A Convergence of Minds? Global Migration and the Distribution of Income Within and Across Advanced Economies

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Abstract

GDP per capita for 17 Advanced Economies remains below 85% of that of the US. Underlying this are large differences in relative incomes across the AE and US income distributions: for most of the income distribution US and AE income differences are modest, but for top income earners the gap are large, with average AE top 1 percent income less than half that of the US. Using data from the World Inequality Database, we show that the top 10 percent of the income distribution can largely account for the AE-U.S. gap in GDP per capita. Our estimates of human capital stocks based on observed income show a widening gap between the US and other AEs since the 1990s and accounts for much of the measured divergence in productivity between AEs and the US. To quantify the contribution of selective emigration of high-ability workers to the US to the human capital gap, we estimate a Pareto distribution of worker ability. We find that selective migration can account for a fifth of the AE-US human capital gap, with over half of the effect due to the cumulative effect of US brain gain from multiple countries.

Keywords: Productivity, Cross Country Income Differences, Human Capital

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1 Introduction

GDP per adult in the United States was over fifteen percent higher than that of most advanced economies in 2019. The longstanding persistence in US exceptionalism is puzzling, as the advanced economies include countries with similar institutions and economic structure, have relatively low barriers to trade, capital mobility and skilled worker mobility. Despite these similarities, recent decades has seen a widening gap in GDP per capita and measured productivity between many advanced economies and the US. This has renewed interest in what accounts for higher US GDP per capita and productivity.

In this paper, we examine the contribution of differences across the income distribution to the GDP per capita gap between the US and other advanced economies. Despite an extensive literature documenting higher levels of income inequality in the US than in most other advanced economies (e.g. Atkinson et al. (2011), Saez and Veall (2005)), surprisingly little work has examined what this implies for differences in cross country income levels. We show that the systematic variation in the gaps across the income distribution is not only informative in accounting for the long-run evolution of the gap in GDP per adult between the US and other advanced economies, but also assessing the importance of cross country differences in human capital and productivity.

We further document that the US is a global talent destination: US-bound migrants from advanced economies are more likely than the US native born to be in the top income percentiles. Migrants to the USA are strongly overrepresented in top income percentiles, at the same time that the top income earners are driving the divergence in average incomes between the AEs and USA. The data strongly point to the US as a talent hub, as top earners from around globe disproportionate locate in the USA. We show that the US brain gain significantly contributes to divergence in average incomes even if brain drain from any given origin country is small because non-US advanced economies have not attracted top talent to the same degree.

We use several data sources to compare pretax income in advanced economies across the income distribution. Our primary data source for GDP and capital stocks is the Penn World Table (Feenstra et al. (2015)). We augment this with data from the World Inequality Database (WID) on the share of income of the top 1 percent, the top 2-10 percentiles, the 50-89 percentiles and the 1-49 percentiles. Although this is a relatively coarse division of the income distribution, the WID provides a long-run perspective as it is available annually from 1980-2022 for all 18 advanced economies we examine, and from 1920-2022 for some. We also use data on employee income for workers aged 25-54 from the Global Repository of Income Dynamics (GRID) over 1998-2016 to confirm that the patterns we document using the WID hold for earnings income.

We show that the top 10 percent of income earners account for nearly all of the average gap in GDP per capita between advanced economies and the US. The average income of the top 1 percent in AEs in 2019 was under half that of the U.S., while the next 9 percentiles average under 70 percent of US incomes. The counterparts to the large income gaps at the top are smaller gaps for the rest of the distribution. We show that if the top 10 percent in AEs had the same income level as their US counterparts that average GDP per adult in AEs would be nearly equal to the US.

The standard growth model offers strong implications for the relationship between cross-country income differences across the distribution and cross differences in capital per worker or productivity. The growth model implies that differences in TFP or capital per worker shift the distribution of income proportionately, so that they cannot directly account for varying cross country gaps across the income distribution. However, differences in the distribution of human capital can lead to differences in income across the distribution. Since commonly used measures of human capital based on educational attainment (such as reported in the PWT) indicate that gaps in human capital between advanced economies (and relative to the US) have steadily narrowed. This convergence in educational attainment makes it difficult to reconcile the large gaps at the top of the distribution with standard growth accounting.

The systematic differences in income levels across the income distribution that we document suggest that there are differences in the distribution of human capital across countries or cross country productivity differences that only impact high ability workers. Moreover, a widening gap in top talent located in the US could help account for the sustained higher levels of GDP per capita in the US. This motivates our construction of human capital stocks that are consistent with the distribution of income within and across advanced economies. The index we construct builds on insights from the income inequality literature (see Jones (2015) for example) as well as those characterizing the role of human capital in accounting for income differences across countries (Caselli and Coleman, 2006; Jones, 2008; Schoellman, 2012; Jones, 2014; Lagakos et al., 2018; Hendricks and Schoellman, 2018; Caselli and Ciccone, 2019; Jones, 2019; Hendricks and Schoellman, 2023). Although our measures of human capital based on the distribution of income track industry standard measures (e.g. PWT human capital per person) that we construct track the educational attainment based measures for advanced economics closely between 1950-1990, they diverge sharply after 1990. Since 1990, the distributional measure suggests that human capital per worker converges in all advanced countries - except the USA. Indeed, distributional measures of human capital per worker suggest a growing gap between the USA and other advanced economies since 1990.

The sustained exceptionalism of US GDP per capita is largely attributable to the increasing importance of the upper tail of the income (and in our accounting human capital) distribution in the USA. By 2019 as much as *three-quarters* of the human capital differences between advanced economies and the USA is attributable to differences between workers in the top 10 percentiles of the human capital distribution across countries. While surprising, the post 1990 divergence

of income based measures of human capital from educational attainment based human capital measures is intuitive. For traditional measures of human capital, the return to skill among the marginal skilled worker pins down differences in human capital across countries. The increase in top incomes, especially in the US, has widened the gap between the marginal skilled worker and the top percentiles. This rise in the relative income of the top earners, and the relative differences across countries, is parsimoniously captured by our distributional measure of human capital.

We use the canonical growth accounting framework to quantify the implications of the differential evolution of human capital per worker for income divergence across countries. Standard measures of human capital per worker imply that the gap between US incomes and those in other advanced economies are largely attributable to a growing divergence in total factor productivity. The distributional measure of human capital instead implies that TFP largely converged across all advanced economies, including the USA, by the early 1990s. As a result, the persistent income (and widening) gaps in GDP per worker between the USA and other advanced economies is largely attributable to rising differences in human capital per worker after 1990.

As a global talent hub, the US draws high-performing migrants from around the globe (e.g., Kerr et al. (2016)), leading to brain gain relative to other advanced economies. We quantify the degree to which the net emigration of high-performing workers from advanced economies to the USA can explain the income divergence between the USA and other advanced economies. Our simple decomposition exercises suggests that although the stock of (net) migrants from advanced accounts for only one percent of US residents, they may explain up to one fifth of the average income gap bewteen AEs and the US.[1] Central to this exercise is the observation that a Pareto distribution of ability that matches the right tail of income also implies that emigration of a relatively small number of high-ability workers can have significant impacts on average output. Moreover, distributional measures of human capital suggest that the marginal impact selective migration of top performers has grown sharply over the past three decades.

Our paper builds on a large literature that studies cross country gaps in GDP per capita and productivity. Our paper is closest to MacGee and Rodrigue (2025) who found that the top 10 percent of the income distribution account for the majority of the long standing gap in GDP per adult between Canada and the US.[2] Although the role of selective emigration of high-ability Canadians ("brain-drain") to the Canada-US GDP per adult gap has been long debated (e.g., Kesselman (2001), Trefler (1999)), in contrast to Helliwell (1999), they found that selective emigration could play a significant role in accounting for the Canada-US GDP gap. This paper shows that the Canada-US comparison documented by MacGee and Rodrigue

[1] While omitting migration from non-advanced economies allows us to make the clearest cross-country comparisons, to the extent that migrants are also drawn selectively from across the globe, this estimate would be biased downwards.

[2] A divergence in measured TFP has been documented during the Great Depression, which saw a more persistent decline in TFP in Canada than in the U.S. over 1929-39 (Amaral and MacGee (2002)).

(2025) holds for other advanced economies compared to the US, and that the migration of high skilled immigrants play a significant role in part due to the fact that the US is a destination for high ability migrants from many countries.

The net migration among high-income earners implied by our analysis may seem surprising. However, they are consistent with the findings of other studies of Canada and the United Kingdom. For example, Cockburn et al. (2023) document suggestive evidence that inventor migration explains the weaker relationship between productivity and patenting in Canada. Likewise, Damas de Matos and Parent (2019) report that among male immigrants to Canada aged 30–39 with a postgraduate degree, over 18 percent move to the United States within a five-year window of arrival. Damas de Matos and Parent (2019) argue that these migration patterns would be even larger for a longer time period, and thus the evidence points toward large outflows from Canada to the United States of young, highly skilled migrants. Advani et al. (2024) document that immigrants are twice as likely to be in the top percentile of the UK income distribution than in any of the bottom 97 percentiles.[3] We show that selective migration may contribute to differences in human capital and GDP between developed economies and the US.[4]

Recent studies build on this research to examine how high-skill migration contributes to innovation, productivity, and growth. Arkolakis et al. (2020) document that US immigrants were disproportionately prolific innovators between 1880 and 1920, developing a spatial quantitative model that demonstrates the substantial impact of selective migration on innovation and growth. Prato (2025) constructs a two-country model of migration and quantifies how migrant sorting across locations affects innovation, patenting, and growth in the US and EU during 1990–2010. This study reveals that concentrating top talent in specific locations generates greater innovation and income for both migrants and natives, though it also widens cross-country income differences. We complement this research by incorporating selective migration into the standard growth accounting framework and quantifying the impact of top talent migration on cross-country income differences across a broader set of countries. Moreover, we address Prato (2025)'s call for further investigation of the relationship between migration, inequality, and growth.

In this sense, our research likewise links closed-economy research on the determinants of

[3] Advani et al. (2024) further document that high-earning immigrants account for over 90 percent of the growth of the share of income accruing to the top income percentile, a particularly striking feature since the large majority of income for international migrants is labour income.

[4] Several papers document that highly educated immigrants in the US have relatively better economic performance than in other advanced economies. For example, Kaushal and Lu (2015) compare the wages on recent immigrants (within 5 years) to Canada and the US using the 1991, 2001 and 2006 Canadian Censuses and the 1990 and 2000 US Census and the 2005-2007 American Community Survey (ACS). They find that the (PPP) ratio of recent immigrants wages in Canada relative to the US fell from 14 % above the US in 1990 to 2 % below in 2006 despite a rise in the fraction of immigrants with at least a BA and English proficiency in Canada compared to the US, suggesting increased selection based on other individual characteristics in the US. This divergence took place following shifts in immigration policy in the 1990s, with an increased share of employer selected migration in the US (via H-1B visa, L-1 visa) as a result of the Immigration Act of 1990 while Canada changed the point system to put more weight on educational attainment and language proficiency.

income inequality and growth in the USA with the literature aimed at understanding cross-income differences. Indeed, recent contributions to the literature on inequality and growth highlight the role of entrepreneurs (Acemoglu et al., 2017; Jones and Kim, 2018), intangible capital (Crouzet et al., 2022a,b; Crouzet and Eberly, 2023), and ownership of physical or human capital (Goldin and Katz, 2008; Autor, 2014; Murphy and Topel, 2016; Saez and Zucman, 2016, 2020b; Auten and Splinter, 2024) for explaining the relationship between aggregate growth and inequality.

The remainder of the paper is organized as follows. Section 2 documents differences in income across the income distribution for AEs relative to the US, and the role of higher income earners in accounting for the AE-U.S. GDP per adult gap. Section 3 examines the role of high-income earners and shifts in hours worked per adult in measured relative labour productivity. In Section 3.4 we examine the implications of migration for the gaps in human capital and GDP per worker between AEs and the U.S. GDP. Section 5 concludes.

2 Advanced Economies - U.S. Income Differences

The gaps in GDP per adult between the US and most advanced economies stopped narrowing – and arguably widened – since the late 1990s. In this section, we draw on data from the Penn World Table (Feenstra et al. (2015)) and the World Inequality Database (WID) to document the role of gaps across the income distribution in accounting for gaps in GDP per adult across the advanced economies.

Our sample of advanced economies includes all countries that in 1960 had a level of GDP per adult that was at least 55 % of that of the US and a population in excess of a million. The 18 (including the US) countries that satisfy these criteria are Australia, Austria, Belgium, Canada, Denmark, Finland, France, Germany, Italy, Japan, The Netherlands, New Zealand, Norway, Spain, Sweden, Switzerland, United Kingdom, and the United States.[5]

The lower degree of income inequality in most advanced economies than in the US is well documented (e.g., see Saez and Veall (2005), Veall (2012)). The implications of these differences in inequality for differences in income across the distribution have been (surprisingly) less explored. Intuitively, the lower level of inequality in advanced economies than in the US should result in relatively smaller gaps for lower income and larger gaps for higher income earners.

We confirm that this intuition holds in the data. What is surprising is the quantitative implications of these gaps. Using data from the WID, we find that over 2010-2019 that the top ten percent of income earners essentially account for the average gap between AEs and the US in GDP per adult. As an alternative way of formalizing this, if incomes for the top 10 percent in each AE were increased to the US level in 2019, this would eliminate almost the entire gap

[5]Our sample excludes a number of countries which the IMF currently classifies as Advanced Economy: Croatia, Cyprus, Czech Republic, Estonia, Greece, Hong Kong SAR, Iceland, Ireland, Israel, Korea, Latvia, Lithuania, Luxembourg, Macao SAR, Malta, Portugal, Puerto Rico, San Marino, Singapore, Slovak Republic, Slovenia, Taiwan Province of China as well as Andorra.

in GDP per adult.

We show that this pattern of large differences in income for high-income earners and smaller gaps lower in the distribution holds in other data sources. We also document a similar pattern for employees in the GRID.

2.1 Penn World Tables

We use the Penn World Tables to document the persistent gaps in GDP per working age adult (WAP) in the US and other advanced economies. We then use data from WID to decompose the contribution across the income distribution to the lack of convergence in advanced economies. Although our analysis using the WID data focuses on the post 1980 period, we start with the PWT coverage from 1950 to 2023.

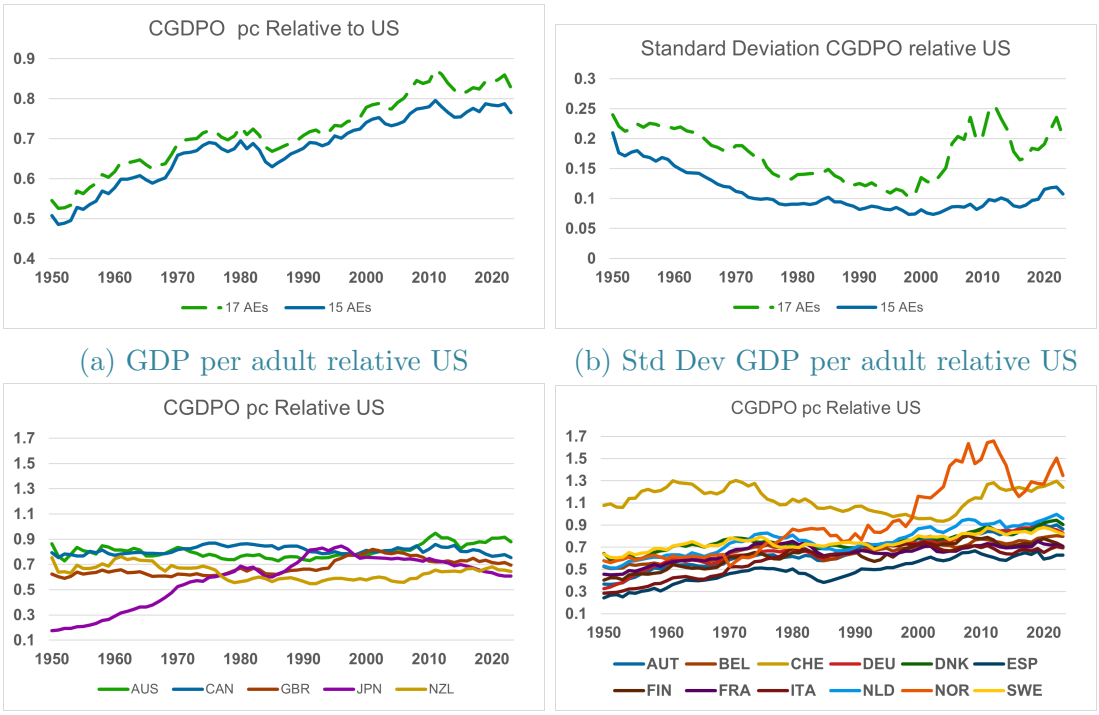
We focus on the ratio of GDP per capita in each advanced economy relative to the US. We report the mean GDP per capita relative to the US for the 17 countries we examine (see Figure 1). The PWT offers several choices of real GDP series that use alternative deflators across countries and over time. We examine the CGDPO series for two reasons. First, we most interested in comparing real output compared to the US. Feenstra et al. (2015) argue that CGDPO is the most appropriate PWT measure for comparing real output across countries within a year since it uses a common set of relative prices in each year. It also captures terms of trade effects on the real value of output. Second, we later compare the implications of our measure of human capital for the role of TFP in accounting for differences in GDP pc relative to the US. We compare our measure to the CTFP series in the PWT, which also uses CGDPO as the output measure.[6]

A striking feature is the persistence gap in GDP pe capita between AEs and the US. The aftermath of WW II saw rapid growth in AE income relative to the US, with the mean GDP pc relative to the US rising from just over half to nearly three quarters of the US. However, between 1980 and the mid 1990s there was no catch up in average AE GDP pc. Although the average gap narrowed slightly in the late 1990s and early 2000s, by the early 2020s the gap in GDP pc remained at nearly 20 percent. This break in (absolute) convergence is also apparent in the dispersion of GDP pc relative to the US. This measure declined until around 1980s, and has actually risen since around 2000 (see Figure 1.b).

The persistent gaps in GDP pc relative to the US have two exceptions: Norway and Switzerland (see Figure 1.d).[7] Excluding Norway and Switzerland, the gap in mean AE GDP relative

[6]The trends GDP relative to the US over time are similar across the 5 PWT GDP measures. The one series which points to different timing in the end of convergene with the US is the RGDPNA series which uses the 2021 PPP exchange rates from the ICP to convert real domestic GDP series for each country. However, the RGDPNA series diverges the most from the other 4 measures, with large gaps in levels relatove to the US for some countries in some years. Alternative deflators do not change the qualitative finding of stalled convergence, but do have different implications for the timing. The RGDPPE series uses the ICP to construct PPP deflators for each year, and shows a larger (but narrowing) gap than RGPNA until 2010.

[7]Norway largely reflects the growth of the oil and gas extraction since the 1970s.



(a) GDP per adult relative US

(b) Std Dev GDP per adult relative US

(c) GDP per adult relative US

(d) Std Dev GDP per adult relative US

Figure 1: Slow or No Convergence to US: AE GDP per 18-65 Relative to US, 1950-2023

Notes: The 15 AE group excludes Norway and Switzerland. All countries are equal weighted.

to the US is larger (over 20 percent) and that there is a smaller increase in dispersion of GDP relative to the US since the early 2000s. What is striking is that the range of GDP pc relative to the US of the other 15 AEs is relatively stable since the early 2000s at roughly 60 to 95 percent of the US. This is perhaps even more striking when one breaks out the 4 anglo economies where if anything the mean gap with the US was slightly larger in the 2000s than in the 1950s.[8]

2.2 The Distribution of Income in Advanced Economies

The growth model implies that differences in TFP and capital per worker across countries should manifest as proportionate gaps in income levels across the income distribution. We use data from WID to construct estimates of real GDP per adult across the income distribution. In this exercise, we focus on 1980-2019, since we have annual data for all of the countries we study since 1980. Importantly, this period also includes the slowing of convergence since 1980. We show that there are systematic differences in the gaps in income across the income distribution

[8]In general, we find that weighting countries equally or by population gives similar trends in the average of advanced economy GDP pc relative to the US. While the magnitude of the convergence is larger for our populated weighted measures between 1950 and 1980, since then the gap between the population weighted and unweighted measures have tracked each other.

between the US and AES: income is much higher for top income earners in the US than in other AEs, while the gaps in income are much smaller for the rest of the distribution.

2.2.1 World Inequality Database

The World Inequality Database (WID) reports the share of income by country for the top percentile (the 99th), the next nine percentiles (90-98), the top 50-89th percentiles, and the bottom 50 percentiles (1-49th) percentiles. The WID is part of the development of distributional national accounts (see Saez and Zucman (2020a), Blanchet et al. (2021)), and provides comparable income distribution data across countries.

The WID measure we look at is "fiscal income", which corresponds to taxable income plus income tax deductions. This yields a pre-tax income measure. The aggregate income concept in the WID is net national income (NNP).[9] In attributing shares of fiscal income to GDP, we assume that capital consumption is allocated proportionately to income. Tax systems vary across countries in whether income is reported by individual tax filers or at the household level (Veall (2012)). To make the cross country data comparable, we use the WID estimates that split taxable income between adults (aged 20 and older) within a household.[10]

2.2.2 Changes in the Distribution of Income in Advanced Economies and the U.S.

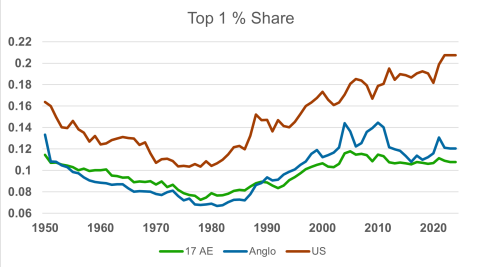
Although top income shares have risen in many countries since the 1980s, the rise has been larger in the US. This has widened the gap between the share of income going to top earners in the US and other Advanced Economies.

Top income shares in the US have risen significantly since the early 1980s, with the top 1 (10) percent share rising from roughly 11 (35) over 1980-84 to 19 (46) over 2015-19 (see Table 1 and Figure 2). The rise in top income shares in the other advanced economies has been smaller: from roughly 8 (30) to 11 (34) for the top 1 (10) percent. The widening gap in top income shares between the US and other AEs has been especially pronounced since the early 2000s, particularly for the top 1 percent (see Figures 2).[11] The mechanical counterpart to this is that the AE average bottom 90 (50) share has declined by less than in the US. As we examine in the next section, these changes in income shares relative to the US imply a widening of the income

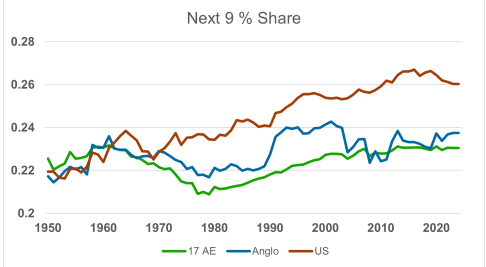
[9] Blanchet et al. (2021) outlines the methodology. Net national income accounts for roughly 82 percent of Canadian GDP. The main difference is that NNP excludes depreciation (Capital Consumption Allowance), although NNP also includes net foreign income. The WID measure of net foreign income includes imputations for income from offshore tax havens as well as reinvested income on net foreign portfolio investment.

[10] Although there is some debate over the share of labour and capital income of high income earners, several studies report that labour income is the key factor behind the surge in top incomes (Atkinson et al. (2011), Saez and Veall (2005) and Veall (2012)). This suggests that the contribution of the top percentile to the gap is not primarily driven by capital income but reflect a mix changes in income per hour worked and hours worked.

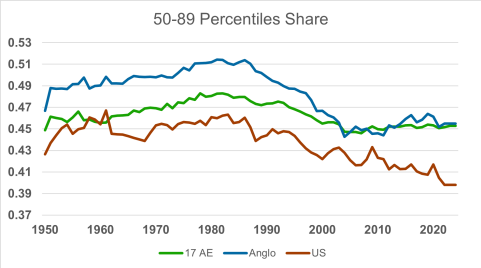
[11] The smaller rise in top income shares in Europe than in the US has been documented in the literature (e.g., Blanchet et al. (2022)).



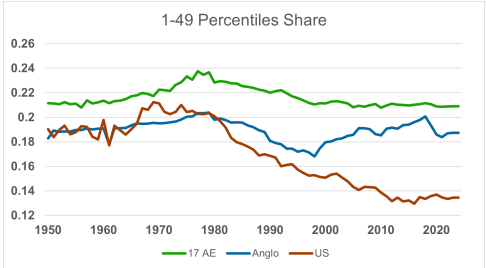
(a) Top 1 %



(b) Next 9 %



(c) 50-89



(d) Bottom 50

Figure 2: Top 1, 10-1, 50-90 and Bottom 50 Shares, 1950-2024

Notes: The income shares are from the World Inequality Database (WID). The AE mean and the Anglo means are equal weighted. Some AEs have missing data in some years between 1950 to 1980.

gaps for top income earners between advanced economies and the US.

Although we focus on the average across advanced economies relative to the US, the gaps across AEs are generally smaller across AEs than with the US.[12] There has been a startling convergence in the difference in top income shares relative to the US. Particularly striking is Switzerland: whereas the top 1 percent share in 1980 was nearly the same as that of the US, by 2019 the share was over 8 percentage points lower. This broad convergence also holds for the four angloe economies (Australia, Canada, New Zealand and the UK).[13]

2.3 Gaps in GDP per adult across the Income Distribution

To construct mean income across the income distribution, we use the income shares to allocate GDP per adult across the top 1 percent, the next 9 percent, the top 50-89 percent and the 1-49 percentiles. The ratio of income for income group i (e.g., the top 1 percentile) in AE country j is $\frac{\text{GDP per adult}^{j}}{\text{GDP per adult}^{US}} \frac{\text{Inc Share}^{j,i}}{\text{Inc Share}^{US,i}}$. Since the top incomes share are larger in the US than other advanced economies, this calculation will yield larger income gaps at the top of the income distribution than at the bottom. More interestingly, these gaps vary with shifts in income shares over time

[12] In the supplementary Appendix we plot the income shares for each country since 1980 as well as the gap with the US.

[13] MacGee and Rodrigue (2025) document similar differences in shares between Canada (which is arguably the most integrated economy with the US) and the US.

Table 1: Income Shares: 1980-85 versus 2015-19

	Top 1		Top 90-98		50-89		1-49	
	1980-84	2015-19	1980-84	2015-19	1980-84	2015-19	1980-84	2015-19
AE	0.08	0.11	0.21	0.23	0.48	0.45	0.23	0.20
US	0.11	0.19	0.24	0.27	0.46	0.41	0.19	0.13

Notes: The AE is the (equal weight) average of the 17 AES countries excluding the US. The income shares are from WID.

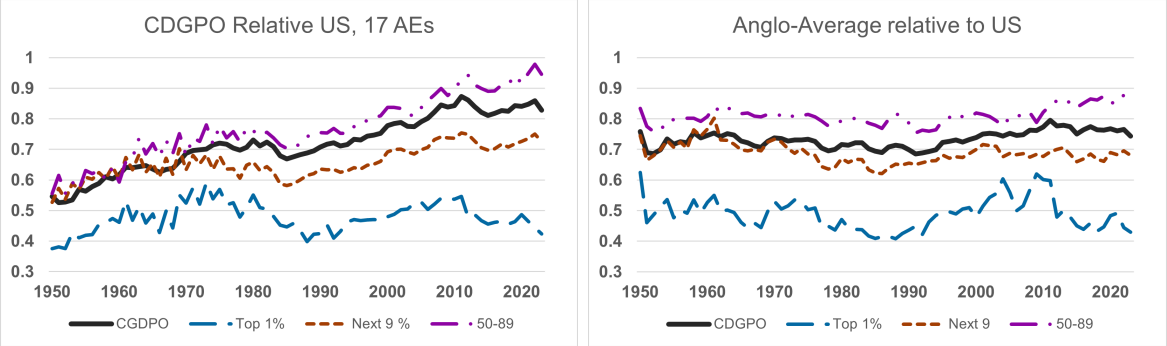
and across countries.

We plot the 17 AE average income relative to the US for each of the PPP adjusted real GDP series in Figure 3.a. As expected, the gaps in income per adult are much larger for high income earners than the gap in GDP per adult. The income of the top 1 percent in advanced economies is on average less than half that of their US counterparts, and that of the next nine percentiles is less than 75 percent of their US counterparts. Strikingly, the gaps for the top 1 percent have shown little signs of narrowing since the 1950s, and have widened since 19800, with a fall for the top 1 % between 1980 and 2019 of over 10 percentage points in AE income relative to the US. The gap for the next nine percentiles has narrowed modestly since 1980, but has remained roughly constant since 2000 at just over 70 percent of the US. In contrast, the income gap with the US for the 50 to 89 percentiles (who account for nearly half of income in the AEs) is smaller than the gap in GDP per capita. This gpa has narrowed significantly since the early 1980s, rising from roughly three quarters to over 90 % by 2020. Indeed, the gap has narrower since 2010 despite the gap in GDP pc widening.

In panel (b) we repeat this plot for the four Anglo economies.[14]The four Anglo economies, in contrast, point to very persistent gaps across the income distribution for over 75 years. This pattern is interesting for several reasons. First, unlike a number of the other AE economies, the Anglo economies did not see significant ground combat actions during WW II. As a result, there was less scope for a rapid recovery in GDP pc relative to the US as the capital stock damaged by war was rebuilt. Second, these economies share many institutional features with the US. The persistence of these gaps across the income distribution suggests that it is a persistent feature of US exceptionalism that drives the relative productivity of top income earners.

To quantify the implications of these differences across the income distribution for the persistent gap in GDP pc, we conduct a simple counterfactual where we increase the income of the top 1 and top 10 percent of each AE to the *level* of their US counterparts. In Figure 4.a we plot the counterfactuals where we impose the US income level for the top 1 percent and the entire top 10 percent. Strikingly, closing the gap for the top 10 percent of income earners would increase average GDP pc in the AEs by roughly 20 percentage points. Since the mid 2000s, this would equalize GDP pc in the 17 AEs with the US. Even when we exclude Norway and

[14]Excluding Norway and Switzerland does not significantly change the results.



(a) 17 AE Average (b) Anglo Average

Figure 3: AE-US GDP per adult across the Income Distribution

The mean AE-US GDP per adult by income group in panel a is equal weighted. The ratio of income for income group i (e.g., the top 1 percentile) in each AE j relative to the US is $\frac{\text{GDP per adult}^{j}}{\text{GDP per adult}^{US}} \frac{\text{Inc Share}^{i,i}}{\text{Inc Share}^{US,i}}$ where the shares are from WID. Panels (b) drops Norway and Switzerland from the AE average, and panel (c) plots the average of the 4 anglo economies relative to the US.

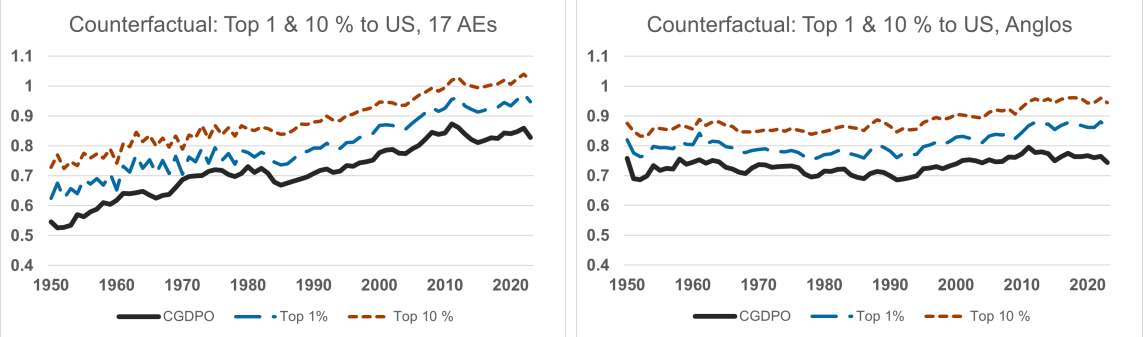
Switzerland, the top 10 percent of income earners account for nearly the entire gap in GDP pc since the mid 2000s. For the Anglo economies, the contribution of the top 10 percent of earners is even more apparent as GDP pc would have been near 90 percent of that of the US since 1950. This suggests that the persistent gap in AE GDP pa relative to the US is largely accounted for by the top 10 percent of earners.

The contribution of the top 1 % is (on average) larger than that of the next 9 percent. The importance of the top 1 % has (mechanically in our accounting) increased with the widening gap between the top income share in the US and AE. Over 1980-84, the top 1 % accounted for roughly 6 percentage points of the gap in GDP pc between the AEs and the US while the next 9 accounted for roughly 8 percentage points. By 2015-19, the top 1 % accounted for roughly 10 percentage points while the next 9 still accounted for roughly 8 percentage points. This suggests an important role for top talent, which we explore later in the paper.

2.4 Other Data Sources: GRID

The WID data has broad coverage over time and countries, but it subject to potential concerns that it mixes multiple income sources and splits income acorss household members. To examine the robustness of our findings from the WID, we this use data on employment income from the Global Repository of Income Dynamics (GRID) to compare individual-level pre-tax (employee) income across the distribution with the US.[15] We find that the GRID data implies a similar

[15]MacGee and Rodrigue (2025)compare household data from the US Survey of Consumer Finance and the Canadian Survey of Financial Security in 1998 and 2019. They find a similar picture to the WID data for households with a head aged 25-64 in 1998 and 2018: there are small gaps in income for



(a) 17 AEs (b) Anglo Economies

Figure 4: Counterfactuals where Top 1 (10) % Equalized to US

The counterfactual brings the income for the top 1 and 10 % to the same level as the US in each year and adds this to GDP per adult for the remaining 99 (90) percentiles in each AE to construct counterfactual income. Panel (a) plots the mean for the 17 AEs, Panel (b) for the 15 AEs where we exclude Norway and Switzerland and Panel (c) plots the mean of the 4 Anglo economies. All means of AE-US GDP per adult are equal weighted. The original ratio of income for income group i (e.g., the top 1 percentile) in each AE j relative to the US is $\frac{\text{GDP per adult}^{j}}{\text{GDP per adult}^{US}} \frac{\text{Inc Share}^{i,i}}{\text{Inc Share}^{US,i}}$ where the shares are from WID.

pattern of income differences relative to the US, with lower percentiles having similar (or higher) income in AEs relative to the US, and top income earners having much smaller levels.

The GRID data overs several advantages for comparing income gaps across the distribution. First, the GRID data is based on administrative records and is gross (pre-tax) employment income, which has been deflated by a domestic CPI to put it in real terms (Guvenen et al. (2014)). Since the income data is reported in 2018 local currency, we use the OECD PPP for 2018 to convert domestic currency into USD. Second, the GRID data are restricted to people aged 25-55 years who are employees, as they exclude self-employment income, and is available by age and gender. Third, there is a (modest) minimum income to be included in the data of 3 months at minimum wage for 20 hrs per wk. This allows for an income measure that is closer to labour productivity for workers with a significant attachment to the labour force.

The GRID data also have several disadvantages compared to WID. First, GRID only covers half of the advanced economies economies we examine and for a limited number of years: Canada (1998-2016); Denmark (1998-2016); France (1991-2016); Germany (2001-2016); Italy (1998-2016); Spain (2005-2018); Sweden (1998-2016), Norway (1998-2017) and the US (1998-2019). Second, although there have been efforts to make the data comparable across countries, some differences in the definition of gross taxable) income remain.[16] Furthermore, differences in the

most households but large gaps for higher income households.

[16]There are some country differences related to either the underlying administrative data as well as the definition of taxable income across countries; for example, in some US states, some corporate officers are not included; the Canadian data are examined in Bowlus et al. (2022) and the US in McKinney et al.

Table 2: Mean Difference in Income Shares to US: GRID

	Bot 50	50-89	Top 10	Top 1
Canada	3.1	2.6	-5.7	-2.6
Denmark	12.3	0.8	-13.1	-6.3
France	8.7	0.3	-8.9	-4.9
Germany	3.7	3.8	-7.5	-4.7
Italy	6.4	2.3	-8.8	-5.4
Spain	4.6	1.9	-6.6	-4.5
Norway	8.3	3.0	-11.2	-6.1
Sweden	11.0	1.4	-12.4	-6.2

Notes: Each cell is the mean of share in country j - share in US. The mean is for 2000-2016, except for Germany (2001-2016) and Spain (2005-2016). SOurce: GRID.

extensive margin of labour force participation (and the minimum income cut-off) may impact our comparison of relative income.

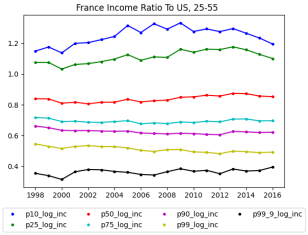
Similarly to WID, the GRID data also imply small differences in the level of income for workers lower in the income distribution and larger gaps for higher-income earners (see Figure 5). Indeed, the tenth percentile of earners has a higher income in most countries than in the US. However, earnings relative to their US counterpart in each AE decrease as one moves further to the right of the income distribution, with incomes at the top 1 percent of employees under 50 percent of the US level in all but Canada (see Figure 5b).

Similar to the WID, the income shares of top (lower) earners in the US are higher (lower) than in other AEs. To compare with the WID shares, we report the average difference between each country in GRID and the US (see Table 2). However, the difference in income shares for the top 1 percent (and the Bottom 50) in GRID is roughly half as large as in the WID. This difference is not surprising for two reasons. First, the GRID restricts attention to employed workers aged 25-55. This reduces differences in top income shares by excluding highly paid workers over 55 as well as those with business income. Second, it excludes transfers to lower paid workers.[17]

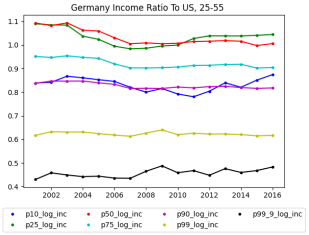
To compare the ratio of incomes relative to the US across the distribution, we use a PPP exchange rate to convert income into USD. We report our gaps across the income distribution using two sets of plot. In Figure 5, we compare the ratio of income for selected percentiles of the income distribution with the US.

(2022).

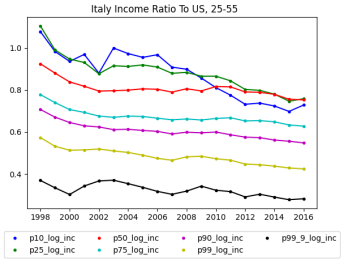
[17]Similarly to the WID, the GRID points to widening income gaps at the top of the earnings distribution. We plot the income shares for the top 1, top 10-2, 50-89, and bottom 50 percentiles over 1998-2016 in the Appendix.



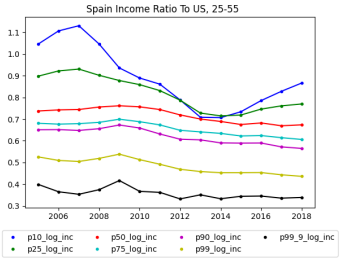
(a) France/ US



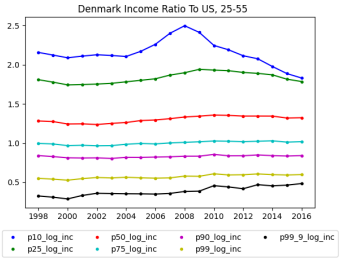
(b) Germany/U.S. Income



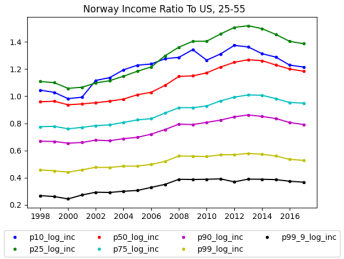
(c) Italy/U.S.



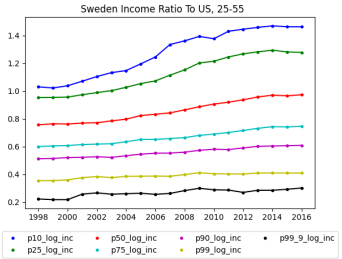
(d) Spain/U.S. Income,



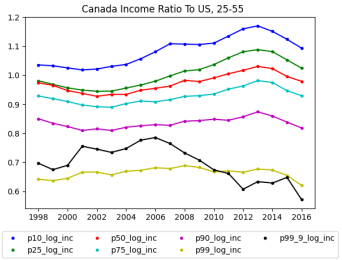
(e) Denmark/U.S. Income,



(f) Norway/U.S. Income,



(g) Sweden/US Income



(h) Canada/US Income

Figure 5: Relative Income Across Income Distribution for Employees, 1998-2016

The percentile ratios are advanced country income (converted to USD using 2018 OECD PPP) divided by US income for that percentile from GRID (GRID data uses a common base year (2018) with income deflated by CPI).

2.5 Summary: Income Gaps Across the Distribution

The gaps in AE and American income vary systematically across the income distribution. We find small differences in pretax income for lower earners and larger differences for higher income earners. This pattern holds both in the WID for total income and in the GRID for employment income. Importantly, this pattern means that the average AE-US gap in GDP per adult is largely accounted for by the top 10 percent of income earners.

2.6 Overrepresentation of Immigrants in Top US Income Percentiles

One channel that could contribute to income differences across the income distribution is selective migration. We draw on data from the Annual Social and Economic Supplement (ASEC) of the Current Population Survey (CPS) to compare individuals born in other countries living in the United States to those born in the United States.

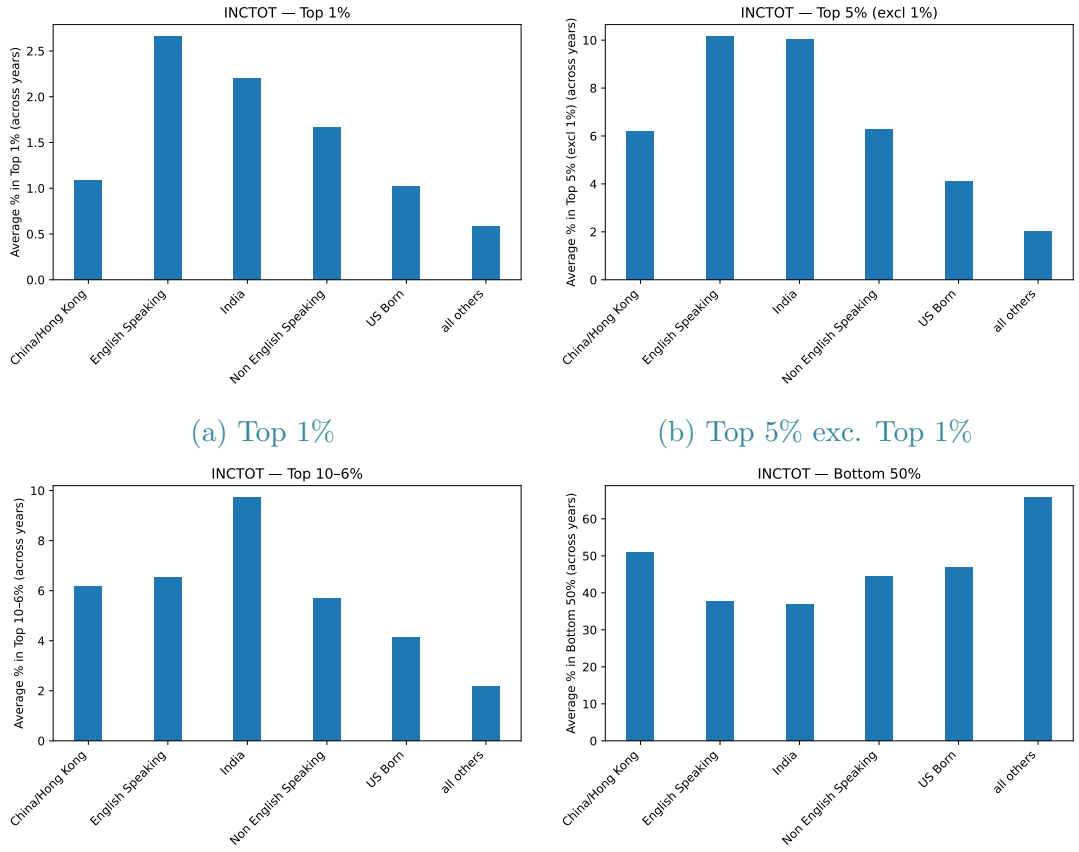
The ASEC surveys roughly 75,000 households each year between February and April (mainly in March). Importantly for our purpose, the survey asks respondents their country of birth, educational attainment, and income. The ASEC has two key limitations for our purposes. The first is that income is top coded, which limits our ability to observe the top 1 percentile of earners. Second, although the annual sample is relatively large, the number of migrants from individual countries each year is small. This leads us to pool the ASEC over 2000–2023 and to group countries into English speaking advanced economies, non-English speaking advanced economies, China, India and Emerging markets.

The selective emigration of high-ability workers implies that the mean income of the immigrants from AEs in the United States would exceed that of the US-born.[18] We document that the foreign born are indeed overrepresented among top earning US residents. Using the ASEC country of birth, we compute the share of migrants from each source country that are in the top 1 percent of all earners. If the share of migrants in the top 1 percent is greater than 1 percent of migrants from that source country, we refer to this group of migrants as "overrepresented" in the top 1%.

Figure 6a-6c documents significant overrepresentation of migrants from AE countries in the top 1, 5 and 10 percent of earners. This pattern holds regardless of whether the migrants originated in English or non-English speaking advanced economies. What is perhaps more interesting is that the income data also suggests that migrants born in China and India are overrepresented among the top income deciles — consistent with selective migration. In con-

[18] MacGee and Rodrigue (2025) show that this holds for (in ASEC) for the Candian born. On average over 2000–2023, the Canadian-born aged 30–65 earn roughly 36 percent more than their American-born counterparts. This premium likely understates the difference in mean income since Canadians are overrepresented in the top 1 percent of income earners, which are top coded. Part of this income gap can be explained by differences in educational attainment. Comparing average income for those with a university or advanced degree (college or less), they find a somewhat smaller mean income gap of roughly 30 percent (21 percent).

trast, those born in other emerging markets economies are over represented in the bottom half of the income distribution. Jointly both data sources signal that the divergence in top incomes across countries can plausibly be attributed to migration patterns.



(a) Top 1%

(b) Top 5% exc. Top 1%

(c) Top 10% exc. Top 5%

(d) Bottom 50%

Figure 6: Overrepresentation of Immigrants Among Top Income Percentiles

Notes: This figure documents the overrepresentation of immigrants among top income percentiles. Panel (a) bars above (below) 1 indicate overrepresentation (underepresentation). In panels (b)-(d) similar interpretation holds for bars above (below) 4, 5 and 50, respectively.

3 Human Capital & Selective Migration

Differences in human capital per capita are a key factor in accounting for aggregate income differences across countries (e.g., see Caselli (2005)). In this section, we develop a measure of human capital consistent with cross-country income differences across the income distribution for the 18 advanced economies we study.

Each step yields an important quantitative insight. First, standard human capital measurement potentially underestimates the role of top talent in accounting for cross-country in-

come differences among advanced economies. Second, even though migration represents a small fraction of the total population in any country, the selective migration of high-human-capital workers to the US—combined with the US's role as a global talent magnet—leads to a larger quantitative contribution from cross-country human capital and smaller measured productivity differences.

Our analysis builds on a standard accounting exercise (e.g., see Caselli (2005); Hsieh and Klenow (2010) among others) for output per capita:

$$\frac{Y_t}{L_t} = \underbrace{A_t}_{\text{Productivity}} \times \underbrace{\left(\frac{K_t}{Y_t}\right)^{\frac{\alpha}{1-\alpha}}}_{\text{Capital Intensity}} \times \underbrace{\frac{H_t}{L_t}}_{\text{Human Cap. per capita}} \tag{1}$$

where Y_t is GDP, A_t is total factor productivity, K_t is the capital stock, L_t is the population adjusted for hours worked, and α is the capital share from a Cobb-Douglas aggregate production function, $Y_t = A_t K_t^{\alpha} H_t^{1-\alpha}$. While each component of equation (1) contributes to our understanding of cross-country income differences, we focus initially on the impact of differences in human capital per capita on measured productivity and income gaps across countries.

3.1 Human Capital and The Income Distribution

There are two standard approaches to constructing human capital stocks. The first approach measures human capital by *educational inputs* (Caselli, 2005). This method aggregates the total number of individuals with particular educational achievement (e.g., college degrees), thereby capturing relative educational achievement across countries (Barro et al., 2001, 2013, 2015; de la Fuente and Doménech, 2006; Cohen and Soto, 2007; Cohen and Leker, 2014). To account for differential levels of educational achievement and quality, country-specific degree rates are often weighted by their respective wage premia (Psacharopoulos, 1994). A well-known human capital index of this variety is produced by the Penn World Tables (PWT) (Feenstra et al., 2015; Zeileis, 2023), which we use as a benchmark for comparison.

The second approach builds measures of human capital from *realized wages* by leveraging the firm's cost minimization problem (Caselli and Coleman, 2006; Jones, 2008, 2014; Caselli and Ciccone, 2019; Jones, 2019). A key advantage is that this approach captures all forms of human capital, including ability heterogeneity among similarly educated workers, through observed wage outcomes. We extend this literature by linking wage-based human capital measures to the *distribution* of wages across workers. This yields new insights into the convergence of human capital across advanced economies and their simultaneous divergence from the USA, driven by differential changes in wage distributions over time and across countries.

Following Jones (2014), we define type i human capital H_{it} as $H_{it} = h_{it} L_{it}$, where L_{it} is the amount of labor and h_{it} is the flow of services per unit of labor. We order N discrete labor types by skill level, with $n = 1$ representing the least skilled workers and $n = N$ representing the most skilled.

We do not directly observe the quantity of each labor type, $L_{1t}, ..., L_{Nt}$, their services flows, $h_{1t}, ..., h_{Nt}$, or the aggregation function $H_t = G(H_{1t}, H_{2t}, ..., H_{Nt})$. However, under the assumption that all factors are paid their marginal products, we can infer human capital quality from the observed vector of wages, $w_{1t}, w_{2t}, ..., w_{Nt}$:

$$w_{it} = \frac{\partial F}{\partial H} G_{it} h_{it}. \tag{2}$$

The wage alone, w_{it}, does not directly identify human capital services, h_{it} since it also reflects the term $(\partial F/\partial H)G_{it}$. To isolate h_{it}, we make two standard assumptions: (i) all types of human capital are perfect substitutes for each other, and (ii) the lowest human capital workers ($n = 1$) have the same human capital across countries, normalized to $h_{1t} = 1$.

While restrictive, these standard assumptions (Jones, 2014) provide a transparent link between realized wages and unobserved human capital per worker:

$$\frac{H_t}{L_t} = \sum_{i}^{N} \frac{w_{it}}{w_{1t}} \frac{L_{it}}{L_t}, \tag{3}$$

where w_{it}/w_{1t} is the normalized wage of type i workers (relative to the lowest-paid workers) and L_{it}/L_t is the employment share of type i workers. As we discuss below, the perfect substitutability assumption has the additional advantage of yielding conservative estimates of selective migration's impact on human capital differences.

We link human capital per worker to the income distribution by exploiting the fact that income distributions are well approximated by Pareto distributions (Jones, 2015)

$$\Pr[Income_t > y] = y^{-1/\eta_t}$$

where η_t governs the shape of the Pareto distribution and incomes are scaled so that the minimum income is 1. Under the Pareto assumption for the wage distribution, the sum of normalized wages per worker is

$$\frac{H_t}{L_t} = \frac{1}{1 - \eta_t} \tag{4}$$

where equation (4) reflects the normalization that the minimum human capital in each location equals 1. Indexing advanced economies by $j = 1, ..., J$, relative human capital per worker can be expressed entirely in terms of the Pareto shape parameters, η_t^j, alone

$$\frac{H_t^j / L_t^j}{H_t^{US} / L_t^{US}} = \frac{1 - \eta_t^{US}}{1 - \eta_t^j} \tag{5}$$

where US denotes the shape parameter of the US income distribution.

Although assuming equal minimum human capital across countries is a common benchmark, because incomes are measured as percentile averages in WID, this assumption means that we implicitly assume that type $n = 1$ workers are equally represented in each economy. However, this assumption is plausible for our purposes, as we focus on comparisons within a group of similarly advanced economies. This is further supported by the evidence in Section 2: real

incomes in the lowest income percentiles of advanced economies show strong evidence of absolute convergence toward or above the US level.[19]

3.2 Selective Migration

This section quantifies the extent to which selective migration—the disproportionate outflow of high human capital workers to the USA—contributes to cross-country differences in measured human capital, productivity, and income. We augment the benchmark growth accounting framework from Section 3 with an additional assumption:

Assumption 1 (Human Capital Generation) Absent migration, the human capital distribution in country j follows a Pareto distribution. The probability that a citizen in country j has human capital h above threshold $\bar{h}$ is:

$$\Pr[h > \bar{h}] = \bar{h}^{-1/\nu_t^j} \tag{6}$$

where ν_t^j governs the shape of the fundamental human capital distribution in country j.

Relative human capital (5) can be decomposed into three multiplicative components: brain drain (country j's loss of high human capital workers), brain gain (the USA's attraction of high human capital workers), and fundamental human capital differences.

$$\frac{H_t^j/L_t^j}{H_t^{US}/L_t^{US}} = \underbrace{\underbrace{\frac{1-\nu_t^j}{1-\eta_t^j}}_{\text{Brain Drain}_t^j} \times \underbrace{\frac{1-\eta_t^{US}}{1-\nu_t^{US}}}_{\text{Brain Gain}_t^{US}}}_{\text{Selective Migration}} \times \underbrace{\frac{1-\nu_t^{US}}{1-\nu_t^j}}_{\text{Fund. Human Cap.}} . \tag{7}$$

The first two terms in equation (7) jointly quantify selective migration's impact. The leftmost term measures brain drain from country j: it compares the counterfactual human capital per person absent migration to the realized level in country j. The center term (brain gain) is US-specific and identical across countries. It measures how the US's human capital per person compares to the counterfactual absent migration, thereby capturing the multilateral benefit the US receives from selective migration by all advanced economies.

A key insight from this decomposition is that even if a country has minimal direct migration to the US (e.g., Australia), selective migration can still have a significant impact on income relative to the US. The reason is that when one country (the US) is a "sink" for high ability migrants globally, the brain gain effect cumulates. As a result, migration of top talent can impact income divergence relative to countries that see little brain drain if the US disproportionately

[19] In principle, one can relax this assumption by allowing country-specific fractions of lowest human capital workers where equation (5) becomes: $\frac{H_t^j/L_t^j}{H_t^{US}/L_t^{US}} = \left(\frac{x^j}{x^{US}}\right)\left(\frac{1-\eta_t^{US}}{1-\eta_t^j}\right)$, where x^j denotes the fraction of lowest human capital workers in country j. In our analysis, we set $x^j = x^{US}$ for all j based on two considerations: (i) observed convergence in income percentiles across economies, and (ii) data limitations.

attracts high human capital workers globally.

The rightmost term in equation (7) measures fundamental human capital differences using the pre-AE-migration distribution (counterfactual), rather than the post-AE-migration distribution (realized). This residual term captures all other sources of cross-country divergence and should be interpreted as such. For instance, if the USA received disproportionate selective migration from developing countries, this effect appears in the rightmost term rather than the brain drain component. Consequently, the "fundamental difference" can be interpreted as encompassing all sources of human capital divergence not attributable to AE-to-AE migration, including differential technology adoption, institutional differences, or migration flows from non-AE countries.

Given equation (7), if country j diverges from the average in relative human capital per person, the divergence must result from brain drain, fundamental differences, or both.

3.3 Quantifying the Impact of Selective Migration

To calibrate our model of human capital distribution, we impose a key assumption on migration selectivity across advanced economies.

Assumption 2 (Migration Selectivity) The net stock of foreign migrants in the USA from country j are randomly drawn from the top x_t^j percentiles of country j's human capital distribution in year t.

Given this assumption, we can recover two parameters for each country: the fundamental human capital distribution parameter ν_t^j (equation 6) and the migration threshold x_t^j. We use annual data on net migration stocks to the USA and wage distributions. With J source countries, we estimate $2J+1$ parameters per year: $(J+1)$ values of ν_t^j (one for each of the J source countries plus the USA) and J migration thresholds x_t^j.

We identify all parameters using two non-linear equations. The first relates average human capital per person among all country j citizens ($H_t^{j,Full}/L_t^{j,Full}$) to a weighted average of two groups: residents ($H_t^{j,Res}/L_t^{j,Res}$) and migrants to the USA ($H_t^{j,Mig}/L_t^{j,Mig}$):

$$\frac{H_t^{j,Full}}{L_t^{j,Full}} = (1-\omega_t^j)\frac{H_t^{j,Res}}{L_t^{j,Res}} + \omega_t^j \frac{H_t^{j,Mig}}{L_t^{j,Mig}} \Rightarrow \frac{1}{1-\nu_t^j} = \frac{1-\omega_t^j}{1-\eta_t^j} + \frac{\omega_t^j (x_t^j)^{-\nu_t^j}}{1-\nu_t^j} \tag{8}$$

where ω_t^j is the share of net emigrants to the USA relative to country j's population,[20] and η_t^j is the estimated Pareto shape parameter of the realized income distribution from Section 3.[21]

[20] We abstract from bilateral migration between non-US countries. To the extent that such flows systematically affect human capital per worker, their impact is captured in the estimated value of ν_t^j.

[21] The second line uses the property that the mean of a Pareto distribution with minimum value m and shape parameter η equals $\frac{m}{1-\eta}$. The minimum migrant human capital $h_t^{j,M}$ can be expressed as

To identify both ν_t^j and x_t^j, we exploit two properties of Pareto distributions: (i) truncation from below preserves the shape parameter, and (ii) selective emigration of high-skill workers creates a disproportionate impact on top-end wages. Specifically, we construct a weighted average of emigrant human capital ($H_t^{j,M}/L_t^{j,M}$) and the human capital of top-50-percentile residents ($H_{t,0.5}^{j,R}/L_{t,0.5}^{j,R}$):

$$\begin{aligned}
\frac{H_{t,0.5+\omega_t^j}^{j,Full}}{L_{t,0.5+\omega_t^j}^{j,Full}} &\equiv \left(\frac{0.5(1-\omega_t^j)}{0.5(1-\omega_t^j)+\omega_t^j}\right)\frac{H_{t,0.5}^{j,Res}}{L_{t,0.5}^{j,Res}} + \left(\frac{\omega_t^j}{0.5(1-\omega_t^j)+\omega_t^j}\right)\frac{H_t^{j,Mig}}{L_t^{j,Mig}} \\
\frac{(0.5+\omega_t^j)^{-\nu_t^j}}{1-\nu_t^j} &= \left(\frac{0.5(1-\omega_t^j)}{0.5(1-\omega_t^j)+\omega_t^j}\right)\frac{0.5^{-\eta_t^j}}{1-\eta_t^j} + \left(\frac{\omega_t^j}{0.5(1-\omega_t^j)+\omega_t^j}\right)\frac{(x_t^j)^{-\nu_t^j}}{1-\nu_t^j}
\end{aligned} \tag{9}$$

where $H_{t,0.5+\omega_t^j}^{j,F}/L_{t,0.5+\omega_t^j}^{j,F}$ is the average human capital per person among all country j citizens in the top $(50+\omega_t^j \times 100)$ percentiles. Since equations (8) and (9) are two equations in two unknowns (ν_t^j and x_t^j), we can solve for both parameters in each year.

A key feature of this approach: each non-US country's parameters can be identified from that country's data alone. Given these estimates, we use a parallel strategy to identify the USA's fundamental human capital parameter, ν_t^{US}. Average US human capital per person—including both native citizens and immigrants—is a weighted average of native human capital ($H_t^{US,Nat}/L_t^{US,Nat}$) and immigrant human capital ($H_t^{j,Mig}/L_t^{j,Mig}$), expressed as:

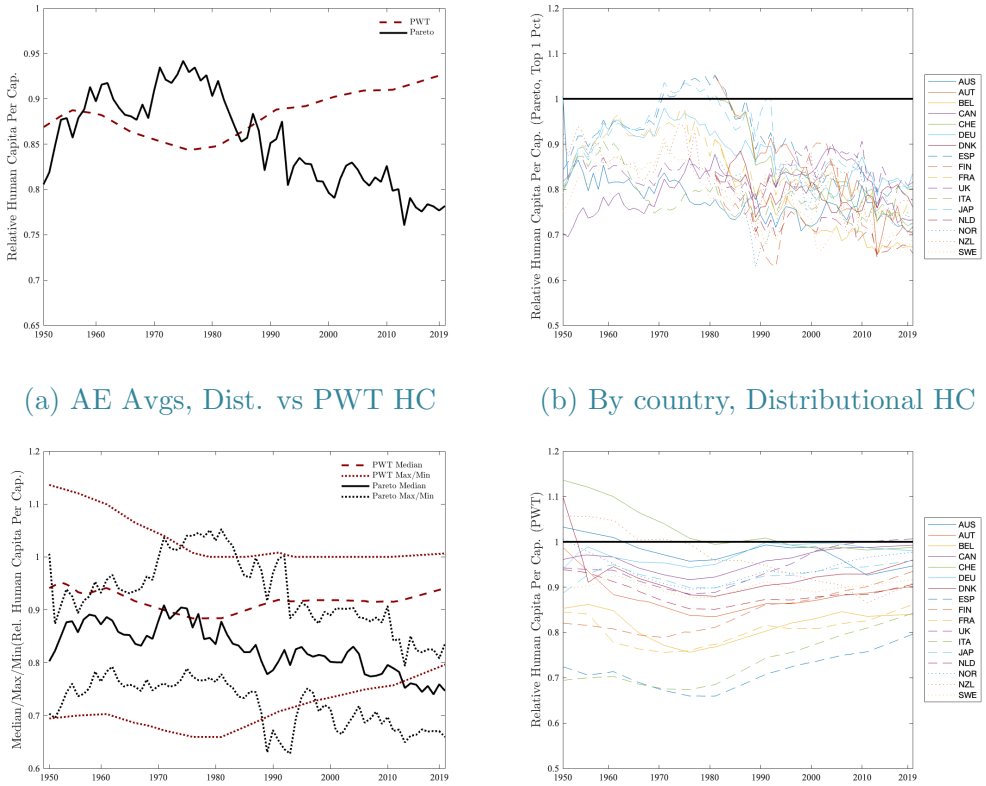
$$\begin{aligned}
\frac{H_t^{US,Res}}{L_t^{US,Res}} &= \left(1-\sum_{j\neq US}\tilde{\omega}_t^j\right)\frac{H_t^{US,Nat}}{L_t^{US,Nat}} + \sum_{j\neq US}\tilde{\omega}_t^j\frac{H_t^{j,Mig}}{L_t^{j,Mig}} \\
\frac{1}{1-\eta_t^{US}} &= \left(1-\sum_{j\neq US}\tilde{\omega}_t^j\right)\frac{1}{1-\nu_t^{US}} + \sum_{j\neq US}\tilde{\omega}_t^j(x_t^j)^{-\nu_t^j}
\end{aligned} \tag{10}$$

where $\tilde{\omega}_t^j$ is the share of immigrants from country j residing in the USA as a fraction of the US population. Equation (10) identifies νt^{US}, the fundamental shape parameter of the human capital distribution. By construction, the model exactly matches three data targets: net migration flows to the USA, average wages, and top-50-percentile average wages in each country, all recovered from WID data via the estimated Pareto shape parameters η_t^j.

3.4 Quantitative Implications of Selective Migration

This section quantifies selective migration's contribution to measured human capital and income differences across countries. We first examine realized (post-migration) human capital differences implied by our income distribution measure, then assess the extent to which migration patterns explain these differences.

$h_t^{j,M} = (x_t^j)^{-\nu_t^j}$, mapping migrants' human capital directly to the percentiles from which they are drawn.



(a) AE Avgs, Dist. vs PWT HC

(b) By country, Distributional HC

(c) Max/Median/Min

(d) By country, PWT HC

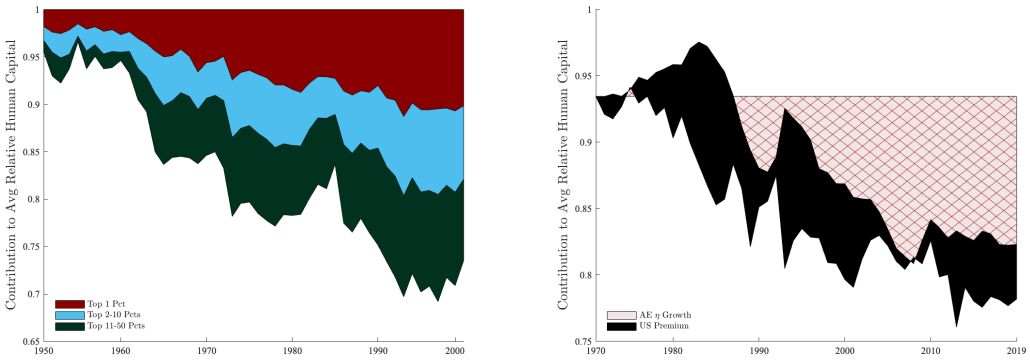
Figure 7: Realized Human Capital Per Worker Relative USA

Panel (a) plots average relative human capital to the USA using PWT and distributional human capital, respectively. Panels (b) and (d) plot each series for each AE separately. Panel (c) plots the maximum, minimum and median relative human capital in each year across AEs.

3.4.1 Realized Human Capital

We estimate the Pareto shape parameter of the realized human capital distribution using the top 1 percent income share in each country and year. Using equation (5), we then compute human capital per person relative to the USA. Figure 7a shows that average human capital relative to the USA declines substantially across all advanced economies: from a peak of 94 percent in 1970 to 78 percent by 2019. Figure 7b documents that this divergence is not isolated; rather, it is ubiquitous across all advanced economies.

In contrast, the PWT measure of human capital per worker suggests that average (population-weighted) human capital relative to the USA rises monotonically from 1975 onwards in Figure 7d. On the one hand, to the extent that the differences in wages and incomes are primarily driven by differences in technology or institutions, the income distribution measure of human capital may be misleading. However, we expect that these differences are relatively modest



(a) By Percentile Group (b) US Growth Premium

Figure 8: Contributions to Relative Human Capital Gaps

Panel (a) plots the relative contribution of the top 1 percentile, the top 2-10 percentiles and the top 11-50 percentiles to the relative human capital gap with the USA for the average (population-weighted) advanced economy in each year since 1970. Panel (b) plots the contribution to US human capital growth from secular (common) changes in the income distribution and a US-specific premium.

among advanced economies, and shrinking over time. Indeed, for most advanced economies, this is precisely what we find in Figure 7b. It is only the USA which is an outlier.

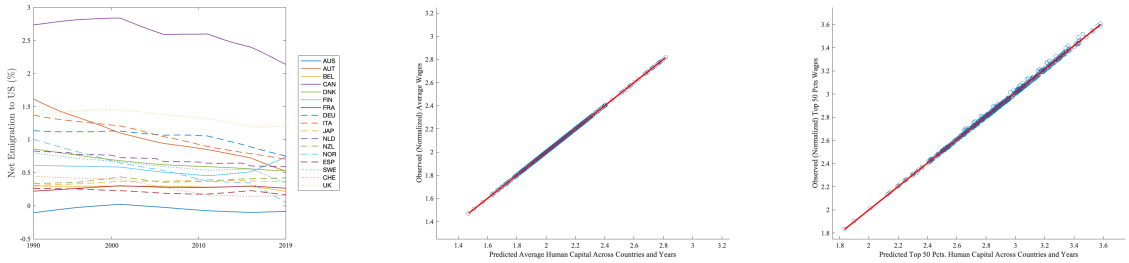
Alternatively, if top human capital has increasingly concentrated in the USA through global selective migration, we would expect top US incomes and income shares to grow disproportionately relative to other advanced economies. If average and marginal returns to skilled labor misrepresent the contributions of top performers to the human capital distribution, the PWT measure could miss the key drivers of aggregate income differences across countries.

To assess the importance of top earners for selective migration, we conduct two decomposition exercises. First, Figure 8 decomposes human capital contributions by income group using raw income data.[22] Workers in the top 11–50 percentiles account for 32 percent of the cross-country human capital gap, those in the top 2–10 percentiles account for 29 percent, and the top 1 percentile accounts for 38 percent. The top 1 percentile alone contributes nearly as much as the broader 11–50 percentile group, underscoring the outsized importance of top earners.

Collectively, the top 10 percentiles explain over two-thirds of human capital differences across advanced economies. This contribution has grown substantially since 1990, increasing by 10 percentage points. Cross-country human capital estimates that omit top percentile contributions risk drawing misleading conclusions about productivity evolution and income growth sources.

The second experiment decomposes US-AE divergence into two components: (i) the contribution from secular growth in the average AE's Pareto shape parameter η, conditional on the

[22]Since workers in the bottom 50 percentiles of each country are normalized to human capital 1, all cross-country differences reflect workers in the top 50 percentiles.



(a) Net Emigration to US (b) Avg Wages, Full Dist. (c) Avg. Wages, Top 50 Pcts

Figure 9: Model Fit: Migration, Wages, and Realized Human Capital

Panel (a) documents the net stock for migrants residing in the USA as a percentage of each country's adult population. Panels (b) and (c) plot the observed and predicted averarge (normalized) wages and the average (normalized) wages among the top 50 percentiles in each country.

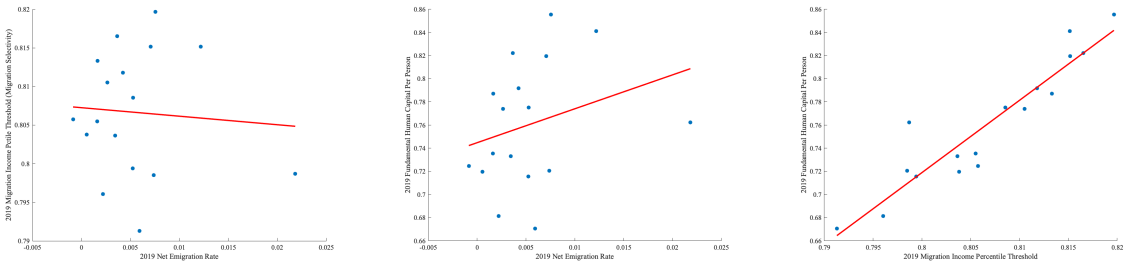
initial US human capital advantage, and (ii) a US-specific growth premium from disproportionate top-income-share growth. By 2019, the US growth premium accounts for 27 percent of the divergence, while the initial US advantage and global top-income-share growth account for 73 percent.

3.4.2 Selective Migration

We use United Nations migration data (UN, 2020) to investigate selective migration's impact on realized human capital differences across countries. Figure 9(a) documents substantial variation in emigration rates across countries. The UK and Canada—culturally, geographically, and historically closest to the USA—experience net emigration stocks of 1.5 and 3 percent of the adult population, respectively. In contrast, distant countries like Japan and Australia have much lower rates: net migration to the USA never exceeds 0.4 percent of Japan's population and is often negative for Australia. All other advanced economies experience positive net migration throughout the sample, reflecting the USA's consistent migration surplus.

By construction, the model exactly matches three data targets: bilateral net migration rates to the USA from each country and year, average human capital (normalized wages) in each country and year, and average human capital among top-50-percentile earners. While this fit is not surprising given the model's structure, it confirms that observed wages and migration patterns are jointly consistent with our framework.

Figure 10 examines the relationship between emigration rates, migration selectivity, and human capital. Panel (a) plots observed net emigration rates against the estimated migration threshold—the percentile of the human capital distribution from which migrants are drawn. The correlation is weakly negative (r = -0.07), suggesting that among AEs the USA does not attract disproportionately more high-skill workers from countries that send large migration flows



(a) Migration Selectivity (b) Fund Human Capital (HC) (c) Selectivity & Fund HC

Figure 10: Emigration Rates, Migration Selectivity and Fundamental Human Capital

Panel (a) plots the estimated 2019 migration threshold for each country, measured as the threshold percentile above which migrants are drawn, against its observed net emigration rate to the USA. Panel (b) plots 2019 relative fundamental human capital for each country against the net emigration rate to the USA. Panel (c) plots the estimated 2019 migration threshold for each country against the 2019 relative fundamental human capital.

overall.

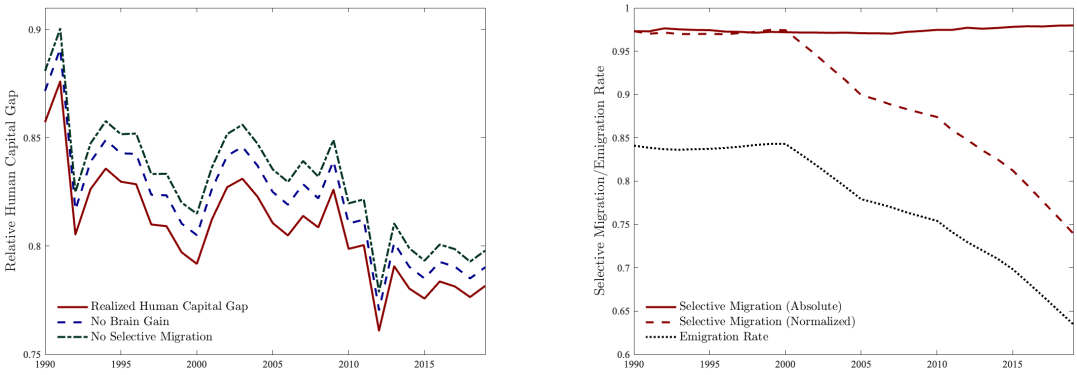
Panel (b) plots fundamental human capital against emigration rates and reveals a stronger positive correlation (r = 0.28). Migrants are disproportionately drawn from countries with higher baseline human capital levels. This relationship, while modest in magnitude, suggests that human capital endowments play a role in determining emigration patterns.

Panel (c) reveals the key relationship: migration selectivity and fundamental human capital exhibit a strong positive correlation (r = 0.93). Countries with higher baseline human capital not only experience higher emigration rates, but their emigrants are more likely to be drawn selectively from the distribution's top tail. This pattern is consistent with selective migration driving income and human capital convergence among advanced economies.

3.4.3 Selective Migration and Realized Human Capital

We next quantify selective migration's impact on relative human capital. Figure 11(a) plots three scenarios. The solid red line shows realized (post-migration) human capital for the average advanced economy relative to the USA. The dotted green line shows the counterfactual without selective migration, where the second and third terms of equation (7) equal one. In this counterfactual, relative human capital reflects only fundamental differences in human capital production across countries. The counterfactual path lies substantially above realized human capital throughout the period. Our benchmark estimates imply that selective migration accounts for 11.7 percent of the human capital gap between the US and advanced economies.

The dashed blue line isolates one selective migration force: US brain gain. This counterfactual assumes each advanced economy experiences the same selective emigration, but departing migrants do not reside in the USA. The gap between the solid red and dashed blue lines mea-



(a) Relative Human Capital (b) Normalized Impact

Figure 11: Human Capital Consequences of Selective Migration

Panel (a) plots average relative human capital with and without selective migration. Panel (b) plots the selective migration term in equation (7), the path of average net emigration to the US, and the selective migration term in equation (7) holding the immigration rate constant in 1990.

sures brain gain's contribution to US-AE divergence, while the gap between the dashed blue and dotted green lines measures the average contribution of brain drain. Notably, brain gain accounts for 57 percent of selective migration's total contribution to human capital divergence with the USA. This asymmetry highlights a critical insight: characterizing selective migration's aggregate impact (e.g., brain drain) without accounting for the concentration of talent in the USA risks drawing misleading conclusions about productivity and income divergence among advanced economies.

Figure 11(b) plots the joint impact of selective migration—the product of the brain drain and brain gain terms in equation (7)—over time. A value of one indicates no impact; smaller values represent larger absolute impacts. Panel (a) reveals that selective migration's overall contribution to the human capital gap is remarkably stable over time.

However, this stability masks an important dynamic. The average net emigration rate (shown in panel (b)) declines substantially from 0.84 percent to 0.63 percent between 1990 and 2019. Naively, we might expect this declining emigration to reduce selective migration's aggregate impact. Instead, the impact remains constant, indicating that each migrant's contribution to human capital divergence has increased. To illustrate this rising per-migrant impact, we construct a counterfactual that holds emigration rates constant at their 1990 levels.[23] Under this counterfactual, selective migration's contribution to human capital divergence grows from approximately 3 percentage points (1990–2000) to 26 percentage points (2019). This sevenfold

[23]The net emigration rate is the net stock of advanced economy emigrants residing in the USA as a fraction of the emigrant country's adult population.

increase reveals that selective migration's per-migrant impact has risen substantially, driven by growing top income shares and increasing human capital selectivity.

3.4.4 Discussion

Although selective migration from advanced economies is small relative to domestic population, its impact on human capital differences across countries is large. These findings are conservative: the USA receives migrants not only from advanced economies but from many countries globally. Since US-bound migrants from non-sample countries are likely also selectively drawn, and these flows have grown substantially over the past 30 years, the true impact of selective migration on income and productivity differences may be considerably larger.

Although we estimate realized human capital using the top 1 percent income share, they are robust across alternative Pareto parameterizations (e.g., top 10 percent income share) and data sources (e.g., GRID). All specifications yield the same qualitative conclusion: modest selective migration generates large effects on cross-country human capital differences.

Our estimates incorporate two assumptions that bias downward the estimated impact of selective migration. First, our sample emphasizes advanced economies with declining emigration to the USA, whereas Global South migration—particularly from China and India—has risen substantially. Incorporating these high-emigration countries would increase the measured impact of selective migration. Second, we assume perfect substitutability of all human capital types. If top-performer human capital is not perfectly substitutable with lower-skilled human capital, selective migration's impact would be significantly larger. We explore both extensions below.

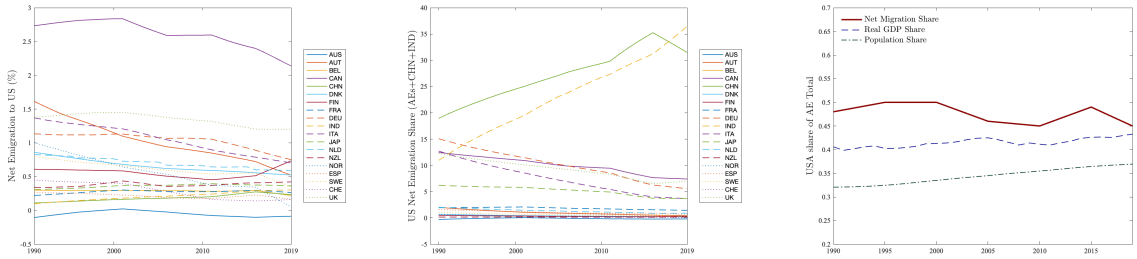
3.5 Asian Migration

We extend the benchmark analysis to include Chinese and Indian migration. Figure 12a shows that Chinese and Indian emigration rates—as a fraction of domestic adult population—are similar to those from advanced economies. However, unlike declining AE emigration, emigration from China and India has increased modestly over time.

China and India's large population base magnifies the importance of migration flows. Figure 12b documents a dramatic reversal: in 1990, Chinese and Indian emigration to the USA was half that of AEs; by 2019, it was double. Over this period, the fraction of US residents from China and India tripled from 0.76 to 2.3 percent. Remarkably, roughly half of all emigrants from China and India are destined for the USA-a far higher concentration than for AE emigrants, despite the USA representing only one-third of advanced-economy population and 40 percent of global advanced-economy GDP.[24]

The rise of Asian migration shares is striking, particularly given the substantial barriers to

[24]This estimate may understate actual flows. Damas de Matos and Parent (2019) document that high-earning new immigrants to Canada frequently emigrate within 5–10 years, suggesting undercount in stock-based measures.



(a) Net Emigration Rate (b) Migration Shares (c) US Share of AE Agg.

Figure 12: Net Migration, including China & India

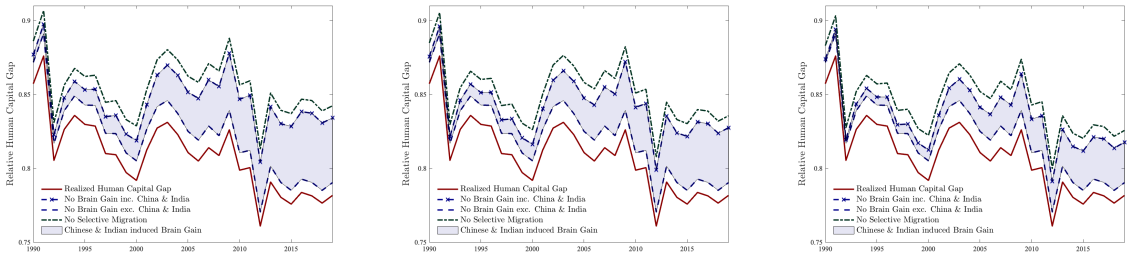
Panel (a) documents the net stock for migrants residing in the USA as a percentage of each country's adult population. Panel (b) plots net migration to the US from each AE, China and India as a share of total net migration. Panel (c) plots the US share of total population, GDP and net out-migration from China and India as share of each measure across all AEs.

migration from Asia to the United States. Despite these obstacles, large absolute flows relative to the existing US population base imply substantial potential gains in human capital and productivity from selective migration. This pattern underscores the economic forces driving migration: selective migration from Asia likely responds to even higher returns to top talent in the USA than from advanced economies.

We extend our benchmark quantification to include Chinese and Indian migration and wage data. We maintain two key assumptions: (i) workers in the lowest human capital group have equal human capital across all source countries, and (ii) we count only net migration to the USA from each source country. The second assumption implies that Asian migration to non-US advanced economies is subsumed into each AE's measured fundamental human capital distribution. Consequently, we may underestimate the global impact of selective Asian migration on relative human capital across advanced economies. Figure 13a shows the contribution of Asian migration to cross-country income differences under this parameterization.

Including Asian migration substantially amplifies selective migration's quantitative importance. By 2019, selective migration accounts for 28 percent of the cross-country human capital gap-nearly double the 11.7 percent found for AE migration alone. Of this 28 percent contribution, 20 percentage points stem from China and India, while 8 percentage points reflect AE migration.

Selective migration's impact has also grown over time. Without selective migration, relative human capital in 2019 would approximate early-1990s levels, indicating that selective migration has become an increasingly important driver of divergence. Nearly all of this additional impact—the incremental 16 percentage points from 11.7 to 28 percent-is attributable to Asian migration to the USA.



(a) No Discount (b) 10% Discount (c) 25% Discount

Figure 13: Human Capital Consequences of Selective Migration, including China & India

Panels (a)-(c) plots average relative human capital with and without selective migration, including brain gain from China and India. Panel (a) assumes that the minimum human capital level in China and India is the same as that in the AEs. Panels (b) and (c) respectively assume that the worker with the minimum human capital in the AEs has 10% and 25% more human capital than that in China and India.

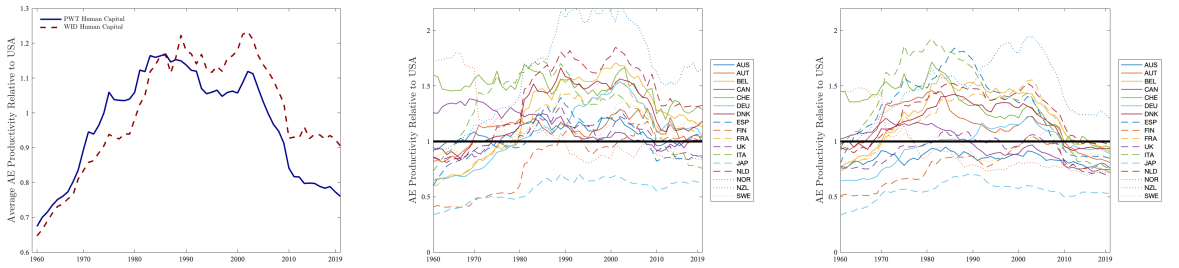
As a robustness check, we allow the least productive worker in China and India to be 10 or 25 percent less productive than their US counterpart. These assumptions reduce selective migration's measured impact: panels (b) and (c) show that selective migration's contribution to 2019 cross-country human capital gaps falls to 25 and 20 percent, respectively. Even with these downward adjustments, selective migration—particularly from China and India-explains a substantial and growing share of realized human capital differences across countries.

4 TFP Convergence

We now embed our distributional measure of human capital (equation 5) into the growth accounting framework (equation 1) to quantify selective migration's contribution to TFP convergence across advanced economies and their divergence from the USA. Using Penn World Table data on output, employment, hours, and capital stock, we decompose the income gap into three components: physical capital intensity, human capital per worker, and residual productivity.[25] We then compare the productivity implications of two human capital measures: our WID-based distributional approach and the standard PWT measure based on educational achievement.

Figure 14(a) compares average AE TFP relative to the USA across two human capital measures. The WID-based and PWT-based measures track closely from 1960 to 1980, when average AE TFP reached parity with the USA. Beyond 1980, the series diverge but both remain at or above parity until 2000. This period of measured parity despite substantial GDP per capita differences indicates that income divergence reflects physical or human capital differences, not

[25] Output is measured as real GDP at constant national prices (rgdpna), physical capital as real capital stock at constant national prices (ck), and labor input as the number of persons engaged (emp) adjusted by average annual hours worked (avh). All data are from the Penn World Tables.



(a) Average AE (b) By country, WID (c) By country, PWT

Figure 14: AE TFP relative to the USA

Panel (a) plots average (population weighted) relative total factor productivity (TFP) among non-US advanced economies relative to the human capital in the USA. Panel (b) plots relative TFP for each advanced economy separately using the WID measure of human capital, while Panel (c) uses the PWT measure of human capital.

productivity differences.

After 2000, both TFP series decline, but diverge sharply from each other. The distributional measure attributes income divergence to changing human capital distributions, while the PWT measure implies declining relative AE productivity. By 2019, the gap between the measures is substantial: the distributional approach suggests AE TFP is 93 percent of the USA's level, while the PWT approach suggests only 76 percent. This 17-percentage-point gap reflects the two measures' fundamentally different treatment of top earners' contributions to productivity.

Figures 14(b) and (c) plot relative TFP for individual advanced economies using the WID-based and PWT-based human capital measures, respectively. Both measures show significant TFP convergence across advanced economies, but with different implications. Under the distributional measure, AE TFP converges toward US levels; under the PWT measure, all countries except Norway converge to below-US levels.[26]

A primary concern is that WID income data, while largely based on labor earnings, may overweight capital income at the top of the distribution. We address this concern by cross-checking our benchmark results using GRID data, which directly controls for capital income in its construction across a smaller sample of countries and years. The distributional human capital findings are robust to this adjustment.

A more fundamental caveat: adjustments that do not generate variation across the income distribution cannot simultaneously explain both within-country and cross-country income divergence. Our growth accounting framework, by construction, requires distributional variation to account for these patterns. Aggregated measures, regardless of their construction, are insufficient for this task.

[26]Notable outliers persist. Norway and Switzerland consistently show TFP above US levels, while Japan persistently lags below the US level.

We omit other potential refinements that could affect the quantitative magnitude of our results. Inklaar et al. (2019) show that capital service differences account for a modest but meaningful share of cross-country TFP differences. Fernald and Inklaar (Fernald and Inklaar) find that much of the UK productivity slowdown is broad-based and comparable to other similarly developed economies. While incorporating such refinements may alter the quantitative importance of the distributional human capital measure, the qualitative conclusions are unlikely to change: both approaches are subject to the same additional adjustments, leaving their relative implications unaffected.

The differential TFP implications reflect a fundamental difference in how the two measures treat top earners. Educational achievement measures cannot adequately capture the highest-ability workers: the wage of a marginal college graduate provides little information about top earners' contributions. In contrast, earnings-based distributional measures directly reflect the outsized impact of top economic performers on aggregate outcomes. Because selective migration concentrates high-earning talent in the USA, this distinction becomes quantitatively critical. Our analysis demonstrates that accounting for the migration of top performers substantially changes estimates of cross-country productivity and income convergence.

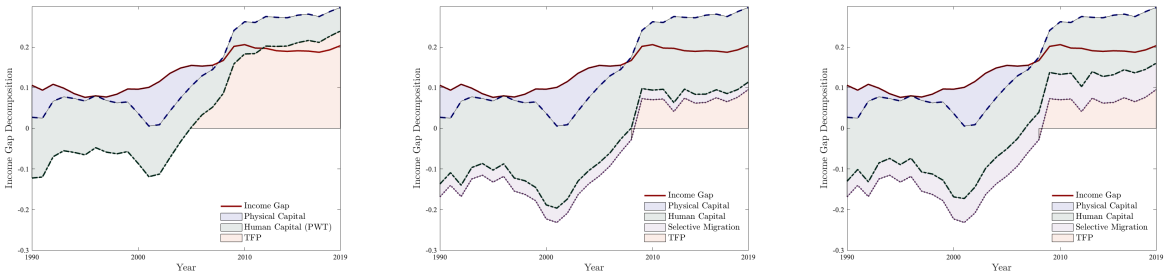
4.1 Human Capital, Selective Migration and TFP Convergence

We decompose the income gap between advanced economies and the USA since 1990 using equations (1), (5), and (7). This decomposition isolates four components: (i) capital-intensity differences, (ii) fundamental human capital differences, (iii) selective migration-driven human capital differences, and (iv) Hicks-neutral total factor productivity. Figure 15(a) shows this decomposition using the PWT human capital measure. In the 1990s, AE income gaps relative to the USA are fully explained by physical and human capital differences. Notably, between 1990 and 2005, advanced economies exhibit a modest TFP advantage relative to the USA.

Over time, physical capital and PWT human capital differences narrow, but a growing TFP gap emerges to explain persistent income per capita divergence. By 2019, TFP differences alone account for the entire income per capita gap between advanced economies and the USA.

Figure 15(b) repeats the decomposition using the distributional human capital measure instead of the PWT measure, revealing two striking contrasts with panel (a). First, TFP and capital-intensity contributions are small and roughly offset each other over time. Second, human capital differences alone explain the entire income gap between advanced economies and the USA.

Panel (b) also decomposes human capital into two sources: selective migration from advanced economies and fundamental human capital differences. While selective migration's contribution is modest relative to fundamental differences, it accounts for approximately 23 percent of the observed income gap between advanced economies and the USA over 1990–2019. This finding underscores that even accounting for selective migration's substantial role in human



(a) PWT Human Capital (b) Distributional HC (c) Dist. HC w/ China+India

Figure 15: AE Income Gap Decomposition

Notes: Equations (1) and (5) are used to decompose revealed income per capita gaps into three components: physical capital intensity, human capital per capita and TFP. In panels (b) and (c) human capita per capita is further decomposed into fundamental differences in human capital and selective migration components using equation (7). Panel (a) uses the PWT measures of human capital per person while panels (b) and (c) use the distributional measure of human capital per person. Panel (b) allocates all non-AE selective migration to differences in human capital, while panel (c) quantifies potential productivity gains from selective from migration from China and India under the assumption that the minimum human capital is equal in China, India and the AEs.

capital divergence, fundamental differences remain the dominant driver of income differences.

Panel (c) shows how selective Asian migration affects the growth accounting decomposition. Including Chinese and Indian migration does not change the overall human capital contribution to income differences, but substantially increases the share attributable to selective migration rather than fundamental human capital differences.

Under the benchmark assumption that minimum human capital is equal across all countries, selective migration accounts for nearly 43 percent of the income gap between the USA and advanced economies by 2019. Remarkably, selective migration's contribution rivals that of total factor productivity. This finding emphasizes a key insight: although migrant stocks represent a small fraction of any country's population, selective migration plausibly produces macroeconomically significant effects on cross-country income and productivity differences.

5 Conclusion

The gap between advanced economies and U.S. GDP per adult is persistent and large, with the average advanced economy GDP per adult remaining below 85 percent of that of the U.S. Behind this average gap in GDP per adult, however, there are large differences across the income distribution. We show that most of the gap in GDP per adult is accounted for by the top ten percent of the income distribution.

We show that the systematic variation in the gaps across the income distribution is also

only informative in accounting for the role of human capital and productivity in the AE-U.S. GDP gaps. Our analysis suggests that selective emigration of high ability people could be a key factor in accounting for persistent cross country income differences. Our work points to several promising directions for future research that can further identify what are the underlying causes of the gap in GDP and productivity.

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