Assessing the Impact of Demographic Composition on Productivity*

Justin-Damien Guénette
Bank of Canada

Lin Shao
Bank of Canada

October 29, 2024

Abstract

This paper examines how demographic factors affect potential output, focusing on how the age distribution of the working-age population and old-age dependence affect aggregate productivity. Based on Feyrer (2007), we emphasize that the contribution to aggregate productivity varies by age group, with middle-aged individuals (aged 40-49) being the most productive. According to our analysis, changes in demographic composition could explain some of the productivity trends observed in China, the U.S. and Canada, indicating the importance of incorporating 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 over the remainder of the decade (2024-2030). On average, TLP growth in China could be reduced by 0.8 percentage point, while that in the United States could rise by 0.1 percentage point. Moreover, Canadian demographic factors tell a similar story to those 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.

JEL Codes: J11, O47, O51.

Keywords: Age composition, dependency ratio, labour productivity, potential output.

*For helpful comments, we thank audiences at the Bank of Canada and the Productivity Conference. Tania Chaar and Aidan Spencer provided excellent research assistance. All remaining errors are our own. The views expressed in this paper are solely those of the authors and may differ from the official Bank of Canada views. Correspondence: Bank of Canada, 234 Wellington Street, Ottawa, ON K1A 0G9, Canada. jdguenette@bank-banque-canada.ca, lshao@bank-banque-canada.ca.

1 Introduction

The working-age population is a key determinant of economic output. At the global level, its growth has declined steadily in recent decades and is expected to slow further in coming years (United Nations, 2022b). The broad-based decline in the contribution from the labour input will place downward pressure on global potential output growth (Benmousa et al. 2024; Celik et al., 2023). At the same time, populations are ageing which has also been associated with weaker trend growth and productivity (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 accelerated ageing—as evidenced by the rapid increase in its dependency ratio.

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—and since it shows up in the residual of standard production functions—labour productivity and total factor productivity (TFP).[1] For instance, research by James Feyrer and others suggests that certain age groups, notably the 40-49 cohort, contribute disproportionately to the level of productivity. Therefore, an increase in the share of workers in that age group could help cushion the impact of declining population growth and rising old age dependency on potential output growth. Indeed, in this note, we demonstrate that considering the age composition of the working-age population is crucial for assessing the impact of demographic structure on productivity growth,

[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 proxied by the working age population (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). To the extent that variations in the age composition of the aggregate workforce would influence trend output, they will show up in the total factor productivity residual (A).

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 cross-country panel dataset from 86 non-oil producing countries, spanning 1964-2019. Following the methodology developed by Feyrer (2007), we exploit variations in demographic structure across countries and over time, focusing on two distinct dimensions: 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. On the other hand, within the working-age population, the contribution to productivity varies across age groups, with the 40-49 age group contributing the most, while the younger (20s) and older (60s) age groups contribute significantly less. These results are found to be robust across different periods and subsets of countries, and they hold with additional controls such as labour participation rates.

Analyzing the impact of population composition on productivity is insightful because a country's population structure is largely pre-determined 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 decompose the observed trend labour productivity growth into three components: (i) growth due to changes in the age composition of the working-age population, (ii) growth due to changes in the dependency ratio, which we label as an aging effect, and (iii) residual labour productivity growth not explained by demographic factors.

We find that demographic structure has played a significant role in driving productivity growth in the US, China, and Canada. In the 1980s, US productivity benefited significantly from a relatively stable dependency ratio and an improving age composition as the Baby

Boomer generation entered their 40s. Demographic factors continued to support productivity growth well into the 1990s, but their impact has declined and turned negative in the 2010s. Similarly, Canada experienced demographic dynamics akin to the US over the past few decades. Accordingly, Canadian productivity significantly benefited from demographic tailwinds in the 1980s and 1990s, but also saw the demographic advantage dissipate in the 2000s and turn sharply negative during the 2010s. As for the case of China, during the 1990s and 2000s, the share of individuals aged 40-49 consistently grew, peaking around 2012 before declining steadily in recent years. This expansion, largely at the expense of younger cohorts, resulted in a reduction in the old-age dependency ratio. Consequently, demographic changes positively impacted productivity growth in the 1990s and 2000s, but by the 2010s, the contribution of demography had significantly declined and turned negative.

Looking ahead into the 2020s, 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 more notable for China, but less so for the US, which benefits from a recent influx of international migration.[2] However, all three countries can expect an eventual boost in productivity growth from an improvement in age composition, as millennials reach an age associated with peak productivity. Taking into account both the aging and composition effects, our results show that demographics represent a meaningful upside risk to US trend labour productivity growth for the period 2023-2030. On the other hand, 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. The case of Canada falls somewhere in between the US and China, where the overall effect is small but becomes positive towards the end of the 2020s.

[2]Like the US, Canada has experienced a recent rise in international migration. However, our current Canadian population data from the UN Population Prospects database has not yet accounted for this increase. We expect this recent wave of immigration to similarly benefit Canada's demographic structure, such as by reducing its dependency ratio, as observed in the US data.

Related literature. Our study belongs to the long strand of literature on the impact of demography on productivity growth. Previous studies have documented the relationship between dependency ratio, age composition, and aggregate productivity, and have examined the underlying mechanisms behind these relationships. As productivity growth relies on people generating new ideas, Jones (2022) argues that a positive population growth rate 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 working-age population growth, and an increase in the dependency ratio, would lead to lower productivity growth.

A slowdown in the growth of 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). In addition, Ouimet and Zarutskie (2014) found that young firms tend to hire young workers disproportionately, and 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 a slower-growing working-age population and aging demographics would put downward pressure on productivity.

Our paper is closely related to Feyrer (2007), where the author emphasizes the contribution to productivity varies across age groups, with the middle-aged group, most notably the 40-49 age group, being the most productive. To understand the hump-shaped relationship between productivity and age, Feyrer (2021) emphasized the life-cycle patterns of innovation activities. Young individuals often require time to study and train to reach the forefront of innovation, making it challenging for them to be the main driver of innovation. On the other hand, cognitive ability tends to decline with age. 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-aged demographic in affecting entrepreneurship and, in turn, the aggregate economic activities and productivity. Azoulay et al. (2020), for instance, found that the average founder age of the fastest-growing firms is 45.

Lastly, similar to the approach in Feyrer (2007) and Feyrer (2021), we utilize 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's work by using a larger sample of countries and the most recent data, applying the framework to the US, China, and Canada—three important countries that are relevant from the perspective of economic policymaking 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.

For the remainder of this note, we first estimate the impact of the demographic structure on productivity in Section 2, following the framework developed by Feyrer (2007). We examine the implications of demographic structure on productivity growth in China, the United States and Canada in Section 3 using the estimates in Section 2. Section 4 concludes with a discussion of possible future works on this topic.

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

We will now provide 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 cross-country panel dataset, 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 (15-19, 20-29, ..., 50-59, 60+) as well as the log dependency ratio.[3] 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 the contribution of each age group and the dependency ratio to overall productivity.

Feyrer (2007) suggests that demographic measures are well-suited for conducting cross-country growth regressions for two reasons. First, a country's demographic structure is mostly predetermined, and the age composition of the working-age population was determined about 20 years ago and is not influenced by current productivity dynamics.[4] Second, demographic transitions have happened or are happening in all countries at varying rates and times (see Delventhal et al., 2021). This generates a substantial heterogeneity in demo-

[3]The dependency ratio is defined as the ratio of the non-working-age population to the working-age population. The working-age population comprises individuals aged 15-64.

[4]It is worth noting that current productivity dynamics may influence immigration levels—and thus demographic structures. However, immigration is typically not substantial enough to materially alter demographics, except in specific historical episodes. We run our estimation across different sample periods and country groups. If immigration—more pronounced in certain periods and regions—were affecting the results, this would be reflected in the estimates. We find it reassuring that our results remain robust, indicating that the impact of immigration is limited.

graphic structures across countries and over time.

Data and measurement. We replicate the Feyrer (2007) estimation using more recent data. Data on demographic structure for China and Canada are taken from the United Nations' World Population Prospects database (United Nations, 2022a), which reports population size by five-year age group. In the case of the United States, the demographic structure is based on a combination of census data and recent Congressional Budget Office projections.[5] For the purpose of estimation, labour productivity measures are constructed using information from the Penn World Tables 10.01, henceforth referred to as PWT (Feenstra et al., 2015).[6] In this note, we focus on labour productivity, defined as real GDP per worker. We opt for labour productivity over TFP because its measurement is not sensitive to different production function specifications and to the measures of capital stock and labour share.[7] Furthermore, the use of 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.

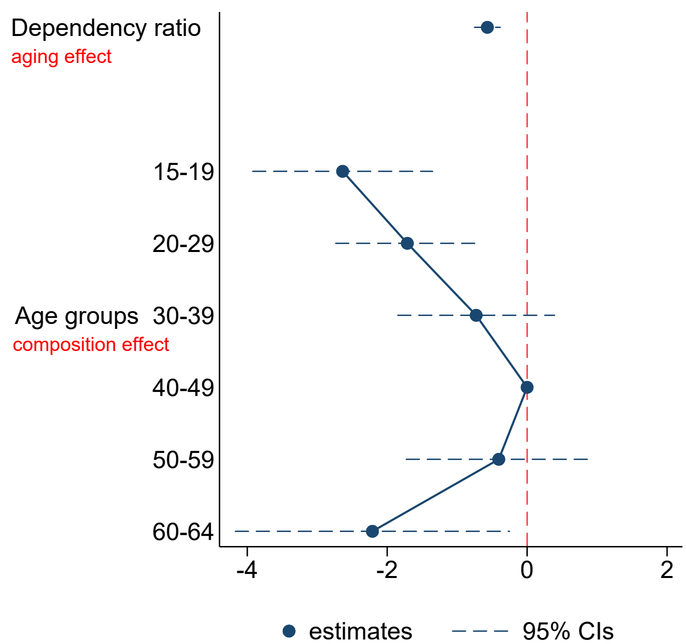
Main findings. Figure 1 presents the estimated coefficients for the working-age dependency rate (aging effect) and each age group (composition effect) from Equation (1) for the sample period 1964–2019, showing each group's contribution to productivity (with ages 40–49 normalized to zero). The estimates and standard errors can be found in column (4) of Table 1. The graph highlights that there is a notable difference in labour productivity contribution across different age groups, with a peak at ages 40-49. This pattern remains consistent across various sample periods used for estimation, as evidenced in Table 1. In

[5]The January 2024 vintage of the CBO demographic projections embed sizable population revisions related to increased illegal immigration. Looking ahead, these updated projections indicate more favourable demographic tailwinds than those embedded in the 2022 vintage of the UN's World Population Prospects database.

[6]The full PWT dataset provides consistent inputs to produce TFP estimates for 183 countries between 1950 and 2019.

[7]Appendix Table A.2 reports the estimated impact on TFP constructed using the PWT.

Figure 1: Contribution of demographic structure to labour productivity, $\hat{\beta}$



Notes: This figure shows the vector of estimated coefficients $\hat{\beta}$ from equation Equation 1 using a cross-country dataset of 86 countries (estimates and se can be found in table 1 column 4). Estimates (represented by the blue dots) are normalized to 0 for age group 40-49. The blue dashed line represents the 95% confidence interval. Data are taken from the Penn World Table 10.1 and the United Nation's World Population Database.

addition, Table 1 indicates that a one percent increase in the dependency ratio correlates with a reduction in labour productivity growth of 0.35 to 0.47 percentage points. As a comparison, Liu and Westelius (2016) found that in Japan, a one percent rise in the dependency ratio leads to a 0.8 percentage point decrease in TFP. The R^2 in our estimations ranges from 0.12 to 0.17, indicating that, on average, 12 to 17 percent of productivity growth across countries can be attributed to demographic factors.[8] In the Appendix Table A.1, we report the estimation results using the sample of OECD countries. While the qualitative pattern remains consistent with the OECD sample, the magnitude of the estimated coefficients is generally smaller compared to the full sample. In Appendix section B, we apply the OECD estimates to examine the role of demographics in the US and Canada. While the influence

[8]The finding that much of the productivity growth across countries is not explained by demographics is consistent with our expectations, as many other factors—such as technological diffusion, FDI, and economic policies—can significantly influence labour productivity growth.

of demographics is generally smaller under this alternative setup, the key message remains unchanged.

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 female labour force participation 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) demonstrated that accounting for shifts in the parental composition of the labour force in the US—specifically, variations in the proportion of households with dual or single 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 contemporaneous productivity dynamics. Nonetheless, Table A.3 confirms that our baseline results remain robust even when including controls of the labour force participation margins.

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. First, population aging, which results in a diminishing proportion of the working-age population in the economy, is linked to negative productivity growth. Second, the age composition within the working-age population itself has significant implications for productivity growth. Notably, the 40-49 age group contributes the most, while the younger (20s) and older (60s) 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.

Table 1: Effects of demographic structure on labour productivity

	(1)	(2)	(3)	(4)
ΔW_{10}	-3.779***	-3.152***	-2.968***	-2.637***
	(0.933)	(0.804)	(0.732)	(0.659)
ΔW_{20}	-2.033**	-1.537**	-1.901***	-1.712***
	(0.826)	(0.665)	(0.612)	(0.526)
ΔW_{30}	-1.208	-0.708	-0.630	-0.728
	(0.856)	(0.750)	(0.663)	(0.575)
ΔW_{50}	-1.145	0.046	-0.393	-0.405
	(1.068)	(0.912)	(0.793)	(0.678)
ΔW_{60}	-2.325	-1.827	-2.917**	-2.211**
	(1.507)	(1.477)	(1.210)	(1.003)
Δ log depen	-0.642***	-0.527***	-0.583***	-0.568***
	(0.142)	(0.129)	(0.115)	(0.097)
Sample	1964-1989	1964-1999	1964-2009	1964-2019
N	430	602	774	946
R^2	0.170	0.121	0.127	0.125

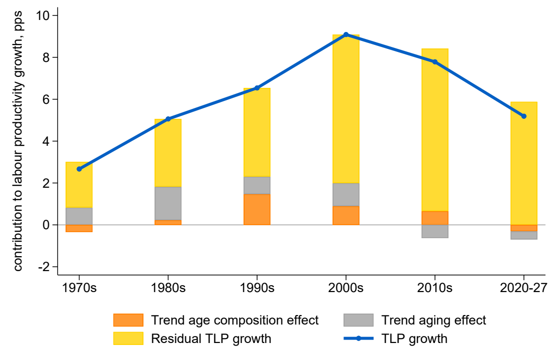
Notes: This table displays the estimated coefficients from the regression Equation 1 for a sample of 86 countries of different sample periods. Standard errors are shown in the parentheses.

3 Implications for productivity growth in major economies

As we now understand the contribution of each age group and have population composition data from the UN, we can examine how demographic shifts have affected and will affect, productivity growth in three major economies: China, the United States and Canada. In order to do so, we first gather publicly-available estimates of trend labour productivity (TLP) growth from Staff Analytical Notes provided by the Bank of Canada (Benmoussa et al., 2024 and Devakos et al., 2024). These estimates remove business-cycle volatility from observed labour productivity growth 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

Figure 2: Demographic drivers of labour productivity growth in China

Figure 3: China TLP Growth Decomposition



Notes: Figure 2 plots the share of the 40–49 age group working-age population (left) and the working-age dependency ratio (right) for each year from 1970 to 2030. The working-age population includes individuals aged 15 to 64, while the dependency ratio is the ratio of the non-working-age population to the working-age population. Demographic data are taken from the UN Population Prospects Database. Figure 3 plots the decomposition of China's trend labour productivity (TLP) growth into three components: trend age composition effect, trend ageing effect and a residual term. The demographic factors are calculated using estimates from Table 1, Column (4), and the UN population data. These values are then HP-filtered to obtain the trends.

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).[9] Demographic factors, including the impact of the age composition of the workforce and the dependency ratio, are also reported as trends to better align with the concept and statistical properties of TLP.[10]

China. As the black line in Figure 2 shows, during the 1990s and 2000s, the share of individuals aged 40-49 within the working-age population consistently grew, peaking around 2012 before declining steadily in recent years.[11] This expansion was largely at the expense

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

[10]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).

[11]The share of the 40–49 age group in China exhibits more variability over time than in the US and Canada. This may be due to China's unique population dynamics, which have been shaped by several significant historical events. Following the population losses of World War II, the establishment of the People's Republic and a relatively stable environment led to a baby boom. However, this was disrupted by the Great Famine of 1959–1961, which resulted in high mortality and a decline in births. The introduction of the One-Child Policy in the 1980s further accelerated a decline in birth rates. These shifts occurred alongside

of younger cohorts, resulting in an improvement in the old-age 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 declined. At the same time, old age dependency began to increase as a growing share of the population entered retirement. Figure 3, which plots the decadal contribution to TLP growth resulting from changes in demographic composition, supports this claim.[12] It shows that productivity growth due to demographic changes contributed sizably to the measured increase in Chinese labour productivity growth from the 1980s to the 2000s, but became a modest drag over the course of the 2010s.

Table 2: Contribution of demographic factors to TLP growth in China

		Demographics contribution to growth, of which:			
	TLP growth	total	age composition effect	ageing effect	counterfactual
1970s	2.7	0.5	-0.3	0.8	2.2
1980s	5.1	1.8	0.2	1.6	3.2
1990s	6.5	2.3	1.5	0.8	4.2
2000s	9.1	2.0	0.9	1.1	7.1
2010s	7.8	0.0	0.7	-0.6	7.8
2020-27	5.2	-0.7	-0.3	-0.4	5.9

Notes: This table displays the trend labour productivity (TLP) growth in China in the data (Column 2), the estimated demographic contribution to growth (ctg) of TLP (Columns 3–5), and a counterfactual TLP growth (Column 6) where the demographic contributions are removed from the data, i.e., the difference between Columns 2 and 3. Note that the counterfactual and demographic contributions may not add up to TLP growth due to rounding. TLP growth from 2001–2027 are Bank of Canada estimates reported in Benmoussa et al. (2024). Prior to 2001, TLP estimates are based on a combination of HP filtered official data and PWT data. The demographic contributions are constructed using the estimates from Column (4) of Table 1 and the population data from the UN Population Prospects Database.

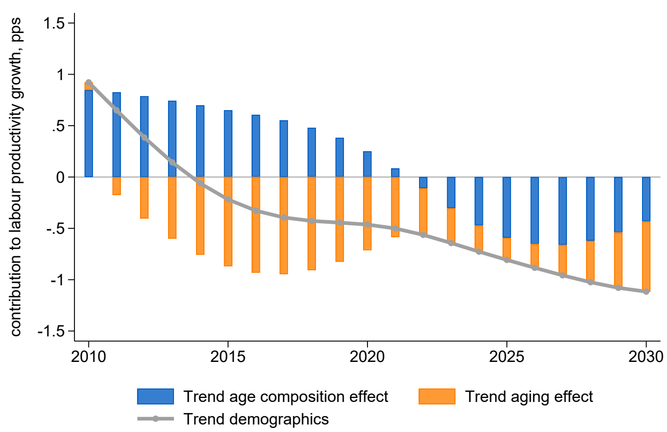
Table 2 quantifies the role demographics could be playing in explaining productivity dynamics in China. To do this, we compare TLP growth across several different historical

a long-term reduction in mortality rates associated with economic development. Together, these factors may account for the less smooth pattern observed in the 40–49 age share.

[12] TLP growth from 2001 to 2027 are Bank of Canada estimates reported in Benmoussa et al. (2024). Prior to 2001, TLP estimates are based on a combination of HP-filtered official data and PWT estimates. We use the estimates from Table 1, column (4), and population data from the UN Population Prospect Database to predict the impacts of aging and age composition on labour productivity growth and apply the HP filter to obtain their trends. The decomposition is obtained by subtracting the trend age composition and ageing effects from the trend labour productivity growth. The figure reports decadal averages.

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 percent per year in the 1970s to a peak of 9 percent in the 2000s, before slowing somewhat in the 2010s. Column (2) suggests that demography may have contributed significantly to the acceleration of the 1980s through the 2000s, with the contribution increasing from roughly 0 in the 1970s to over 2 percentage points. 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 (Column 5).[13] More recently, the observed slowdown in TLP over the 2010s in China could be largely attributed to unfavorable developments in the demographic structure. Considering the impact of demographics thus provides us with a new perspective to understand historical productivity dynamics in China.

Figure 4: Projected contribution from demographic drivers in China



Notes: Figure 4 displays the projected demographic contribution to trend labour productivity (TLP) growth in China for the period 2010–2030. The contributions are calculated using estimates from Table 1, Column (4), and the projected population data from the UN Population Prospects Database. These values are then HP-filtered and displayed in this figure.

Looking ahead, demographic shifts are anticipated to weigh on China's TLP over the remainder of the decade. As shown in Figure 4, demographic factors are projected to subtract about 0.9 percentage points to the annual trend labour productivity over 2023-30. While the drag from shifts in the age composition of the working-age population is set to lessen

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

over the second half of the decade, this will be more than offset by the effects of an increase in China's dependency ratio. If we incorporate these demographic headwinds in the TLP growth projection of Benmoussa et al. (2024), projected TLP growth would be reduced from 4.8 percent to 3.9 percent over 2023-27. Nearly three-quarters of the downgrade would be due to a less favourable age composition of the workforce. In short, China's Demographic composition could thus be expected to significantly intensify potential growth headwinds from China's 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 Figure 5, demographic drivers may have contributed strongly to TLP in the 1980s as the Baby Boomer generation entered their 40s. In the 2000s, the dependency and age-composition effects began to wane, likely resulting in a drag on TLP. Figure 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.[14] The disproportionate contribution of demographics in the 1980s likely reflects in part headwinds to TLP growth from several cyclical developments in the early 1980s, including two recessions. later on, tailwinds from the shifting age composition of the workforce may have laid the groundwork for rapid labour productivity growth during the early phases of the ICT revolution.

Similar to Table 2 for China, Table 3 provides decadal quantification for the demographic drivers of TLP growth in the United States.[15] The contribution to TLP growth from demographic drivers peaks at 1.1 percent in the 1980s.[16] These factors, in particular the age

[14]TLP growth from 2001 to 2027 are estimates reported in Benmoussa et al. (2024). Prior to 2001, TLP estimates are based on HP-filtered data obtained from the US Bureau of Labour Statistics. Contributions to the growth of the demographic factors are reported as HP-filtered trends.

[15]TLP growth estimates for the United States are obtained by backcasting Bank of Canada 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.

[16]During the 1980s, the US economy encountered several cyclical headwinds from non-demographic factors, such as the oil shock of the late 1970s and the recessions of 1980 and 1982, while the demographic structure improved significantly, with a rise in the share of the 40–49 age group and a declining dependency ratio.

Figure 5: Demographic drivers of labour productivity growth in the US

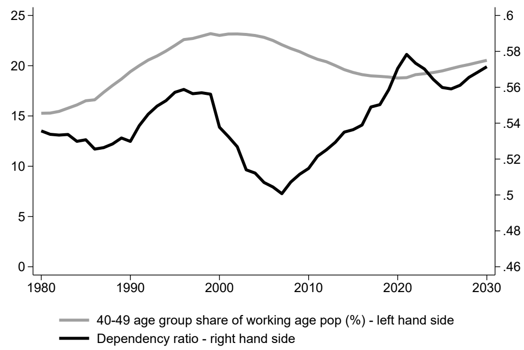
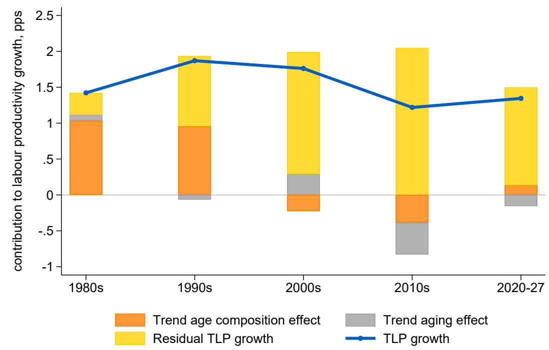


Figure 6: US TLP Growth Decomposition



Notes: Figure 5 plots the share of the 40–49 age group in the US working-age population (left) and the working-age dependency ratio (right) for each year from 1980 to 2030. The working-age population includes individuals aged 15 to 64, while the dependency ratio is the ratio of the non-working-age population to the working-age population. Figure 6 plots the decomposition of US trend labour productivity (TLP) growth into three components: trend age composition effect, trend ageing effect, and a residual term. TLP growth from 2001 to 2027 are estimates reported in Benmoussa et al. (2024). Prior to 2001, TLP estimates are based on HP-filtered data obtained from the US Bureau of Labour Statistics. The demographic factors are calculated using estimates from Table 1, Column (4), and population data from the Census and CBO. These values are then HP-filtered to obtain the trends.

Table 3: Contribution of demographic factors to TLP growth in the United States

		Demographics contribution to growth, of which:			
	TLP growth	total	age composition effect	ageing effect	counterfactual
1980s	1.4	1.1	1.0	0.1	0.3
1990s	1.9	0.9	1.0	-0.1	1.0
2000s	1.8	0.1	-0.2	0.3	1.7
2010s	1.2	-0.8	-0.4	-0.4	2.0
2020-27	1.3	0.0	0.1	-0.2	1.4

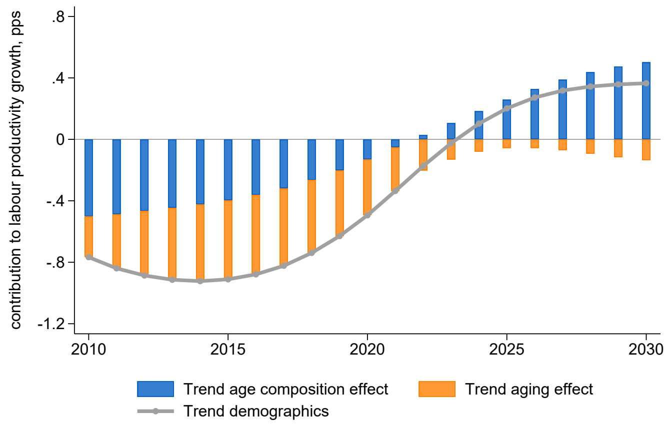
Notes: This table displays the trend labour productivity (TLP) growth in the US in the data (Column 2), the estimated demographic contribution to TLP growth (Columns 3–5), and a counterfactual TLP growth where the demographic contributions are removed from the data (Column 6), i.e., the difference between Columns 2 and 3. Note that the counterfactual and demographic contributions may not add up to TLP growth due to rounding. The demographic contributions are constructed using the estimates from Column (4) of Table 1 and the population data from the Census and CBO.

composition of the workforce, then contribute disproportionately to the estimated decline in TLP from the 1990s through the 2010s. Excluding the contributions from demographics, TLP growth would have strengthened from 1 percentage point in the 1990s to an average of 1.9 percent over the 2000s and the 2010s. Over the period of 2015 to 2025, our estimated de-

These changes may explain why demographic factors accounted for a substantial share of overall growth during this period (1.1 out of 1.4 percent).

mographic drag of 0.4 percentage points on labour productivity growth is somewhat smaller than that implied by Aksoy et al. (2019), which estimates that demographics could reduce potential output growth by about 0.6 percentage points on average across OECD countries.

Figure 7: Projected contribution from demographic drivers in the US



Notes: Figure 7 displays the projected demographic contribution to trend labour productivity (TLP) growth in the US for the period 2010–2030. The contributions are calculated using estimates from Table 1, Column (4), and the projected population data from the Census and CBO. These values are then HP-filtered and displayed in this figure.

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 -0.5 percentage point in around 2015, the drag from an ageing population is set to have almost fully dissipated by 2023. Meanwhile, the contribution from the age composition of the workforce is set to rise steadily, reaching 0.5 percentage point per year by 2029 (Figure 7). The renewed tailwind from demographic composition aligns with millennials reaching an age associated with peak labour productivity.[17] Following the counterfactual exercise applied for China above, if we incorporate demographic tailwinds in the TLP growth projection embedded in Benmoussa et al. (2024), projected TLP growth would be increased by 0.2 percentage point on average over 2024-27, from 1.4 percent to 1.6 percent, and could rise even further in the second half of the decade. Thus, despite headwinds from an ageing population, demographics represent a meaningful upside risk to US TLP growth over the outlook.

[17]A millennial is defined as anyone born over the period of 1981-1996. As such, the millennial generation would begin entering the 40-49 age cohort in 2021.

Canada. Similar to the United States, TLP growth in Canada benefited significantly from demographic tailwinds in the 1980s and the 1990s as the Baby Boomer generation entered their most productive years (Figures 8 and 9). As in the United States, the benefits from demographics dissipated in the 2000s with the contribution turning sharply negative in the 2010s.

Figure 8: Demographic drivers of labour productivity growth in Canada

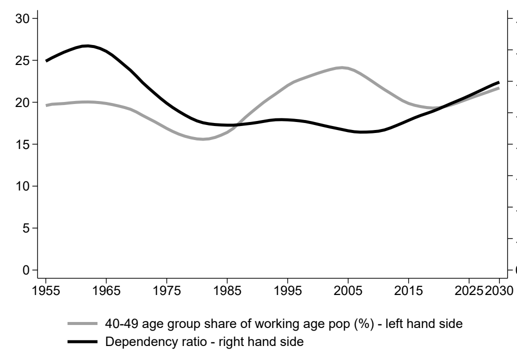
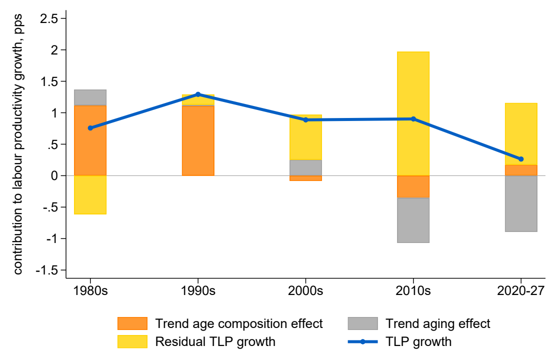


Figure 9: Canada TLP Growth Decomposition



Notes: Figure 8 plots the share of the 40–49 age group in Canada's working-age population (left) and the working-age dependency ratio (right) for each year from 1955 to 2030. The working-age population includes individuals aged 15 to 64, while the dependency ratio is the ratio of the non-working-age population to the working-age population. Demographic data are taken from the UN Population Prospects Database. Figure 9 plots the decomposition of Canada's trend labour productivity (TLP) growth into three components: trend age composition effect, trend ageing effect and a residual term. The demographic factors are calculated using estimates from Table 1, Column (4), and the UN population data. These values are then HP-filtered to obtain the trends.

As presented in Table 4, the relative stability of average TLP growth in Canada from the 1980s to the 2010s masks a marked deterioration in the contribution from demographics.[18] The decline in the contribution from demographics from 1.4 percentage points in the 1980s to -1.1 percentage points in the 2010s mostly reflects an increasingly unfavourable age composition of the workforce, with the broader ageing of the Canadian population playing a lesser role (Columns 2, 3 and 4). Excluding demographic effects, this implies that TLP growth in Canada would have accelerated meaningfully over the last 4 decades (Column 5).

Lastly, looking ahead over the next several years, although demographics will be a head-

[18]TLP growth estimates for Canada are obtained by backcasting Bank of Canada estimates reported in Devakos et al. (2024) using an HP-filtered trend of output per employed person computed using official StatCan data.

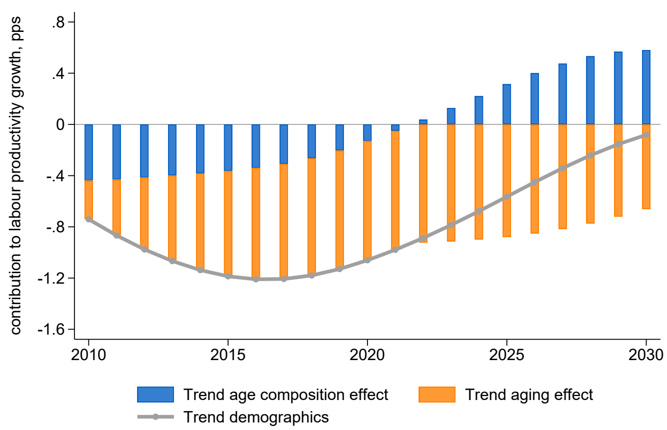
Table 4: Contribution of demographic factors to TLP growth in Canada

	TLP growth	Demographics contribution to growth, of which: total	age composition effect	ageing effect	counterfactual
1980s	0.8	1.4	1.1	0.3	-0.6
1990s	1.3	1.1	1.1	0.0	0.2
2000s	0.9	0.2	-0.1	0.3	0.7
2010s	0.9	-1.1	-0.4	-0.7	2.0
2020-27	0.3	-0.7	0.2	-0.9	1.0

Notes: 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), i.e., the difference between Columns 2 and 3. Note that the counterfactual and demographic contributions may not add up to TLP growth due to rounding. TLP growth estimates for Canada are obtained by backcasting Bank of Canada estimates reported in Devakos et al. (2024) using an HP-filtered trend of output per employed person computed using official StatCan data. The demographic contributions are constructed using the estimates from Column (4) of Table 1 and the population data from the UN Population Prospects Database.

wind overall, the age composition of the workforce is expected to become increasingly conducive to stronger TLP growth (Figure 10). This aligns with the millennial generation entering their peak productivity years (40-49).

Figure 10: Projected contribution from demographic drivers in Canada



Notes: Figure 10 displays the projected demographic contribution to trend labour productivity (TLP) growth in Canada for the period 2010–2030. The contributions are calculated using estimates from Table 1, Column (4), and the UN Population Prospects Database. These values are then HP-filtered and displayed in this figure.

4 Concluding remarks

Few concepts are as consequential as demographic transitions for understanding the macroeconomy. 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), which demonstrates that different age groups contribute differently to aggregate productivity, with the age group of 40-49 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 population ageing, defined as an increasing share of those of non-working age in the general population, on labour productivity growth across countries.

Combining the findings from our updated Feyrer regressions and available population projections, we develop projections of 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 ageing and age composition, suggesting downside risks to Chinese potential output growth beyond an accelerating decline in the working-age population. In Contrast, TLP 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.

The case of 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, it will likely face much more pronounced headwinds from population ageing than in the United States, resulting in only 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.

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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 the set of OECD countries. In Table A.2, log TFP is used as the dependent variable instead of log labour productivity, applied to the full sample. TFP is calculated using the PWT's real output, capital stock, employment, human capital, and labour share, 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, i.e., we drop countries with missing values for labour force participation rates from the sample.

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

	(1)	(2)	(3)	(4)
ΔW_{10}	-2.660**	-1.836*	-2.036**	-1.932**
	(1.210)	(1.023)	(0.885)	(0.817)
ΔW_{20}	-2.903***	-1.812***	-1.887***	-1.620***
	(0.845)	(0.695)	(0.615)	(0.533)
ΔW_{30}	-1.983**	-0.962	-0.998	-0.854
	(0.808)	(0.674)	(0.607)	(0.529)
ΔW_{50}	-1.178	-0.102	-0.053	-0.261
	(0.935)	(0.710)	(0.633)	(0.570)
ΔW_{60}	-1.069	-0.256	-0.006	-0.161
	(1.377)	(1.179)	(0.952)	(0.843)
Δ log depen	-0.086	-0.068	-0.174	-0.242**
	(0.203)	(0.158)	(0.137)	(0.121)
Sample	1964-1989	1964-1999	1964-2009	1964-2019
N	145	203	261	319
R^2	0.321	0.253	0.250	0.258

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

Table A.2: Effects of demographic structure on TFP

	(1)	(2)	(3)	(4)
ΔW_{10}	-1.364	-0.399	-0.463	-0.026
	(1.061)	(0.907)	(0.840)	(0.756)
ΔW_{20}	-1.484	0.144	-0.512	-0.184
	(0.937)	(0.743)	(0.695)	(0.602)
ΔW_{30}	-0.971	-0.052	-0.227	-0.192
	(0.951)	(0.824)	(0.741)	(0.644)
ΔW_{50}	-1.978*	0.128	-0.051	0.222
	(1.173)	(0.990)	(0.877)	(0.749)
ΔW_{60}	0.144	1.403	-0.425	-0.060
	(1.649)	(1.596)	(1.335)	(1.109)
Δ log depen	-0.459***	-0.209	-0.316**	-0.235**
	(0.165)	(0.148)	(0.133)	(0.113)
Sample	1964-1989	1964-1999	1964-2009	1964-2019
N	370	518	666	814
R^2	0.087	0.046	0.046	0.058

Notes: 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 TFP, where TFP is constructed using PWT data on real output, capital stock, employment, labour share and human capital, assuming a Cobb-Douglas production function. Standard errors are shown in the 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}	-2.637***	-2.661***	-2.653***	-2.087***	-2.085***	-2.074***
	(0.659)	(0.714)	(0.715)	(0.760)	(0.762)	(0.762)
ΔW_{20}	-1.712***	-1.844***	-1.835***	-1.408**	-1.407**	-1.390**
	(0.526)	(0.558)	(0.559)	(0.601)	(0.602)	(0.602)
ΔW_{30}	-0.728	-0.672	-0.664	-0.616	-0.614	-0.602
	(0.575)	(0.613)	(0.614)	(0.650)	(0.652)	(0.653)
ΔW_{50}	-0.405	-0.198	-0.189	-0.003	-0.003	0.004
	(0.678)	(0.714)	(0.714)	(0.744)	(0.744)	(0.744)
ΔW_{60}	-2.211**	-1.923*	-1.931*	-1.489	-1.487	-1.541
	(1.003)	(1.071)	(1.072)	(1.110)	(1.111)	(1.113)
Δ log depen	-0.568***	-0.541***	-0.542***	-0.430***	-0.430***	-0.435***
	(0.097)	(0.106)	(0.106)	(0.112)	(0.112)	(0.112)
Δfemale lfpr		-0.001	-0.001		-0.000	-0.001
		(0.001)	(0.001)		(0.001)	(0.001)
Δmale lfpr			0.000			0.001
			(0.001)			(0.001)
Sample period	1964-2019	1964-2019	1964-2019	1964-2019	1964-2019	1964-2019
Balanced sample	Y	N	N	Y	Y	Y
N	946	863	863	671	671	671
R^2	0.125	0.131	0.131	0.121	0.121	0.122

Notes: This table displays the estimated coefficients from the regression Equation 1 with additional controls of 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 additional 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 the parentheses.

B US and Canada results using estimates from the OECD subsample

B.1 United States

Table B.4: Contribution of demographic factors to TLP growth in the United States

		Demographics contribution to growth, of which:			
	TLP growth	total	age composition effect	ageing effect	counterfactual
1980s	1.4	0.7	0.6	0.0	0.7
1990s	1.9	0.8	0.8	0.0	1.1
2000s	1.8	0.4	0.3	0.1	1.4
2010s	1.2	-0.2	0.0	-0.2	1.4
2020-27	1.3	-0.1	0.0	-0.1	1.4

Notes: This table displays the trend labour productivity (TLP) growth in the US 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), i.e., the difference between Columns 2 and 3. Note that the counterfactual and demographic contributions may not add up to TLP growth due to rounding. The demographic contributions are constructed using the estimates from Column (4) of Table A.1 and the population data from the Census and CBO.

Figure B.1: US TLP Growth Decomposition

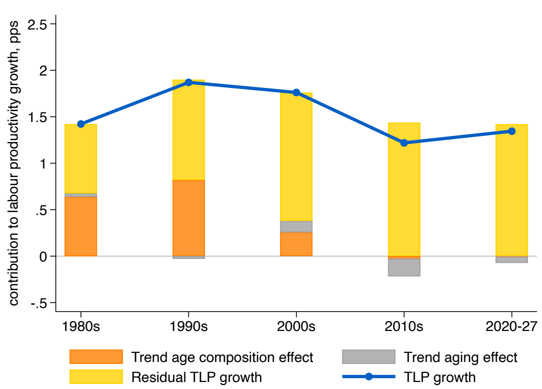
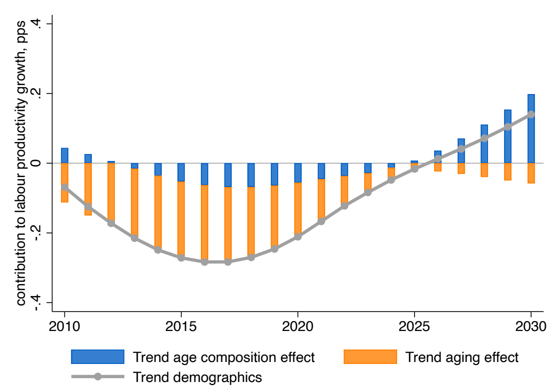


Figure B.2: Projected contribution from demographic drivers in the US



Notes: Figure B.1 plots the decomposition of US trend labour productivity (TLP) growth into three components: trend age composition effect, trend ageing effect and a residual term. TLP growth from 2001 to 2027 are estimates reported in Benmoussa et al. (2024). Prior to 2001, TLP estimates are based on HP-filtered data obtained from the US Bureau of Labour Statistics. Figure B.2 displays the projected demographic contribution to trend labour productivity (TLP) growth in the US for the period 2010–2030. The demographic factors are calculated using estimates from Table A.1, Column (4), and population data from the Census and CBO. These values are then HP-filtered to obtain the trends.

B.2 Canada

Table B.5: Contribution of demographic factors to TLP growth in Canada

	TLP growth	Demographics contribution to growth, of which: total	age composition effect	ageing effect	counterfactual
1980s	0.8	0.9	0.8	0.1	-0.2
1990s	1.3	1.0	1.0	0.0	0.3
2000s	0.9	0.5	0.4	0.1	0.4
2010s	0.9	-0.3	0.0	-0.3	1.2
2020-27	0.3	-0.3	0.1	-0.4	0.6

Notes: 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), i.e., the difference between Columns 2 and 3. Note that the counterfactual and demographic contributions may not add up to TLP growth due to rounding. TLP growth estimates for Canada are obtained by backcasting Bank of Canada estimates reported in Devakos et al. (2024) using an HP-filtered trend of output per employed person computed using official StatCan data. The demographic contributions are constructed using the estimates from Column (4) of Table A.1 and the population data from the UN Population Prospects Database.

Figure B.3: Canada TLP Growth Decomposition

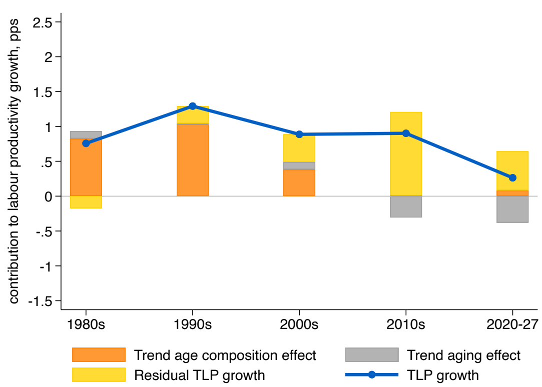
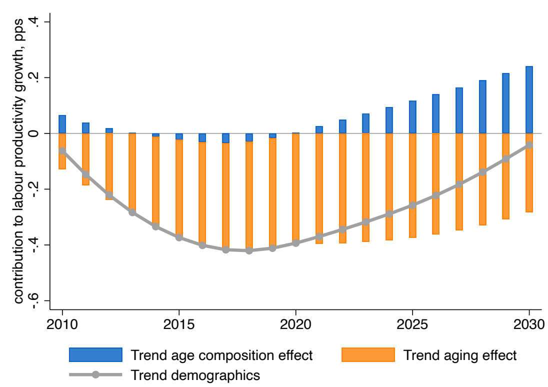


Figure B.4: Projected contribution from demographic drivers in Canada



Notes: Figure B.3 plots the decomposition of Canada's trend labour productivity (TLP) growth into three components: trend age composition effect, trend ageing effect and a residual term. Figure B.4 displays the projected demographic contribution to trend labour productivity (TLP) growth in Canada for the period 2010–2030. The demographic factors are calculated using estimates from Table A.1, Column (4), and the UN population data. These values are then HP-filtered to obtain the trends.