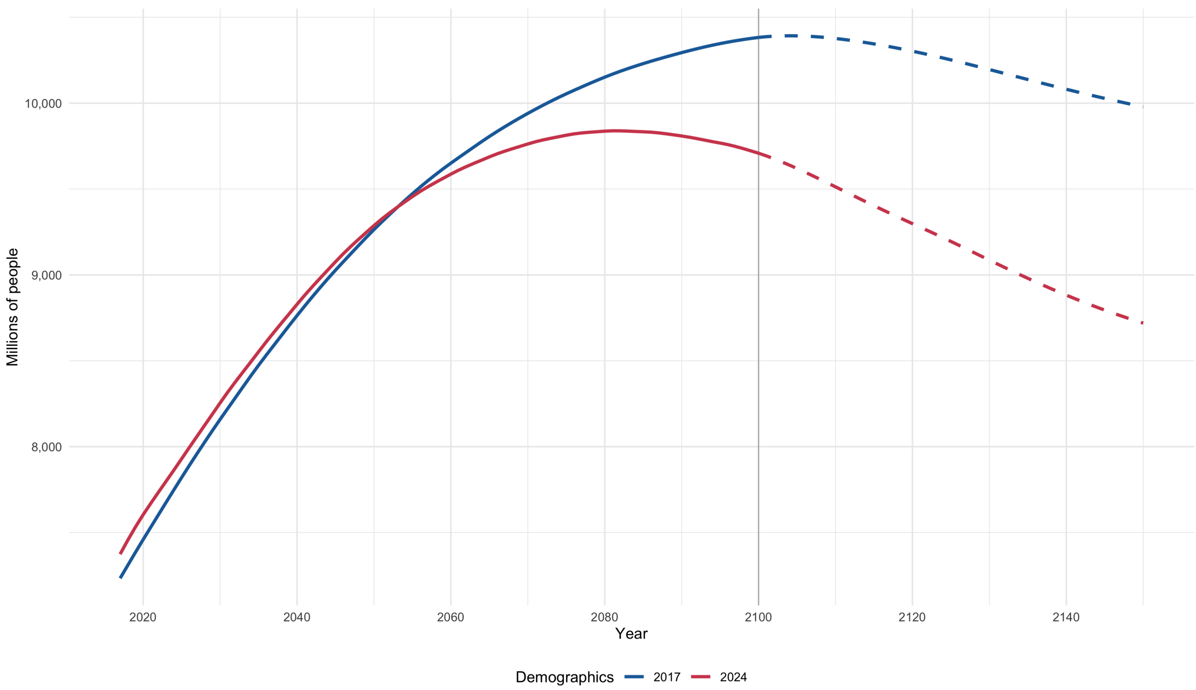


Figure 1: Global Population, 2017 and 2024 UN Projections, Stable Births After 2100

As table 1 shows, South Korea, whose 0.72 fertility rate is the world's lowest, will see, per the UN's latest prognosis, its population fall by more than half – from 52 million to 22 million – a 57% drop – between now and 2100. China's fertility rate is now 1.02 and its population is scheduled to drop by 55% by century's end – from 1.4 billion today to 639 million. The fertility rates of Western Europe and the U.S. are also far below 2.1. The population of western Europe will fall, according to the UN, by 7% by 2100. As for the U.S., its population rises by 22% through 2100 thanks to assumed high and growing foreign net immigration and increasing life expectancy.[1] Although the UN projects that

[1]Given current U.S. immigration policy, the UN may well revise downward its assumed net migration to

fertility rates will rise in particular countries later in the century, it foresees, as figure 2 shows, an ongoing decline in global fertility.

Table 1: 2020-2025 Fertility Rate, Current and Projected Populations, Selected Countries/Regions

Country/Region	TFR (2020-2025)	2024 Population	2100 Population	Change
United States	1.57	344.9 million	421.0 million	+22%
Western Europe	1.54	199.3 million	185.4 million	-7%
China	1.02	1,419 million	638.7 million	-55%
South Korea	0.72	51.7 million	22.0 million	-57%

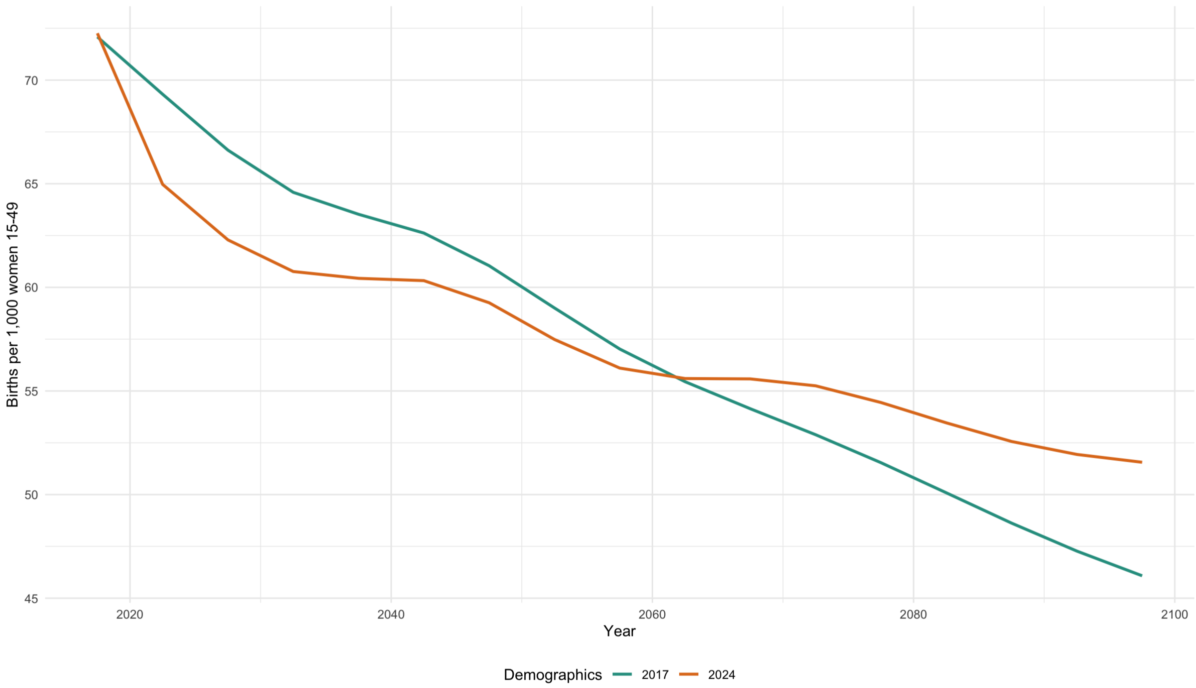


Figure 2: Global Fertility Rate, 2017 and 2024 UN Projections

How will the demographic transition impact global, regional, and national growth rates, living standards, wage and interest rates, fiscal policies, and the distribution of economic power? And will the concomitant automation/AI (henceforth AU/AI) technology transformation offset or reinforce demographic impacts?

Our paper addresses these questions using a large scale dynamic, computable general equilibrium life-cycle model. Our model, developed in Benzell et al. (2021), aggregates over 150 countries, comprising over 98% of global GDP and 99% of global population, within 17 regions. Its agents live up to 100 years, the first 17 to 20 as children whose consumption during those ages impacts their parents' utility. Although agents aren't altruistic toward their adult children, they do bequeath, albeit involuntarily due to their incomplete annuitization.

Our model features region- and age-specific demographics as well as region-specific CES preferences over consumption and leisure, region-specific TFP growth, region-specific endogenous AU/AI adoption (with region-specific frontier technologies having higher

the U.S.

capital-share and high-skilled labor-share coefficients), and region-specific fiscal policy. Each region's production of the world's single product is governed by a Cobb-Douglas technology that use internationally mobile capital as well as region-specific high-, middle-, and low-skilled labor.

We consider three alternative expansions in the frontier technology through 2050. The first, referenced by BAU (Business as Usual), extrapolates recent changes in factor-income shares, foreseeing a gradual rise in the U.S. capital share from 34% in 2017 to 37% in 2050. Under BAU, high-skilled U.S. labor's share rises from 22% to 27%, its middle skill's share falls from 22% to 21%, and its low skill falls from 22% to 16%. Under what we dub Accelerating AU/AI and Transformative AI (TAI), the US capital shares in 2050 are 44% and 60%, respectively. The shares of high-skilled labor in 2050 are 23% and 17%, the shares of middle-skilled labor in 2050 are 18% and 13%, while the shares of low-skilled labor in 2050 are 14% and 10%.

With 17 regions, four factors of production, agents that plan for consumption through 100 – their maximum age of life – and for leisure through their region-specific, exogenously set retirement age, frontier-technology-adoption decisions, and international capital mobility, the model comprises over three million equations with an equal number of unknowns. Notwithstanding the computation challenge, the model's solution algorithm converges, typically within two hours, to machine precision.[2] Notwithstanding its multiple moving parts, the model produces qualitative results that agree fully with theory and, indeed, simulations of two-period models.[3]

Our means of assessing demography's global, regional, and national economic importance is to compare our model's results taking as demographic inputs the UN's 2017 and 2024 age- and country-specific fertility, mortality, and migration projections, and fully calibrating the model to the same base year under the two demographic assumptions.[4] Although these two forecasts are just seven years apart, the 2100 global population projected in 2024 is 8.9% lower than that projected in 2017.

To summarize our main findings, our model's baseline (BAU) simulations show a 10% decline in 2100 global GDP under the 2024 forecast compared with the 2017 forecast. The world's average output growth rate between 2050 and 2100 declines from 2% to 1.8%. Switching from 2017 to 2024 UN projections cuts China's 2100 share of world GDP from 25.6% to 14.9%, near parity with the US, whose 2100 share *rises* from 11.2 to 14.4%. China's 2100 GDP falls by 48% – 218 to 115 trillion 2017 USD, a decline of 104 trillion, whereas US 2100 GDP rises 16%. The channel through which demographics shift global GDP is primarily headcount, not productivity or labor force participation effects. Real GDP-per-worker growth is essentially identical based on either projection.[5]

The 2100 global average wage drops by roughly 3% in switching from 2017 to 2024 demographics. China's 2100 average wage is slightly higher under 2024 demographics – by 3.3% in 2050 and 2% in 2100. The real rate of return to capital, which is 5.9% in 2017, falls dramatically under both projections. Under the 2017 demographic forecast,

[2]We use a modified version of the Auerbach and Kotlikoff (1987)'s iterative, perfect-foresight solution algorithm.

[3]As Auerbach and Kotlikoff (1983) and Auerbach and Kotlikoff (1987) show, one can easily test whether large-scale dynamic life-cycle models generate economically intuitive results by examining the impacts of simulating changes in model elements, such as the extent of deficit finance, one element at a time.

[4]In the case of multi-country regions, we form weighted regional demographic projections.

[5]The world's (China's) annual rate is 2.1% (3.7%) over 2017–2100 in both cases.

the 2100 return is 1.9%. It is 1.6% under 2024 demographics. So, the life-cycle model's basic message – aging leads to capital deepening – comes across loud and clear. Interest rates are however much higher under transformative AU/AI. With TAI, the 2100 rate is 6.6% under the 2017 projection and 6.1% under the 2024 projection. The switch from 2017 to 2024 demographics, however, has little impact on frontier-technology adoption regardless of the pace of AU/AI. With the exception of Mexico, which adopts toward the end of century and only under faster AU/AI growth scenarios, regions that never adopt the frontier technology under the 2017 demographic projection also don't adopt under the 2024 projection.

Although the never-adopting regions' population shares rise through the century under both projections, their share of global GDP falls. This reflects the increased demand for capital in advanced economies as they adopt frontier production methods. Take Sub-Saharan Africa for example. Its 2100 GDP is 20% lower under the 2024 demographic projection than under the 2017 projection with baseline (BAU) frontier-technology expansion, and 19.8% lower with the TAI expansion.

What about global living-standard inequality? In our baseline, Sub-Saharan African per capita GDP, which is 5.9% of the US level in 2017, falls to 5.4% by 2100 with 2017 demographics and to 4.6% with 2024 demographics. These figures are 2.0% and 1.6%, respectively, under the two forecasts assuming 10x AU/AI expansion. Both aging demographics and transformative AU/AI thus widen the economic divide between today's most and least economically prosperous regions.

Fiscal systems are stressed by aging under both projections. Our base case holds benefits per retiree fixed relative to per-capita GNI. Therefore, aging raises pension budgets through the beneficiary count alone. Under both demographic projections, the world average payroll tax rate roughly doubles, from 13.1% of covered earnings in 2017 to 24.1% in 2100 under the 2017 forecast, and 25.4% under the 2024 one. World pension outlays rise from 5.8% of GDP to 11.9%. The 2024 demographics compound an already severe burden. China accounts for a large share of the global increment: its 2100 payroll rate is 38.1% under the 2024 projection against 28.1% under the 2017 one, and its pension outlays 15.1% of GDP against 11.1%. The US is less affected. Its 2100 payroll rate rises only from 27.7% to 28.2% as the 2024 projection includes not just lower fertility but also substantially higher immigration. The effective average tax rate on total income rises over the century from 31.4% to 40.8% worldwide, from 38.3% to 47.0% in the US, and reaches 56.7% in Western Europe.

2 Background

Our model is an updated version of Benzell et al. (2021), which extends Benzell et al. (2025) along a number of dimensions, particularly the inclusion of endogenous AI and other automating technologies. As for Benzell et al. (2025), it descends from a long list of large-scale, dynamic life-cycle CGE frameworks. The list includes Auerbach and Kotlikoff (1981), Auerbach and Kotlikoff (1983), Judd (1985), Fullerton and Rogers (1996), Altig et al. (2001), Auerbach et al. (1989a), Fehr, Jokisch, and Kotlikoff (2003), Fehr et al. (2013), Fehr, Jokisch, and Kotlikoff (2013), Benzell et al. (2015a), and Nelson et al. (2019).

Auerbach and Kotlikoff (1987), Auerbach et al. (1989b), Fehr, Jokisch, and Kotlikoff (2003), and Fehr, Jokisch, and Kotlikoff (2013) are early studies of demographic change in closed and partially open economies. Fiscal policy aside, these studies confirm what basic life-cycle economics predicts: Population aging leads to capital deepening – higher labor and lower capital returns – as the ratio of retirees with wealth increases relative to the number of workers. However, the studies also deliver a warning. The inclusion of pay-go state-pension plans and other young-to-old redistribution policies can reverse the long-term beneficial impacts of aging. Intuitively, life-cycle models feature young savers and old spenders. But young people will have less capacity to save if payroll and other taxes increase dramatically to maintain the benefits of a growing number of retirees.

Similar to Benzell et al. (2025), our model combines the world's nations into 17 large regions, some of which, including US, Russia, and China, are single countries. It features UN-based region-specific demographics, including age- and region-specific fertility, mortality, and net immigration rates, demographic projections that fully align with the UN's (through 2100 when we assume region-specific births stabilize), region-specific fiscal policy calibrated to IMF data, inclusion of children and unintended bequests, as mentioned, three labor skill groups (high, medium, and low), and region-specific fiscal policies, TFP levels, and work and saving preferences.

Benzell et al. (2021) incorporates AU/AI via increases in capital's and high-skilled labor's output shares in the frontier technology. Per Zeira (1998), regions are free to adopt the frontier technology based on output maximization. This decision depends on relative factor prices. In particular, regions with relatively expensive labor and relatively cheap capital benefit more from new, more automated production functions, and therefore adopt these new technologies sooner.[6] Conversely, regions with lower wages and high costs of capital will delay adoption.[7]

Since capital is internationally mobile, a disproportionate reduction in a region's labor supply due to a particularly low fertility rate will not materially impact its wage rates and will encourage adoption of frontier technologies. But if a very large region has a very high saving rate, e.g., China, low fertility will, over time, reduce the world's supply of capital. This can alter global factor prices and, in turn, impact non-Chinese regional adoption of the frontier technology.

In summary, prior life-cycle demographic modeling suggests that a major global fertility decline can, over time, have dramatic global, regional, and national economic consequences. These impacts depend on the extent and persistence of fertility decline, the extent and form of intergenerational redistribution (e.g., pay-go state-pension systems) and immigration policies, and the nature of technological change.

There are, of course, many different ways to model technological change.[8] We incorporate two forms here. The first is TFP growth paths that differ by region. The second is adopting frontier AU/AI technology. Karabarbounis and Neiman (2014) document a major global decline in labor's share, which they attribute largely to a decline in the

[6]The frontier automation/AI technology is defined by the speed at which new production technologies shift income from labor toward capital, which we detail in section 3.4.

[7]Note, factor-price equalization, measured on an efficiency-wage basis, doesn't hold in our model notwithstanding the mobility of capital. The reason is that the number of factors (four) exceeds the number of products (one) and that capital mobility effectively comprises only one more product equation.

[8]For example, Benzell et al. (2015b) takes a very different approach to AU/AI than the Zeira (1998) approach considered here or the task model of Acemoglu and Restrepo (2018).

cost of investment goods. But as labor's share has declined globally, wage inequality has risen (Autor, Katz, and Kearney 2006). The best-known model of AU/AI adoption is Acemoglu and Restrepo (2018)'s task model. It predicts a rising capital share arising from increased automization in line with Karabarbounis and Neiman (2014). The rising share of high-skilled labor reflects stronger complementarity between AU/AI, for example due to advanced training being required to integrate AU/AI into the production process.

However, Zeira (1998) notes that changes in the frontier technology – modeled here as increases in capital and high-skilled labor factor shares – do not necessarily translate into automatic adoption. Regions that have particularly low relative cost of labor, due to lower than average levels of TFP or high fertility, may be more productive using their existing rather than frontier tech. In our context, this means producing based on Cobb-Douglas production functions that feature lower capital and high-skilled labor shares until conditions become ripe (which may not arise) to switch to the frontier technology.

Benzell and Ye (2024) investigate the consequences of Transformative AI (TAI) – raising capital's share of U.S. income from roughly 34% to 60% by 2060, roughly ten times the rate of capital share shifting in comparison to U.S. historical experience. Doing so raises U.S. GDP by a striking 71% in 2050 relative to the 2024-demographic projection baseline. Yet, it leaves 2050 global GDP nearly unchanged: regions with cheap labor and expensive capital, including China, rationally delay adopting the frontier technology and fall behind as global investment is bid away, reinforcing U.S. economic hegemony.

There is a vast literature on demographic change beyond the immediately relevant studies just cited. Doing even cursory justice here to this body of work is infeasible. However, one recent study, Auclert et al. (2025), bears mention. The authors focus on the evolution of the return to capital as a race between asset demand and supply. Yet, neither seems well defined.[9] They also substitute steady-state for dynamic analysis, when the half-life of dynamic transitions can be decades. Finally, they treat the US as a partially open economy. Consequently, they conclude that the 2100 return to capital will rise relative to its current value, not dramatically decline as our study suggests. They also find that the US can substantially expand its already massive intergenerational redistribution policies with no impact on its return to capital. But the return to internationally mobile capital is set, in our model as well as practice, not by US fiscal policy, but the international capital market. Of real relevance is the impact on US lifetime net tax rates of such policy. Our model, as well as recent US fiscal gap and generational accounting (see Dicarlo et al. 2025), suggests little to no scope for additional take-go (take from the young and give to the old) policies, let alone policies that raise the US debt-to-GDP ratio to 250% or do the equivalent with different labels.

3 Model

The description of our model in this section draws heavily and often verbatim from Benzell et al. (2021). The model has seventeen regions, each with three sectors: a household sector whose agents work, save, and consume, a government, which taxes, transfers, and spends, and a business sector, which hires labor, rents capital and produces a single output that

[9]For example, as explained in Green and Kotlikoff (2008), government debt, which figures prominently in their study, is a figment of language, not a well-defined economic concept.

can be consumed or invested. Regions receive fossil fuel rents that accrue to both private investors and governments. The regions and their acronyms are listed in table 2.

Acronym	Region	Acronym	Region
USA	U.S.	MENA	Middle East and North Africa
WEU	Western Europe	MEX	Mexico
JKSH	Japan, South Korea, Singapore and Hong Kong	SAF	South Africa
CHI	China	SAP	South Asia Pacific excluding Australia
IND	India	SLA	Latin America excluding Mexico and Brazil
RUS	Russian Federation	SOV	Former Soviet Central Asia
BRA	Brazil	SSA	Sub-Saharan Africa excluding South Africa
GBR	The U.K.	EEU	Eastern Europe
CAN	Canada, Australia and New Zealand		

Table 2: Regions and Acronyms

3.1 Modeling Demographics

The model has 101 overlapping generations of agents of ages 0 to 100 comprising three skill levels: high, middle and low. Children are born with the same skill as their parents and retain that skill for life. Children receive consumption from their guardians (either parents or grandparents) before entering the workforce. At a region- and skill-group k specific age, a_{w_k} between 18 and 21, agents enter the workforce and receive labor income until a region-specific retirement age, after which they receive pensions.[10] Agents give birth to fractional children between age 15 and 49. Children of agents who are too young to work (those from 15 to $a_{w_k} - 1$) are raised by their grandparents. Henceforth, we use the term "guardians" to refer to the parents and grandparents responsible for a given cohort of children and "dependents" to refer to their children and grandchildren. Agents can die at any age from 0 through 100, after which they die with certainty. Figure 3 summarizes the agent's life-cycle.

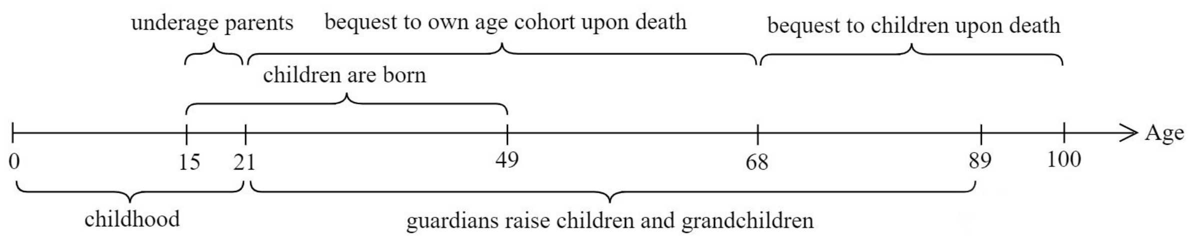


Figure 3: The individual life-cycle

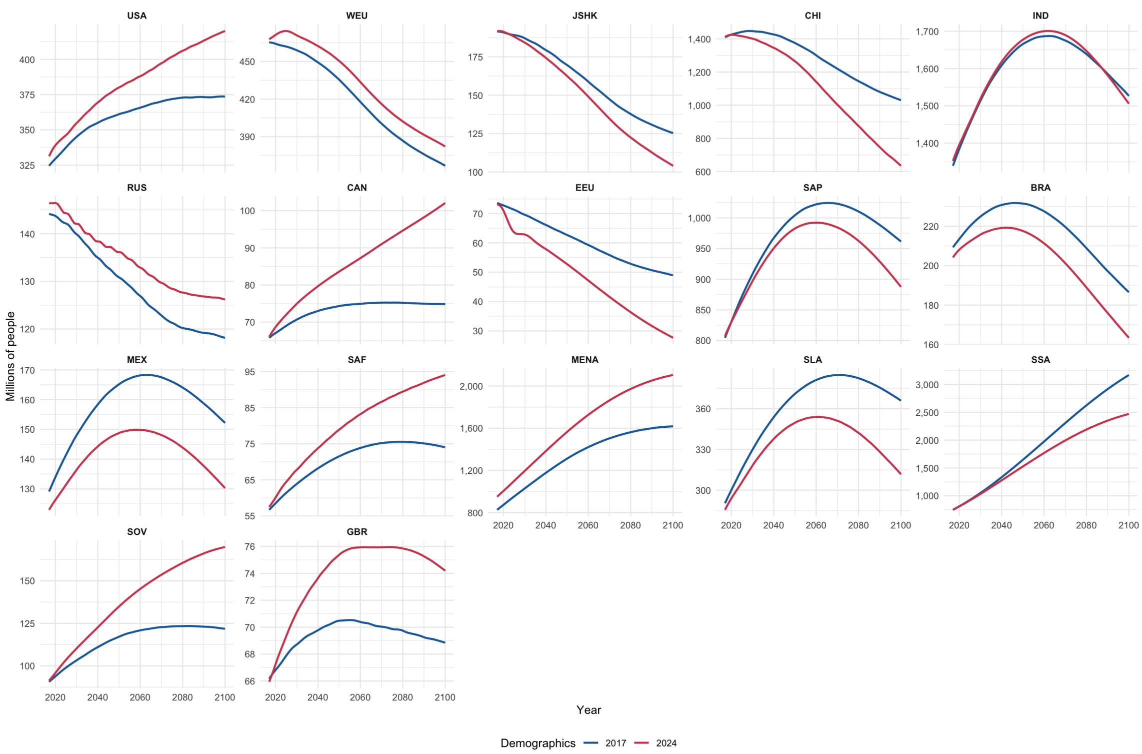
We simulate the model under two alternative demographic baselines. The first sets the paths of demographics in each region, including year- and age-specific births and deaths, to match the United Nations' 2017 World Population Prospects projections through 2100.

[10]We set the age of entry into the labor force to roughly match the fraction of individuals in a region that receive some college education. Low- and mid-skilled agents of developing and least-developed regions enter the labor force at 18. For the U.S. and other developed regions, all three skill groups enter the labor force at 21. See section 3.2.3 for a detailed discussion of treatment of pension benefits.

The second instead matches the UN's 2024 projections (United Nations 2024).[11] We smooth the region- and projection-specific estimates to generate births, deaths, and total population projections of agents in each region at each age in each future year. We calculate annual net immigration by age and year to reconcile the smoothed age- and year-specific UN births and deaths to the smoothed age- and year-specific UN population totals. Beyond 2100, the last year covered by the UN projections, fertility in every region moves to its replacement rate, so that each region's population stabilizes; mortality and migration are held at their 2100 values.[12]

Both sets of projections imply striking disparities across regions in population trends, but they differ sharply from one another in level. As shown in figures 1 and 4, global population in 2100 is roughly 10.4 billion under the 2017 projection but 9.7 billion under the 2024 update. The starkest revision concerns China: its population in 2100 is 1.03 billion in the 2017 forecast, but only 0.63 billion in the 2024 forecast. This reflects the sustained collapse in Chinese fertility since the earlier projection was prepared. Much of the developed world – Western Europe, Japan, and Korea – experiences major population declines through the century's end in both forecasts. Sub-Saharan Africa and the Middle East, including North Africa, grow by nearly 3 billion people by 2100 due to persistently high fertility combined with rapidly declining mortality, and regions such as MENA and South Africa see their population projections revised upward in the update.

Figure 4: Population by Region under 2017 and 2024 UN Projections



These demographic dynamics have major implications for the adoption of technologies

[11] In both cases, the UN projects births, deaths, and total population by country in every fifth year for five-year age groups. We aggregate these country-specific projections to generate region-specific projections.

[12] Benzell et al. (2021) instead held UN-projected fertility behavior fixed after 2100, with stabilization occurring only in the mid-2200s. This trajectory is no longer feasible under the 2024 version of demographics, as it entails countries such as China approaching zero population after 2100.

that substitute to capital and specifically away from low- and mid-skilled labor. As the world ages, the pool of labor shrinks, tending to raise wages. Further, retirees have more assets relative to young workers. Hence, global aging lowers interest rates. The changes in factor prices favor automation and AI, particularly in developed regions with high wage rates and aging populations. A key question this paper addresses is how much the 2024 forecast revision shifts these margins.

3.2 Sectors

3.2.1 Households

Households are made up of agents who decide how much to work, save, and consume each year. Agents receive a fixed time endowment, h, in each period and maximize lifetime utility given by a nested, time-separable CES utility function. For a working agent of age a in time t and skill-group k, dropping regional subscripts, we have

$$U_{a,t,k} = V_{a,t,k} + H_{a,t,k}, \tag{1}$$

where $U_{a,t,k}$ is the agent's utility, the sum of his or her utility $V_{a,t,k}$ derived from consumption and leisure, and $H_{a,t,k}$, is the utility derived from the consumption of their dependents, including both children and grandchildren of underage parents. The function $V_{a,t,k}$ is given by:

$$V_{a,t,k} = \frac{1}{1-\frac{1}{\gamma}} \sum_{i=a}^{100} \left(\frac{1}{1+\delta_t}\right)^{i-a} P_{a,i,t} \left[c(i,t+i-a,k)^{1-\frac{1}{\rho}} + \varepsilon_{t,k}\ell(i,t+i-a,k)^{1-\frac{1}{\rho}}\right]^{\frac{1-\frac{1}{\gamma}}{1-\frac{1}{\rho}}}. \tag{2}$$

This equation represents discounted CES utility over consumption and leisure over the agent's remaining lifetime. $P_{a,i,t}$ is the probability that an agent of age a at time t survives to age i, which is not specific to skill group. $c(i,t+i-a,k)$ is the consumption of an agent of age-a, skill-group k, at time $t+i-a$, the period when they reach age i, and $\ell(i,t+i-a,k)$ is leisure for this group in the same period. The function $H_{a,t,k}$ is given by:

$$H_{a,t,k} = \frac{1}{1-\frac{1}{\gamma}} \sum_{i=a}^{100} \left(\frac{1}{1+\delta_t}\right)^{i-a} P_{a,i,t} D_{a,i,t,k} c_{D_{a,i,t,k}}^{1-\frac{1}{\gamma}}, \tag{3}$$

which represents discounted utility over consumption $c_{D_{a,i,t,k}}$ of all of the agent's dependents $D_{a,i,t,k}$. δ_t denotes the time preference rate, which is assumed to be constant across age and skill but varies across regions and with time. ρ and γ are, respectively, the intratemporal elasticity of substitution (ELS) between consumption and leisure and the intertemporal ELS of utility over time. Both are assumed to be fixed across age-skill groups, regions, and time. $\varepsilon_{t,k}$ is the time- and skill-group specific subjective leisure preference parameter.

Assets of surviving agents evolve according to

$$A_{a+1,t+1,k} = (A_{a,t,k} + I_{a,t,k})R_{t+1} + (h - \ell_{a,t,k})w_{a,t,k} - T_{a,t,k} - C_{a,t,k}. \tag{4}$$

Agents earn a pre-tax rate of return, R_{t+1}, on their time-t assets, $A_{a,t,k}$, and on total inheritances received by age-a individuals $I_{a,t,k}$. $h - \ell_{a,t,k}$ represents the fraction of the fixed time endowment, h, spent on labor, and $w_{a,t,k}$ is the pre-tax wage of the sub-scripted agent. $T_{a,t,k}$ references an agent's personal taxes net of pensions and other transfer payments received. And $C_{a,t,k} = c_{a,t,k} + D_{a,t,k} \cdot c_{D_{a,t,k}}$.

The model's bequests arise not from a agents' desires to bequeath, but to our assumed absence of annuity markets; i.e., they are not intentional. Agents give birth and leave bequests exclusively to agents in their own skill cohort. We assume that agents below age 68 bequeath to their spouses, represented as other agents in their own age cohort. Agents at or above age 68 bequeath proportionally to all of their adult children.[13] Note also that while grandparents raise children of their "underage" children, bequests always go to the grandparents' own adult children.

3.2.2 Production

Regional gross domestic product is the sum of output from a production sector, Q_t, and a natural resource endowment flow, X_t

$$Y_t = Q_t + X_t. \tag{5}$$

Energy endowments are modeled as an annual flow of the consumption good net of extraction and transportation costs. They accrue, in part, to households as a private asset and, in part, to the government as revenue. We calibrate the size of the flow in each region, the fraction of which accrues to the public sector, and the date of exhaustion based on World Bank (2021) fossil-fuel and IMF (2017) fiscal data.

We define regional gross national income, N_t, as the sum of GDP and net foreign asset income $r_t F_t$,

$$N_t = Y_t + r_t F_t, \tag{6}$$

where r_t is the global rate of return and F_t is net foreign assets.

Production is governed by

$$Q_t = \phi_t (\varphi_K K_t)^{\alpha_t} L_{t,1}^{\beta_{t,1}} L_{t,2}^{\beta_{t,2}} L_{t,3}^{\beta_{t,3}}, \tag{7}$$

where $L_{t,k} = \varphi_{l_k} l_{t,k}$, $k \in (1,2,3)$ are productivity-adjusted labor inputs, $l_{t,k}$ is labor supply of group k, φ_{l_k} is a skill-group specific labor productivity term, and φ_K is capital productivity.[14] Both K_t and output are denominated in real 2017 dollars. The term ϕ_t

[13]For example, an agent dying at 68 bequeaths to his or her age and skill cohort's distribution of working children, all of whom are between ages a_{w_k} and 53.

[14]Henceforth we use $k = 1$ to represent low-skilled workers, $k = 2$ for the mid-skilled, and $k = 3$ for the high-skilled.

captures time-varying total factor productivity, the calibration of which is detailed in Appendix section A2.

In each region's initial (2017) technology, each skill group earns an equal share of total labor income. I.e.,

$$\beta_{t,k} = \frac{1-\alpha_t}{3}, \tag{8}$$

for $k \in (1,2,3)$. As described in section 3.4, regions may in any year instead operate a frontier technology with a larger capital coefficient and skill-biased labor coefficients. Total labor supply, measured in efficiency units, of skill group k at time t, $l_{t,k}$ satisfies

$$l_{t,k} = \sum_{a=a_{w_k}}^{100} (h - \ell_{a,t,k}) E_{a,t,k} \cdot N_{a,t,k}, \tag{9}$$

where $N_{a,t,k}$ is the population of skill-group k at age a and time t. $E_{a,t,k}$ is an age- and time-specific productivity profile. This profile is that in Auerbach and Kotlikoff (1987), but modified to allow for different ages of labor force entry. To be precise,

$$E_{a,t,k} = e^{4.47+0.033(a-a_{w_k}-1)-0.00067(a-a_{w_k}-1)^2}(1+\lambda)^{a-a_{w_k}}. \tag{10}$$

We assume that $\lambda = 0.01$, i.e. the time-endowment, rises at 1% per year. This assumption that cohorts' effective time endowments grow at a fixed rate through time ensures the global economy will reach a steady state given our CES preferences.

Our perfectly competitive firms hire factors to maximize profits. Thus,

$$w_{t,k} = \frac{\beta_{t,k} Q_t}{l_{t,k}}, \; k \in (1,2,3) \tag{11}$$

$$r_t = (1-\tau_t^K)\left(\frac{\alpha_t Q_t}{K_t} - \delta_K\right), \tag{12}$$

where $w_{t,k}$ are wages per efficient unit of labor for the respective skill groups, τ_t^K is the marginal effective tax rate (METR) on capital, and δ_K is a region-specific depreciation rate. Note that, other things equal, higher TFP and use of frontier technology means higher Q, which implies a higher marginal product of capital, attracting more capital inflows.[15]

3.2.3 Government

Each region's government (which comprises federal, state and provincial, and local governments) collects taxes, borrows, and spends on both consumption and transfer payments. Spending includes direct government purchases of goods and services, C_t^g, a fraction, ϱ, of

[15] In our calibration, the US has higher TFP than China, a lower corporate income tax rate, and almost as advanced a level of frontier technology. This translates, in our high AU/AI TAI growth scenario, to more US output relative to Chinese output.

state-pension payments, e_t, which are not covered by payroll taxes, a variety of transfer payments to the private sector, f_t, and interest payments, $r_t B_t$, on debt, B_t.

Government receipts comprise the government's share of energy sector rents, X_t^g, net borrowing, ΔB_t, corporate income taxes, T_t^K, and personal taxes collected from each cohort within a given year, $T_{a,t,k}$. The government's flow budget is

$$\sum_{k=1}^{3} \sum_{a=a_{w_k}}^{100} T_{a,t,k} N_{a,t,k} + T_t^K + X_t^g + \Delta B_t = C_t^g + \varrho e_t + f_t + r_t B_t. \tag{13}$$

Households face taxes on capital, wage, and total income, as well as consumption. Firms face corporate income taxes. Capital income, corporate income and payroll tax rates are fixed, with the payroll tax financing a fixed, region-specific fraction of state pensions. In our calibration, governments endogenously set income and consumption tax rates to maintain a constant level of debt-to-GDP, with the level of income tax progressivity fixed through time.[16] Time-t income tax revenue, R_t, is given by

$$R_t = \sum_{k=1}^{3} \sum_{a=a_{w_k}}^{100} \left(\tau_t w_{a,t,k} + \frac{\xi_t w_{a,t,k}^2}{2} \right) l_{a,t,k}, \tag{14}$$

where τ_t endogenously adjusts to keep regional debt-to-GDP fixed. ξ_t is a progressivity term calibrated to the ratio between the U.S. METR of high-skilled households by labor earnings and the U.S. average income tax rate among all working households. $w_{a,t,k} = w_{t,k} \cdot E(a,t,k)$ is the age-skill group's wage rate. Corporate income taxes are assessed on all domestic output net of labor costs and depreciation.

$$T_t^K = \tau_t^K \left(Y_t - \sum_{k=1}^{3} \sum_{a=a_{w_k}}^{100} w_{a,t,k} l_{a,t,k} - \delta_K K_t \right), \tag{15}$$

where δ_K is the depreciation rate.

In each region, the payroll tax finances a fraction of pension payouts, and the remainder, ϱ, is financed through the general account.[17] Payroll taxes are assumed to be proportional up to a region-specific contribution ceiling, after which the marginal payroll tax rate is zero.[18]

Education and healthcare expenditures are treated as a combination of direct government consumption (public schools, government purchases of medical infrastructure and supplies, etc.) and transfer payments to households. Both categories are calibrated separately. Program-p transfers are given by

$$Tr_{p,t} = \zeta_{p,t} Q_t v_p \sum_{k=1}^{3} \sum_{a=a_{w_k}}^{100} Z_{p,a} N_{a,t,k}, \tag{16}$$

[16] We set the rates endogenously such that the ratio of revenues raised by the two taxes is held constant at their initial regional values. This ratio is calibrated to fiscal data.

[17] In some regions $\varrho < 0$, in which case the payroll tax subsidizes other government spending.

[18] As discussed in section 3.3, our calibration implies that the highest skill group in all regions faces a marginal payroll tax rate of zero. This precludes kinks in budget frontiers.

where $Z_{p,a}$ is the region- and spending-program specific age-expenditure profile, and $\zeta_{p,t}$ is a region- and program-specific shift term. This term is calibrated to match program expenditure as a share of GDP and assumed to evolve through time to keep transfers constant as a ratio of per capita GNI. v_p is the share of government expenditure on p that is treated as a transfer. General welfare transfers include disability insurance and similar programs and are evenly distributed across adults.

Pensions and general welfare transfers are fungible. Healthcare and education transfers are not. This prevents young agents from borrowing against healthcare benefits received later in life. In-kind consumption is inframarginal and, thus, doesn't impact utility maximization. Pension payouts are a time-varying and region- and skill-group specific fraction of an agent's average career earnings. An agent who retires at age a_r in year t receives benefits as a constant fraction of their average lifetime wage income.

$$PB_{a_r,t,k} = \nu_k \frac{1}{a_r - a_{w_k}} \sum_{a=a_{w_k}}^{a_r} w_{a,t-a_r+a,k}, \tag{17}$$

where ν_k is skill group k's replacement rate.

3.3 Solution Method and Calibration

This section describes our iterative solution method for precisely solving our model's over three million equations in an equal number of unknowns. It then summarizes the calibration of its 400 plus parameters; details are provided in Benzell et al. (2021).

3.3.1 Solution Method

We solve the model using a variant of Auerbach and Kotlikoff (1987)'s Gauss-Seidel method. Solving the model means estimating region-specific paths of skill-specific wages and a global path of the return to capital such that region- and skill-specific supplies of labor equal their corresponding demands and the path of global capital supply equals the path of global capital demand.

The model's factor demands are governed by equations (11) and (12). The model's factor supplies are governed by equations (1) through (4). The model's solution begins with a guess of the time path of the U.S. capital stock and region-specific paths of skill-specific labor supplies. Given the guessed paths of U.S. skill-specific labor supplies, the guessed path of U.S. capital, and the U.S. METR on capital, we determine the path of the world interest rate, r_t. From the world interest-rate path and region- and skill-specific leisure guesses, we determine region-specific capital demand paths.

The implied paths of region-specific wages and r_t as well as guessed paths of region-specific average and marginal household tax rates lets us update region- and skill-specific paths of leisure and consumption demands and, thus, region- and skill-specific labor and region-specific asset supplies. Subtracting off the paths of the values of non-capital assets (debt and claims to energy endowments), yields a path of the world supply of capital. Subtracting the sum of paths of all non-U.S. capital demands from the path of the world supply of capital produces our new guess of the path of the U.S. capital stock.

We also update all endogenous region-specific taxes to satisfy region-specific annual government budget constraints and the paths of market values of non-capital assets.[19] A weighted average of the new and prior guesses of the U.S. capital stock path is then used in the model's next iteration.

The initial year of the simulation is set at 2017, the base year of the earlier of our two demographic projections and the most recent year for which comprehensive macro and fiscal data are available at the time of the model's original calibration. The initial conditions consist of asset holdings by age, skill group, and region. We allow a maximum of 500 years for the model to converge.[20] Updating stops when, for all years, the year-specific difference between global output demand and supply converges to within 0.005% of that year's global output.

3.3.2 Calibration

We calibrate the model's parameters to fiscal aggregates, macro aggregates, and microeconomic estimates. This subsection summarizes these targets and their sources; Appendix section A2 provides details, and Benzell et al. (2021) documents the automated calibration method itself. Critically for the present exercise, the model is calibrated separately under each demographic projection to the *same* set of fiscal and economic targets.[21]

Region-specific shares of population in each skill-group are estimated using the World Inequality Database (Alvaredo et al. 2020). Capital shares in each region are calibrated to IMF capital stock data (IMF 2019b). Within each region, the three skill groups are then defined so that each collects one third of base-year labor income, following Benzell et al. (2021) – with automation subsequently tilting the shares toward capital and high-skill labor as described in Section 3.4. Table 3 reports the calibrated 2017 shares for all 17 regions.[22] Production input shares and population shares by skill-group are reported in table A13. Region-specific macro and government fiscal targets are obtained from a number of data sources.[23] We use the microeconomic estimates of Acemoglu, Lelarge, and Restrepo (2020) and Altig et al. (2020) to calibrate, respectively, φ_K, and the 2019 progressivity of the U.S. federal income tax. We assume all regions maintain this degree of income-tax progressivity through time.

[19]To be precise, region-specific paths of payroll tax rates endogenously adjust to pay for region-specific shares of government pension benefits per equation (17). Paths of pension benefits are calculated based on workers' past average wage earnings and are set within each region and year such that average benefits per retiree remain at their 2017 level relative to per-capita GNI. Regional-specific paths of non-pension transfer payments, both fungible and in-kind, are also calculated at this stage based on equation (16). As the equation indicates, non-pension transfer payments grow with gross national income (GNI) per capita and population. The same is true of region-specific government consumption. As for income tax functions, the region-specific linear components are adjusted to maintain region-specific debt to GDP ratios. This routine also updates region-specific paths of debt stocks.

[20]With demographics stabilizing from 2100 onward, this allows more than 400 years beyond the year each region's demographics stabilize.

[21]The calibration was re-run for each projection using the model's automated calibration machinery; see Benzell et al. (2021) for the methodology. Because targets are identical across the two calibrations, differences in simulated outcomes are attributable to the change in demographic inputs rather than to changes in fiscal or technological assumptions.

[22]Table A8 shows factor shares under our business-as-usual scenario by region in 2100.

[23]Most are sourced from the IMF, the World Bank, and the International Labor Organization (ILO). The remainder are sourced from country-specific treasury department (or equivalent) websites.

Table 3: Calibrated Production-Function Shares by Region, Base Year

Region	α	β_1	β_2	β_3
USA	0.338	0.221	0.221	0.221
WEU	0.365	0.212	0.212	0.212
JSHK	0.488	0.171	0.171	0.171
CHI	0.380	0.207	0.207	0.207
IND	0.266	0.245	0.245	0.245
RUS	0.398	0.201	0.201	0.201
CAN	0.387	0.204	0.204	0.204
EEU	0.413	0.196	0.196	0.196
SAP	0.323	0.226	0.226	0.226
BRA	0.285	0.238	0.238	0.238
MEX	0.362	0.213	0.213	0.213
SAF	0.299	0.234	0.234	0.234
MENA	0.332	0.223	0.223	0.223
SLA	0.262	0.246	0.246	0.246
SSA	0.278	0.241	0.241	0.241
SOV	0.352	0.216	0.216	0.216
GBR	0.332	0.223	0.223	0.223

Base-year shares differ by less than 0.01 for all factors and regions across the two demographic projections.

Region-specific pension replacement rates in 2017 are calibrated to IMF (2017) data. Beyond the base year, average benefits per retiree are held at base year levels relative to per-capita GNI, mirroring the indexation of the model's other transfer programs.[24] Region-specific 2017 TFP values are based on each region's 2017 GDP. Their growth rates are calibrated to long-term per capita GDP estimates from Müller, Stock, and Watson (2019), who use a Bayesian model to predict country-specific output levels through 2100. We grow TFPs in each region at a constant, region-specific rate between 2017 and 2100 such that each region's GDP in 2100 under the business-as-usual automation baseline, and assuming 2017 UN demographic projections, equals the average of the authors' multivariate and univariate 2100 projections.[25]

Growth in the model therefore has two sources: a common time-augmenting technological growth of 1% per year shared by all regions, and a region-specific catch-up which governs how much of each region's initial productivity gap closes by the end of the century. Table 4 reports the calibrated values; Appendix section A2 details the construction. China's catch-up is the largest, lifting its TFP from 37% to 104% of the 2017 U.S. level, whereas the Müller-Stock-Watson projections imply essentially no convergence for Sub-Saharan Africa or South Africa, whose output growth in our simulations comes from factor accumulation and the common trend alone.

We calibrate private consumption as a fraction of GDP by adjusting δ_t, the time preference rate, to match IMF fiscal data. Each region's δ_t is assumed to slowly converge to the GDP-weighted average time-preference rate of developed regions as of 2017, with

[24] Aggregate pension outlays therefore equal this GNI-indexed average times the retiree headcount, so demographic change moves pension budgets through the number of beneficiaries rather than through per-retiree generosity. Appendix section A3 reports a sensitivity analysis in which pension outlays instead track official projections of pension expenditure as a share of GDP through 2050, with per-capita GNI indexation thereafter; the headline results are largely unaffected.

[25] Because these increments are calibrated against the 2017-vintage projections and then held fixed, they are identical across our two demographic calibrations.

Table 4: Calibrated Productivity Catch-Up by Region

Region	TFP, 2017 (U.S. = 1)	Catch-up increment (percent of U.S. 2017 TFP per year)	TFP, 2100 (U.S. 2017 = 1)	Implied annual TFP growth, 2017-2100 (percent)
USA	1.000	0.445	1.370	0.38
WEU	0.706	0.435	1.067	0.50
JSHK	0.704	0.643	1.238	0.68
CHI	0.374	0.798	1.036	1.24
IND	0.282	0.440	0.647	1.01
RUS	0.493	0.169	0.633	0.30
CAN	0.692	0.280	0.924	0.35
EEU	0.356	0.457	0.735	0.88
SAP	0.313	0.332	0.589	0.76
BRA	0.471	0.313	0.731	0.53
MEX	0.638	0.134	0.749	0.19
SAF	0.420	0.017	0.434	0.04
MENA	0.421	0.134	0.532	0.28
SLA	0.499	0.275	0.727	0.45
SSA	0.175	0.000	0.175	0.00
SOV	0.373	0.481	0.773	0.88
GBR	0.781	0.354	1.075	0.39

TFP is normalized so that U.S. 2017 total factor productivity equals one. The catch-up increment is added to the level each year from 2018 through 2100, after which TFP is held constant and growth proceeds at the common 1 percent trend rate. Increments are calibrated so that each region's 2100 GDP, under business-as-usual automation and the 2017 UN demographic projection, matches the average of the multivariate and univariate projections of Müller, Stock, and Watson (2019); they are held fixed across both demographic calibrations. The final column is the annualized growth of the TFP level implied by the first three, and is additional to the common trend.

full convergence occurring in 2100. Conceptually, it is unlikely that China and India maintain their strong desire to save as their economies develop. Hence, we assume time preferences of all regions gradually evolve toward our best guess of a single, global steady-state rate.

The shape of the initial age-skill asset distribution is calibrated to U.S. Survey of Consumer Finances (SCF; Bricker et al. 2017) data. Fossil fuel rent flows and the shares of rents that accrue to governments are calibrated to World Bank (2021) data. We interpret leisure as measuring labor force participation and calibrate leisure preferences to a combination of SCF and ILO data. Finally, we calibrate distributional aspects of each region's pension system (e.g., benefits by skill-group and contribution ceilings) to a combination of IMF and Social Security Administration (SSA) data.

3.4 Modeling Business-as-Usual Automation

We model automation and skill-biased technological change as permitting regions to produce using their initial Cobb-Douglas technology or a year-specific frontier technology, which is also Cobb-Douglas, but with larger capital and high-skilled labor coefficients.[26] Unlike Benzell et al. (2021), whose reference scenario assumed no automation after 2017 and treated automation as the object of study, the present paper takes endogenous,

[26] Assessing the impact of changes in production-share coefficients is more complex than simply considering improvements to TFP. To understand the issue, take the production of output, Q_e, based on a Cobb-Douglas function of capital, K_e, and labor, L_e, with TFP of ϕ_e, share coefficient, α_e, and productivity coefficients (conditional on input scaling), φ_{K_e}, and φ_{L_e}, where e denotes example.

$$Q_e = \phi_e(\varphi_{K_e} K)^{\alpha_e}(\varphi_{L_e} L)^{1-\alpha_e}. \tag{18}$$

business-as-usual automation as its baseline. In every simulation, and under both demographic projections, regions choose freely, year by year, between their legacy technology and the evolving frontier. The experiment here is the change in demographics; the (year-specific) technology menu is held fixed. The frontier's factor-share coefficients change through 2050 at the same pace as the corresponding U.S. shares changed between 1980 and 2017, with other regions' frontier coefficients changing at the U.S. percentage pace.[27]

3.4.1 Calibrating Labor and Capital Productivity Coefficients

In our model, we have five productivity parameters. We use the same first and second normalization, i.e. $\phi = 1$ and $\varphi_K^{\alpha}\varphi_{l_1}^{\beta_1}\varphi_{l_2}^{\beta_2}\varphi_{l_3}^{\beta_3} = 1$, as in the example. A third is provided by Acemoglu, Lelarge, and Restrepo (2020). Using French factory-level data, the authors estimate that, holding inputs fixed, a one percentage point increase in capital's share, α, is related to a 0.3% increase in productivity.

The remaining two equations needed to determine the four unknowns are provided by two assumptions biased conservatively with regard to finding major impacts of automation on output. Specifically, we assume that a rise in the high-skilled or mid-skill labor shares coupled with an equal-sized decline in the low-skilled share lead to no change in output.[28]

The following four equations make our calibration of the four productivity coefficients precise. Our first normalization sets U.S. TFP to 1.0 in 2017. Equation (19) is the aforementioned second normalization,

$$\varphi_K^{\alpha} \cdot \varphi_{l_1}^{\beta_1}\varphi_{l_2}^{\beta_2}\varphi_{l_3}^{\beta_3} = 1. \tag{19}$$

Differentiating equation (7), dropping time subscripts, and holding inputs constant yields

$$\frac{1}{Q}\frac{dQ}{d\alpha} = \log(\varphi_K K) - \frac{1}{3}\sum_{k=1}^{3}\log(\varphi_{l_k} l_{t,k}) = 0.3. \tag{20}$$

The two remaining equations come from differentiating Q with regard to β_2 and β_3 assuming β_1 declines pari passu.

For given measured output, Q_e, given measured inputs, K_e and L_e, and given share parameter, α_e, the product $\phi_e(\varphi_{K_e})^{\alpha_e}(\varphi_{L_e})^{1-\alpha_e}$ is defined, but not ϕ_e, $(\varphi_{K_e})^{\alpha_e}$, or $(\varphi_{L_e})^{1-\alpha_e}$ separately. Were α_e fixed, it would suffice to call the product $\hat{\phi}_e$ and consider how output changes when this product, K, L, or some combination changes. But we need separate values for ϕ_e, φ_{K_e}, and φ_{L_e} to assess the impact on output of a change in α_e. Two normalizations are available to help pin down these three values. The first is TFP scaling, namely $\phi_e = 1$. The second is the normalization $(\varphi_{K_e})^{\alpha_e}(\varphi_{L_e})^{1-\alpha_e} = 1$. This gives us one equation in φ_{K_e} and φ_{L_e}. An empirical estimate or an assumed relationship can provide the second equation.

[27] Baseline capital and labor shares through time for selected regions are presented in table 15.

[28] Unlike capital-use intensity, there are no empirical estimates of the output effects of changes in labor skill-group coefficients. However, given the well-documented, global increase in the share of income of high earners, it stands to reason that replacing low-skilled tasks with higher-skilled ones should not lower output.

$$\frac{1}{Q}\frac{dQ}{d\beta_2} = \log(\varphi_{l_2} l_2) - \log(\varphi_{l_1} l_1) \quad = \quad \chi_2 \tag{21}$$

and

$$\frac{1}{Q}\frac{dQ}{d\beta_3} = \log(\varphi_{l_3} l_3) - \log(\varphi_{l_1} l_1) \quad = \quad \chi_3, \tag{22}$$

where χ_2 and χ_3 are both set to 0.[29]

This system of four equations in φ_K, φ_{l_1}, φ_{l_2}, and φ_{l_3} is solved for the U.S. for 2017. The derived coefficients are then applied to the U.S. and all other regions through time.

3.4.2 Endogenous Automation Choice

Producers in each region choose between legacy and frontier technology to maximize output. They decide whether to use the frontier technology, in each period, based on whether

$$\frac{Q^*}{Q} \quad = \quad \frac{\phi(\varphi_K \hat{K})^{\alpha^*} \hat{L}_1^{\beta_1^*} \hat{L}_2^{\beta_2^*} \hat{L}_3^{\beta_3^*}}{\phi(\varphi_K K)^{\alpha} L_1^{\beta_1} L_2^{\beta_2} L_3^{\beta_3}}, \tag{23}$$

the ratio of output Q^* using the frontier technology (α^* and β^* and resulting inputs $\hat{L}$ and $\hat{K}$) to output Q using the legacy technology and corresponding equilibrium inputs, exceeds 1.[30]

Note that the frontier technology changes neither the TFP term, nor how it evolves, nor factor productivities. However, a region's adoption of the frontier technology impacts its capital and labor demands. Such changes to regional factor demands impact the course of region-specific wage-rates as well as the evolution of the global interest rate. Moreover, changes in the world interest-rate path as well as region- and skill-specific wage paths will change each region's annual saving as well as skill-specific annual labor supply. These supply-side changes will further impact the evolution of interest and wage rates. Thus, one region's adoption of technology, in one or more years, influences all other regions' paths of automation by altering the global, dynamic equilibrium. Because demographics shift both the supply of labor and the supply of savings, the two demographic projections can generate different regional adoption dates.

[29] To be precise, we set $\chi_2 = \chi_3 = \epsilon = 0.01$ to weakly prefer the frontier production function under scenarios when either the mid-skilled or high-skilled labor-share coefficients increase with a commensurate decline in the low-skilled labor-share coefficient.

[30] It is easy to show, as detailed in Benzell et al. (2016), in the two-factor case that if a range of Cobb-Douglas production functions are available, firms will only choose between functions with the most extreme β values available. Therefore, our algorithm compares only the 2017 technology and the frontier technology. The adoption of frontier technology is *not* a permanent decision. A region that automated in the past may choose, in any year, to return to its 2017 production method. And, of course, it can opt to never adopt.

4 Results

Table 5 reports total population by region under the UN's two forecasts. It shows the previously noted dramatic reduction (increase) in China's (the U.S.) 2100 projected population. The table also records much smaller projected growth in Sub-Saharan Africa's, South Asian, and South America (ex-Brazil) populations, much higher projected growth in Middle East and North Africa's population, a much larger projected population decline in EEU (Eastern Europe) and JSHK (Japan, South Korea, and Hong Kong), and much larger growth in Canada, South Africa, and SOV's (non-Russian former Soviet Union) population.

Table 5: Population by Region, Millions

	2017 UN Demographics			2024 UN Demographics		
Region	2017	2050	2100	2017	2050	2100
USA	324	361	374	331	380	420
WEU	465	435	367	468	450	382
JSHK	192	170	125	192	163	104
CHI	1409	1375	1030	1412	1265	635
IND	1339	1666	1527	1352	1677	1506
RUS	144	131	118	146	136	126
CAN	66	74	75	66	84	102
EEU	74	63	49	73	53	28
SAP	804	1004	962	807	983	887
BRA	209	232	187	204	218	163
MEX	129	165	152	123	149	130
SAF	57	72	74	58	79	94
MENA	826	1311	1618	951	1565	2104
SLA	290	371	366	286	350	312
SSA	747	1646	3169	748	1526	2470
SOV	91	117	122	91	135	170
GBR	66	70	69	66	75	74
World	**7,234**	**9,264**	**10,383**	**7,374**	**9,287**	**9,708**

Table 6 details regional changes in the UN's fertility projections. Interestingly, its 2024 global fertility rate is 1.80 compared with 1.59 in 2017. But its projected fertility increase comes late in the century. Compared to its 2017 forecast, the UN's 2024 forecast envisions lower fertility in 2100 in ten of the 17 regions.

Table 7 presents global GDP shares under each projection in 2017, 2050, and 2100. Based on the UN 2017 forecast, China's was slated to become the world economic hegemon with a 2100 GDP share of 25.6% – over twice the US share of 11.2%. But under the 2024 forecast, China accounts for only 14.9% of end-of-century world GDP, only slightly higher than the US share of 14.4%. This is largely due to the newly forecasted sustained drop in Chinese fertility over the rest of the century. The UN also foresees lower US fertility, but the reduction in Chinese fertility rates is larger. In addition, China has had a longer history of low fertility, which has knock-on effects in terms of simulated Chinese births compared to US births. Demographic change, not just with respect to population totals but also working population totals, is a complex dynamic process that can depend as much if not more on the history of fertility, mortality, and immigration rates as it can on the future of these rates. Table 7's other notable result is the major increases in projected Indian and MENA end-of-century GDP shares. In 2017, their shares were 7.0% and 8.7%, respectively. They are now slated to rise to 11.8% and 13.3%, respectively.

Table 6: Total Fertility Rate by Region, Children per Parent Over a Lifetime

	2017 UN Demographics			2024 UN Demographics		
Region	2017	2050	2100	2017	2050	2100
USA	1.86	1.88	1.86	1.70	1.59	1.60
WEU	1.56	1.73	1.78	1.54	1.50	1.59
JSHK	1.38	1.63	1.75	1.21	1.24	1.47
CHI	1.53	1.63	1.72	1.60	1.10	1.38
IND	2.20	1.66	1.50	2.14	1.69	1.68
RUS	1.69	1.81	1.83	1.62	1.50	1.59
CAN	1.69	1.70	1.76	1.63	1.48	1.53
EEU	1.50	1.70	1.77	1.35	1.24	1.45
SAP	2.20	1.77	1.67	2.19	1.72	1.69
BRA	1.69	1.60	1.69	1.73	1.53	1.58
MEX	2.12	1.66	1.70	2.10	1.67	1.67
SAF	2.37	1.71	1.44	2.27	1.88	1.74
MENA	3.14	2.09	1.60	3.31	2.31	1.84
SLA	2.25	1.77	1.67	2.16	1.71	1.68
SSA	5.09	2.84	1.50	5.01	2.81	2.03
SOV	2.40	1.90	1.69	2.71	2.22	1.87
GBR	1.85	1.81	1.82	1.72	1.51	1.58
World	**2.35**	**1.99**	**1.59**	**2.37**	**1.94**	**1.80**

Table 7: Region Share of World GDP, Percent

	2017 UN Demographics			2024 UN Demographics		
Region	2017	2050	2100	2017	2050	2100
USA	16.4	13.8	11.2	16.4	14.3	14.4
WEU	17.2	13.1	10.4	17.1	13.5	12.2
JSHK	6.9	6.6	6.4	6.9	6.6	6.0
CHI	16.5	20.3	25.6	16.6	19.2	14.9
IND	7.0	9.5	11.4	6.9	9.4	11.8
RUS	3.2	2.0	1.5	3.2	2.1	1.8
CAN	2.7	2.4	2.0	2.7	2.8	3.2
EEU	0.8	0.8	0.8	0.8	0.7	0.5
SAP	6.6	7.7	7.7	6.6	7.5	7.8
BRA	2.5	2.1	1.4	2.5	2.0	1.5
MEX	2.1	2.0	1.3	2.1	1.9	1.4
SAF	0.6	0.5	0.4	0.6	0.5	0.6
MENA	8.7	9.6	9.9	8.7	9.9	13.3
SLA	3.2	3.2	2.4	3.2	3.0	2.3
SSA	2.2	3.3	4.4	2.2	3.1	3.9
SOV	0.9	1.2	1.5	0.9	1.2	2.4
GBR	2.6	2.0	1.5	2.6	2.2	1.9

Table 8 repeats table 7, but records annual growth rates over the periods 2017-2050, 2050-2100, and 2017-2100. China, under the new demographics, experiences a much lower – 2.1% – rather than 3.0% GDP growth rate. The other noticeable change in projected growth is the EEU's decline from 0.8% to 0.5%. As for the global growth rate, figure 5 charts annual global GDP growth rates under both projections as well as their smoothed values in dashed lines. In roughly 2050, red (2017 projection) and blue (2024 projection) annual growth rates begin to diverge, with an end-of-century gap of 0.3%.

Table 8: Annualized Real GDP Growth, Percent Per Year

	2017 UN Demographics			2024 UN Demographics		
Region	2017-2050	2050-2100	2017-2100	2017-2050	2050-2100	2017-2100
USA	2.5	1.6	1.9	2.6	1.8	2.1
WEU	2.1	1.6	1.8	2.3	1.6	1.9
JSHK	2.9	2.0	2.3	2.9	1.6	2.1
CHI	3.6	2.5	3.0	3.5	1.2	2.1
IND	4.0	2.4	3.0	4.0	2.2	2.9
RUS	1.5	1.5	1.5	1.8	1.5	1.6
CAN	2.6	1.6	2.0	3.2	2.0	2.5
EEU	3.1	2.2	2.5	2.6	1.1	1.7
SAP	3.5	2.0	2.6	3.5	1.9	2.5
BRA	2.5	1.2	1.7	2.4	1.1	1.6
MEX	2.8	1.2	1.8	2.8	1.1	1.7
SAF	2.6	1.4	1.9	2.7	1.8	2.2
MENA	3.3	2.1	2.6	3.5	2.4	2.8
SLA	2.9	1.5	2.1	2.9	1.2	1.9
SSA	4.3	2.6	3.3	4.2	2.2	3.0
SOV	3.8	2.6	3.1	4.1	3.1	3.5
GBR	2.2	1.5	1.8	2.6	1.4	1.9
World	**3.0**	**2.0**	**2.4**	**3.1**	**1.8**	**2.3**

Table 9 also repeats Table 7, but considers regional shares of global national income rather than shares of GDP. The two can differ due to net foreign capital ownership. Consider the 2024 projection. Table 9 shows that China's 15.6% share of 2100 global national income exceeds the US 13.6% share. This reflects China's accumulation of net foreign assets: by 2100 it owns considerably more capital than it employs, while the U.S. employs far more than it owns.

Table 10 documents this gap, showing the major mismatch between domestic capital stocks and national wealth holdings for our four largest regions. Clearly, China is a major supplier of capital to the world. By 2100, roughly one third of China's assets will be invested abroad – an amount that will exceed that year's total wealth holdings of the entire US population. Although the US capital stock in 2100 will be almost as large as China's, over half will be owned by foreigners. The 2100 foreign ownership share of capital will exceed two-fifths in the WEU and reach nearly one-third in JSHK.

4.1 Selected Regional Results

Table 11 shows absolute GDP values, under both projections, for 2017, 2050, 2075, and 2100 for the US, China, Sub-Saharan Africa (SSA), and the world. Regardless of projection, there is a massive rise in world GDP over the century. Under the UN's 2024 demographics, world output in 2100 is 6.47 times higher than in 2017. China's output is 5.8 times higher, US output is 5.7 times higher, and Sub-Saharan Africa output is 11.5

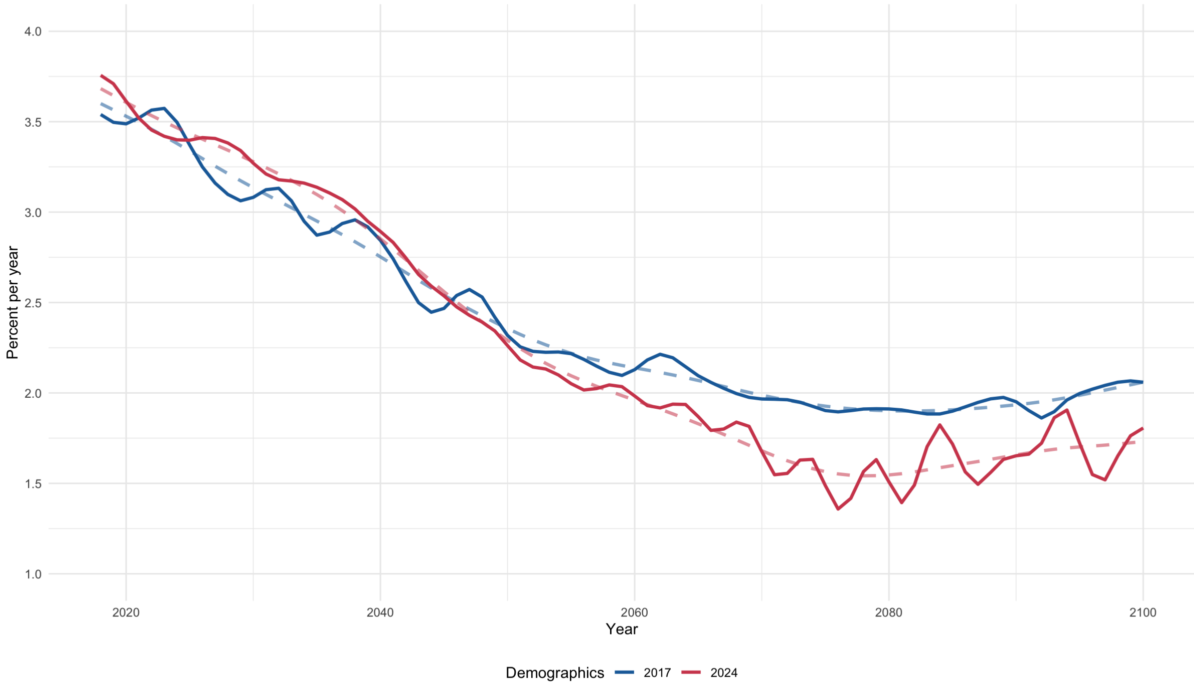


Figure 5: Annual Global GDP Growth Rate (Percent)

Table 9: Share of World GNI, Percent

	2017 UN Demographics			2024 UN Demographics		
Region	2017	2050	2100	2017	2050	2100
USA	16.0	12.5	10.5	16.1	12.9	13.6
WEU	17.3	12.7	10.0	17.2	13.1	11.8
JSHK	7.2	6.3	6.2	7.2	6.3	5.8
CHI	16.7	22.1	26.1	16.8	21.0	15.6
IND	6.9	9.9	11.6	6.9	9.7	12.1
RUS	3.2	2.0	1.5	3.2	2.1	1.8
CAN	2.7	2.3	1.9	2.7	2.7	3.1
EEU	0.8	0.7	0.8	0.8	0.6	0.5
SAP	6.6	8.0	8.3	6.4	7.8	8.4
BRA	2.6	2.1	1.4	2.4	1.9	1.4
MEX	2.1	1.9	1.3	2.1	1.8	1.3
SAF	0.6	0.6	0.4	0.6	0.5	0.6
MENA	8.7	9.7	10.0	8.7	10.0	13.4
SLA	3.2	3.2	2.6	3.2	3.0	2.5
SSA	2.1	3.2	4.6	2.1	3.0	4.0
SOV	0.8	1.2	1.5	0.8	1.2	2.4
GBR	2.6	1.8	1.5	2.6	2.1	1.8

National income is defined as GDP net of depreciation and net of foreign factor payments.

Table 10: Domestic Assets and Capital Stock, Trillions of 2017 USD

Region	Year	2017 UN Demographics Assets	2017 UN Demographics Capital	2024 UN Demographics Assets	2024 UN Demographics Capital
USA	2017	66	59	66	59
	2050	90	201	100	220
	2100	245	536	297	647
CHI	2017	68	61	68	61
	2050	492	307	518	308
	2100	1,555	1,299	1,046	714
WEU	2017	63	54	63	54
	2050	134	158	140	172
	2100	236	401	256	441
JSHK	2017	36	27	36	27
	2050	76	96	83	102
	2100	206	299	183	262

Assets are defined as the aggregate private wealth of a region's residents; capital is the stock employed in a region's production.

times higher. Hence, although SSA GDP doesn't grow by its factor of 14.3 under 2017 demographics, its projected growth is still striking.

Table 11: World/Selected Region GDP, Trillions of 2017 USD

Region	Year	2017 UN Demographics	2024 UN Demographics	Percent Diff
USA	2017	19.5	19.5	0.0
	2050	43.4	46.0	6.0
	2075	65.2	73.2	12.2
	2100	95.7	110.7	15.7
CHI	2017	19.6	19.7	0.6
	2050	63.8	61.9	-2.9
	2075	119.2	85.5	-28.3
	2100	218.4	114.6	-47.6
SSA	2017	2.6	2.6	0.2
	2050	10.3	10.0	-3.4
	2075	21.7	19.4	-10.7
	2100	37.2	29.8	-20.0
World	2017	118.8	118.7	-0.1
	2050	313.5	321.7	2.6
	2075	526.6	513.2	-2.5
	2100	852.4	767.5	-10.0

Figure 6 charts GDP shares over time of four selected large economies: the U.S., Western Europe, China, and JSHK.[31] Figure 7 charts annual GDP growth rates for the U.S., Western Europe, China, and JSHK. Annual growth rates in the US and Western Europe are generally higher under the new projections. Those for JSHK and China are considerably lower after mid century.

4.2 Factor Prices

Table 12 displays region-specific average wages relative to the 2017 US value, which is normalized to 1. The region-specific values are largely invariant to the choice of demographic projection. Each region's path of wages reflects our endogenous region-specific calibration of TFP rates consistent with Müller, Stock, and Watson (2019) and the endogenous adoption of region-specific frontier technology. Western Europe and China catch up almost

[31] Figure A3 charts GDP shares for India, Russia, CAN, and Eastern Europe.

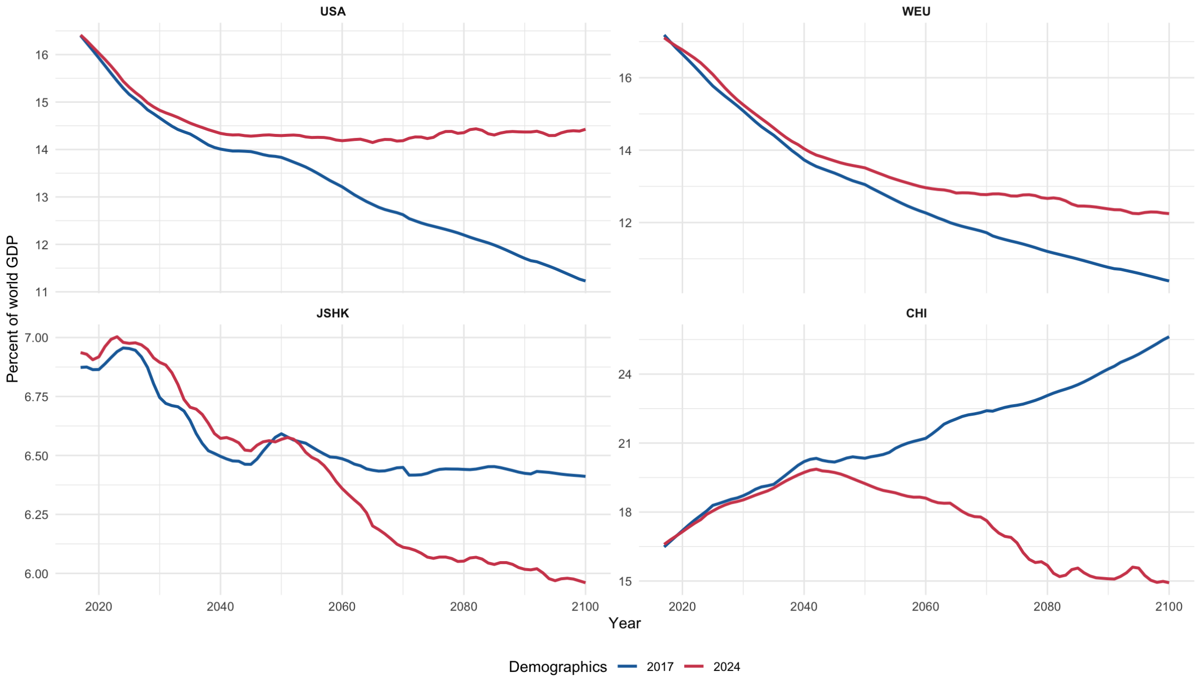


Figure 6: Share of Global Economy by Region, Largest Economies

Figure 7: Annual GDP Growth Rate, Largest Economies

fully to the US average wage by 2100. JSHK's average wage surpasses that of the US.[32] As for other regions, their catch up to the US ranges from substantial to non-existent. Take EEU: its 2017 wage is only 17 percent of the US value. By 2100, it's almost half. SSA, on the other hand, loses tremendous ground. Its 2017 wages average only 8.0% of the US average. In 2100, they average just 5.3% of the US average. Globally, average wages rise by a factor of almost 2.5 over the rest of the century. A factor of 2.5 is small compared to China's 8.7-fold growth in average wages, but it's actually larger than that of the US, whose average wages increase by a factor of only 2.1.

Table 12: Average Real Wage by Region, Normalized to U.S. 2017 = 1

	2017 UN Demographics			2024 UN Demographics		
Region	2017	2050	2100	2017	2050	2100
USA	1.00	1.50	2.10	0.97	1.48	2.09
WEU	0.70	1.23	2.00	0.69	1.24	2.01
JSHK	0.63	1.59	3.46	0.63	1.65	3.57
CHI	0.20	0.61	1.78	0.21	0.64	1.83
IND	0.12	0.24	0.61	0.11	0.24	0.61
RUS	0.37	0.58	0.87	0.37	0.60	0.89
CAN	0.74	1.23	1.78	0.73	1.24	1.81
EEU	0.17	0.42	1.01	0.17	0.43	1.03
SAP	0.17	0.32	0.62	0.17	0.33	0.63
BRA	0.23	0.37	0.61	0.24	0.38	0.62
MEX	0.29	0.42	0.59	0.31	0.45	0.63
SAF	0.23	0.30	0.40	0.21	0.29	0.38
MENA	0.20	0.28	0.44	0.18	0.25	0.40
SLA	0.24	0.35	0.51	0.24	0.36	0.52
SSA	0.08	0.10	0.11	0.08	0.10	0.11
SOV	0.17	0.36	0.81	0.17	0.36	0.82
GBR	0.79	1.17	1.63	0.79	1.19	1.65
World	**0.27**	**0.43**	**0.68**	**0.27**	**0.43**	**0.67**

Table 13 and figure 8 show the huge decline in the return to capital over the century regardless of demographic forecast. This reflects our model's predicted global massive capital glut as well as declining, in most regions, work forces. The 2024 UN demographics further depress rates by 0.3 percent in both mid-century and end of the century, reflecting the impact of an even older global population.

Table 13: Global After-tax Rate of Return (percent)

UN Demographics Year	2017	2050	2100
2017	5.9	3.1	1.9
2024	5.9	2.8	1.6
Diff	0.0	-0.3	-0.3

Table 14 shows the years in which different regions adopt frontier technology. It also shows regions that fail to adopt, at least in this century. Those that do adopt, generally do so immediately. The exceptions are SAP and SOV. SAP adopts in 2071 (2065) under the 2017 (2024) demographic projections. SOV adopts in 2064 (2061) under the 2017 (2024) projections.

[32] This reflects, in part, our calibration that shows JSHK producing in 2017 with a higher capital coefficient – one that grows at the BAU-assumed growth rate through 2050. Even though the US adopts its own available frontier technology, that technology remains less capital-intensive relative to Japan's since their frontier share coefficients grow at the same rate.

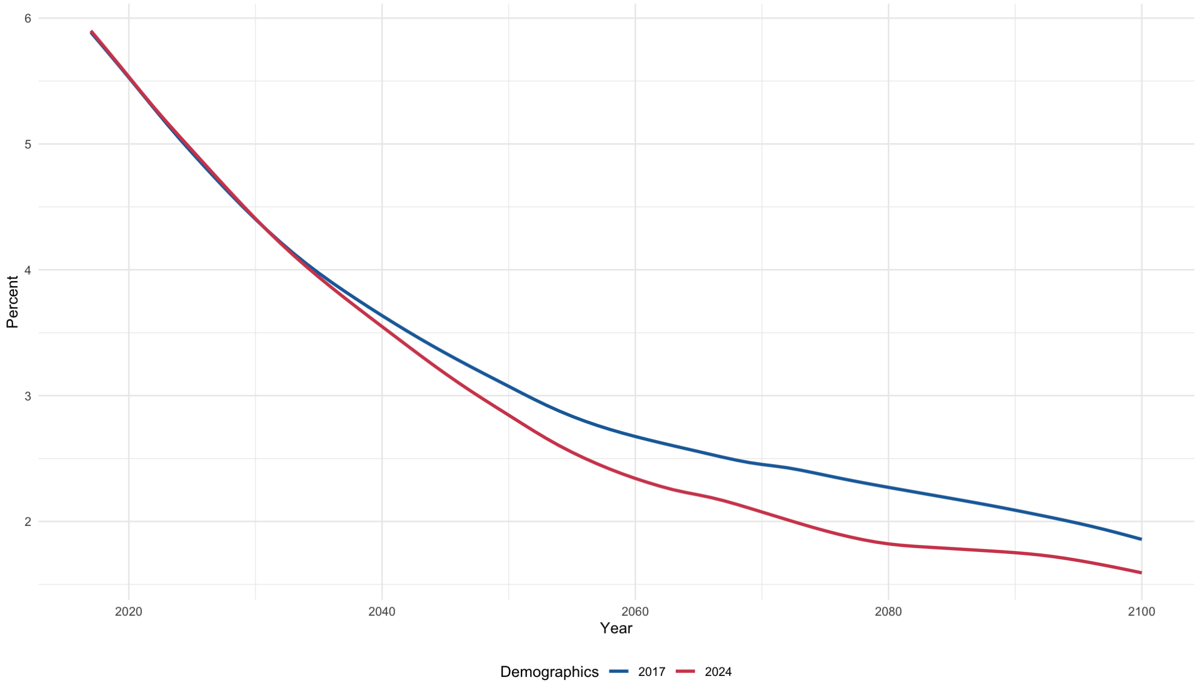


Figure 8: Global After-tax Rate of Return (percent)

Table 14: First year each region adopts the frontier production function, by demographic projection

Region	2017 UN Demographics	2024 UN Demographics
USA	2018	2018
WEU	2018	2018
JSHK	2018	2018
CHI	2028	2024
IND	>2100	>2100
RUS	2019	2018
CAN	2018	2018
EEU	2018	2018
SAP	2071	2065
BRA	>2100	>2100
MEX	>2100	>2100
SAF	>2100	>2100
MENA	>2100	>2100
SLA	>2100	>2100
SSA	>2100	>2100
SOV	2064	2061
GBR	2018	2018

Once a region adopts its frontier technology, it generally continues to operate with frontier technology as output share coefficients evolve due to assumed improvements in AU/AI.[33] Table 15 shows how these shares evolve in our baseline scenario. Note that China and JSHK utilize more capital-intensive technology than the US in 2017. SSA, in contrast, never adjusts its technology. As the table shows, adoption is ar best partial, on a production-weighted basis, for the world as a whole.

Table 15: Capital and Labor Shares by Skill Group and Demographic Projection Year for Selected Regions

		2017 UN Demographics				2024 UN Demographics			
Region	Year	Alpha	B1	B2	B3	Alpha	B1	B2	B3
USA	2017	0.338	0.221	0.221	0.221	0.338	0.221	0.221	0.221
	2025	0.345	0.206	0.217	0.232	0.345	0.206	0.217	0.232
	2050	0.366	0.162	0.206	0.266	0.366	0.162	0.206	0.266
CHI	2017	0.380	0.207	0.207	0.207	0.380	0.207	0.207	0.207
	2025	0.386	0.193	0.203	0.217	0.386	0.193	0.203	0.217
	2050	0.406	0.152	0.193	0.249	0.406	0.152	0.193	0.249
JSHK	2017	0.485	0.172	0.172	0.172	0.488	0.171	0.171	0.171
	2025	0.490	0.160	0.169	0.181	0.493	0.159	0.168	0.179
	2050	0.507	0.126	0.161	0.207	0.510	0.125	0.159	0.206
SSA	2017	0.278	0.241	0.241	0.241	0.278	0.241	0.241	0.241
	2025	0.278	0.241	0.241	0.241	0.278	0.241	0.241	0.241
	2050	0.278	0.241	0.241	0.241	0.278	0.241	0.241	0.241
World	2017	0.352	0.216	0.216	0.216	0.352	0.216	0.216	0.216
	2025	0.356	0.207	0.214	0.223	0.356	0.207	0.214	0.223
	2050	0.365	0.183	0.209	0.243	0.365	0.183	0.209	0.243

[33] It should be noted that we do not require regions to stay on the frontier technology. Firms are free to revert to the legacy technology if doing so is profitable.

4.3 Fiscal Systems

Aging strains fiscal systems due to a rising ratio of beneficiaries to contributors. Because our base case holds average benefits per retiree fixed relative to per-capita GNI, aging moves pension budgets entirely through the retiree headcount. The resulting burden is significant under *both* demographic projections. Table 16 reports payroll tax rates as a share of covered earnings. The world rate roughly doubles from 13.1% in 2017 to 21.6% by 2050 – a figure the two projections agree on almost exactly – before reaching 24.1% under 2017 demographics and 25.4% under 2024. World pension outlays follow the same path, rising from 5.8% of GDP in 2017 to 9.5% by 2050 and 11.9% by 2100.

Table 16: Fiscal Burdens by Demographic Projection

Region	Year	Payroll tax rate, percent of covered payroll: 2017 Proj. Demographics	Payroll tax rate, percent of covered payroll: 2024 Proj. Demographics	Effective average tax burden, percent of total income: 2017 Proj. Demographics	Effective average tax burden, percent of total income: 2024 Proj. Demographics
USA	2017	13.5	13.6	38.6	38.3
	2050	21.7	22.2	41.2	40.4
	2100	27.7	28.2	46.9	47.0
WEU	2017	23.9	23.8	46.2	46.4
	2050	41.2	40.1	53.2	52.5
	2100	42.3	42.5	56.2	56.7
JSHK	2017	22.4	22.4	34.8	34.4
	2050	34.6	34.5	42.0	41.7
	2100	33.0	35.2	47.0	48.3
CHI	2017	10.8	10.7	27.2	27.0
	2050	28.6	30.5	39.2	38.3
	2100	28.1	38.1	41.0	43.5
IND	2017	3.7	3.6	14.6	14.6
	2050	6.8	7.5	18.9	19.3
	2100	10.8	12.6	24.6	26.4
World	2017	**13.2**	**13.1**	**31.5**	**31.4**
	2050	**21.6**	**21.7**	**36.4**	**36.0**
	2100	**24.1**	**25.4**	**39.6**	**40.8**

The payroll rate is the statutory rate applied to covered earnings. The effective average burden is average tax revenue per individual divided by average income. World rows are GDP-weighted.

China accounts for most of the global increase in payroll taxes. Its payroll rate rises from 10.8% in 2017 to 28.1% by 2100 under the older projection but to 38.1% under the newer one. Chinese pension outlays show a similar trend, climbing from 4.9% of GDP in 2017 to 11.1% under the 2017 projection and 15.1% under the 2024 one. A four-point-of-GDP difference in permanent pension cost, arising purely from revised fertility, goes a long way toward explaining why China legislated pension reform in 2024.

The demographic revision is however not uniformly costly: regions whose populations were revised upward see their burdens fall, with payroll rates in 2100 declining by 2.7 percentage points in MENA and by roughly a point in Canada and Mexico. The United States also sees its pension burden increase only slightly, with its 2100 payroll rate rises only from 27.7 to 28.2%. This is because the 2024 projection offsets lower U.S. fertility with substantially higher immigration. Section 4.5 shows that payroll taxes must increase substantially if the immigration channel is turned off.

Rising pension costs result in significant and across-the-board growth in regions' broader fiscal burden. Table 16 reports the effective average non-corporate tax burden on total income: income, consumption, and payroll revenue divided by total household income. Under the 2024 projection, the U.S. burden rises 8.7 percentage points over the century, from 38.3 to 47.0%, while U.S. pension outlays rise 4% of GDP. Worldwide, the burden rises 9.3 points, from 31.4 to 40.8%, against a 6.1% rise in pension outlays. The overall effective rate on income in Western Europe reaches 56.7%, and even India, whose population is relatively young throughout our 2017-2100 horizon, sees its burden rise from 14.6 to 26.4%. Aging therefore raises the total price of government, and it does so in regions at every stage of the demographic transition.

4.4 AI Technology Scenarios

Our two alternate frontier technology scenarios, dubbed "Accelerating AI" and "Transformative AI" respectively, accelerate the capital share growth process the baseline already contains, assuming the same relative labor income share dispersion.[34] Under BAU, the U.S. capital share increases from 0.34 to 0.37 by 2050. As shown in table 17, the Accelerating AI scenario multiplies that drift roughly fourfold, to 0.44, and TAI tenfold to 0.6.[35] Non-U.S. regions receive frontier capital share advancements proportional to their 2017 capital share, with a cap of 60 percent capital under both scenarios.[36] Frontier technology shares are assumed to stabilize after 2050, although a region can move on to, or off of, the frontier technology in any year after 2017.

Table 17: Capital and Labor Shares for the U.S. by Demographic Projection and Automation Scenario

		2017 UN Demographics				2024 UN Demographics			
Scenario	Year	Alpha	B1	B2	B3	Alpha	B1	B2	B3
Business as Usual	2017	0.338	0.221	0.221	0.221	0.338	0.221	0.221	0.221
	2050	0.366	0.162	0.206	0.266	0.366	0.162	0.206	0.266
	2100	0.366	0.162	0.206	0.266	0.366	0.162	0.206	0.266
Accelerating AI	2017	0.338	0.221	0.221	0.221	0.338	0.221	0.221	0.221
	2050	0.443	0.142	0.181	0.234	0.443	0.142	0.181	0.234
	2100	0.443	0.142	0.181	0.234	0.443	0.142	0.181	0.234
Transformative AI	2017	0.338	0.221	0.221	0.221	0.338	0.221	0.221	0.221
	2050	0.596	0.103	0.131	0.169	0.596	0.103	0.131	0.169
	2100	0.596	0.103	0.131	0.169	0.596	0.103	0.131	0.169

Table 18 presents adoption dates by region and demographic projection and technology scenarios. The U.S. and JSHK adopt all frontier technologies immediately, while most regions delay adoption under Accelerating AI and TAI. China, for example, adopts in 2024 under BAU and 2024 demographics. Under TAI it delays adoption until 2042. Other regions, such as the Middle East and SSA, never adopt the frontier technology.

Equation (23) explains why the U.S. always adopts immediately. A region adopts when producing with the frontier factor shares – more capital, more high-skill labor, less low-skill labor – yields more output at equilibrium input mix than its legacy technology

[34] In other words, capital substitutes for the three types of labor proportionately to their respective input shares.

[35] Tables A3 and A4 show the same shares, respectively, for China and the whole world under each region's adopted technology.

[36] Tables A9 and A12 show, respectively, input shares under Accelerating AI and TAI in 2100 for all regions given their endogenous adoption decisions. Note that our assumption implies that frontier shares advance faster in regions with higher capital use intensity, such as JSHK and China. However, no region is allowed to exceed 60 percent capital share in any scenario.

Table 18: First Year Each Region Adopts the Frontier Production Function, by Demographic Vintage and Automation Scenario

Region	2017 UN Demographics			2024 UN Demographics		
	BAU	Accelerating AI	Transformative AI	BAU	Accelerating AI	Transformative AI
USA	2018	2018	2018	2018	2018	2018
WEU	2018	2018	2023	2018	2018	2022
JSHK	2018	2018	2018	2018	2018	2018
CHI	2028	2038	2044	2024	2037	2042
IND	>2100	>2100	>2100	>2100	>2100	>2100
RUS	2019	2031	2035	2018	2030	2034
CAN	2018	2018	2021	2018	2018	2020
EEU	2018	2046	2069	2018	2043	2063
SAP	2071	2085	>2100	2065	2074	2092
BRA	>2100	>2100	>2100	>2100	>2100	>2100
MEX	>2100	>2100	>2100	>2100	2097	2097
SAF	>2100	>2100	>2100	>2100	>2100	>2100
MENA	>2100	>2100	>2100	>2100	>2100	>2100
SLA	>2100	>2100	>2100	>2100	>2100	>2100
SSA	>2100	>2100	>2100	>2100	>2100	>2100
SOV	2064	2072	2083	2061	2066	2075
GBR	2018	2023	2030	2018	2022	2029

does. The U.S. starts out with the world's highest TFP and the most expensive labor per efficiency unit. The input that costs America the most is precisely the factor that the frontier economizes on. It also holds the largest pool of high-skill labor the frontier upweights, replenished by a large immigration inflow, and it enjoys a low cost of accessing capital due to low corporate taxes. As shown in tables 19 and 20, U.S. GDP under updated demographics and TAI runs 90% above its BAU path by 2050 and 115% by 2100 – $238 trillion v. $111 trillion – and its share of world output in 2050 doubles from 14.3% to 26.7%.

Table 19: Share of World Real GDP for Selected Regions, Percent, by Demographic Vintage and Automation Scenario

Region	Year	2017 UN Demographics			2024 UN Demographics		
		BAU	Accelerating AI	Transformative AI	BAU	Accelerating AI	Transformative AI
USA	2017	16.4	16.4	16.3	16.4	16.4	16.3
	2050	13.8	16.3	26.1	14.3	16.8	26.7
	2075	12.4	14.6	22.9	14.3	16.7	26.2
	2100	11.2	12.9	20.3	14.4	16.7	25.3
CHI	2017	16.5	16.4	16.3	16.6	16.5	16.4
	2050	20.3	19.8	16.4	19.2	18.8	15.6
	2075	22.6	23.4	23.1	16.7	17.0	16.9
	2100	25.6	27.2	29.5	14.9	16.0	16.9
SSA	2017	2.2	2.2	2.2	2.2	2.2	2.2
	2050	3.3	3.0	2.6	3.1	2.9	2.4
	2075	4.1	3.7	3.0	3.8	3.3	2.6
	2100	4.4	3.8	2.9	3.9	3.3	2.4

China delays adoption due to the opposite dynamics. China's near-future comparative advantage is inexpensive labor. Its TFP starts at 37 percent of the U.S. 2017 level, and its wage per efficiency unit starts at 20 percent. A technology that saves labor is not worth utilizing where labor is cheap. The more capital- and skill-intensive the frontier, the further it is removed from China's current factor mix, and the *longer* China rationally

Table 20: Real GDP, Trillions of 2017 USD, by Demographic Projection and AI Scenario

		2017 UN Demographics			2024 UN Demographics		
Region	Year	BAU	Accelerating AI	Transformative AI	BAU	Accelerating AI	Transformative AI
USA	2017	19.5	19.5	19.4	19.5	19.5	19.4
	2050	43.4	51.1	82.5	46.0	54.2	87.5
	2075	65.2	78.7	130.5	73.2	88.6	152.7
	2100	95.7	116.1	201.0	110.7	135.9	238.0
CHI	2017	19.6	19.5	19.4	19.7	19.6	19.5
	2050	63.8	62.1	51.8	61.9	60.6	51.2
	2075	119.2	126.6	131.6	85.5	90.5	98.8
	2100	218.4	245.1	292.2	114.6	130.3	159.6
SSA	2017	2.6	2.6	2.6	2.6	2.6	2.6
	2050	10.3	9.5	8.4	10.0	9.2	8.0
	2075	21.7	20.0	17.2	19.4	17.8	15.3
	2100	37.2	33.9	28.7	29.8	27.1	23.0
World	2017	118.8	118.9	118.9	118.7	118.8	118.9
	2050	313.5	313.6	316.3	321.7	322.9	328.1
	2075	526.6	540.4	570.8	513.2	531.7	583.6
	2100	852.4	899.7	991.4	767.5	816.0	941.7

waits. Consequently, China's adoption date recedes from 2024 under business as usual to 2042 under TAI (2028 to 2044 under 2017 demographics). China is not unique in this respect – every region that adopts under BAU waits longer the more aggressive the frontier. Russia slips from 2018 to 2034, Canada from 2018 to 2020, and Western Europe from 2018 to 2022.

What ultimately pushes China across the adoption threshold is wage growth due to TFP catch-up, which is the fastest in our calibration. TFP convergence raises Chinese wages until the frontier technology becomes profitable. While China's 2017–2050 annual growth rate falls by roughly half a percentage point, TAI ultimately raises China's 2100 GDP by 39% (159.6 versus 114.6 trillion). Technology therefore arrives too late to reverse the negative impact of demography: China ends the century at 16.9% of world output, above its 14.9% under BAU, but far below the 29.5% it reaches under the technology-optimistic scenario paired with the older 2017 UN demographics.

The combination of the 2024 demographic revision and TAI restores American economic hegemony. Demographics move the U.S. 2100 share from 11.2% to 14.4%. Transformative AI moves it to 25.3%, one and a half times China's 16.9%. For perspective, the U.S. last commanded a global GDP share of similar size at the height of its early Cold War primacy: Bolt and van Zanden (2025) estimate the U.S. at 27.3% of world output in 1950, which eroded to 21% by the fall of the Berlin Wall, and sits at 15% as of 2024. In this scenario the American century, pronounced dead by two generations of convergence literature, runs twice.

Transformative AI's capital demand reverses the global savings glut. As shown in Figure 9, under TAI and 2024 demographics the world interest rate returns to 7.4% by 2050 and 6% by 2100. This represents a reversal of the capital-abundance narrative that runs through the rest of this paper. Part of the rise in rates arrives through households rather than firms. Households have perfect foresight, and per our calibration income effects dominate substitution effects in determining household labor-supply responses to changes in real wage rates.[37] Therefore, households in adopting regions consumption-

[37] Income effects offsetting substitution effects in labor supply is standard in life-cycle models (Auerbach

smooth against the higher incomes delivered by the frontier technology, and the U.S. saving rate dips below its baseline path. Hence, though higher long-run incomes are more than sufficient to replenish the capital stock, in the short run TAI generates significant capital scarcity. This is precisely the mechanism of Chow, Halperin, and Mazlish (2025), who argue that if markets genuinely expected TAI, anticipatory borrowing against future growth should already be visible in long-term real rates.

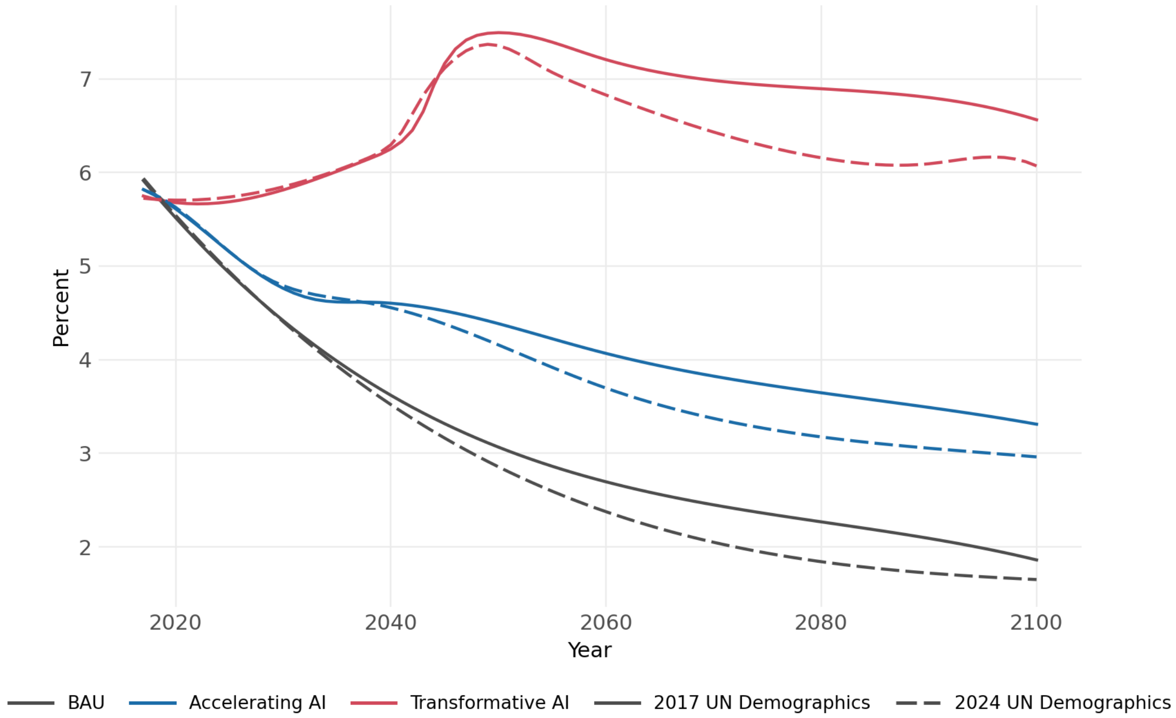


Figure 9: Global Real Interest Rate by Automation Scenario and Demographic Projection

Due to this short-run capital scarcity, TAI is nearly zero-sum on a global GDP basis through mid-century. World output in 2050 is up only 0.9% (2017 demographics) to 2.0% (2024) despite the boom in the U.S., Europe, and Japan. This is, as previously discussed, because the early gains are largely investment reallocated toward early adopters. Sub-Saharan Africa's share, for instance, falls from 3.9% to 2.4% by 2100 as capital migrates to where the frontier employs it. By century's end, capital accumulation dominates: world output is 16.3% above BAU under 2017 demographics, and 22.7% above under 2024. The aged world gains more due to the labor-substituting nature of the technology. Indeed, the 2024-demographics TAI world out-produces the 2017-demographics baseline world by a not inconsiderable margin ($941.7 versus $852.4 trillion). A sufficiently advanced frontier more than repays demography's global output loss. Though, as the GDP shares indicate, it does not repay China's portion of it.

TAI lowers aggregate fiscal burdens across-the-board. Table A10 reports the effective tax burden on total income by region and AI scenario. Under 2024 demographics, TAI cuts the U.S. effective tax burden on total income from 40.4% to 24.0% in 2050 and from

and Kotlikoff 1987), where leisure is a normal good and the calibrated intratemporal elasticity between consumption and leisure lies below one. Kimball and Shapiro (2008), for example, finds that income and substitution effects roughly cancel and leave the uncompensated wage elasticity of labor supply negligible.

47.0% to 25.9% by 2100, and Western Europe's from 56.7% to 36.2% by century's end. Pay-go pensions, however, come under major structural stress, due to the AI technology collapsing the share of output earned as wages. As presented in table A11, the U.S. statutory payroll rate climbs from 22.2% to 25.6% by 2050 and from 28.2% to 37.5% by 2100. Western Europe and pre-adoption China would require combined rates on labor near or beyond 100% were benefits not cut to cap payroll rates. Consistent with the VAT-financed transfer results of Benzell and Ye (2024), we find that wage-based social insurance and Transformative AI are structurally incompatible; pension financing must migrate toward consumption or capital bases.

4.5 U.S. Immigration

The 2024 UN demographic revision did not merely lower fertility forecasts; it also roughly doubled assumed U.S. immigration. As shown in table 21, 2017 UN demographics estimated 0.9 million net arrivals per year in 2017, falling to 0.6 million by century's end, yet 2024 demographics estimated 1.8 million in 2017 and 1.3 million by 2100. The U.S. gains in our baseline results therefore rest substantially on policy. To measure how much, we place the U.S. alone on the UN's zero-migration variant beginning in 2025, leaving every other region on the 2024 medium variant.[38] The demographic consequence is stark: rather than growing to 421 million by 2100, the U.S. population peaks at 347 million in 2035 and declines to 268 million in 2100. Figure 10 charts the two paths.

Table 21: United States Net Migration and Population Under Alternate Demographic Assumptions

Year	Measure	2017 UN Demographics	2024 UN Demographics	2024, Zero U.S. Migration
2017	Net migration (millions per year)	0.9	1.8	1.8
	Population (millions)	324.5	330.4	330.4
2050	Net migration (millions per year)	1.0	1.3	0.0
	Population (millions)	389.6	380.4	338.9
2100	Net migration (millions per year)	0.6	1.3	0.0
	Population (millions)	447.5	421.0	267.5

UN World Population Prospects, US rows only. The zero-migration column follows the UN Zero-migration variant from 2025.

The economic consequences are striking. U.S. GDP falls 11.8% below the base case by 2050, from 46.0 to 40.6 trillion 2017 USD, and 39.4% below by 2100 (110.7 to 67.1). Table 22 contrasts U.S. GDP and GDP shares under the two scenarios. The U.S. share of world output falls from 14.3% to 12.8% in 2050 and from 14.4% to 9.2% in 2100. We show in section 4 that seven years of revised UN forecasts raised the 2100 U.S. share from 11.2% to 14.4%, ending the century at rough parity with China. Ending immigration more than cancels out this result. At 9.2% against China's 15.9%, the United States holds barely three fifths of China's share, a wider shortfall than under the 2017 projections.

Unsurprisingly, the U.S.'s fiscal arithmetic deteriorates. Immigrants arrive disproportionately of working age and are payroll contributors long before they are beneficiaries.

[38] It should be noted that this assumption makes global net migration unbalanced: the foregone immigrants would, in reality, stay in their country of origin and work and consume there. However, it is difficult to directly infer cross-border flows from UN migration data. We chose this approach to more cleanly isolate the impact on the U.S. economy, and the impact on global GDP should be considered an upper-bound number which understates GDP of major sources of U.S. immigration in North and South America.

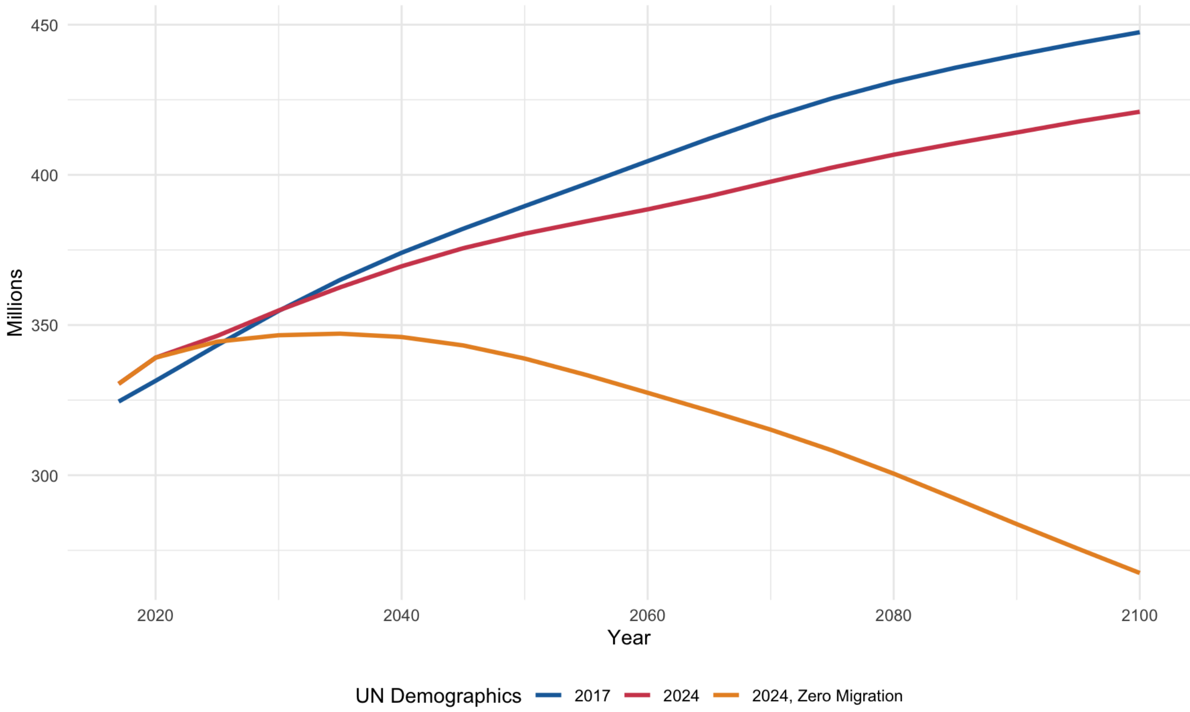


Figure 10: U.S. Population Under Baseline and Zero-immigration Demographics, 2017-2100

Table 22: United States GDP and Share of World GDP With and Without Immigration After 2025

Year	Measure	2024 UN Demographics Baseline	2024 UN Demographics Zero Migration	Difference
2017	US GDP (trillions of 2017 USD)	19.5	19.5	0.0
	US share of world GDP (percent)	16.4	16.4	0.0
2050	US GDP (trillions of 2017 USD)	46.0	40.6	-5.4
	US share of world GDP (percent)	14.3	12.8	-1.5
2100	US GDP (trillions of 2017 USD)	110.7	67.1	-43.7
	US share of world GDP (percent)	14.4	9.2	-5.3

Remove them and the payroll tax rate (under 2024 UN demographics) rises from 22.2% to 24.6% of covered payroll in 2050 and from 28.2% to 33.9% in 2100. Pension outlays climb from 12.0% to 14.5% of GDP, and the total revenue requirement rises from 39.5% to 43.2%. Immigration is therefore sustaining a sizable share of the U.S.'s fiscal burden, and ending it is a massive benefit cut or tax increase deferred, not avoided.

The loss is almost entirely American. World GDP is only 1.3% lower in 2050 and 4.5% lower in 2100, virtually all of it the U.S. decline itself. Every other region ends the century slightly ahead, all by less than 3%. Those gains are due to capital reallocating toward non-U.S. labor: the world interest rate falls from 1.6% to 1.5% in 2100, and China's share of world GDP rises from 14.9% to 15.9%. As noted above, because the experiment removes migrants from the U.S. without returning them to the regions they would have left, the model counts the labor America forgoes but not the labor kept by sending regions. The 4.5% world loss should therefore be considered a ceiling on the global cost, and the U.S. relative decline a floor.

4.6 Low Variant UN Population Projections

Our second sensitivity analysis asks what happens if fertility arrives even lower than our 2024 demographic baseline. We rerun the 2024 calibration with every region on the UN's low variant, which holds TFR half a birth below the medium variant through 2100. Other aspects of the model are held constant.[39] Figure 11 shows the demographic experiment: rather than peaking near 9.8 billion in the 2080s, world population crests at 8.6 billion around 2052 and falls to 6.7 billion by 2100 – 31.5% below the medium variant.

The economics of the low variant differ dramatically between mid- and end-of-century. Through mid-century, lower fertility is a small output dividend. As table 23 shows, world GDP in 2050 is 1.3% *higher* than the base case, and output per person is 9.5% higher. This is because the missing children have not yet become missing workers, so the same output is shared among fewer people who can save more because of fewer children. Consequently, the working-age share of the population and private savings temporarily swells.

The second half of the century is a different story. World growth from 2050 to 2100 falls from 1.8% to 0.9% per year, and 2100 world GDP comes in 32.3% below the base case. As with the 2017-to-2024 revision in our main results, the channel is headcount rather than productivity: 2100 per capita output sits within approximately 1% of the baseline. In other words, the low variant UN demographics runs the paper's central experiment in fast forward, delivering globally the type of economics shortfall that seven years of forecast revisions delivered for China.

Uniformly lower fertility does not affect regions uniformly. As shown in table 24, the U.S. 2100 share of world GDP *rises* from 14.4% to 16.5%, while China's falls from 14.9% to 11.3%, and India's from 11.8% to 11.1%. China's 2100 GDP is 48.9% below its medium-variant level, against 22.6% for the United States. The asymmetry is due to immigration. A fertility variant leaves migration untouched, and (as detailed in section 4.5), migration is a substantive part of U.S. population growth. The same logic lifts

[39] Under the low variant and our standard stabilization assumption, China's post-2100 population would collapse to under 60 million, taking its fiscal system past the point of solvency. We instead raise Chinese fertility after 2100 so that its population stabilizes at roughly 100 million. The adjustment takes effect only outside the 2017–2100 window reported here.

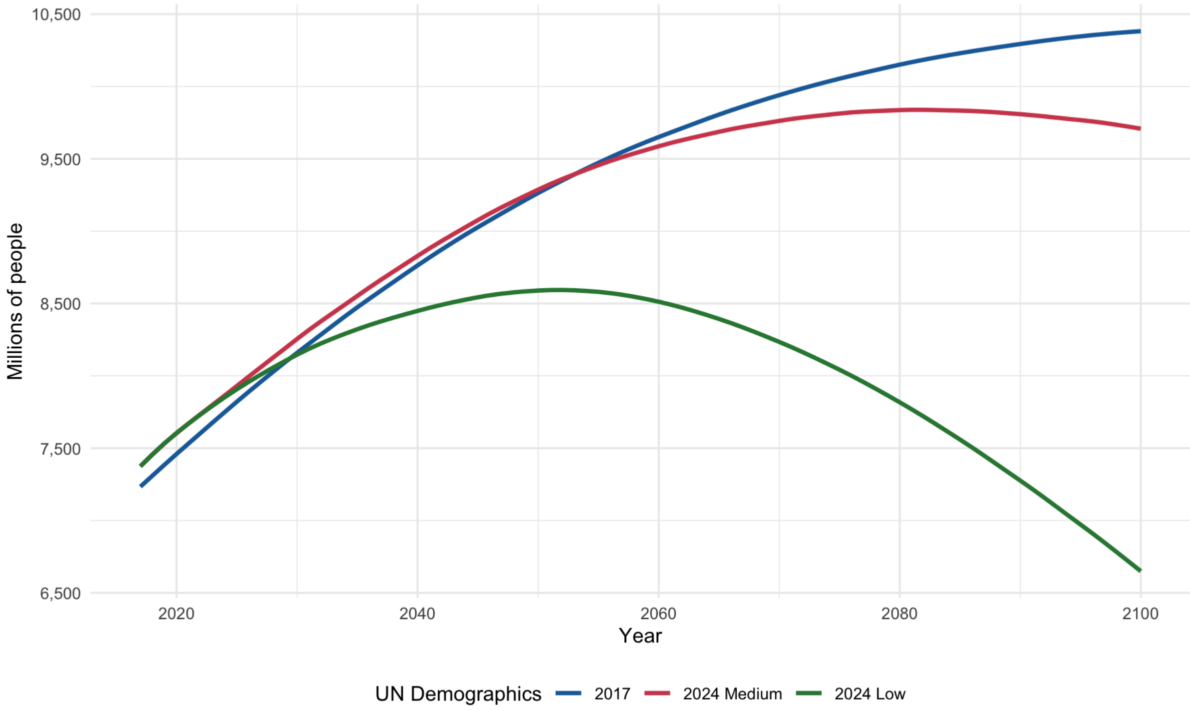


Figure 11: World Population 2017-2100, Millions

Table 23: Real GDP in Trillions of 2017 USD, 2024 Medium v. Low UN Demographic Variant

Region	Year	2024 UN Proj. Medium	2024 UN Proj. Low	Percent difference
USA	2017	19.5	19.5	0.0
	2050	46.0	46.6	1.4
	2075	73.2	68.1	-6.9
	2100	110.7	85.7	-22.6
CHI	2017	19.7	19.8	0.4
	2050	61.9	63.5	2.5
	2075	85.5	69.5	-18.7
	2100	114.6	58.5	-48.9
SSA	2017	2.6	2.6	0.1
	2050	10.0	10.0	0.2
	2075	19.4	17.9	-7.7
	2100	29.8	22.7	-23.8
World	2017	118.7	118.8	0.1
	2050	321.7	325.9	1.3
	2075	513.2	453.7	-11.6
	2100	767.5	519.9	-32.3

other destination economies – Western Europe's share increases from 12.3% to 12.8%, and Canada, Australia, and New Zealand's combined share rises from 3.2% to 3.9%. Low fertility, like the 2024 revision itself, reinforces demography's reordering of economic power rather than reversing it.

Table 24: Share of World GDP, Percent, 2024 Medium v. Low UN Demographic Variant

Region	2024 Medium UN Demographics			2024 Low UN Demographics		
	2017	2050	2100	2017	2050	2100
USA	16.41	14.29	14.43	16.39	14.30	16.48
WEU	17.10	13.51	12.25	17.09	13.56	12.79
JSHK	6.94	6.57	5.96	6.93	6.66	5.84
CHI	16.59	19.24	14.93	16.64	19.48	11.26
IND	6.94	9.37	11.84	6.95	9.29	11.14
RUS	3.20	2.10	1.83	3.19	2.13	2.07
CAN	2.71	2.82	3.20	2.71	2.84	3.93
EEU	0.78	0.68	0.49	0.78	0.68	0.39
SAP	6.56	7.46	7.85	6.57	7.38	7.38
BRA	2.53	2.02	1.46	2.54	2.02	1.37
MEX	2.08	1.89	1.35	2.08	1.87	1.24
SAF	0.60	0.54	0.56	0.60	0.54	0.65
MENA	8.67	9.93	13.34	8.65	9.79	14.33
SLA	3.23	3.02	2.34	3.23	2.96	2.17
SSA	2.19	3.10	3.88	2.19	3.06	4.37
SOV	0.89	1.25	2.42	0.89	1.24	2.61
GBR	2.56	2.21	1.88	2.56	2.19	1.98

Finally, the savings glut deepens to the point of near-zero capital returns. The world interest rate, which falls to 1.6% by 2100 in the base case, falls to 2.6% in 2050 and 0.8% in 2100 under the low fertility variant. Figure 12 shows a comparison between interest rates across the two demographic variants. Capital is the factor in surplus and labor the factor in scarcity, and with a third fewer workers to equip, end-century returns to capital halves again. Fiscal arithmetic tightens concomitantly. The U.S. payroll tax rate reaches 35.3% of covered payroll by 2100 against 28.2% in the 2024 demographics base case, and Western Europe, China, and Eastern Europe all must cut benefits by mid-century to prevent aggregate tax rates above 100 percent.

5 Conclusion

The baby bummer – current and/or projected future fertility rates below ZPG in most countries/territories – is as much an economic as a demographic phenomenon. We ask how the global demographic transition will reshape the world economy, and whether the automation and AI revolution will offset or reinforce demography's effects. Our tool is a 17-region, 101-period, global overlapping generations equilibrium model, calibrated precisely to UN demographic and IMF fiscal data. Our experiment is simple. Holding preferences, technology, and fiscal systems fixed, we compare model outcomes calibrated to the UN's 2017 population projection to those calibrated to the UN's 2024 projections. Although just seven years apart, the 2024 forecast is markedly different. In particular, the UN now foresees, for the first time, an end to global population growth. The latest projection also foresees very different country-specific demographic paths. For example, China's mid-century fertility rate is projected at 1.10 compared with the UN's 2017 projection of 1.63. The steady, deep, and sustained drop in Chinese fertility leaves its

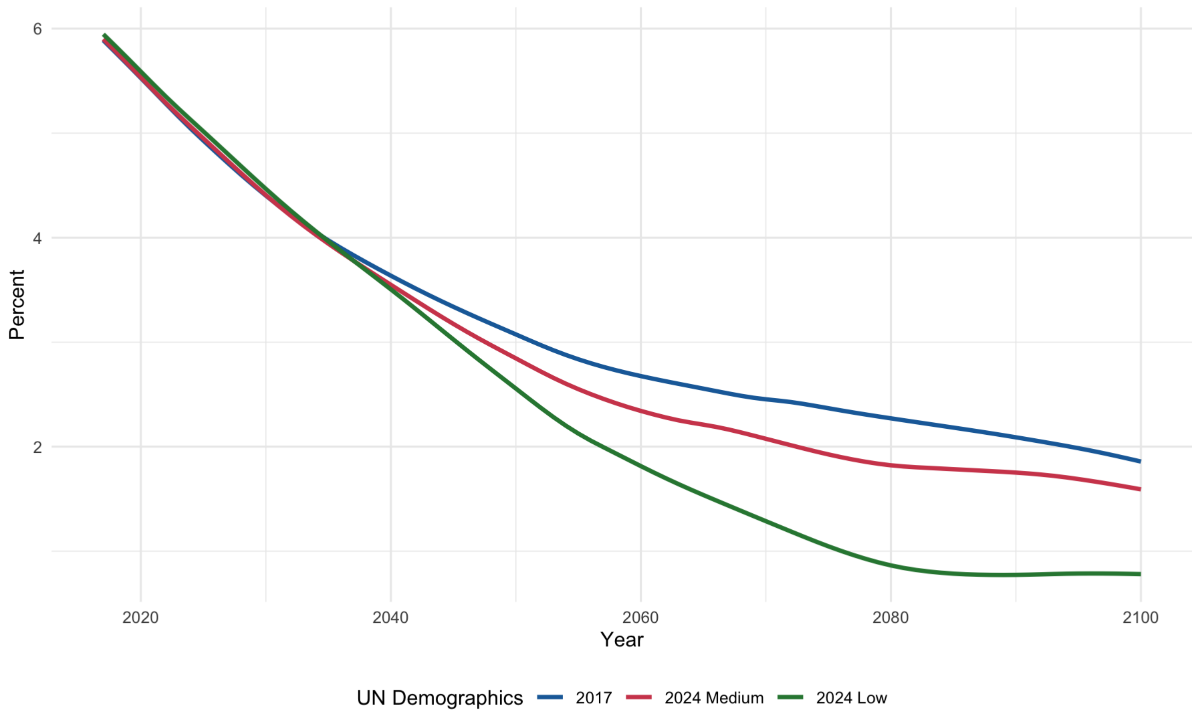


Figure 12: World Real Interest Rate 2017-2100, Percent

projected (in 2024) end-of-century population roughly 40 percent lower than the UN 2017 forecast. As for the US, its 2024-projected 2100 population is 12% larger than the 2017-projected value.

The economic impact of the demographic transition, as assessed by these and many other differences in the UN's two forecasts, is sizable. China's simulated 2100 share of world output is 25.6% based on the UN's 2017 demographic forecast. It's 14.9% based on the 2024 forecast. The changed forecasts raise the U.S. 2100 global-GDP share from 11.2% to 14.4%. China's end-of-century GDP falls from 218 to 115 trillion dollars; the U.S.'s rises from 96 to 111 trillion. In short, under the UN's new demograhics, the economic baton no longer passes from the US to China.

In addition, world GDP in 2100 is 10% lower, and world growth after 2050 slows from 2.0% to 1.8% per year. The channel is primarily headcount, i.e., fewer workers, not labor productivity. Output per worker between 2017 and 2100 grows at an average of 2.1% per year worldwide under both projections.

The demographic/economic transition features catch-up growth in many high saving-rate countries, including China. Consequently, our model evinces a massive, supply-driven capital gut under both sets of demographics. The global return to internationally mobile capital falls from 5.9% in 2017 to 1.9% in 2100 under the 2017 projection and to 1.6% under the 2024 forecast. Hence, global aging produces a deep global savings glut.

Our baseline assumes that the advent of automation/AI (AU/AI) raises each region's frontier technology's capital and high-skilled-labor Cobb-Douglas output-share coefficients materially – in line with observation. But we also speculate that AU/AI will produce far more rapid change in frontier technologies. Following Zeira (1998), we permit regions to adopt more capital- and high-skilled labor intensive technology when doing so makes them more productive given their factor costs.

With sufficiently rapid automation, what we call Transformative AI (TAI), many regions with relatively expensive labor switch to highly capital-intensive production. This produces a capital demand glut leaving the global capital return in 2100 at 7.4% in 2050 and 6.0% in 2100. Under TAI and 2024-projected demographics, U.S. output in 2050 is 90% above its baseline path and the U.S. 2100 share of world GDP doubles to 26.7%. China's 2100 share under these assumptions is 16.9%. This goes beyond the impact of revised demographics, namely the maintenance of relative US economic power. It spells ongoing US economic hegemony.

With TAI, 2100 world output is 22.7% higher than would otherwise arise. TAI-adopting regions receive substantial fiscal relief with, for example, the U.S. effective tax burden on total income falling from 47.0% to 25.9% by 2100. The growth dividend, not reform, pays down the welfare state.

Fiscal relief arrives unevenly. Because automation lowers labor's share, payroll rates rise dramatically even as pension burdens fall. Western Europe and pre-adoption China must cut benefits starting mid-century or otherwise face combined labor tax rates approaching 100%. Wage-based social insurance and Transformative AI are not compatible; financing requires consumption or capital income taxation.

We conduct two main demographic sensitivity analyses. Ending U.S. immigration in 2025 – the UN's zero-net-migration variant, applied to the U.S. alone makes a major difference in the global economic power picture. With zero net immigration, the US population falls to 268 million by 2100, ending the century producing just 9.2% rather than 14.4% of world output – three fifths of China's level. Because most immigrants arrive of working age, the US fiscal position further deteriorates even though pensions are fixed in per capita terms. The U.S.'s covered payroll rate in 2100 increases from 28.2% to 33.9%.

We also simulate our model using the UN's low-fertility variant instead of the baseline's medium. Under this variant, 2100 world output is 32.3% lower, and the world's capital return falls below 1%. Even a uniform fertility shock reorders economic power unevenly due to migration not shrinking with births: the U.S. 2100 share of world GDP rises to 16.5%, in large part due to immigration sustaining its population, while China's falls to 11.3%.

To conclude, the global baby bummer – the baby bust's bust – spells significant global aging. This spells more wealth-holding retirees relative to workers, which spells capital deepening, which spells higher wages and lower returns to capital. Given take-go fiscal policies, aging could, theoretically speaking, more than offset capital's deepening due to higher taxation of our life-cycle model's savers – the young. But, as shown here, tax rates can skyrocket without overcoming capital deepening. The reason appears to be the very high saving rates of China and other Asian countries. Technological change in the form of automation and AI represent an independent force determining the global transition. As modeled, adoption of AU/AI-based technologies arise most rapidly in regions with higher TFP levels. The US, based on our calibration, has and retains its TFP advantage over other regions/nations, particularly China. Hence, our paper delivers two negative messages to those predicting the 21st Century as belonging to China. First, the latest UN demographic forecast, if it holds, means China and the US will hold roughly equal global power through the century. But if AU/AI proceeds at the extremely rapid pace predicted by many, US GDP will substantially exceed Chinese GDP throughout this century and, likely, the next.

References

Acemoglu, Daron, Claire Lelarge, and Pascual Restrepo. 2020. "Competing with robots: Firm-level evidence from France." 110:383–88.

Acemoglu, Daron and Pascual Restrepo. 2018. "The Race between Man and Machine: Implications of Technology for Growth, Factor Shares, and Employment." *American Economic Review* 108 (6):1488–1542.

Altig, David, Alan J Auerbach, Erin F Eidschun, Laurence J Kotlikoff, and Victor Yifan Ye. 2025. "Inflation's Impact on American Households." In *NBER Macroeconomics Annual*, vol. 39, edited by Martin S. Eichenbaum, John V. Leahy, and Valerie A. Ramey. University of Chicago Press, 159–207.

Altig, David, Alan J Auerbach, Laurence J Kotlikoff, Elias Ilin, and Victor Yifan Ye. 2020. "Marginal Net Taxation of Americans' Labor Supply." Working Paper 27164, National Bureau of Economic Research. URL http://www.nber.org/papers/w27164.

Altig, David, Alan J Auerbach, Laurence J Kotlikoff, Kent A Smetters, and Jan Walliser. 2001. "Simulating Fundamental Tax Reform in the United States." *American Economic Review* :574–595.

Alvaredo, Facundo, Anthony B. Atkinson, Thomas Blanchet, Lucas Chancel, Luis Bauluz, Matthew Fisher-Post, Ignacio Flores, Bertrand Garbinti, Jonathan Goupille-Lebret, Clara Martínez-Toledano, Marc Morgan, Theresa Neef, Thomas Piketty, Anne-Sophie Robilliard, Emmanuel Saez, Li Yang, and Gabriel Zucman. 2020. "Distributional National Accounts Guidelines: Methods and Concepts Used in the World Inequality Database." .

Auclert, Adrien, Hannes Malmberg, Matthew Rognlie, and Ludwig Straub. 2025. "The race between asset supply and asset demand." Tech. rep., National Bureau of Economic Research.

Auerbach, Alan J and Laurence J Kotlikoff. 1981. "National Savings, Economic Welfare, and the Structure of Taxation." Working Paper 729, National Bureau of Economic Research. URL http://www.nber.org/papers/w0729.

———. 1983. "National Savings, Economic Welfare, and the Structure of Taxation." In *Behavioral Simulation Methods in Tax Policy Analysis*. University of Chicago Press, 459–498.

———. 1987. *Dynamic Fiscal Policy*, vol. 11. Cambridge University Press Cambridge.

Auerbach, Alan J., Laurence J. Kotlikoff, Robert P. Hagemann, and Giuseppe Nicoletti. 1989a. "The Economic Dynamics of an Ageing Population." (62). URL https://www.oecd-ilibrary.org/content/paper/054502801660.

Auerbach, Alan J, Laurence J Kotlikoff, Robert P Hagemann, and Giuseppe Nicoletti. 1989b. "The Dynamics of an Aging Population: The Case of Four OECD Countries."

Autor, David H, Lawrence F Katz, and Melissa S Kearney. 2006. "The polarization of the US labor market." *The American economic review* 96 (2):189–194.

Balestra, Carlotta and Richard Tonkin. 2018. "Inequalities in household wealth across OECD countries." URL https://www.oecd-ilibrary.org/content/paper/7e1bf673-en.

Benzell, Seth G, Eugene Goryunov, Maria Kazakova, Laurence J Kotlikoff, Guillermo LaGarda, Kristina Nesterova, and Andrey Zubarev. 2015a. "Simulating Russia's and Other Large Economies' Challenging and Interconnected Transitions." *National Bureau of Economic Research Working Paper* .

Benzell, Seth G, Laurence J Kotlikoff, Maria Kazakova, Guillermo Lagarda, Kristina Nesterova, Victor Yifan Ye, and Andrey Zubarev. 2025. "The future of global economic power." *Oxford Review of Economic Policy* 41 (2):519–554.

Benzell, Seth G, Laurence J Kotlikoff, Guillermo LaGarda, and Jeffrey D Sachs. 2015b. "Robots are us: Some economics of human replacement." Tech. rep., National Bureau of Economic Research.

Benzell, Seth G, Laurence J Kotlikoff, Guillermo Lagarda, and Jeffrey D Sachs. 2016. "Robots Are Us: Some Economics of Human Replacement." *NBER Working Paper* .

Benzell, Seth G, Laurence J Kotlikoff, Guillermo Lagarda, and Victor Yifan Ye. 2021. "Simulating Endogenous Global Automation." Working Paper 29220, National Bureau of Economic Research.

Benzell, Seth G and Victor Yifan Ye. 2024. "Simulating the Global Effect of Transformative AI: Growth, Welfare, Economic Power, and Policy Responses." *Stanford Digital Economy Lab Working Paper* .

Bolt, Jutta and Jan Luiten van Zanden. 2025. "Maddison-Style Estimates of the Evolution of the World Economy: A New 2023 Update." *Journal of Economic Surveys* 39 (2):631–671.

Bricker, Jesse, Lisa Dettling, Alice Henriques, Joanne W. Hsu, Lindsay Jacobs, Kevin B. Moore, Sarah Pack, John Sabelhaus, Jeffrey Thompson, and Richard A. Windle. 2017. "Changes in U.S. Family Finances from 2013 to 2016: Evidence from the Survey of Consumer Finances." *Board of Governors of the Federal Reserve System* URL https://www.federalreserve.gov/econres/scf_2016.htm.

Chow, Trevor, Basil Halperin, and J. Zachary Mazlish. 2025. "Transformative AI, Existential Risk, and Real Interest Rates." *Working Paper* .

Dicarlo, Emanuele, Laurence J Kotlikoff, Mauro Marè, and Marco Olivari. 2025. "Measuring what matters: Why Italy may be in better fiscal shape than the US." Tech. rep., National Bureau of Economic Research.

Fehr, Hans, Sabine Jokisch, Ashwin Kambhampati, and Laurence J Kotlikoff. 2013. "Simulating the Elimination of the U.S. Corporate Income Tax." .

Fehr, Hans, Sabine Jokisch, and Laurence Kotlikoff. 2003. "The Developed World's Demographic Transition - The Roles of Capital Flows, Immigration, and Policy." (10096).

———. 2013. "The world's interconnected demographic/fiscal transition." *The Journal of the Economics of Ageing* .

Fullerton, Don and Diane Lim Rogers. 1996. "Lifetime Effects of Fundamental Tax Reform." *Economic Effects of Fundamental Tax Reform* :321–354.

Green, Jerry and Laurence J. Kotlikoff. 2008. "7th Chapter On the General Relativity of Fiscal Language." *Institutional Foundations of Public Finance: Economic and Legal Perspectives* :241.

ILOStat. 2020. "Statistics on the working-age population and labour force." URL https://ilostat.ilo.org/topics/population-and-labour-force/.

IMF. 2019a. "Balance of Payments and International Investment Position Statistics." .

———. 2019b. "IMF Investment and Capital Stock Dataset, 2019." .

International Monetary Fund. 2017. "Government Finance Statistics." *IMF* .

Judd, Kenneth L. 1985. "Redistributive taxation in a simple perfect foresight model." *Journal of Public Economics* 28 (1):59–83. URL https://www.sciencedirect.com/science/article/pii/0047272785900209.

Karabarbounis, Loukas and Brent Neiman. 2014. "The global decline of the labor share." *The Quarterly journal of economics* 129 (1):61–103.

Kimball, Miles S. and Matthew D. Shapiro. 2008. "Labor Supply: Are the Income and Substitution Effects Both Large or Both Small?" NBER Working Paper 14208, National Bureau of Economic Research.

Müller, Ulrich K, James H Stock, and Mark W Watson. 2019. "An Econometric Model of International Long-run Growth Dynamics." Tech. rep., National Bureau of Economic Research.

Nelson, Jaeger, Kerk Phillips, Seth G. Benzell, Efraim Berkovich, Robert Carroll, Jason DeBacker, John Diamond, Richard Evans, Jagadeesh Gokhale, Laurence Kotlikoff, Guillermo LaGarda, James Mackie, Rachel Moore, Brandon Pecoraro, Brandon Pizzola, Victor Yifan Ye, and George Zodrow. 2019. "Macroeconomic Effects of Reducing OASI Benefits: A Comparison of Seven Overlapping-Generations Models." *National Tax Journal* 72 (4):671–692.

United Nations, Department of Economic and Social Affairs, Population Division. 2024. "World Population Prospects 2024." Online Edition. URL https://population.un.org/wpp/.

World Bank. 2021. "Fossil Fuel Rents, Natural Resource Rents." Data Retrieved from World Development Indicators, http://data.worldbank.org/indicator.

Zeira, Joseph. 1998. "Workers, machines, and economic growth." *The Quarterly Journal of Economics* 113 (4):1091–1117.

Appendix

A1 Additional Figures and Tables

Region	Countries
BRA	Brazil
CAN	Canada, Australia, New Zealand
CHI	China
EEU	Belarus, Republic of Moldova, Ukraine, Albania, Bosnia and Herzegovina, Montenegro, Serbia
GBR	United Kingdom
IND	India
JSHK	China, Hong Kong SAR, Japan, Republic of Korea, Singapore
MENA	Ethiopia, Algeria, Egypt, Libya, Morocco, Sudan, Tunisia, Western Sahara, Mali, Afghanistan, Iran (Islamic Republic of), Pakistan, Bahrain, Iraq, Jordan, Kuwait, Lebanon, Oman, Qatar, Saudi Arabia, Syrian Arab Republic, Turkey, United Arab Emirates, Yemen
MEX	Mexico
RUS	Russian Federation
SAF	South Africa
SAP	Bangladesh, Nepal, Sri Lanka, Brunei Darussalam, Cambodia, Indonesia, Lao People's Democratic Republic, Malaysia, Philippines, Thailand, Timor-Leste, Viet Nam
SLA	Sao Tome and Principe, Antigua and Barbuda, Bahamas, Barbados, Dominican Republic, Grenada, Haiti, Jamaica, Saint Lucia, Saint Vincent and the Grenadines, Trinidad and Tobago, Belize, Costa Rica, El Salvador, Guatemala, Honduras, Nicaragua, Panama, Argentina, Bolivia (Plurinational State of), Chile, Colombia, Ecuador, Guyana, Paraguay, Peru, Suriname, Uruguay, Venezuela (Bolivarian Republic of)
SOV	Mongolia, Kazakhstan, Kyrgyzstan, Tajikistan, Turkmenistan, Uzbekistan, Armenia, Azerbaijan, Georgia
SSA	Eritrea, Kenya, Madagascar, Mozambique, Rwanda, South Sudan, Uganda, United Republic of Tanzania, Zambia, Zimbabwe, Angola, Cameroon, Central African Republic, Congo, Democratic Republic of the Congo, Equatorial Guinea, Gabon, Botswana, Lesotho, Namibia, Swaziland, Burkina Faso, Côte d'Ivoire, Gambia, Ghana, Liberia, Niger, Nigeria, Senegal, Sierra Leone, Togo, Tonga
USA	United States of America
WEU	Cyprus, Israel, Bulgaria, Czechia, Hungary, Poland, Romania, Slovakia, Channel Islands, Denmark, Estonia, Finland, Iceland, Ireland, Latvia, Lithuania, Norway, Sweden, Croatia, Greece, Italy, Malta, Portugal, Slovenia, Spain, Austria, Belgium, France, Germany, Luxembourg, Netherlands, Switzerland

Table A1: Full List of Countries in Each Region

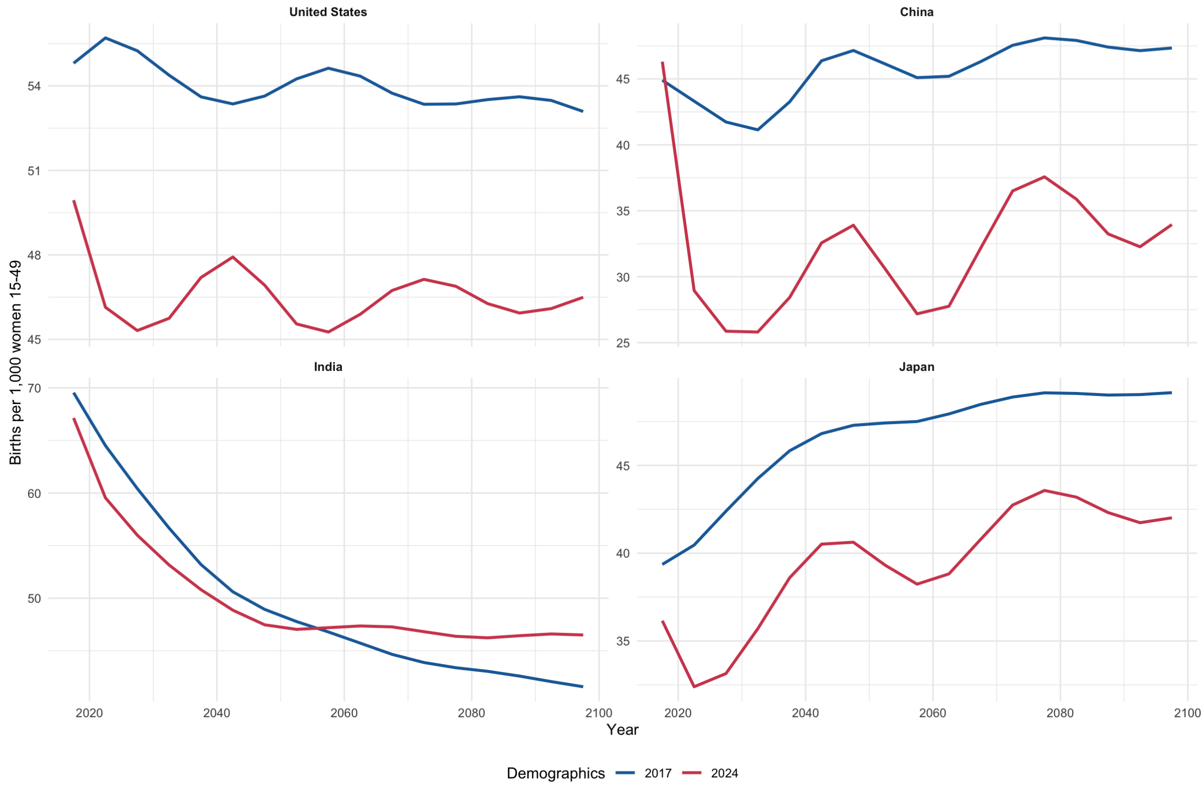


Figure A1: Country-specific Fertility Rate Under 2017 and 2024 UN Projections

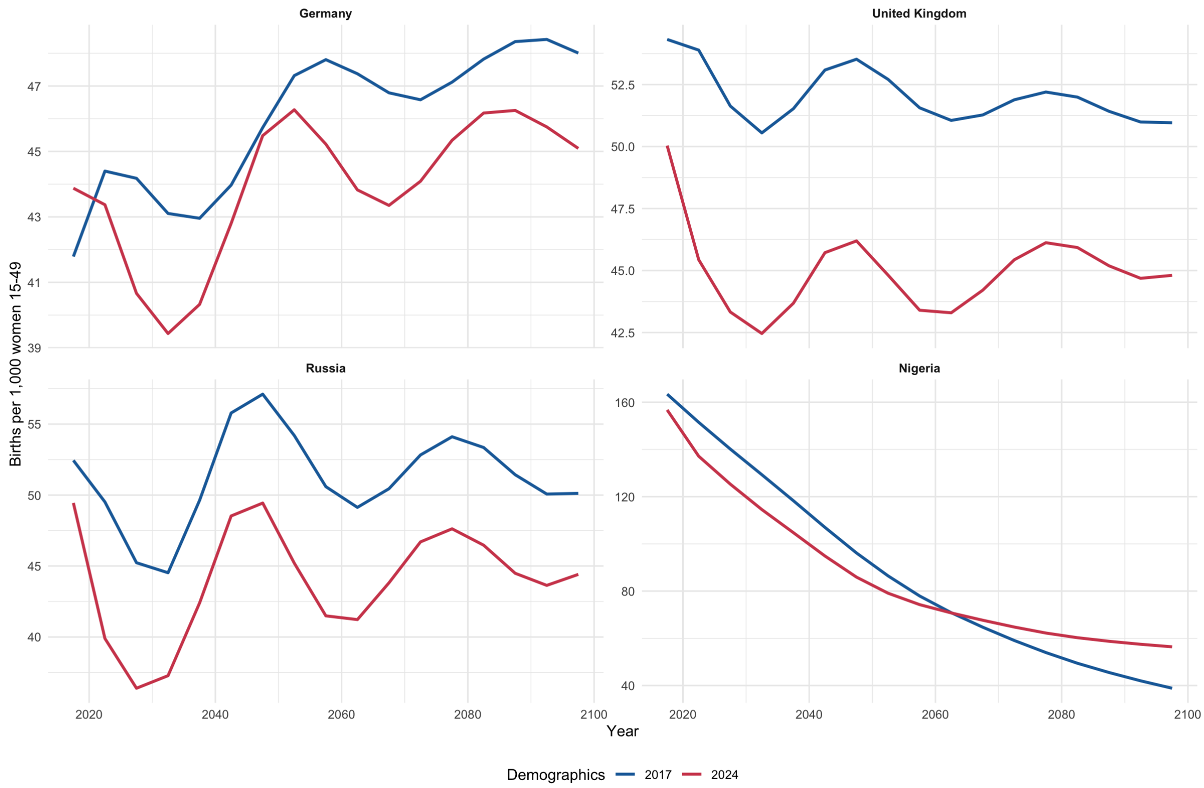


Figure A2: Country-specific Fertility Rate Under 2017 and 2024 UN Projections (Continued)

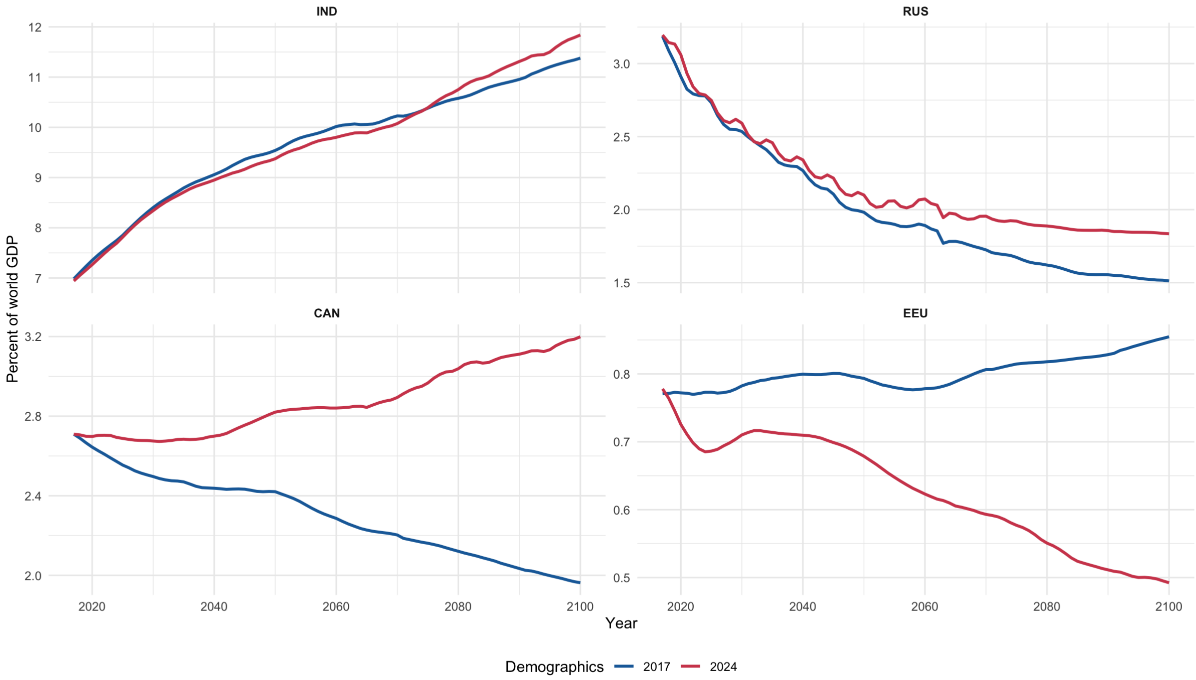


Figure A3: Share of Global Economy by Region, Continued

Table A2: Prime-Age Population by Region (Ages 25-54), Millions

	2017 UN Demographics			2024 UN Demographics		
Region	2017	2050	2100	2017	2050	2100
USA	128	130	126	133	144	147
WEU	191	145	119	192	155	126
JSHK	78	52	39	78	52	31
CHI	675	474	340	660	459	170
IND	541	707	551	542	709	511
RUS	64	47	42	65	50	45
CAN	27	26	25	27	31	36
EEU	32	22	17	32	19	8
SAP	337	409	340	331	404	305
BRA	92	89	60	90	84	53
MEX	53	66	49	50	61	43
SAF	23	30	28	24	32	37
MENA	313	527	609	350	625	810
SLA	116	148	125	113	143	105
SSA	224	599	1255	225	577	994
SOV	38	47	45	38	51	63
GBR	27	24	23	26	28	25
World	**2,958**	**3,541**	**3,792**	**2,976**	**3,627**	**3,511**

Table A3: Capital and Labour Shares for China by Demographic Projection and Automation Scenario

		2017 UN Demographics				2024 UN Demographics			
Scenario	Year	Alpha	B1	B2	B3	Alpha	B1	B2	B3
Business as Usual	2017	0.380	0.207	0.207	0.207	0.380	0.207	0.207	0.207
	2050	0.406	0.152	0.193	0.249	0.406	0.152	0.193	0.249
	2100	0.406	0.152	0.193	0.249	0.406	0.152	0.193	0.249
Accelerating AI	2017	0.380	0.207	0.207	0.207	0.380	0.207	0.207	0.207
	2050	0.478	0.133	0.170	0.219	0.478	0.133	0.170	0.219
	2100	0.478	0.133	0.170	0.219	0.478	0.133	0.170	0.219
Transformative AI	2017	0.380	0.207	0.207	0.207	0.380	0.207	0.207	0.207
	2050	0.600	0.102	0.130	0.168	0.600	0.102	0.130	0.168
	2100	0.600	0.102	0.130	0.168	0.600	0.102	0.130	0.168

Table A4: Capital and Labor Shares for the World by Demographic Projection and Automation Scenario

		2017 UN Demographics				2024 UN Demographics			
Scenario	Year	Alpha	B1	B2	B3	Alpha	B1	B2	B3
Business as Usual	2017	0.352	0.216	0.216	0.216	0.352	0.216	0.216	0.216
	2050	0.365	0.183	0.209	0.243	0.365	0.183	0.209	0.243
	2100	0.367	0.179	0.208	0.247	0.362	0.182	0.210	0.247
Accelerating AI	2017	0.352	0.216	0.216	0.216	0.352	0.216	0.216	0.216
	2050	0.414	0.169	0.193	0.224	0.415	0.168	0.192	0.224
	2100	0.425	0.162	0.189	0.225	0.420	0.164	0.190	0.226
Transformative AI	2017	0.352	0.216	0.216	0.216	0.352	0.216	0.216	0.216
	2050	0.508	0.142	0.162	0.188	0.511	0.141	0.161	0.187
	2100	0.524	0.135	0.156	0.185	0.534	0.130	0.153	0.183

World coefficients are averages of the 17 regional coefficients weighted by each region's GDP in the year and scenario shown.

Table A5: Low-skilled Real Wage by Region, Normalized to U.S. 2017 Average Wage Rate

	2017 UN Demographics			2024 UN Demographics		
Region	2017	2050	2100	2017	2050	2100
USA	0.44	0.51	0.71	0.42	0.50	0.70
WEU	0.37	0.49	0.80	0.36	0.50	0.81
JSHK	0.33	0.64	1.39	0.33	0.66	1.43
CHI	0.09	0.21	0.62	0.09	0.22	0.64
IND	0.05	0.10	0.25	0.05	0.10	0.25
RUS	0.17	0.21	0.31	0.17	0.21	0.32
CAN	0.39	0.49	0.71	0.38	0.50	0.73
EEU	0.08	0.16	0.38	0.08	0.16	0.38
SAP	0.07	0.14	0.21	0.08	0.15	0.21
BRA	0.10	0.15	0.25	0.10	0.16	0.26
MEX	0.12	0.17	0.24	0.13	0.19	0.26
SAF	0.10	0.13	0.17	0.09	0.12	0.16
MENA	0.08	0.12	0.18	0.07	0.11	0.17
SLA	0.10	0.14	0.21	0.10	0.15	0.22
SSA	0.04	0.04	0.05	0.04	0.04	0.05
SOV	0.08	0.17	0.29	0.08	0.17	0.29
GBR	0.40	0.45	0.63	0.40	0.46	0.64
World	**0.12**	**0.16**	**0.25**	**0.12**	**0.16**	**0.25**

Wages are normalized to the 2017 U.S. per-worker average wage across all skill groups, assuming 2017-vintage demographics.

Table A6: Middle-skilled Real Wage by Region, Normalized to U.S. 2017 Average Wage Rate

	2017 UN Demographics			2024 UN Demographics		
Region	2017	2050	2100	2017	2050	2100
USA	1.67	2.45	3.42	1.61	2.41	3.40
WEU	0.92	1.57	2.55	0.91	1.58	2.57
JSHK	0.82	2.03	4.41	0.82	2.11	4.56
CHI	0.32	0.94	2.75	0.33	0.99	2.82
IND	0.23	0.47	1.19	0.22	0.48	1.20
RUS	0.54	0.82	1.22	0.54	0.84	1.26
CAN	0.97	1.56	2.27	0.96	1.58	2.31
EEU	0.25	0.60	1.45	0.25	0.62	1.48
SAP	0.29	0.56	1.04	0.29	0.57	1.07
BRA	0.43	0.69	1.12	0.44	0.71	1.15
MEX	0.54	0.78	1.09	0.57	0.84	1.17
SAF	0.46	0.60	0.80	0.43	0.57	0.77
MENA	0.40	0.56	0.87	0.35	0.51	0.81
SLA	0.44	0.64	0.95	0.45	0.66	0.96
SSA	0.16	0.19	0.22	0.16	0.19	0.22
SOV	0.25	0.52	1.14	0.25	0.53	1.15
GBR	1.05	1.53	2.12	1.06	1.55	2.14
World	**0.46**	**0.75**	**1.22**	**0.46**	**0.76**	**1.20**

Wages are normalized to the 2017 U.S. per-worker average wage across all skill groups, assuming 2017-vintage demographics.

Table A7: High -skilled Real Wage by Region, Normalized to U.S. 2017 Average Wage Rate

	2017 UN Demographics			2024 UN Demographics		
Region	2017	2050	2100	2017	2050	2100
USA	8.33	15.77	22.04	8.04	15.53	21.89
WEU	2.16	4.75	7.70	2.13	4.78	7.75
JSHK	1.92	6.14	13.32	1.92	6.37	13.76
CHI	1.18	4.52	13.27	1.22	4.65	13.47
IND	1.43	2.90	7.22	1.41	2.90	7.24
RUS	2.47	4.87	7.26	2.47	5.00	7.47
CAN	2.28	4.72	6.85	2.25	4.78	6.97
EEU	0.63	1.99	4.83	0.63	2.03	4.86
SAP	1.18	2.22	5.33	1.20	2.26	5.43
BRA	4.20	6.55	10.68	4.29	6.75	10.95
MEX	5.32	7.43	10.39	5.66	8.03	11.17
SAF	2.13	2.73	3.57	1.95	2.60	3.47
MENA	1.84	2.54	3.92	1.64	2.32	3.62
SLA	4.34	6.15	9.03	4.44	6.30	9.19
SSA	0.66	0.76	0.85	0.66	0.77	0.86
SOV	1.24	2.58	7.21	1.26	2.63	7.34
GBR	2.92	5.47	7.58	2.93	5.57	7.67
World	**1.89**	**3.72**	**6.06**	**1.87**	**3.76**	**5.94**

Wages are normalized to the 2017 U.S. per-worker average wage across all skill groups, assuming 2017-vintage demographics.

Table A8: Production-Function Shares in 2100, Business as Usual, 2017 UN Demographics

Region	Capital Share	Labor share Low skill	Labor share Mid skill	Labor share High skill
USA	0.366	0.162	0.206	0.266
WEU	0.392	0.155	0.198	0.255
JSHK	0.507	0.126	0.161	0.207
CHI	0.406	0.152	0.193	0.249
IND	0.265	0.245	0.245	0.245
RUS	0.428	0.146	0.186	0.240
CAN	0.411	0.150	0.192	0.247
EEU	0.438	0.144	0.183	0.236
SAP	0.353	0.165	0.211	0.271
BRA	0.285	0.238	0.238	0.238
MEX	0.362	0.213	0.213	0.213
SAF	0.289	0.237	0.237	0.237
MENA	0.332	0.223	0.223	0.223
SLA	0.262	0.246	0.246	0.246
SSA	0.278	0.241	0.241	0.241
SOV	0.381	0.158	0.202	0.260
GBR	0.361	0.163	0.208	0.268

Shares of the production function in use in 2100 under business-as-usual automation, after the endogenous technology choice.

Table A9: Production-Function Shares in 2100 Under Accelerating AI and 2017 UN Demographics

Region	Capital Share	Labor share Low skill	Labor share Mid skill	Labor share High skill
USA	0.443	0.142	0.181	0.234
WEU	0.466	0.136	0.174	0.224
JSHK	0.566	0.111	0.141	0.182
CHI	0.478	0.133	0.170	0.219
IND	0.265	0.245	0.245	0.245
RUS	0.497	0.128	0.164	0.211
CAN	0.483	0.132	0.168	0.217
EEU	0.506	0.126	0.161	0.207
SAP	0.431	0.145	0.185	0.239
BRA	0.285	0.238	0.238	0.238
MEX	0.362	0.213	0.213	0.213
SAF	0.289	0.237	0.237	0.237
MENA	0.332	0.223	0.223	0.223
SLA	0.262	0.246	0.246	0.246
SSA	0.278	0.241	0.241	0.241
SOV	0.456	0.139	0.177	0.228
GBR	0.438	0.143	0.183	0.236

Shares of the production function in use in 2100 under Accelerating AI, after the endogenous technology choice. The 2024-vintage calibration gives the same shares to within 0.01, except in MEX, which adopts the frontier technology before 2100 under the 2024 projection but not under the 2017 one.

Table A10: Effective Average Tax Burden, Percent of Total Income, by Demographic Projection and Automation Scenario

Region	Year	2017 UN Demographics BAU	2017 UN Demographics Accelerating AI	2017 UN Demographics Transformative AI	2024 UN Demographics BAU	2024 UN Demographics Accelerating AI	2024 UN Demographics Transformative AI
USA	2017	38.6	38.4	38.0	38.3	38.1	37.7
	2050	41.2	36.2	24.6	40.4	35.8	24.0
	2100	46.9	40.2	27.6	47.0	40.0	25.9
WEU	2017	46.2	46.2	46.2	46.4	46.3	46.3
	2050	53.2	50.4	43.0	52.5	49.6	42.5
	2100	56.2	50.5	37.1	56.7	50.4	36.2
CHI	2017	27.2	27.4	27.6	27.0	27.2	27.4
	2050	39.2	38.5	42.3	38.3	37.5	39.7
	2100	41.0	35.2	25.7	43.5	37.9	26.3
JSHK	2017	34.8	34.9	35.1	34.4	34.4	34.6
	2050	42.0	37.9	44.4	41.7	36.8	43.4
	2100	47.0	39.0	40.8	48.3	39.2	41.0
World	2017	31.5	31.5	31.6	31.4	31.4	31.5
	2050	36.4	35.7	34.5	36.0	35.3	33.6
	2100	39.6	36.8	32.2	40.8	37.9	31.6

Each cell is average tax revenue per adult individual divided by average income. World rates are GDP weighted.

Table A11: Statutory Payroll Tax Rate by Demographic Projection and Automation Scenario

Region	Year	2017 UN Demographics BAU	2017 UN Demographics Accelerating AI	2017 UN Demographics Transformative AI	2024 UN Demographics BAU	2024 UN Demographics Accelerating AI	2024 UN Demographics Transformative AI
USA	2017	13.5	13.5	13.5	13.6	13.6	13.6
	2050	21.7	22.9	25.0	22.2	23.5	25.6
	2100	27.7	29.9	36.5	28.2	30.5	37.5
WEU	2017	23.9	23.9	23.8	23.8	23.7	23.7
	2050	41.2	45.0	45.0	40.1	44.1	45.0
	2100	42.3	45.0	45.0	42.5	45.0	45.0
CHI	2017	10.8	10.8	10.8	10.7	10.7	10.7
	2050	28.6	33.0	45.0	30.5	35.5	45.0
	2100	28.1	31.7	38.6	38.1	43.8	45.0
JSHK	2017	22.4	22.4	22.4	22.4	22.4	22.3
	2050	34.6	38.0	45.0	34.5	37.9	45.0
	2100	33.0	36.4	40.2	35.2	38.9	43.3
World	2017	13.2	13.2	13.2	13.1	13.1	13.1
	2050	21.6	23.5	26.1	21.7	23.7	26.1
	2100	24.1	26.6	31.2	25.4	28.2	32.5

Payroll taxes are capped at 45 percent to prevent combined tax rates on labor exceeding 100 percent, with uniform benefit reductions after the cap has been reached

Table A12: Production-Function Shares in 2100 Under Transformative AI and 2017 UN Demographics

Region	Capital Share	Labor share Low skill	Labor share Mid skill	Labor share High skill
USA	0.596	0.103	0.131	0.169
WEU	0.600	0.102	0.130	0.168
JSHK	0.600	0.102	0.130	0.168
CHI	0.600	0.102	0.130	0.168
IND	0.265	0.245	0.245	0.245
RUS	0.600	0.102	0.130	0.168
CAN	0.600	0.102	0.130	0.168
EEU	0.600	0.102	0.130	0.168
SAP	0.324	0.225	0.225	0.225
BRA	0.285	0.238	0.238	0.238
MEX	0.362	0.213	0.213	0.213
SAF	0.289	0.237	0.237	0.237
MENA	0.332	0.223	0.223	0.223
SLA	0.262	0.246	0.246	0.246
SSA	0.278	0.241	0.241	0.241
SOV	0.600	0.102	0.130	0.168
GBR	0.593	0.104	0.132	0.171

Shares of the production function in use in 2100 under Transformative AI, after the endogenous technology choice. The 2024-vintage calibration gives the same shares to within 0.010, except in SAP and MEX, which adopt the frontier technology before 2100 under the 2024 projection but not under the 2017 one.

A2 Calibration Details

We first consider the Cobb-Douglas coefficients of the production function. In each region, we define skill groups such that $\beta_{t,k} = (1 - \alpha_t)/3$, $k \in (1, 2, 3)$, i.e., that each skill group, in 2017, collects a third of total labor income under the region's initial technology. In the business-as-usual automation baseline, regions may replace these coefficients with the frontier technology's as described in section 3.4. The population share of each group is estimated with the World Inequality Database (Alvaredo et al. 2020) by interpolating country-specific income shares by population quintile (or decile, if data is available). Shares are summarized in table A13.

	USA	WEU	JSHK	CHI	IND	RUS	CAN	EEU	SAP	BRA	MEX	SAF	MENA	SLA	SSA	SOV	GBR
Capital Income Share																	
	0.341	0.368	0.487	0.383	0.267	0.405	0.388	0.416	0.326	0.288	0.365	0.292	0.335	0.265	0.281	0.356	0.335
Initial Technology Labor Income Share Per Skill Group																	
	0.220	0.211	0.171	0.206	0.244	0.198	0.204	0.195	0.225	0.237	0.212	0.236	0.222	0.245	0.240	0.215	0.222
Share of Population by Skill Group																	
High	0.040	0.109	0.109	0.060	0.030	0.050	0.109	0.093	0.052	0.020	0.020	0.040	0.040	0.020	0.048	0.050	0.090
Med	0.200	0.255	0.255	0.210	0.170	0.230	0.255	0.226	0.193	0.180	0.180	0.166	0.166	0.180	0.170	0.230	0.250
Low	0.760	0.636	0.636	0.730	0.800	0.720	0.636	0.681	0.755	0.800	0.800	0.795	0.795	0.800	0.782	0.720	0.660

Table A13: Input Shares by Region and Population Shares by Skill Group and Region

Capital income shares are calibrated such that, in 2017, each region's capital demand matches its capital stock as calculated from the IMF Investment and Capital Stock Database (ICSD; IMF 2019b). To achieve this, we scale the overall model so that one unit of model output is equal to 100 billion real U.S. dollars in 2017 value. The total global stock of capital is set such that the amount of global capital in a given period is equal to the period's global supply of net wealth assets – total private plus government assets (including the present value of fossil fuel rents) less the world-wide private and government liabilities and official debt. The depreciation rate in each region is calibrated to the average difference between its net capital accumulation rate, from 2012 to 2017, and gross domestic investment rate for the same period. Both estimates are obtained from ICSD data; we assume that depreciation rates are fixed through time.

The total factor productivity term, ϕ_t, is used to calibrate output in each region. We calibrate ϕ_t in 2017 to each region's GDP in the same year, adjusting the overall scaling factor to express the model's output in real dollar units. The path of ϕ_t is calibrated to long-term economic growth projections from Müller, Stock, and Watson (2019). The authors use a Bayesian model to provide two sets of estimations for GDPs through 2100, one estimating growth paths of countries jointly in a multivariate approach, and the other estimating each country individually. We adopt a simple average of the two output paths as the calibration target, and adjust ϕ_t in 2100 to match output in each region under the business-as-usual automation baseline.[40] ϕ_t is assumed to grow linearly between 2017 and 2100. After 2100, TFP in all regions grows at a fixed rate of 1% per year.

Specifically, the calibration assigns each region a constant annual increment, c, to the level of its productivity term, so that $\phi_{t+1} = \phi_t + c$ from 2018 through 2100, with ϕ_t held at its 2100 value thereafter and growth continuing at the common trend rate alone. Table 4 reports the 2017 levels, increments, the resulting 2100 levels and the annualized TFP growth each implies. The 2017 levels capture the productivity gap each region starts from – Western Europe, JSHK and Britain begin at 0.70 to 0.78 of the U.S. level, China at 0.37, India at 0.28 and Sub-Saharan Africa at 0.17 – and the increments determine how much of it closes. China's increment of 0.80% of U.S. base-year TFP per year implies TFP growth of 1.2% per year on top of the common trend, while Sub-Saharan Africa's is zero and South Africa's is 0.02%. The fact that two regions receive virtually no TFP convergence at all is a property of the underlying projections: the Müller-Stock-Watson posterior for these regions implies end-of-century output that their factor accumulation and the common trend already deliver. One decision deserves emphasis for the present exercise. The increments are calibrated once, against the 2017-vintage demographic projection, and then held fixed when the model is re-calibrated to the 2024 vintage. Productivity assumptions are therefore identical across our two calibrations by construction, and differences in simulated output between them are attributable to demography alone.

The initial age- and skill-distribution of assets is calibrated to the distribution of total household assets in the 2016 Survey of Consumer Finances (SCF; Bricker et al. 2017). For the age profile, the age-asset distribution is spline smoothed and weighted so that, depending on the region-specific age of labor force entry, agents in their first working year own zero assets. For the skill-group profile, we sort SCF households by annual wage income and calculate the fraction of assets owned by each bin corresponding to the population shares of the U.S's skill groups. Because of the lack of large-sample household-level data for non-U.S. regions, we apply the U.S's age-skill-group asset profile to all regions.[41]

[40] While we assume 1% long-term technological growth in the model, individual regions are allowed to grow at a rate of less than 1% in the short run if required to match projections.

[41] Non-U.S. regions are assumed to take the U.S profile, but scaled to their specific age of labor force entry, i.e. workers in regions where labor force entry occurs at age 18 have zero assets at age 18. We assign

The total amount of initial assets in each region is calibrated such that the model's net foreign asset stock, as a fraction of GDP, matches data from the International Investment Position (IIP) Database (IMF 2019a). We measure a region's net foreign asset position as the difference between its net national wealth and its stock of capital. The total stock of global assets in 2017 is set to generate an initial world interest rate of approximately 6%.

Government consumption, taxes, and expenditures are calibrated to IMF macro-fiscal data. We set the rate of the (proportional) corporate income tax to raise, as a percentage of GDP, the amount of corporate income tax revenue in each region. We set the rate of the payroll tax to raise the share of pension benefits financed by payroll taxes. Income and consumption taxes adjust endogenously to balance the budget with the ratio between the two revenue sources calibrated to IMF data. We do not directly incorporate any other tax types in our model. Hence, we assume that non-tax government revenue (e.g. user fees and permit sales) is raised from our three main types of taxes – income, consumption, and corporate income – proportionate to their revenue and increase the revenue-to-GDP ratio targets accordingly.

On the expenditure side, we calibrate spending levels on five different categories: healthcare, education, general welfare expenditures, pensions, and other general public purchases of goods and services ("miscellaneous" expenditures, e.g. expenditure on military and federal administration). We treat miscellaneous expenditures as government consumption. The share of healthcare and education expenditure that is not government consumption is rebated to households according to equation (16). We set each region's initial debt-to-GDP ratio to match the model's net interest payments on debt with 2017 data. We assume that debt is fixed as a share of GDP.

We calibrate fossil fuel rent flows to World Bank (2021) data and match rents as a share of GDP in the initial year. The share of this flow owned by the government is calibrated to the share of natural resource revenue that accrues to the government. We estimate the region-specific exhaustion date using data on the average rate of extraction and proven reserves. If a region's fossil fuel stock is projected to last beyond 2150, we exhaust the flow at the end of 2150.

We interpret leisure in our model as a measure of labor force participation (LFP). The intratemporal ELS, ρ, is calibrated to roughly match the ratio of LFP between 21-year-old and 60-year-old Americans in 2017, which is estimated to be approximately 1.17.[42] We adjust the leisure preference parameter, $\varepsilon_{t,k}$, to match the LFP of each skill group in each region. These targets are derived by combining a non-region-specific distribution target of relative LFP by skill-group and a region-specific target of the average LFP.[43]

the U.S. profile globally for two reasons. First, while OECD collects data on wealth inequality (Balestra and Tonkin 2018), this data is limited with regard to our model's scope and does not include countries such as China and India. Second, the initial asset distribution has very little influence on long-term household dynamics. Beyond the immediate future, asset stocks are determined by agents' consumption and leisure preferences, which are calibrated to region-specific macro data.

[42] Age 21 is chosen as the year that Americans enter the labor force. Age 60 is chosen to represent an age when LFP declines, but is still sufficiently far away from age 66 when the model assumes that all Americans retire. Since the actual LFP-age curve does not exhibit a kink at 66, it is difficult to match leisure taken by individuals in the years immediately prior to turning 66. LFP by age is estimated from 2016 Survey of Consumer Finance data.

[43] Specifically, all regions share the same ratio of LFPs between skill-group as estimated by SCF data, but each region's average LFP across skill-groups, which we draw from ILO data, is region-specific. In other

The ratios of relative leisure taken by skill groups in a given region are estimated by calculating the fraction of non-participants of the labor force among low-, middle- and high-skilled American households – defined (as above) as those in the bottom 76, middle 20, and top 4% by wage income – in SCF 2016. In each region, the target for the weighted average level of leisure taken across all skill groups is estimated with ILO data (ILOStat 2020).[44] Table A14 summarizes leisure targets by skill-group and region.

	High-skilled	Mid-skilled	Low-skilled
USA	11.7	8.5	17.1
WEU	14.9	10.9	21.8
JSHK	15.0	10.9	21.9
CHI	17.1	12.5	25.0
IND	28.2	20.6	41.2
RUS	8.2	6.0	12.0
CAN	7.3	5.3	10.7
EEU	24.0	17.5	35.1
SAP	11.9	8.7	17.4
BRA	17.5	12.8	25.6
MEX	20.8	15.1	30.3
SAF	23.0	16.8	33.6
MENA	26.3	19.2	38.5
SLA	14.9	10.9	21.8
SSA	9.1	6.6	13.3
SOV	20.3	14.8	29.7
GBR	8.3	6.1	12.1

Table A14: Leisure Targets As Percent of Time Endowment (%)

We calibrate the income tax system by using ξ_t, the progressivity term, to adjust the ratio between the METR of the high-skilled group and the average tax rate across all workers. The target for this ratio is the ratio between the METR of the top 4% of households by labor earning (i.e. high-skilled households) and the average effective tax rate of U.S. households as estimated by Altig et al. (2020) and Altig et al. (2025). This ratio, approximately 1.72, is set as the income tax progressivity target for all regions.

The region and skill-group specific pension replacement rate ν_k is calibrated to the progressivity of the Social Security Administration's payout schedule assuming maximum-taxable earnings since age 22 and withdrawal at age 66 in 2017.[45] The pension system is highly redistributive, with high-skilled and middle-skilled U.S. workers only receiving 2.3 and 2.0 times the pension benefits of low-skilled workers, respectively.[46] We set these ratios as the pension progressivity targets in all regions.

words, SCF data determines the (non-region-specific) shape of the LFP profile by income, and ILO data determines the overall, region-specific level of participation. Leisure preferences coefficients are larger for agents with higher income. This is because LFP does not vary substantially across skill groups. Hence, high-skilled individuals must have a stronger preference for leisure. Otherwise they would spend a much larger than observed amount of their time endowment on leisure.

[44] We aggregate ILO data using the same working age interval as the model's assumption. For example, in the U.S. we calibrate leisure to the fraction of non-participants among 21 to 65-year-old Americans.

[45] See https://www.ssa.gov/oact/cola/examplemax.html for benefit examples of workers with maximum-taxable earnings since 22. We translate the model's average wage rates for each skill group into Averaged Indexed Monthly Earnings (AIME).

[46] The average middle- and high-skilled worker's wage rates are 3.5 and 18 times that of the average low-skilled worker, respectively.

The contribution ceiling on payroll taxes is calibrated to the ratio between the 2017 Old Age, Survivor and Disability Tax (OASDI) tax contribution limit and the average 2017 U.S. wage rate of the model.[47] This ratio, approximately 2.72, is set as the target for all regions. Consequently, all high-skilled workers and some middle-skilled workers in the U.S. experience a marginal payroll tax of zero percent, but some high-skilled workers globally experience a non-zero marginal payroll tax depending on their age and the level of local wage inequality.

We additionally calibrate non-region-specific factor productivities for each type of labor and capital utilizing estimates of cost-saving productivity gains from automation (Acemoglu, Lelarge, and Restrepo 2020). Details of this procedure are discussed in Section 3.4.

A3 Pension Benefit Sensitivity Analysis

Our base case holds average pension benefits per retiree at their 2017 level relative to per-capita GNI. Therefore, aging moves pension budgets purely through the retiree headcount and per-retiree generosity remains constant. As a sensitivity analysis, we recalibrate the model under both demographic projections so that each region's pension outlays instead track official 2017-level projections of pension expenditure as a share of GDP through 2050, with per-capita GNI indexation thereafter. We refer to this alternative as "Official Projection" benefits.[48]

The pension rule does not significantly affect output levels. Switching from GNI-indexed pensions to officially projected benefits moves China's annualized growth by less than 0.1 percentage points per year over any window between 2017 and 2100; the 2024 fertility revision moves post-2050 growth by 1.25 points per year, an order of magnitude more. End-of-century world GDP shares shift by less than one percentage point across pension assumptions. Table A15 shows the comparison: under 2017 demographics China's 2100 GDP is 218.4 trillion with GNI-indexed benefits and 225.8 with Official Projection benefits, a 3% difference.

The pension rule does decide how much retirees receive, due to official projections carrying implicit benefit cuts. Under 2024 demographics, holding U.S. per-retiree generosity constant costs 9% of GDP by 2100 against 7.6% under the official trajectory. In other words, the projections assume per-retiree support falling about 15% relative to per-capita GNI. China's case is similar. Under 2017 demographics its official expenditure path was almost exactly generosity-preserving, reaching 11.1% of GDP by 2100. Under 2024 demographics, preserving per-capita generosity costs 15.2% of GDP against the official 14%, and 12.2% versus 11.4% in 2050. This increase in the GDP-denominated cost of maintaining pension benefits is no doubt a major motivation for the pension reforms China adopted in 2024.

Payroll taxes must increase sharply to keep promises made to retirees. Table A16 shows that preserving 2017 generosity pushes China's payroll rate from 10.8% today

[47] The limit is set at $127,200 following https://www.ssa.gov/oact/cola/cbb.html

[48] There are countries that have pass significant pension reforms since 2017 (Brazil, China) although we do not model those reforms to keep everything in the model consistent with 2017 targets with the exception of demographics.

Table A15: Real GDP, Trillions of 2017 USD, by Demographic Projection and Pension Assumption

Region	Year	2017 UN Demographics		2024 UN Demographics	
		GNI-indexed	Official Projection	GNI-indexed	Official Projection
USA	2017	19.5	19.5	19.5	19.5
	2050	43.4	44.4	46.0	46.7
	2075	65.2	67.1	73.2	74.8
	2100	95.7	98.6	110.7	113.7
CHI	2017	19.6	19.7	19.7	19.7
	2050	63.8	65.3	61.9	63.0
	2075	119.2	123.3	85.5	87.9
	2100	218.4	225.8	114.6	118.1
SSA	2017	2.6	2.6	2.6	2.6
	2050	10.3	10.3	10.0	10.0
	2075	21.7	21.8	19.4	19.6
	2100	37.2	37.3	29.8	30.0
World	2017	118.8	118.5	118.7	118.6
	2050	313.5	320.7	321.7	327.8
	2075	526.6	541.7	513.2	526.1
	2100	852.4	875.8	767.5	787.5

to 30.5% by 2050, and 38.1% by 2100 under 2024 demographics, and the U.S. rate to 22.2% and then 28.2%.[49] The starkest gaps are where official projections already assume retrenchment: Western Europe's 2050 rate is 40.1% with generosity preserved against 26.9% under the official path, and Japan/Korea's 34.5% against 22.2%.

Table A16: Payroll Tax Rate, Percent of Covered Payroll, by Demographic Projection and Pension Assumption

Region	Year	2017 UN Demographics		2024 UN Demographics	
		GNI-indexed	Official Projection	GNI-indexed	Official Projection
USA	2017	13.5	13.6	13.6	13.6
	2050	21.7	19.1	22.2	18.8
	2100	27.7	24.3	28.2	23.8
WEU	2017	23.9	24.0	23.8	23.8
	2050	41.2	27.5	40.1	26.9
	2100	42.4	28.5	42.5	28.7
CHI	2017	10.8	10.7	10.7	10.7
	2050	28.6	29.1	30.5	28.5
	2100	28.1	28.3	38.1	35.4
JSHK	2017	22.4	22.9	22.4	22.6
	2050	34.6	22.8	34.5	22.2
	2100	33.0	21.9	35.2	22.7
World	2017	13.2	13.3	13.1	13.1
	2050	21.6	17.1	21.7	16.7
	2100	24.1	19.5	25.4	19.7

Worldwide, the effective payroll rate over covered earnings reaches 25.4% by 2100 with GNI-indexed benefits, to be contrasted against 19.7% under official projections. Those higher labor taxes are not free: world GDP with generosity preserved runs about 2% below the official-projection path in 2050, and 2.5% below by 2100 as payroll and income taxes crowd out labor supply and young workers' saving.

[49] It should be noted that even this rate depends heavily on continued immigration, as discussed in Section 4.5.