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Assessing the Impact of Demographic Composition on Productivity

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Abstract

We examine how demographic factors influence potential output, focusing on how the age distribution of the working-age population and the old-age dependency ratio affect aggregate productivity. Following Feyrer (2007), we emphasize that the contribution to aggregate productivity varies by age group, with middle-aged individuals (aged 40 to 49) being the most productive. Our analysis shows that changes in demographic composition could explain some of the productivity trends observed in China and the United States over the past few decades. This demonstrates why it is important to incorporate the impact of demographic composition when estimating potential output. In particular, demographic factors are expected to narrow the differential in trend labour productivity (TLP) growth between China and the United States by nearly 1 percentage point between 2024 and 2030. On average, TLP growth in China could be reduced by 0.8 percentage points, while that in the United States could rise by 0.1 percentage point. Moreover, demographic factors in Canada portray a similar story to that of the United States. After averaging about 1 percentage point per year from 2010 to 2019, demographic headwinds are expected to dissipate fully through the 2020s, which could signal an upside risk to Canadian TLP growth.

Topics: Productivity; Potential output; International topics

JEL codes: J11, O47, O51

Résumé

Nous examinons comment les facteurs démographiques influencent la production potentielle, en mettant l'accent sur l'incidence de la répartition par âge de la population en âge de travailler et du ratio de dépendance des personnes âgées sur la productivité globale. Comme Feyrer (2007), nous soulignons que la contribution de ces facteurs à la productivité globale varie selon le groupe d'âge, les personnes d'âge moyen (de 40 à 49 ans) étant les plus productives. Notre analyse montre que l'évolution de la composition démographique pourrait expliquer certaines des tendances de productivité observées en Chine et aux États-Unis au cours des dernières décennies. Cela démontre pourquoi il est important d'intégrer l'effet de la composition démographique dans l'estimation de la production potentielle. En particulier, les facteurs démographiques devraient réduire de près de 1 point de pourcentage l'écart de croissance de la productivité tendancielle du travail entre la Chine et les États-Unis de 2024 à 2030. En moyenne, la croissance de la productivité tendancielle du travail en Chine pourrait être réduite de 0,8 point de pourcentage, tandis que celle des États-Unis pourrait augmenter de 0,1 point de pourcentage. De plus, les facteurs démographiques au Canada montrent une situation semblable à celle des États-Unis. Après s'être établis en moyenne à environ 1 point de pourcentage par année de 2010 à 2019, les effets défavorables des facteurs démographiques devraient se dissiper complètement au cours des années 2020, ce qui pourrait signaler une possible hausse de la croissance de la productivité tendancielle du travail au Canada.

Sujets : Productivité; Production potentielle; Questions internationales

Codes JEL : J11, O47, O51

1 Introduction

The size of the working-age population is a key determinant of economic output. Globally, growth in the working-age population has declined steadily in recent decades and is expected to slow further in the coming years (United Nations, 2022b). As population growth declines, so too will its contribution to output—known as the labour input—placing downward pressure on global potential output growth (Benmousa et al., 2024; Celik et al., 2023). At the same time, populations are aging, which has also been associated with weaker growth in productivity and trend output (Favero and Galasso, 2015; Aiyar et al., 2016; Aksoy et al., 2019). These trends are readily apparent in demographic projections of advanced economies, with few exceptions (Kotschy and Bloom, 2023). Among major emerging-market economies, China faces a particularly difficult combination of an outright decline in the working-age population combined with a rapidly aging population.

Amid this demographic doom and gloom, there may be a silver lining hidden in the age composition of the workforce. This often-overlooked dimension of demographics is associated with important shifts in potential output. As well, since the effects of age composition show up in the residual of standard production functions, this dimension of demographics is also associated with labour productivity and total factor productivity (TFP).[1] For instance, research by James Feyrer and others suggests that certain age groups, notably the 40- to 49-year-old cohort, contribute disproportionately to the level of productivity. Therefore, an increase in the share of workers in that age group could help cushion the impacts of slowing population growth and a rising age dependency ratio, henceforth dependency ratio, on potential output growth.[2] Indeed, we demonstrate that considering the age composition

[1] Standard formulations of the Cobb-Douglas production functions used for growth accounting ($Y = AK^{\alpha}L^{1-\alpha}$) define the labour input (L) as a function of total trend hours worked by active workers, often using the working-age population as a proxy (e.g., Celik et al., 2023). The labour input is sometimes converted into human capital by adding aggregate levels of education (Feenstra et al., 2015). Any effect that variations in the age composition of the overall workforce has on trend output will show up in the total factor productivity residual (A).

[2] The age dependency ratio is defined as the ratio of the non-working-age population to the working-age

of the working-age population is crucial for assessing the impact of demographic structure on productivity growth, particularly in terms of growth potential over the next decade.

We begin our analysis by estimating the impact of demographic structure on labour productivity using a panel dataset from 86 non-oil-producing countries, spanning the period of 1964 to 2019. Applying the methodology developed by Feyrer (2007), we exploit variations in demographic structure across countries and over time, focusing on the dependency ratio and the age composition of the working-age population to estimate their impact on labour productivity. The results show that these two dimensions impact productivity in distinct ways:

- Population aging—signified by a higher dependency ratio and a smaller proportion of the working-age population in the economy—is associated with negative productivity growth.
- The contribution to productivity varies across age groups in the working-age population. The 40–49 age group contributes the most, while workers younger than 40 and older workers in their 50s and 60s contribute significantly less.

These results are robust across different periods and subsets of countries, and they hold with additional controls such as labour participation rates.

Analyzing the impact of population structure on productivity is insightful because it is largely unaffected by contemporaneous business cycle developments and does not correlate with current productivity trends. This analysis thus enables us to examine how demographic factors have contributed to productivity growth in the past and to predict their influence on future productivity growth. Using these predicted values, we break down the observed trend labour productivity growth into three components:

population. The working-age population comprises individuals aged 15–64.

- growth due to changes in the age composition of the working-age population
- growth due to changes in the dependency ratio, which we label as an aging effect
- residual labour productivity growth not explained by demographic factors

We find that demographic structures have played a significant role in driving productivity growth in the United States, China and Canada. In the 1980s, US productivity benefited significantly from a relatively stable dependency ratio and an improving age composition as baby boomers entered their forties. Demographic factors continued to support productivity growth well into the 1990s, but their impact has declined and turned negative in the 2010s. Canada has experienced similar demographic dynamics over the past few decades. Canadian productivity benefited significantly from demographic tailwinds in the 1980s and 1990s before the demographic advantage dissipated in the early 2000s and turned sharply negative during the 2010s. As for China, the share of individuals aged 40–49 grew consistently during the 1990s and early 2000s before peaking around 2012. This expansion came largely at the expense of younger cohorts but improved the dependency ratio. Consequently, demographic changes positively impacted productivity growth in the 1990s and early 2000s. However, the contribution of demography had declined significantly by the 2010s, and it has turned negative in recent years as the share of individuals aged 40–49 has steadily declined.

Looking at the current decade, all three countries face the demographic challenge of population aging, with slower growth in the working-age population leading to higher dependency ratios. This trend is particularly severe for China. The trend is less severe for the United States, which benefits from a recent influx of international migration. However, all three countries can expect an eventual boost in productivity growth from an improvement in age composition as more millennials reach an age associated with peak productivity. Taking into account both aging and composition effects, our results show that:

- Demographics represent a meaningful upside risk to US trend labour productivity growth for the period 2023–30.

- The demographic structure in China is expected to amplify the potential growth challenges arising from a declining working-age population, although the situation might not be as dire when the age-composition effect is also considered.
- Canada falls somewhere between the United States and China, with the overall effect small but turning positive toward the end of the 2020s.

Related literature Our study adds to the long strand of literature on the impact of demography on productivity growth. Previous studies have documented the relationship between the dependency ratio, age composition and aggregate productivity and have examined the underlying mechanisms behind these relationships. Since productivity growth relies on people generating new ideas, Jones (2022) argues that a positive rate of population growth is essential for sustained productivity gains. Conversely, productivity growth is likely to stagnate when an economy experiences negative population growth. To the extent that productive ideas are mostly generated by people who are actively participating in the production process, a slowdown in growth of the working-age population and an increase in the dependency ratio would lower the rate of productivity growth.

Slow growth of the working-age population has been associated with a slowdown in business dynamism, which is characterized by a decline in firm entry, a rise in firm concentration and a decrease in job reallocation across firms (Karahan et al., 2019; Hopenhayn et al., 2022). Additionally, Ouimet and Zarutskie (2014) find that young firms tend to disproportionately hire young workers and that young workers are more likely to join innovative, high-growth firms. Therefore, the presence of young workers affects the formation of new firms in an economy. All these factors indicate that an aging population with slow growth in the working-age population would put downward pressure on productivity growth.

Our paper is closely related to Feyrer (2007), who emphasizes the varying contributions to productivity from different age groups, with the middle-aged group—most notably the 40–49 age group—being the most productive. This creates a hump-shaped relationship between productivity and age, which Feyrer (2021) explores by using the life-cycle patterns of innovation activities. Young individuals in their 20s and early 30s often require time to study and train to reach the forefront of innovation. At the same time, cognitive ability tends to decline with age, making it challenging for older workers to be the main driver of innovation. These opposing forces create a life-cycle pattern of innovation that typically peaks around middle age.

The age distribution of the working-age population also influences entrepreneurship, since the propensity to start a business differs by age. In general, business success increases with experience and financial stability but decreases as one approaches retirement. Empirical evidence shows the importance of the middle-age demographic in affecting entrepreneurship and, in turn, the aggregate economic activities and productivity. Azoulay et al. (2020), for instance, find that founders of the fastest-growing firms were on average 45 years old when they started their companies.

Lastly, similar to the approach in Feyrer (2007) and Feyrer (2021), we use estimates from a simple regression framework and population data to understand the role of demography in explaining productivity dynamics. We extend the findings from Feyrer (2007) by using more recent data and a larger sample of countries. We apply the framework to Canada as well as the United States and China—two countries that are important to economic policy-making in Canada. Our results highlight the importance of considering both dimensions of demographic structure, especially the age composition of the working-age population, which is often overlooked in policy analysis.

The remainder of this paper is structured as follows. We first estimate the impact of the demographic structure on productivity in **section 2**, following the framework developed in Feyrer (2007). We then use the estimates to examine the implications of demographic structure on productivity growth in China, the United States and Canada in **section 3**. **Section 4** concludes with a discussion of possible future work on this topic.

2 An empirical analysis of the impact of demographic composition on productivity

We begin this section by providing a brief overview of an important empirical framework by Feyrer (2007). This framework examines the effect of demographic structure on productivity.

Framework In a seminal paper on this topic, Feyrer (2007) studied the impact of demographic composition on productivity using a panel dataset of multiple countries, employing the following regression model:

$$y_{i,t} = f_i + \mu_t + \beta x_{i,t} + u_{i,t}, \tag{1}$$

where the dependent variable $y_{i,t}$ refers to productivity (log TFP or log labour productivity) and the independent variables include a country fixed effect f_i, a time trend μ_t and a vector $x_{i,t}$ representing the share of the workforce or population in each age group (10–19, 20–29, 30–39, 40–49, 50–59, 60+) as well as the log dependency ratio. To deal with the possibility of a unit-root output process, the estimations are carried out in first differences over five-year intervals.

The model assumes that the current level of productivity is a function of the current demographic structure. Therefore, any changes in the demographic structure would have an impact on the rate of growth of productivity. The main focus is on the vector of estimated coefficient $\hat{\beta}$, which shows how much each age group contributes to overall productivity.

Feyrer (2007) suggests that demographic measures are well-suited for conducting multi-country growth regressions for two reasons. First, a country's current demographic structure is mostly predetermined—the age composition of the working-age population was determined about 20 years ago and is not influenced by current productivity dynamics. Second, demographic transitions have happened or are happening in all countries at varying rates and times (see Delventhal et al., 2021). This generates substantial heterogeneity in demographic structures across countries and over time.

Data and measurement We replicate the Feyrer (2007) estimation using more recent data. Data on the demographic structures for China and Canada are taken from the United Nations' World Population Prospects dataset (United Nations, 2022a), which reports population size by five-year age group. The demographic structure for the United States is based on a combination of data from the 2020 US Census and recent projections from the Congressional Budget Office (CBO).[3] For the purpose of our estimation, we construct labour productivity measures using information from the Penn World Table 10.01 (Feenstra et al., 2015).[4] In this paper, we focus on labour productivity, defined as real gross domestic product (GDP) per worker. We opt for labour productivity over TFP because its measurement is not sensitive to different production function specifications or to the measures of capital stock and labour share.[5] Furthermore, using labour productivity affords a longer time series, which is important to ensure the robustness of our estimation results. Our final sample consists of a balanced panel of 86 non-oil-producing countries, spanning the period from 1964 to 2019.

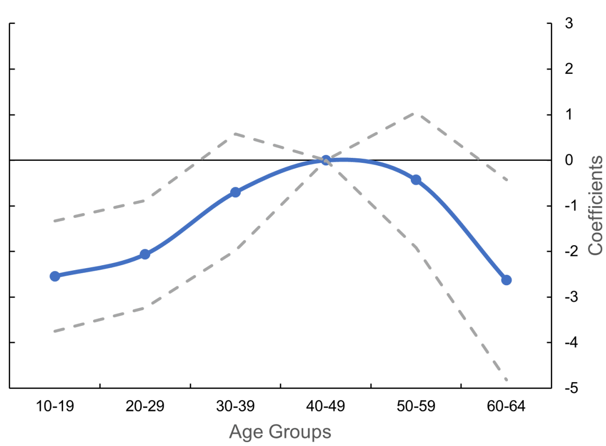
[3]The January 2024 vintage of the CBO demographic projections includes sizable population revisions due to an increase in the number of illegal immigrants entering the United States in the last two to three years. Looking ahead, these updated projections indicate more favourable demographic tailwinds than those embedded in the World Population Prospects dataset, which excludes recent increase in immigration.

[4]The full Penn World Table 10.01 dataset provides consistent inputs to produce TFP estimates for 183 countries between 1950 and 2019.

[5]**Table A.2** in the **Appendix** shows the estimated impact on TFP constructed using the Penn World Table 10.01.

Main findings **Chart 1** shows the coefficients estimated for each age group in equation 1 for the sample period 1964–2019, which represents each group's contribution to productivity (the 40–49 age group is normalized to zero). The estimates and standard errors can be found in column 4 of **Table 1**. **Chart 1** highlights a notable difference in contributions to labour productivity across different age groups, with a peak between the ages of 40 and 49. This pattern remains consistent across various sample periods used for estimation, as evidenced in **Table 1**. In addition, **Table 1** indicates that a 1% increase in the dependency ratio correlates to a reduction of 0.35 to 0.47 percentage points in labour productivity growth. As a comparison, Liu and Westelius (2016) finds that in Japan, a 1% rise in the dependency ratio leads to a decrease of 0.8 percentage points in TFP. In the **Appendix**, we report the estimation results using the sample of countries in the Organisation for Economic Co-operation and Development (OECD) in **Table A.1**. While the qualitative pattern remains consistent with the OECD sample, the magnitude of the estimated coefficients is generally smaller than the full sample.

Chart 1: Contribution to labour productivity by age group



Note: The blue line shows estimated coefficients from equation 1 using a dataset of 86 countries (estimates and standard errors can be found in column 4 of **Table 1**). Estimates for the 40–49 age group are normalized to 0. The two gray dashed lines represent the 95% confidence intervals. Sources: Penn World Table 10.1, United Nations (2022) and authors' calculations.

Table A.3 in the **Appendix** complements the baseline regressions by including changes in labour market participation rates for both men and women over the age of 15. These adjustments lead to minimal changes in the estimates, which is reassuring given the significant increase in labour force participation rates for women observed during our sample period. This increase might affect the composition of the labour force and, consequently, measures of labour productivity. For instance, Dunbar and Easton (2013) demonstrate that accounting for shifts in the parental composition of the US labour force—specifically, variations in the proportion of households with one or two working parents—could explain approximately 50% of the productivity downturn in the 1970s and the subsequent rise in the 1990s. In our baseline regression, we do not control for labour force participation rates to avoid potential biases stemming from the endogeneity of labour force participation to concurrent productivity dynamics. Nonetheless, **Table A.3** confirms that our baseline results remain robust even when including controls for the labour force participation margins.

Table 1: Effects of demographic structure on labour productivity

	(1)	(2)	(3)	(4)
Δw_{10}	-3.345***	-2.893***	-2.847***	-2.544***
	(0.895)	(0.758)	(0.693)	(0.617)
Δw_{20}	-2.338**	-1.846**	-2.252***	-2.065***
	(0.961)	(0.762)	(0.699)	(0.601)
Δw_{30}	-1.163	-0.600	-0.534	-0.701
	(0.984)	(0.859)	(0.754)	(0.651)
Δw_{50}	-1.058	0.263	-0.321	-0.431
	(1.234)	(1.038)	(0.895)	(0.758)
Δw_{60}	-2.632	-1.989	-3.298**	-2.623**
	(1.731)	(1.685)	(1.361)	(1.118)
Δ log depden	-0.469***	-0.349**	-0.437***	-0.456***
	(0.157)	(0.141)	(0.127)	(0.106)
Sample period	1964–89	1964–99	1964–2009	1964–2019
N	430	602	774	946
R^2	0.147	0.106	0.114	0.112

Note: This table displays the estimated coefficients from the regression equation 1 for a sample of 86 countries over different sample periods. Standard errors are shown in parentheses. * is significant at 10%, ** significant at 5% and *** significant at 1%.

Overall, our regression estimates reaffirm the findings of Feyrer (2007) and are broadly consistent with more recent estimates discussed in Aiyar et al. (2016) and Feyrer (2021).

As in these previous studies, our results demonstrate that demographic structure influences productivity in two distinct ways:

- Population aging, which reduces the proportion of the working-age population in the economy, is linked to negative productivity growth.
- The age composition within the working-age population has significant implications for productivity growth. Notably, the 40–49 age group contributes the most, while the 20–29 and over-60 age groups contribute significantly less. Moreover, Aiyar et al. (2016) and Feyrer (2007) both find that the majority of the impact of demographics on labour productivity comes from its effect on TFP.

3 Implications for productivity growth in major economies

We now move on to examining how demographic shifts have affected and could affect productivity growth going forward in three major economies: China, the United States and Canada. To do so, we use the most recent estimates of trend labour productivity (TLP) growth made by Bank of Canada staff (Benmoussa et al., 2024 and Devakos et al., 2024). These estimates remove business-cycle volatility from observed growth in labour productivity to better capture slow-moving underlying dynamics, giving us a clearer picture of where labour productivity has been. Moreover, these sources provide projections of TLP out to 2027, which can be compared with demographic factors extrapolated using UN population projections (United Nations 2022b). Specifically, TLP estimates for the United States and China are obtained from Benmoussa et al. (2024), and estimates for Canada are taken from Devakos et al. (2024).[6] Demographic factors, including the impact of the age composition

[6]The TLP growth estimates obtained from these sources are then projected backward using trends from available official data computed using a Hodrick-Prescott (HP) filter, and historical employment estimates from the Penn World Table 10.01 in the case of China.

of the workforce and the dependency ratio, are also reported as trends to better align with the concept and statistical properties of TLP.[7]

China As shown in **Chart 2**, the share of individuals aged 40–49 within the working-age population grew consistently during the 1990s and 2000s, before peaking around 2012. However, the share has declined in recent years. The expansion was largely at the expense of younger cohorts, resulting in an improvement in the dependency ratio. Given the results in the previous section, this pattern suggests that demographic changes positively impacted productivity growth in the 1990s and 2000s. However, during the 2010s, the contribution from the age composition of the workforce was likely minimal or even negative. At the same time, dependency began to increase as a growing share of the population entered retirement. The data in **Chart 3**, which plots the decadal contribution to TLP growth resulting from changes in demographic composition, support this claim.[8] The results show that productivity growth due to demographic changes made sizable contributions to the measured increase in Chinese labour productivity growth from the 1980s to the early 2000s but became a modest drag over the course of the 2010s.

Table 2 helps explain the productivity dynamics by quantifying the role demographics could be playing. To do this, we compare TLP growth across several different historical periods. Column 1 indicates that TLP growth differs across time, following the broad contours of Chinese economic development. TLP growth accelerates sharply from less than 3%

[7] Trends for demographic variables are computed using an HP filter with a standard parameterization for the annual frequency (lambda = 100; see for example Backus and Kehoe, 1992). Our broad conclusions on the evolution of demographic factors are robust to the use of alternative statistical methods to compute the trend, including the HP-filter parameterization of Ravn and Uhlig (2002) and the bandpass filter of Christiano and Fitzgerald (2003).

[8] TLP growth estimates from 2001 to 2027 are Bank of Canada estimates reported in Benmoussa et al. (2024). Before 2001, TLP estimates are based on a combination of HP-filtered official data and Penn World Table 10.01 estimates. We use the estimates from **Table 1**, column 4, and population data from the UN World Population Prospects database to predict the impacts of aging and age composition on labour productivity growth. We then apply the HP filter to obtain their trends. We obtain the decomposition by subtracting the trend age composition and aging effects from TLP growth. **Chart 3** reports decadal averages.

Chart 2: Demographic drivers of labour productivity growth in China

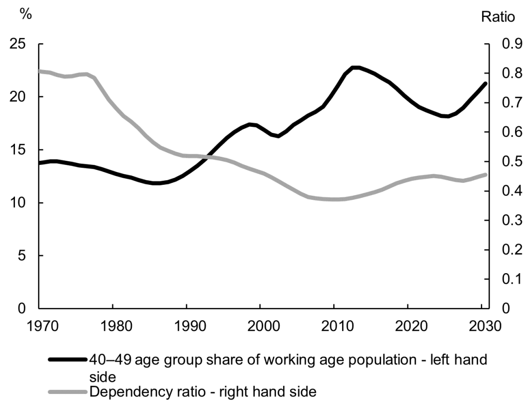
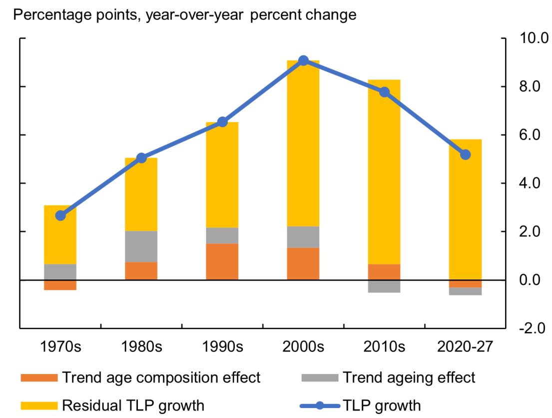


Chart 3: Decomposition of trend labour productivity growth in China



Note: **Chart 2** plots the share of China's working-age population in the 40–49 age group (left-hand side) and the dependency ratio, which is defined as the population not aged 15 to 64 divided by the population aged 15 to 64 (right-hand side). Sources: United Nations (2022) and author's calculations. **Chart 3** plots the decomposition of China's trend labour productivity (TLP) growth into three components: trend age composition effect, trend aging effect and a residual term. Sources: United Nations (2022), estimates from column 4 of **Table 1** and authors' calculations. These values are then HP-filtered to obtain the trends.

per year in the 1970s to a peak of 9% in the 2000s, before slowing somewhat in the 2010s. Column 2 suggests that demography may have contributed significantly to the acceleration from the 1980s through to the early 2000s, rising from roughly 0 percentage points in the 1970s to over 2 percentage points by the end of the period. The counterfactual TLP growth rates—once we fix the demographic structure—still point to a durable acceleration following Deng Xiaoping's sweeping economic reforms starting in the late 1970s (**Table 2**, column 5).[9] More recently, the observed slowdown in TLP over the 2010s in China could be largely attributed to unfavourable developments in the demographic structure. Considering the impact of demographics thus provides us with a new perspective to understand historical productivity dynamics in China.

Looking ahead, demographic shifts are anticipated to weigh on China's TLP over the remainder of the decade. As shown in **Chart 4**, demographic factors are projected to subtract about 0.7 percentage points from the annual TLP growth over 2023–30. While the

[9]As discussed by Zhu (2012), China has experienced a dramatic acceleration in growth of real GDP per capita since 1978, driven primarily by productivity growth rather than capital investment.

Table 2: Contribution of demographic factors to trend labour productivity growth in China

	TLP growth	Total	Age composition effect	Aging effect	Counterfactual
1970s	2.7	0.2	-0.4	0.7	2.4
1980s	5.1	2.0	0.8	1.3	3.0
1990s	6.5	2.2	1.5	0.7	4.4
2000s	9.1	2.2	1.3	0.9	6.9
2010s	7.8	0.2	0.7	-0.5	7.6
2020–27	5.2	-0.6	-0.3	-0.3	5.8

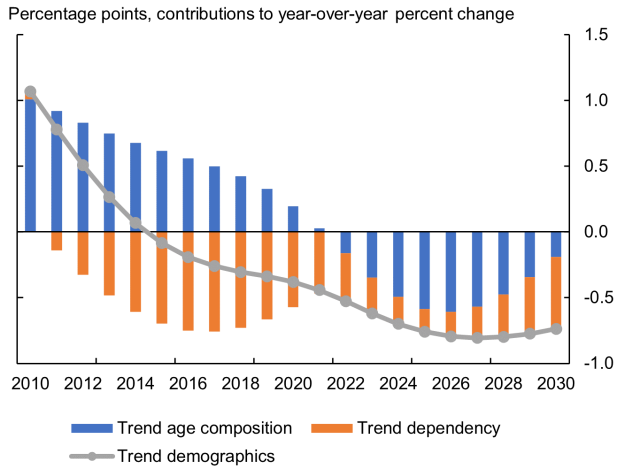
Note: This table displays the trend labour productivity (TLP) growth in China in the data (column 2), the estimated demographic contribution to TLP growth (columns 3–5), and a counterfactual TLP growth where the demographic contributions are removed from the data (column 6). Growth rates are shown as percent and demographic contributions are shown as percentage points. TLP growth estimates from 2001–27 are estimates reported in Benmoussa et al. (2024). Before 2001, TLP estimates are based on a combination of HP-filtered official data and Penn World Tables 10.01 data. The demographic contributions are constructed using the estimates from column 4 of **Table 1** and the population data from the UN World Population Prospects database.

drag from shifts in the age composition of the working-age population is set to lessen over the second half of the decade, this will be largely offset by the effects of an increase in China's dependency ratio. If we incorporate these demographic headwinds into the projections for TLP growth by Benmoussa et al. (2024), projected TLP growth would be reduced from 4.9% to 4.2% over 2023–27. Roughly three-fifths of the downgrade would be due to an increasingly suboptimal age composition of the workforce. In short, China's demographic composition could significantly intensify potential growth headwinds because of a shrinking working-age population.

United States Much as in China, the United States also benefited from demographic dividends in the later parts of the 20th century. As shown in **Chart 5**, demographic drivers may have contributed strongly to TLP growth in the 1980s as members of the baby boomer generation entered their forties. In the 2000s, the dependency and age-composition effects began to wane, likely resulting in a drag on TLP growth. **Chart 6** shows that demographic factors played an important role in holding up TLP growth in the 1980s and 1990s, before contributing to a steady decline through the 2000s and 2010s.[10] In particular, tailwinds

[10] TLP growth estimates from 2001 to 2027 are those reported in Benmoussa et al. (2024). Before 2001, TLP estimates are based on data from the US Bureau of Labor Statistics to which we apply an HP-filter.

Chart 4: Projected contributions from demographic drivers in China



Note: **Chart 4** displays the projected demographic contribution to trend labour productivity (TLP) growth in China for the period 2010–30. Sources: United Nations (2022), estimates from column 4 of **Table 1** and authors' calculations. These values are then HP-filtered and displayed in this figure.

from the shifting age composition of the workforce may have laid the groundwork for rapid labour productivity growth during the early phases of the information and communications technology revolution in the 1980s.

Chart 5: Demographic drivers of US labour productivity growth

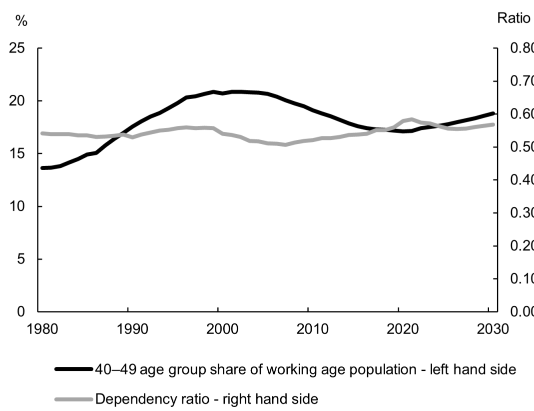
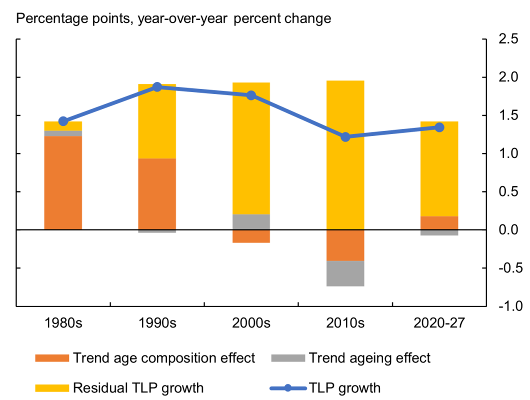


Chart 6: Decomposition of US trend labour productivity growth



Note: **Chart 5** plots the share of the US working-age population that is 40–49 (left-hand side) and dependency ratio (right-hand side). Sources: Congressional Budget Office, US Census Bureau and author's calculations. **Chart 6** plots the decomposition of US trend labour productivity (TLP) growth into three components: trend age composition effect, trend aging effect and a residual term. TLP growth estimates from 2001 to 2027 are those reported in Benmoussa et al. (2024). Before 2001, TLP estimates are based on HP-filtered data obtained from the US Bureau of Labor Statistics. Sources: Congressional Budget Office, US Census Bureau, estimates from column 4 of **Table 1** and authors' calculations. These values are then HP-filtered to obtain the trends.

Contributions to the growth of the demographic factors are reported as HP-filtered trends.

Table 3: Contribution of demographic factors to trend labour productivity growth in the United States

	TLP growth	Total	Age composition effect	Aging effect	Counterfactual
1980s	1.4	1.3	1.2	0.1	0.1
1990s	1.9	0.9	0.9	0.0	1.0
2000s	1.8	0.0	-0.2	0.2	1.7
2010s	1.2	-0.7	-0.4	-0.3	2.0
2020–27	1.3	0.1	0.2	-0.1	1.2

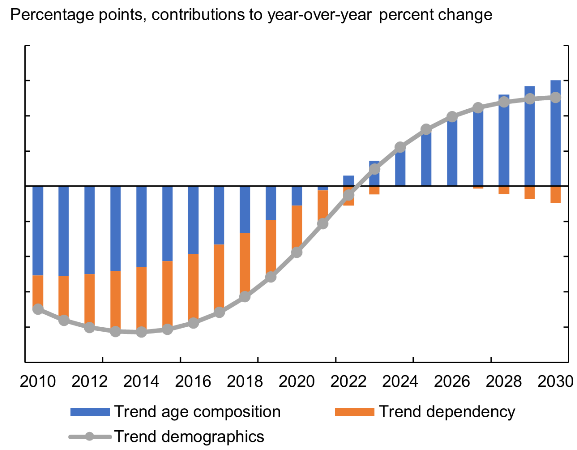
Note: This table displays trend labour productivity (TLP) growth in the United States in the data (column 2), the estimated demographic contribution to TLP growth (columns 3–5) and a counterfactual TLP growth where the demographic contributions are removed from the data (column 6). Growth rates are shown as percent and demographic contributions are shown as percentage points. The demographic contributions are constructed using the estimates from column 4 of **Table 1** and the population data from the 2020 US Census and the Congressional Budget Office.

Similar to **Table 2** for China, **Table 3** quantifies by decade the demographic drivers of TLP growth in the United States.[11] The contribution to TLP growth from demographic drivers peaks at 1.3% in the 1980s. These factors, in particular the age composition of the workforce, then contribute disproportionately to the estimated decline in TLP from the 1990s through to the 2010s. Excluding the contributions from demographics, TLP growth would have strengthened from 1% in the 1990s to an average of 1.8% over the early 2000s and the 2010s. Over the period of 2015 to 2025, our estimated demographic drag of 0.3 percentage points on labour productivity growth is somewhat smaller than that implied by Aksoy et al. (2019). The authors estimate that demographics could reduce potential output growth by about 0.6 percentage points on average across OECD countries.

The decadal averages presented above mask a steady improvement in the contribution from demographics that began in the mid-2010s. After reaching a trough of -0.4 percentage points around 2015, the drag from an aging population should have fully dissipated by 2023. Meanwhile, the contribution from the age composition of the workforce is set to rise steadily, reaching 0.5 percentage points per year by 2028 (**Chart 7**). The renewed tailwind

[11] TLP growth estimates for the United States are obtained by backcasting estimates reported in Benmoussa et al. (2024) using an HP-filtered trend of output per hours worked provided by the US Bureau of Labor Statistics.

Chart 7: Projected contribution from demographic drivers in the United States



Note: **Chart 7** displays the projected demographic contribution to trend labour productivity (TLP) growth in the United States for the period 2010–30. Sources: Congressional Budget Office, US Census Bureau, estimates from column 4 of **Table 1** and authors' calculations. These values are then HP-filtered.

from demographic composition aligns with millennials reaching an age associated with peak labour productivity.[12] Following the counterfactual exercise applied to China, we incorporate demographic tailwinds in the TLP growth projection embedded in Benmoussa et al. (2024). The results show that projected TLP growth would increase on average by 0.3 percentage points over 2023–27, from 1.4% to 1.7%, and could rise even further in the second half of the decade. Thus, despite headwinds from an aging population, demographics represent a meaningful upside risk to TLP growth in the United States over the outlook.

Canada Similar to the situation in the United States, TLP growth in Canada benefited significantly from demographic tailwinds in the 1980s and the 1990s as the baby boomers entered their most productive years (**Chart 8** and **Chart 9**). These benefits dissipated in the early 2000s, with the contribution turning sharply negative in the 2010s, just like in the United States.

The relative stability of average TLP growth in Canada from the 1980s to the 2010s

[12] A millennial is defined as anyone born in the period 1981–96. Therefore, the first millennials would have entered the 40–49 age cohort in 2021.

Chart 8: Demographic drivers of labour productivity growth in Canada

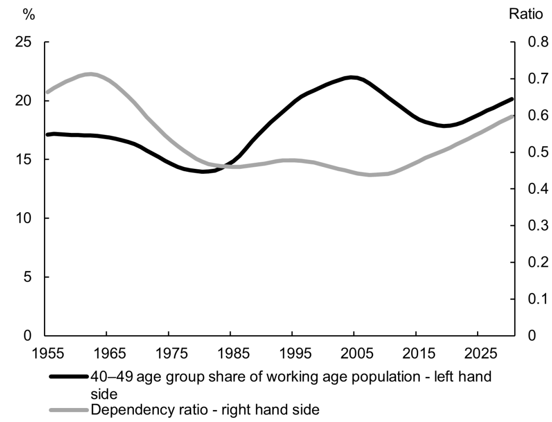
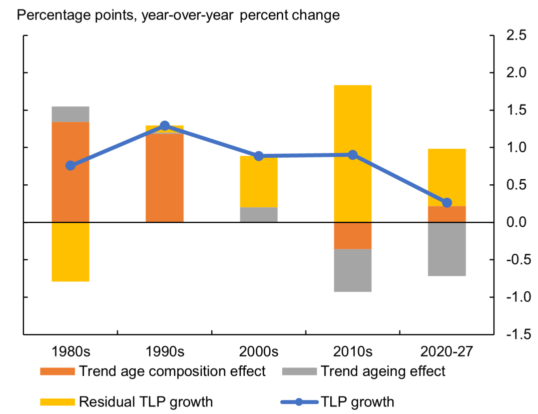


Chart 9: Decomposition of trend labour productivity growth in Canada



Note: **Chart 8** plots the share of Canada's working age population in the 40–49 age group (left-hand side) and the dependency ratio (right-hand side). Sources: United Nations (2022) and author's calculations. **Chart 9** plots the decomposition of Canada's trend labour productivity (TLP) growth into three components: trend age composition effect, trend aging effect and a residual term. Sources: United Nations (2022), estimates from column 4 of **Table 1** and authors' calculations. These values are then HP-filtered to obtain the trends.

masks a marked deterioration in the contribution from demographics (**Table 4**).[13] The contribution decreased from 1.5 percentage points in the 1980s to -0.9 percentage points in the 2010s. This decline mostly reflects an increasingly unfavourable age composition of the workforce, with the broader aging of the Canadian population playing a lesser role (**Table 4**, columns 2, 3 and 4). Excluding demographic effects, TLP growth in Canada would have accelerated meaningfully over the last four decades (**Table 4**, column 5).

Lastly, demographics should be a headwind to TLP growth over the next several years. However, the age composition of the workforce is expected to become increasingly conducive to stronger TLP growth (**Chart 10**). The reason is that more millennials will be entering their 40s, which we estimate to be their peak productivity years.

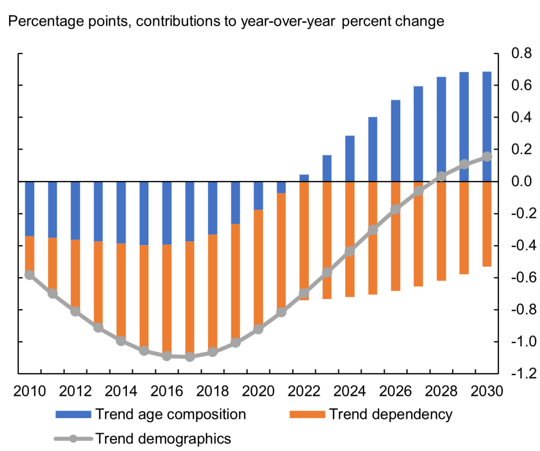
[13]TLP growth estimates for Canada are obtained by backcasting estimates reported in Devakos et al. (2024) using an HP-filtered trend of output per employed person that we calculated using official data from Statistics Canada.

Table 4: Contribution of demographic factors to trend labour productivity growth in Canada

	TLP growth	Total	Age composition effect	Aging effect	Counterfactual
1980s	0.8	1.5	1.3	0.2	-0.8
1990s	1.3	1.2	1.2	0.0	0.1
2000s	0.9	0.2	0.0	0.2	0.7
2010s	0.9	-0.9	-0.4	-0.6	1.8
2020–27	0.3	-0.5	0.2	-0.7	0.8

Note: This table displays the trend labour productivity (TLP) growth in Canada in the data (column 2), the estimated demographic contribution to TLP growth (columns 3–5), and a counterfactual TLP growth where the demographic contributions are removed from the data (column 6). Growth rates are shown as percent and demographic contributions are shown as percentage points. TLP growth estimates for Canada are obtained by backcasting estimates reported in Devakos et al. (2024) using an HP-filtered trend of output per employed person that we calculated using official data from Statistics Canada. The demographic contributions are constructed using the estimates from column 4 of **Table 1** and population data from the UN World Population Prospects database.

Chart 10: Projected contribution to trend labour productivity from demographic drivers in Canada



Note: Chart 10 displays the projected demographic contribution to trend labour productivity growth in Canada for the period 2010–30. Sources: United Nations (2022), estimates from column 4 of **Table 1** and authors' calculations. These values are then HP-filtered.

4 Concluding remarks

Few concepts are as consequential for understanding the macroeconomy as demographic transitions. This paper serves as an initial exploration of the role of demographic factors in shaping potential output beyond merely considering the size of the working-age population. We emphasize the significant impact age composition has on productivity dynamics across several major economies. Central to these findings is a key insight from Feyrer (2007): that different age groups contribute differently to aggregate productivity, with the 40–49 age group being the most productive. We reaffirm this finding by replicating and extending the original Feyrer (2007) analysis using nearly 30 years of additional data. In doing so, we also discover the highly significant headwind of a rising dependency ratio on labour productivity growth across countries.

We combine the findings from our updated Feyrer regressions with available population projections to forecast the demographic drivers of TLP over the remainder of the decade. In the case of China, TLP growth is likely to face significant headwinds from a combination of aging and age composition. This suggests downside risks to potential output growth in China beyond an accelerating decline in the size of the working-age population. In contrast, TLP growth in the United States is set to benefit from an increasingly favourable age composition of the workforce, pointing to modest upside risks to potential output growth in the second half of the decade.

Canada falls somewhere in between our results for China and the United States. Although it is expected to benefit from an improved age composition of the workforce, Canada will likely face much more pronounced headwinds from population aging than the United States, resulting in a minimal demographic tailwind later in the decade. That said, the 2022 UN population projections that underlie our demographic predictions for Canada do not account for the remarkable surge in immigration since 2021. Future iterations of our estimates incorporating this development may thus show a stronger demographic contribution to labour productivity growth over the coming decades.

Appendix

A Alternative specifications of the baseline regressions

As a robustness exercise, we ran several different specifications of the benchmark regressions. **Table A.1** presents the outcomes of estimating equation 1, with the sample limited to countries in the Organisation for Economic Co-operation and Development (OECD). In **Table A.2**, log total factor productivity (TFP) is used as the dependent variable instead of log labour productivity and applied to the full sample. TFP is calculated using real output, capital stock, employment, human capital and labour share from the Penn World Table 10.01, based on the assumptions of a Cobb-Douglas production function. **Table A.3** adds controls for changes in labour force participation rates for men and women over the age of 15. Column 1 reproduces the benchmark regression results for the period 1964–2019. The subsequent two columns introduce changes in labour force participation rates for women only (column 2) and for both men and women (column 3). Due to missing data on labour force participation rates, columns 2 and 3 are estimated using an unbalanced panel. For comparison, columns 4–6 present analogous results to columns 1–3 but for a balanced panel of countries, meaning we drop from the sample countries with missing values for labour force participation rates.

Table A.1: Effects of demographic structure on labour productivity, OECD sample

	(1)	(2)	(3)	(4)
Δw_{10}	-2.577**	-1.895**	-1.965**	-1.663**
	(1.030)	(0.870)	(0.766)	(0.698)
Δw_{20}	-3.229***	-2.161***	-2.244***	-1.851***
	(0.955)	(0.790)	(0.701)	(0.604)
Δw_{30}	-2.089**	-0.991	-1.044	-0.832
	(0.898)	(0.740)	(0.666)	(0.576)
Δw_{50}	-1.172	0.0439	0.102	-0.181
	(1.042)	(0.782)	(0.698)	(0.626)
Δw_{60}	-1.122	-0.251	0.0946	-0.124
	(1.532)	(1.307)	(1.052)	(0.927)
Δ log depden	-0.0154	-0.00147	-0.108	-0.186
	(0.201)	(0.160)	(0.141)	(0.127)
Sample period	1964–89	1964–99	1964–2009	1964–2019
N	145	203	261	319
R^2	0.269	0.210	0.210	0.218

Note: This table displays the estimated coefficients from the regression equation 1 for a sample of 29 OECD countries of different sample periods. Standard errors are shown in parentheses.

Table A.2: Effects of demographic structure on total factor productivity

	(1)	(2)	(3)	(4)
Δw_{10}	-1.355	-0.483	-0.637	-0.255
	(1.001)	(0.846)	(0.787)	(0.702)
Δw_{20}	-1.778	0.0709	-0.670	-0.280
	(1.083)	(0.849)	(0.794)	(0.685)
Δw_{30}	-1.082	-0.0209	-0.215	-0.218
	(1.086)	(0.939)	(0.840)	(0.726)
Δw_{50}	-2.204	0.267	-0.0150	0.257
	(1.351)	(1.124)	(0.988)	(0.837)
Δw_{60}	0.192	1.708	-0.447	-0.0903
	(1.887)	(1.818)	(1.499)	(1.233)
$\Delta \log depden$	-0.452**	-0.155	-0.290**	-0.224*
	(0.178)	(0.158)	(0.144)	(0.122)
Sample period	1964–89	1964–99	1964–2009	1964–2019
N	370	518	666	814
R^2	0.0619	0.0250	0.0266	0.0389

Note: This table displays the estimated coefficients from the regression equation 1 for a sample of 74 countries of different sample periods. The dependent variable is log total factor productivity (TFP), where TFP is constructed using Penn World Tables 10.01 data on real output, capital stock, employment, labour share and human capital, assuming a Cobb-Douglas production function. Standard errors are shown in parentheses.

Table A.3: Effects of demographic structure on labour productivity, controlling for labour force participation rates of individuals over the age of 15

	(1)	(2)	(3)	(4)	(5)	(6)
Δw_{10}	-2.544***	-2.588***	-2.584***	-2.067***	-2.066***	-2.062***
	(0.617)	(0.654)	(0.655)	(0.696)	(0.697)	(0.697)
Δw_{20}	-2.065***	-2.192***	-2.180***	-1.708**	-1.706**	-1.687**
	(0.601)	(0.635)	(0.636)	(0.681)	(0.683)	(0.683)
Δw_{30}	-0.701	-0.601	-0.591	-0.633	-0.631	-0.619
	(0.651)	(0.690)	(0.690)	(0.730)	(0.733)	(0.733)
Δw_{50}	-0.431	-0.207	-0.194	0.0518	0.0522	0.0627
	(0.758)	(0.797)	(0.798)	(0.831)	(0.832)	(0.832)
Δw_{60}	-2.623**	-2.340**	-2.351**	-1.775	-1.773	-1.834
	(1.118)	(1.187)	(1.188)	(1.227)	(1.229)	(1.231)
$\Delta \log dependent$	-0.456***	-0.423***	-0.424***	-0.339***	-0.339***	-0.344***
	(0.106)	(0.116)	(0.116)	(0.121)	(0.121)	(0.121)
Δfemale $l_f pr$	-0.000795	-0.00105	-0.000454	-0.000618		
	(0.000857)	(0.00103)	(0.00101)	(0.00117)		
Δmale $l_f pr$	0.000429	0.000972				
	(0.000950)	(0.000985)				
Sample period	1964–2019	1964–2019	1964–2019	1964–2019	1964–2019	1964–2019
Balanced panel	Y	N	N	Y	Y	Y
N	946	863	863	671	671	671
R^2	0.112	0.116	0.115	0.102	0.101	0.101

Note: This table displays the estimated coefficients from the regression equation 1 with additional controls for labour force participation rates for men and women. Column 1 replicates the baseline regression for the sample period 1964–2019. Columns 2 and 3 add controls for changes in labour force participation rates in an unbalanced sample (due to missing values in the labour force participation data). Columns 4–6 are analogous to the first three columns, but we impose a balanced sample. Standard errors are shown in parentheses.

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