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Will Today's Children Be Richer than Their Parents? Projecting Future Absolute Intergenerational Income Mobility

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Will Today's Children Be Richer than Their Parents? Projecting Future Absolute Intergenerational Income Mobility*

Abstract

We propose an approach for *projecting* future absolute intergenerational income mobility. This approach combines the 'copula and marginals' approach Chetty et al. (2017) for examining historical trends, with existing projections of national income and population. A key insight is that half of the required data (the marginal income distribution of parents) are already observable. We apply this approach to 28 OECD countries under two scenarios: (i) projected income growth with no change to inequality, and (ii) income growth combined with extrapolations of inequality trends. We also produce historical absolute mobility estimates, including for 16 countries where none previously existed to our knowledge. The results show significant historical declines in mobility for most countries. The projections suggest potential recovery under sustained economic growth, but rising inequality systematically attenuates these gains.

JEL classification

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Keywords

absolute intergenerational mobility, mobility projections

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1 Introduction

A popular measure of absolute intergenerational income mobility is the share of children whose real income is higher than that which their own parents had at a similar age. This salient concept was first introduced by [Chetty et al. \(2017\)](#) and captures the aspiration for children to grow up to lead better lives than their parents. It depends on economic growth as well as inequality and intergenerational income persistence. Over the past half-century, many advanced economies have witnessed a significant decline in absolute mobility. For US cohorts born in 1940, over 90 percent of children earned more than their parents, whereas by the 1984 cohort, this had fallen to around 50 percent ([Chetty et al., 2017](#)). Similar patterns emerge internationally, with absolute mobility rates dropping markedly for many, though not all, advanced economies for which there are estimates ([Berman, 2022](#); [Manduca et al., 2024](#)). These substantial declines in mobility, occurring across many different countries, represent profound changes in the lived experience of mobility with potential political and social repercussions ([Chinoy et al., 2023](#)).

This paper addresses a critical question: will today’s children be richer than their parents? To address this, we develop an approach for *projecting* absolute intergenerational income mobility. A long established challenge for the intergenerational mobility literature is that we often only measure mobility well for cohorts born decades ago. The key insight in this paper is that the same factors that make absolute mobility easier to measure in the past also make it easier to project into the future.

To illustrate our approach we apply it to 28 OECD countries. Extending beyond the typical historical analyses, we project mobility prospects for cohorts born up to 2020 using widely available databases. We do this under two scenarios: (i) future income distributions that grow with projected GDP per capita with no change to inequality, and (ii) distributions that evolve with both income growth and country-specific inequality projections. Our approach exploits a key insight: since parental income distributions for cohorts born up to 2020 are already observed, projecting absolute mobility reduces to the more tractable problem of modelling the corresponding children’s future income distributions.

We contribute to a relatively small but growing literature on absolute intergenerational income mobility.¹ Seminal work by [Chetty et al. \(2017\)](#) introduced the specific measure we examine and the ‘copula-and-marginals’ approach to its estimation, which allows absolute mobility to be estimated without panel data. The copula captures intergenerational income interdependency, while the marginals are the cross-sectional income distributions of both generations. [Berman \(2022\)](#) showed that such estimates are generally insensitive to the assumed copula. He also showed that reasonable estimates are feasible using only summary statistics on the marginal distributions. These contributions greatly broadened the potential application of the copula-and-marginals approach to more countries and years. More recently, [Manduca et al. \(2024\)](#) used intergenerationally-linked administrative and survey data to produce direct absolute mobility measures for seven European and North American countries. They confirmed that the copula-and-marginals approach generally performs well. However, existing studies remain retrospective, limited to observed cohorts and a relatively small set of countries.²

Our study makes several contributions to the intergenerational mobility literature. First and foremost, we propose a new approach for projecting future absolute income mobility which combines the copula-and-marginals approach with projections of national income and population.

We apply this approach to project absolute mobility for 28 OECD countries. For this, we draw on retrospective marginal income distributions from the World Income Database (WID) ([World Inequality Lab, 2025](#)) and the World Income Inequality Database (WIID) ([UNU-WIDER, 2023](#)), combined with existing projections for real GDP ([OECD, 2024](#)) and population ([United Nations, 2024](#)). We also show historical estimates of absolute

¹There is an important distinction between relative and absolute mobility, each reflecting different normative concerns and methodological frameworks ([Deutscher and Mazumder, 2023](#)). Relative mobility is the extent to which children’s economic position depends on their parents’ position, typically measured through intergenerational elasticity, rank–rank slopes, or transition matrices. These are measures of persistence—the degree to which parental economic status predicts children’s outcomes. There is a much larger literature on relative mobility, which we do not review here. Relative mobility, however, is one determinant of absolute mobility, as we will discuss.

²See ([Katz and Krueger, 2017](#)) for an alternate approach for estimating absolute mobility, and [Bloomer and Opacic \(2024\)](#) for a critique of the absolute mobility concept. Other studies which estimate absolute mobility for specific countries include [Kennedy and Siminski \(2022\)](#) and [Deutscher and Mazumder \(2023\)](#) for Australia, [Liss et al. \(2022\)](#) for Sweden, [Bönke et al. \(2024\)](#) and [Stockhausen \(2021\)](#) for Germany.

mobility for these same countries. For 16 of these, no previous estimates are available, to our knowledge. This includes middle-income countries Mexico and Türkiye.

We find substantial cross-national heterogeneity in both historical patterns and projected trajectories, showing that mobility outcomes are not predetermined by global economic forces but are sensitive to national circumstances and policy choices. We also decompose how economic growth versus distributional change affects future mobility prospects. While a recovery in per capita real GDP growth following the weakness that accompanied the Global Financial Crisis (GFC) could partially restore historical mobility levels, rising inequality would attenuate these gains, as has been shown through decompositions using retrospective data (Chetty et al., 2017; Berman, 2022; Manduca et al., 2024).

Absolute mobility is typically measured with reference to a single year of age. As a result it can be particularly sensitive to the economic cycle, more than would be expected if measuring incomes over a lifetime. We can see this clearly in our projections. Countries that experienced particularly sharp falls in incomes with the GFC have sharp falls in absolute mobility for those born 30 years beforehand, and sharp rebounds 30 years later for their children. Lifetime measures would look through this, but would lose the tractability and salience benefits of current measurement practices.

Finally, one of the key ingredients for our absolute mobility projections—a projection of real per capita incomes—is routinely projected by international bodies such as the OECD and national fiscal authorities such as the US Congressional Budget Office, the UK Office for Budget Responsibility and the Australian Treasury’s Intergenerational Report. Our approach highlights that with extra assumptions about inequality trends it is possible to examine likely trajectories of absolute mobility. Policymakers and researchers can readily substitute any preferred set of aggregate forecasts and examine the implied trajectory of absolute intergenerational mobility under alternative scenarios.

The remainder of this paper proceeds as follows. Section 2 describes the projection methodology. Section 3 describes the data and how they are combined. Section 4 presents our main results and Section 5 concludes.

2 Methodology

This section describes the methodology in detail. It begins by reviewing the key methodological details of seminal studies, especially [Chetty et al. \(2017\)](#) and [Berman \(2022\)](#), which we rely on heavily. It then describes the projection methodology itself.

Let Y_p and Y_c denote parent and child incomes, respectively. Absolute mobility A , defined as the fraction of children earning more than their parents at a similar age, is:

$$A = \Pr(Y_c > Y_p).$$

Estimating A directly is trivial if the required data exist. But this requires long-running intergenerationally-linked panel data, which exists only for a few countries, mostly for relatively recent cohorts ([Manduca et al., 2024](#)). The limitations of available data have hence inspired alternate, indirect, approaches.

2.1 Decomposition into Copula-and-Marginals

The required data to directly observe absolute mobility do exist for the United States, but only for recent cohorts. [Chetty et al. \(2017\)](#) estimated the evolution of absolute mobility in the United States over a longer period. They proposed an approach which overcomes this data limitation by decomposing the joint income distribution into marginal distributions and their copula. Let $Q_p(r_p)$ and $Q_c(r_c)$ denote the r_p -th and r_c -th quantiles of parent and child incomes, and $C(r_c, r_p)$ represent their copula (joint rank distribution). Absolute mobility becomes:

$$A = \int \mathbf{1}\{Q_c(r_c) \geq Q_p(r_p)\} C(r_c, r_p) dr_c dr_p.$$

For cohorts lacking panel data, [Chetty et al. \(2017\)](#) derived bounds on A by solving a linear programming problem over all feasible copulas C that satisfy first-order stochastic dominance. This innovation reduced reliance on longitudinal data, enabling estimation for U.S. cohorts born between 1940–1984 using cross-sectional surveys (CPS, Census) and

tax records.

2.2 Parametric Simplification and Cross-Country Analysis

[Berman \(2022\)](#) proposed a parameterization, which allows absolute mobility to be estimated with even less data. Assuming a bivariate log-normal income distribution for parents and children, $\ln Y_p \sim N(\mu_p, \sigma_p^2)$ and $\ln Y_c \sim N(\mu_c, \sigma_c^2)$ with rank correlation ρ , absolute mobility simplifies to:

$$A = \Phi \left(\frac{\mu_c - \mu_p}{\sqrt{\sigma_p^2 + \sigma_c^2 - 2\rho\sigma_p\sigma_c}} \right), \quad (1)$$

where Φ is the standard normal cumulative distribution function (CDF). This closed-form equation separates the contribution of income growth ($\mu_c - \mu_p$), inequality (σ_p, σ_c), and relative mobility (ρ) to absolute income mobility.

As justification for this parametrisation, [Berman \(2022\)](#) shows that copulas across countries share similar structures, and are sufficiently summarized with rank correlations alone. Further, [Berman \(2022\)](#) demonstrates that estimates of absolute mobility, A , are reliable even when the copula is misspecified. Instead, absolute mobility estimates are almost entirely determined by the marginal distributions. This implies that absolute mobility can be estimated using summary statistics for income inequality and income growth without the need for panel data, or even income distribution microdata. [Manduca et al. \(2024\)](#) verify that this approach generally works well. They do caution, however, that some error is introduced if using national income inequality statistics (as in [Berman \(2022\)](#) and here) instead of the distribution amongst the appropriate age group, as these may follow different paths.

2.3 Determinants of Absolute Mobility

All key studies, beginning with [Chetty et al. \(2017\)](#), have highlighted that absolute mobility is driven by three factors: income growth, inequality and, to a small extent, by relative mobility.

Income growth can be summarised as the difference of child and parental mean log real income ($\mu_c - \mu_p$), reflecting aggregate economic growth. This will increase absolute mobility. Inequality can be summarised through standard deviations of log income for each generation (σ_c and σ_p). An increase in child income inequality, all else equal, tends to reduce absolute mobility. Relative mobility, summarised by the rank correlation coefficient ρ , plays a secondary role. [Berman \(2022\)](#) showed that absolute mobility estimates are highly insensitive to the assumed ρ .³

The effect of changes in these factors on A is quantified via partial derivatives of equation (1):

$$\frac{\partial A}{\partial(\mu_c - \mu_p)} > 0, \quad \frac{\partial A}{\partial(\sigma_c/\sigma_p)} < 0, \quad \frac{\partial A}{\partial \rho} > 0. \quad (2)$$

Empirically, [Chetty et al. \(2017\)](#) attributed 71% of the U.S. decline in A to inequality and 29% to slower growth, while [Berman \(2022\)](#) found cross-country heterogeneity, with growth dominant in Europe and inequality in the U.S. and Australia.⁴

To estimate mobility trends, the copula-and-marginals approach requires some assumptions about changes to the copula over time. [Chetty et al. \(2017\)](#) assumed a stable copula across cohorts, allowing them to apply a single estimate of relative mobility across all birth cohorts. They also showed that estimates for some years can be sensitive to extreme violations of the stable-copula assumption. [Berman \(2022\)](#) and [Manduca et al. \(2024\)](#) extended this by showing that absolute mobility estimates are generally insensitive to any reasonable copula assumptions. Collectively, this work has shown that absolute intergenerational mobility can be accurately estimated using marginal income distributions alone. This also implies that absolute mobility is primarily shaped by structural economic forces (growth and inequality) rather than relative mobility.

³Nonetheless, it is interesting and perhaps not immediately obvious that increased relative mobility will reduce absolute mobility, all else equal. This is perhaps clearest with little change between parent and child income distributions. When there is even a small amount of income growth with no relative mobility—if ranks persist perfectly across generations—then all children will outearn their parents. But with even modest relative mobility children may fall below their parents.

⁴Using detailed microdata, [Kennedy and Siminski \(2022\)](#) found growth to be the dominant factor in Australia.

2.4 Projection

We now describe our approach for projecting absolute mobility under two scenarios: one assuming GDP-based mean income growth with constant inequality, and another with an extrapolation of current inequality trends.

Let $\mathcal{C}$ denote the set of countries and $\mathcal{P} = \{1, \dots, 100\}$ the percentile ranks. We define $\mu_{c,p}(t)$ as the mean income in percentile p for country c in year t . Our baseline year for each country is T_c : the most recent year in which the income distribution is observed. To measure inequality across the income distribution, we next define

$$\mathcal{P}_c^+(t) = \{p \in \mathcal{P} : \mu_{c,p}(t) > 0\}$$

as the set of percentiles with strictly positive incomes in country c at year t . The cross-percentile standard deviation of log-incomes, our measure of inequality, is then

$$\sigma_c(t) = \sqrt{\frac{1}{|\mathcal{P}_c^+(t)|} \sum_{p \in \mathcal{P}_c^+(t)} \left(\ln \mu_{c,p}(t) - \bar{\ell}_c(t) \right)^2},$$

with

$$\bar{\ell}_c(t) = \frac{1}{|\mathcal{P}_c^+(t)|} \sum_{p \in \mathcal{P}_c^+(t)} \ln \mu_{c,p}(t)$$

denoting the mean log-income across all percentiles in $\mathcal{P}_c^+(t)$.⁵

2.4.1 GDP-based Mean Income Growth Projections

We project aggregate mean income growth using country-specific real GDP per capita forecasts (the data are described in Section 3). Other long-run projections of income growth could also be used. Let $Y_c(t)$ denote GDP per capita for country c at time t . We define the growth factor as:

$$g_c(t) = \frac{Y_c(t)}{Y_c(T_c)}.$$

⁵In practice, zero or negative incomes would render $\ln(\mu_{c,p}(t))$ undefined. Therefore, whenever $\mu_{c,p}(t) \leq 0$, we omit that percentile p from both the summation and the count $|\mathcal{P}_c^+(t)|$. Such non-positive values are rare in our data; when they occur, those percentiles are excluded from the inequality calculation for that country-year.

Assuming proportional income growth across the distribution, the GDP-only projection ($\mu_{c,p}^{\text{GDP}}(t)$) simply scales the baseline income at each percentile:

$$\mu_{c,p}^{\text{GDP}}(t) = \begin{cases} \mu_{c,p}(t), & t \leq T_c, \\ \mu_{c,p}(T_c) \times g_c(t), & t > T_c. \end{cases}$$

where $\mu_{c,p}(T_c)$ denotes the observed income at percentile p in the baseline year T_c .

2.4.2 Inequality Trajectory Estimation

We model the temporal evolution of income inequality using a linear time trend, estimated for each country separately for the period 1980 onwards. Let $\sigma_c(t)$ denote the standard deviation of log-income across percentiles for country c in year t , and let β_c be the country-specific slope estimated via

$$\sigma_c(t) = \alpha_c + \beta_c t \quad \text{for observed years } t \geq 1980.$$

We anchor projections at the final observed year T_c , and extrapolate linearly:

$$\hat{\sigma}_c(t) = \begin{cases} \sigma_c(t) & t \leq T_c \\ \sigma_c(T_c) + \hat{\beta}_c(t - T_c) & t > T_c \end{cases} \quad (3)$$

2.4.3 Inequality-Based Distributional Reshaping

To model how changing inequality reshapes the income distribution, we first decompose the baseline log-income distribution into its mean components:

$$\begin{aligned} \ell_{c,p} &= \ln(\mu_{c,p}(T_c)), \\ \bar{\ell}_c &= \frac{1}{100} \sum_{p=1}^{100} \ell_{c,p} \end{aligned}$$

We compute the deviation of each percentile's log-income from the baseline mean and project future log-income profiles by scaling these deviations proportionally to the pro-

jected change in cross-percentile inequality. For $t \geq T_c$,

$$\tilde{\ell}_{c,p}(t) = \bar{\ell}_c + (\ell_{c,p} - \bar{\ell}_c) \frac{\hat{\sigma}_c(t)}{\sigma_c(T_c)}. \quad (4)$$

This formulation ensures that when inequality increases (decreases), the distribution stretches (compresses) while preserving rank ordering. To ensure this process is mean-preserving, we apply a normalization when exponentiating:

$$\mu_{c,p}^{\text{ineq0}}(t) = \frac{\exp[\tilde{\ell}_{c,p}(t)]}{\frac{1}{100} \sum_{q=1}^{100} \exp[\tilde{\ell}_{c,q}(t)]} \times \bar{\mu}_c(T_c) \quad (5)$$

where $\mu_{c,p}^{\text{ineq0}}(t)$ now reflects the inequality adjustment for year t and q denotes a dummy index over percentiles used to compute the normalization factor. Exponentiating and rescaling ensures that mean income across the percentiles remains fixed at its baseline level of $\bar{\mu}_c(T_c) = \frac{1}{100} \sum_{p=1}^{100} \mu_{c,p}(T_c)$.

2.4.4 Integrated Inequality Projection Model

Our final inequality projection combines the growth and inequality components:

$$\mu_{c,p}^{\text{ineq}}(t) = \begin{cases} \mu_{c,p}(t), & t \leq T_c, \\ \mu_{c,p}^{\text{ineq0}}(t) \times g_c(t), & t > T_c. \end{cases}$$

This formulation captures both the overall economic growth through $g_c(t)$ and distributional changes through $\mu_{c,p}^{\text{ineq0}}(t)$.

2.4.5 Intergenerational Income Mobility Estimation Using Projected Distributions

To project intergenerational income mobility across time, we use the copula-and-marginals approach with the projected income distributions. For each birth cohort b , we define the parent's income observation year as $t_p = b$ and the child's income observation year as

$t_c = b + 30$, reflecting the standard assumption in the literature of a 30-year generational gap (Chetty et al., 2017; Berman, 2022).⁶

For each country c , the absolute mobility estimate $A_c(b)$ is the proportion of children born in cohort b who will have a higher income than their parents in real terms. Ideally, this would be calculated by integrating over the joint parent-child income distribution:

$$A_c(b) = \iint \mathbf{1}\{y_c > y_p\} \cdot f(y_c, y_p) dy_c dy_p$$

where y_c and y_p are the real incomes of children and parents, respectively, $f(y_c, y_p)$ is their joint density function, and $\mathbf{1}\{\cdot\}$ is the indicator function.

We operationalize this by discretizing the income distributions into percentiles. The discrete implementation sums over all parent-child percentile pairs, weighted by their copula-based conditional probabilities.

To model the joint distribution of parent and child incomes, we use a bivariate log-normal copula with a rank correlation parameter ρ of 0.25, which approximates the average intergenerational rank correlation observed in cross-country empirical studies (Appendix F, Berman (2022)). While the specific copula choice has been shown to have minimal impact on absolute mobility estimates (Berman, 2022; Manduca et al., 2024), this parameter value provides a reasonable approximation across diverse economic contexts. We implement this using a discretized 100×100 transition matrix where each element $C_{q,p}$ represents the probability mass for a child in percentile q given a parent in percentile p .

The conditional probabilities are normalized within each parent percentile:

$$\pi_c(q | p) = \frac{C_{q,p}}{\sum_{q'=1}^{100} C_{q',p}}$$

The probability that a child whose parent is in percentile p will earn more than that

⁶This approach involves associating each birth cohort in year t with their parents' incomes recorded in the same year t , and the children's incomes observed three decades later, in year $t + 30$. For instance, for individuals born in 1980, parental income is taken from 1980 data, while the corresponding child income is drawn from 2010 data. This allows a comparison of the income distributions of parents and their children at similar ages.

parent is:

$$A_{c,p}(b) = \sum_{q=1}^{100} \pi_c(q | p) \cdot \mathbf{1}\{\mu_{c,q}(t_c) > \mu_{c,p}(t_p)\}$$

where $\mu_{c,p}(t)$ represents the mean income of percentile p in country c at time t , derived from our projected income distributions.

The overall absolute mobility estimate is hence:⁷

$$A_c(b) = \sum_{p=1}^{100} A_{c,p}(b) \quad (6)$$

This mobility estimate is then computed separately using different projected marginal distributions—one assuming GDP-driven mean growth with constant inequality ($\mu_{c,p}^{\text{GDP}}$), and another incorporating both income growth and evolving inequality ($\mu_{c,p}^{\text{ineq}}$)—allowing us to decompose mobility trends into growth and distributional effects.

3 Data

For the historical and baseline marginal income distributions, we draw on two comprehensive income distribution databases. WID ([World Inequality Lab, 2025](#)) provides detailed pre-tax income percentile data from 1910 to 2023. It implements the Distributional National Accounts (DINA) approach, which combines national accounts, household surveys and fiscal data (e.g., tax records) ([Piketty et al., 2018](#)). We extracted the average pre-tax income in each percentile of the distribution, amongst individuals aged 20 and older, assigning an equal split of total household income to each adult. All monetary amounts in the WID are expressed in local currency at constant prices, with the reference year being the most recent year (2023) in the database, which is generally updated every summer.⁸

We complement this with data from the WIID, which contains standardized income

⁷To ensure accurate probability calculations in practice, we account for potential missing data through a normalization procedure. Specifically, we divide the sum of mobility probabilities across all parent percentiles by the actual number of valid parent percentiles for which data is available, then multiply by 100 to express the result as a percentage. This normalization prevents bias that could arise when some percentiles lack sufficient data and ensures that mobility estimates remain comparable across countries with different data coverage patterns.

⁸The data were extracted from January to April 2025.

distribution data for 201 countries for various years up to 2022. The WIID provides mean incomes for each percentile and year in constant 2017 PPP USD ([UNU-WIDER, 2023](#)). The income construct is net (post-tax) income.

The marginal income distributions are of course critical for the mobility estimates. We construct these using both WID and WIID data as a form of triangulation to help navigate data quality concerns, as well as sensitivity to their fundamentally different income definitions. There have been significant critiques made of both databases. For example, [Galbraith \(2019\)](#) argues that WID’s reliance on tax records creates sparse coverage (many countries have fewer than six years of data), selection bias toward wealthy nations, and smoothing algorithms that can obscure genuine inequality changes, with even OECD countries experiencing data breaks and artificial discontinuities—such as the apparent US inequality jump in 1986-88 reflecting tax code changes rather than economic reality. [Jenkins \(2015\)](#) and [Atkinson and Brandolini \(2009\)](#) discuss WIID limitations, describing a “bewildering variety of estimates” with multiple series per country-year reflecting different income concepts, reference units, and equivalence scales, where definitional inconsistencies can produce 2-4 percentage point Gini coefficient differences for identical country-years. The different income concepts also have substantive implications: WID’s pre-tax measures reflect market inequality and structural economic changes, while WIID’s post-tax, post-transfer construct incorporates redistributive policies.

For countries and years with missing data, we interpolate along both the percentile and year dimensions. Specifically, we first interpolate along percentiles for each country-year pair, then interpolate along years for each country-percentile pair.

To project future intergenerational mobility, we use two additional datasets. The first is the OECD Real GDP Forecast, released in December 2023 ([OECD, 2024](#)), which provides projections of real Gross Domestic Product (GDP) to 2060 for OECD countries in US dollars at 2015 Purchasing Power Parities. The OECD constructs these projections using a structural economic model based on a Cobb-Douglas production function that incorporates labour efficiency, employment trends, and capital stock growth ([OECD,](#)

2024). We considered several alternative sources for GDP projections.⁹ We chose the OECD GDP projections due to their transparent methodology with documented assumptions, incorporation of expert judgment from national statistical offices and economic research departments, comprehensive coverage of countries with consistent methodology, and projections extending to 2060. Of course such projections are subject to the inherent uncertainties in any forecasting exercise—particularly regarding structural breaks, technological disruptions, or policy regime changes over a four-decade horizon.

We also draw on the United Nations Population Division’s World Population Prospects (2024 revision, medium variant), which provides historical population data from 1950 to 2023 and projections through 2070 (United Nations, 2024). Importantly, this is the same population series that the OECD itself uses as an input into its GDP projections (OECD, 2024). Combining the OECD real GDP projections with the UN WPP population figures yields real GDP per capita series for both historical periods and future projections.

4 Results

4.1 Summary Statistics

Table 1 shows descriptive statistics for one year (2015). Inequality in the WID data is substantially higher than in WIID across all 28 OECD countries. This is expected, as WID measures pre-tax, pre-transfer income while WIID captures post-tax, post-transfer income. The gaps between the two sets of inequality indicators may be indicative of the redistributive effect of taxes and transfers in each country, but they may also reflect other differences between the income constructs in each source.

Two countries warrant attention. Mexico exhibits an extreme P90/P10 ratio (27.834) in WID, solely attributable to the bottom of the distribution: WID’s use of equal-split pre-

⁹These alternatives have various strengths and limitations. The International Monetary Fund (IMF) World Economic Outlook (International Monetary Fund, 2024) provides detailed economic projections but extends only to 2029, which is too short for our analysis. The World Bank offers growth scenarios in its Global Economic Prospects series (World Bank, 2024) but lacks the systematic, annually updated country coverage that characterises the OECD projections. The Penn World Table (Feenstra et al., 2015) provides historical data that could be extrapolated, but this would require making our own assumptions about future growth patterns for each country. Private sector forecasting services such as Oxford Economics offer extended projections (Oxford Economics, 2024).

Table 1: Comparison of Inequality Measures: WID vs. WIID

Country	WID data				WIID data				Differences (WID–WIID)			
	Gini	P90/P10	Theil	Atkinson	Gini	P90/P10	Theil	Atkinson	Gini	P90/P10	Theil	Atkinson
Australia	0.462	10.595	0.406	0.187	0.341	4.400	0.204	0.096	0.121	6.195	0.202	0.092
Austria	0.407	6.059	0.344	0.151	0.307	3.864	0.163	0.078	0.101	2.195	0.181	0.074
Belgium	0.409	6.862	0.318	0.147	0.279	3.617	0.131	0.064	0.130	3.246	0.187	0.084
Canada	0.466	10.986	0.431	0.194	0.338	4.858	0.194	0.093	0.129	6.128	0.237	0.100
Czechia	0.357	4.293	0.297	0.128	0.262	3.125	0.122	0.058	0.095	1.168	0.175	0.070
Denmark	0.401	5.625	0.365	0.154	0.261	3.035	0.119	0.057	0.139	2.590	0.245	0.097
Finland	0.413	6.841	0.337	0.152	0.272	3.266	0.127	0.060	0.141	3.574	0.210	0.092
France	0.422	7.269	0.359	0.160	0.328	4.332	0.189	0.089	0.094	2.938	0.169	0.071
Germany	0.464	8.223	0.457	0.193	0.309	4.064	0.162	0.078	0.155	4.158	0.294	0.115
Greece	0.455	12.288	0.435	0.197	0.351	5.307	0.210	0.102	0.105	6.981	0.225	0.095
Iceland	0.367	5.392	0.270	0.125	0.277	3.121	0.139	0.064	0.090	2.271	0.131	0.061
Ireland	0.452	7.862	0.418	0.181	0.319	4.186	0.173	0.082	0.133	3.676	0.245	0.099
Italy	0.466	30.585	0.431	0.216	0.362	5.977	0.225	0.115	0.104	24.608	0.206	0.101
Japan	0.490	8.477	0.548	0.226	.	.	.	.	.	.	.	.
KoreaRep	0.446	6.831	0.477	0.189	0.316	4.396	0.169	0.083	0.130	2.435	0.308	0.106
Luxembourg	0.422	7.173	0.363	0.161	0.308	4.034	0.162	0.077	0.114	3.139	0.201	0.084
Mexico	0.710	27.834	1.173	0.431	0.497	8.201	0.492	0.206	0.213	19.633	0.682	0.225
Netherlands	0.380	6.512	0.265	0.129	0.287	3.518	0.142	0.068	0.093	2.994	0.123	0.061
NewZealand	0.397	5.540	0.352	0.150	0.354	4.615	0.222	0.102	0.043	0.925	0.130	0.048
Norway	0.368	5.058	0.296	0.131	0.274	3.297	0.132	0.064	0.094	1.761	0.165	0.067
Poland	0.449	7.134	0.464	0.188	0.337	4.643	0.196	0.094	0.113	2.490	0.268	0.094
Portugal	0.464	8.949	0.425	0.187	0.356	5.255	0.222	0.105	0.108	3.695	0.203	0.082
Spain	0.434	6.917	0.412	0.174	0.363	6.102	0.223	0.111	0.071	0.815	0.189	0.063
Sweden	0.374	5.287	0.303	0.134	0.300	3.667	0.159	0.076	0.074	1.620	0.144	0.058
Switzerland	0.384	5.547	0.319	0.140	0.330	4.270	0.190	0.088	0.055	1.277	0.129	0.052
Turkiye	0.579	8.954	0.814	0.298	0.438	7.018	0.351	0.157	0.141	1.936	0.463	0.141
United Kingdom	0.441	7.227	0.412	0.176	0.331	4.406	0.188	0.089	0.109	2.821	0.224	0.087
United States	0.582	22.654	0.750	0.304	0.415	6.930	0.301	0.141	0.167	15.724	0.448	0.162

Note: Gini, P90/P10, Theil and Atkinson indices are computed by the authors using WID and WIID data for 2015. Because observed data for many countries are unavailable for 2020, we use 2015 as the reference year to illustrate differences between the two datasets. Differences are computed as WID minus WIID. Blank cells denote unavailable data.

tax national income—calibrated to national accounts—assigns zero or near-zero income to a large share of Mexican adults in the informal sector who have no recorded formal earnings or capital income, producing an extremely low P10, which substantially inflates the ratio. Japan’s coverage ends in 2014 in the version of WIID that we use, so there are no 2015 data, without drawing on projections.

4.2 Historical and Projected Mean Incomes

Figure 1 shows historical trends of mean incomes in WID and WIID, indexed to 2020 levels, combined with the OECD projections. The countries are displayed in alphabetical order throughout the paper.

There was great variation between OECD countries in average income growth between 1980 and 2020. In WID, the indexed value in 1980 ranges from South Korea’s exceptionally low 22 (which indicates that mean income rose more than four-fold to 2020) to

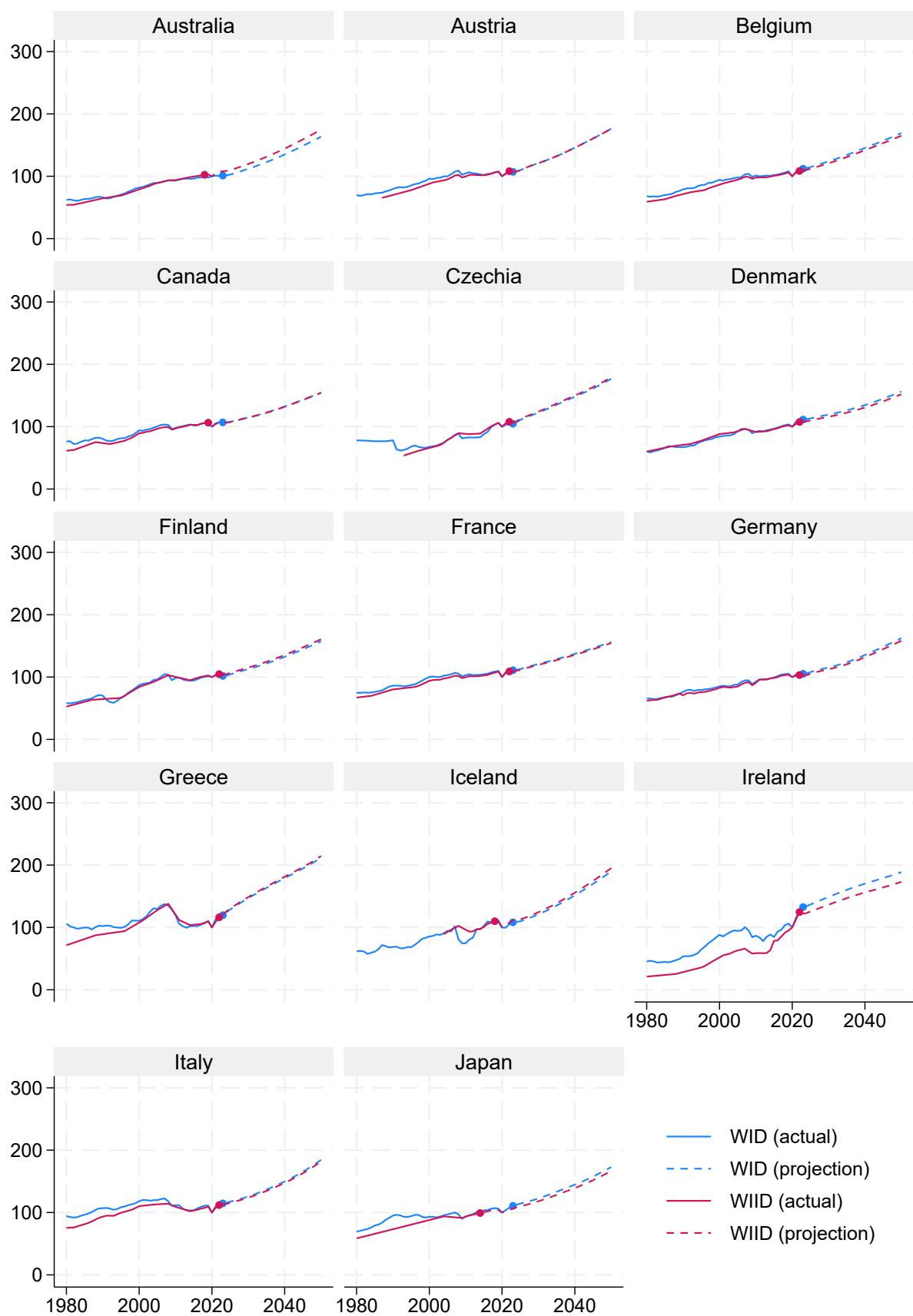


Figure 1: Indexed real mean income (2020=100)

Note: Dots indicate where projections begin.

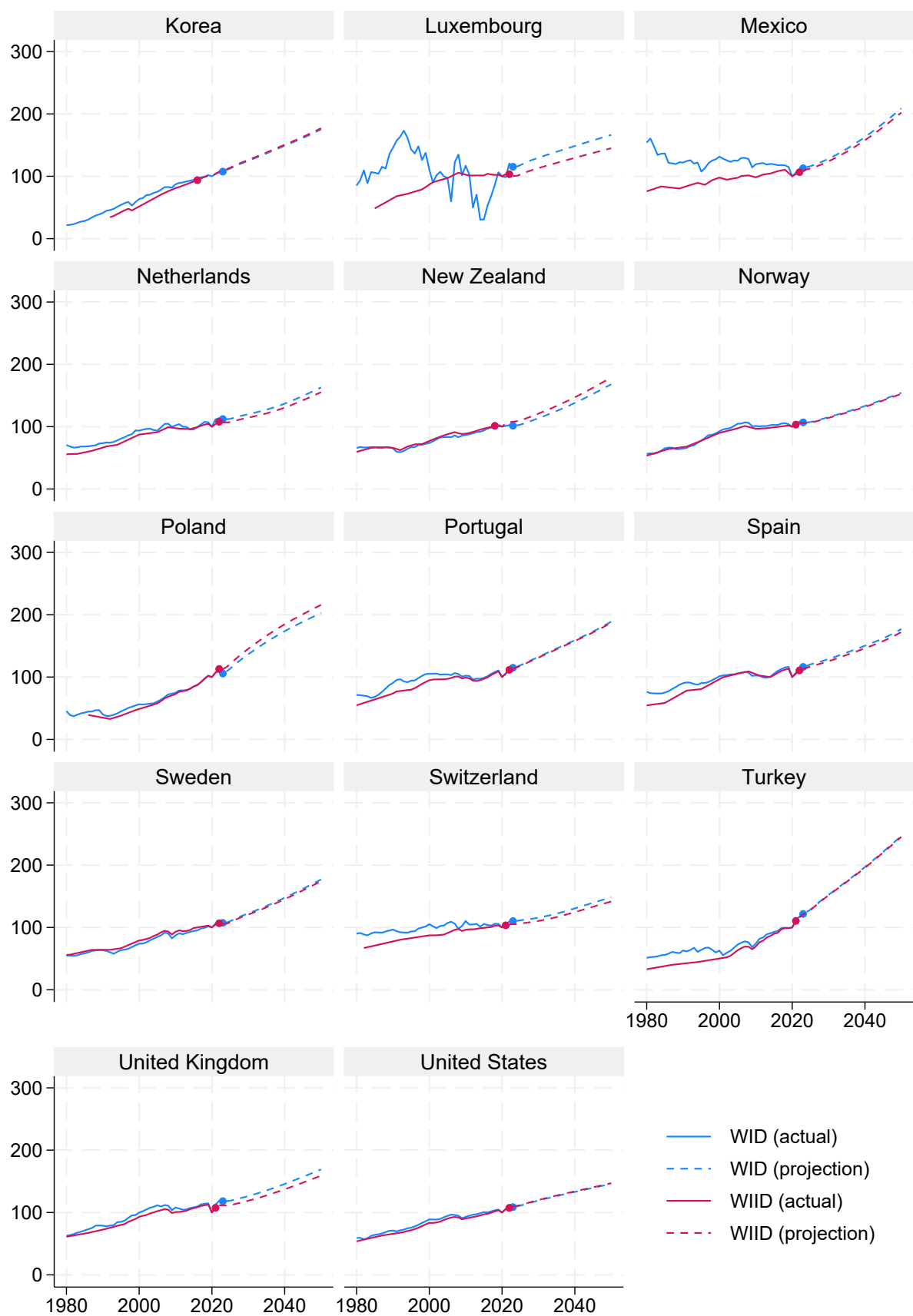


Figure 1 (cont.): Indexed real mean income (2020=100)

Note: Dots indicate where projections begin.

Mexico’s elevated 154. Several emerging economies—South Korea, Ireland and Poland, began from particularly low starting values, reflecting significant growth over this period. Some established economies like Italy and Switzerland experienced almost no per capita income growth over this period, while growth was actually negative for Mexico.

The corresponding trends in WIID data are generally similar, albeit often with less historical coverage. WIID trends are often more stable. There are some notable discrepancies. WIID suggests much stronger (post-tax) mean income growth for Mexico and Luxembourg, as well as for Ireland. These discrepancies translate to corresponding differences in the absolute mobility results, as will be shown.

The growth projections through 2050 also show considerable variation. The countries projected to achieve the strongest mean income growth are Turkey, Greece, Mexico, Poland and Ireland. These countries are characterized either by relatively low baseline incomes or strong underlying growth dynamics. Growth projections are moderate for most established economies include most mature Western countries, with projected 2050 values ranging from 146.45 (United States) to 178.99 (Spain). Countries in this cluster—including Switzerland (149.91), Canada (157.01), France (157.82), and Australia (164.72)—represent stable, developed economies with more modest but steady growth trajectories.

4.3 Inequality Trends and Projections

We now plot the historical and projected income inequality for these same years and data sources. As described in Section 2, inequality is summarised using the standard deviation of log incomes across income percentiles. The projections are as described in equation (3). Results are shown in Figure 2.

WID Countries that began the period with low inequality levels (below 0.85 in WID), such as Czechia, Poland, Sweden, and the Netherlands, generally experienced moderate increases in inequality over time. Moderate starters (between 0.85 and 1.00), including France, Germany, and Korea, displayed a mixed trajectory, with some showing significant

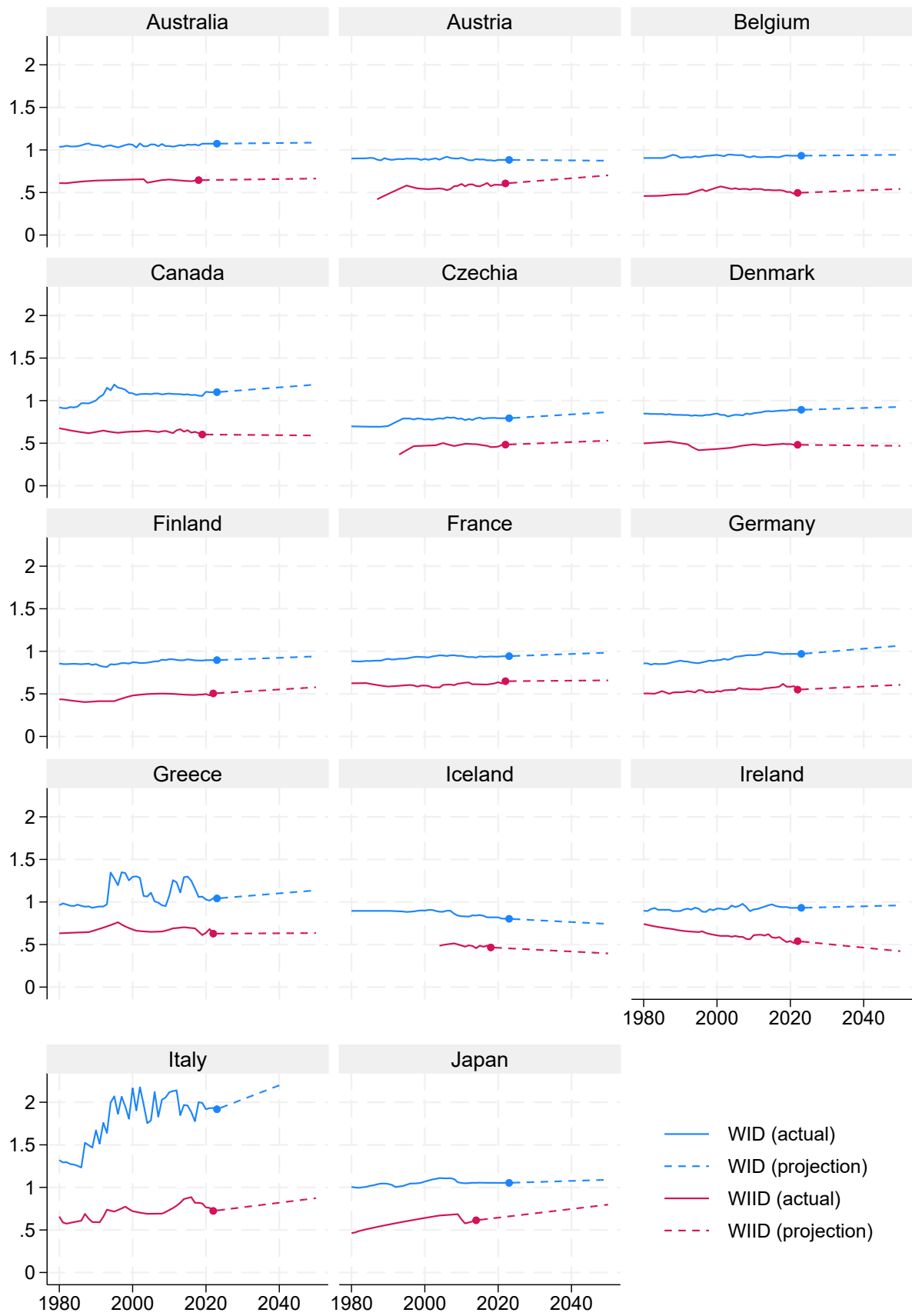


Figure 2: Inequality extrapolation (1980-2050)

Note: Dots indicate where projections begin.

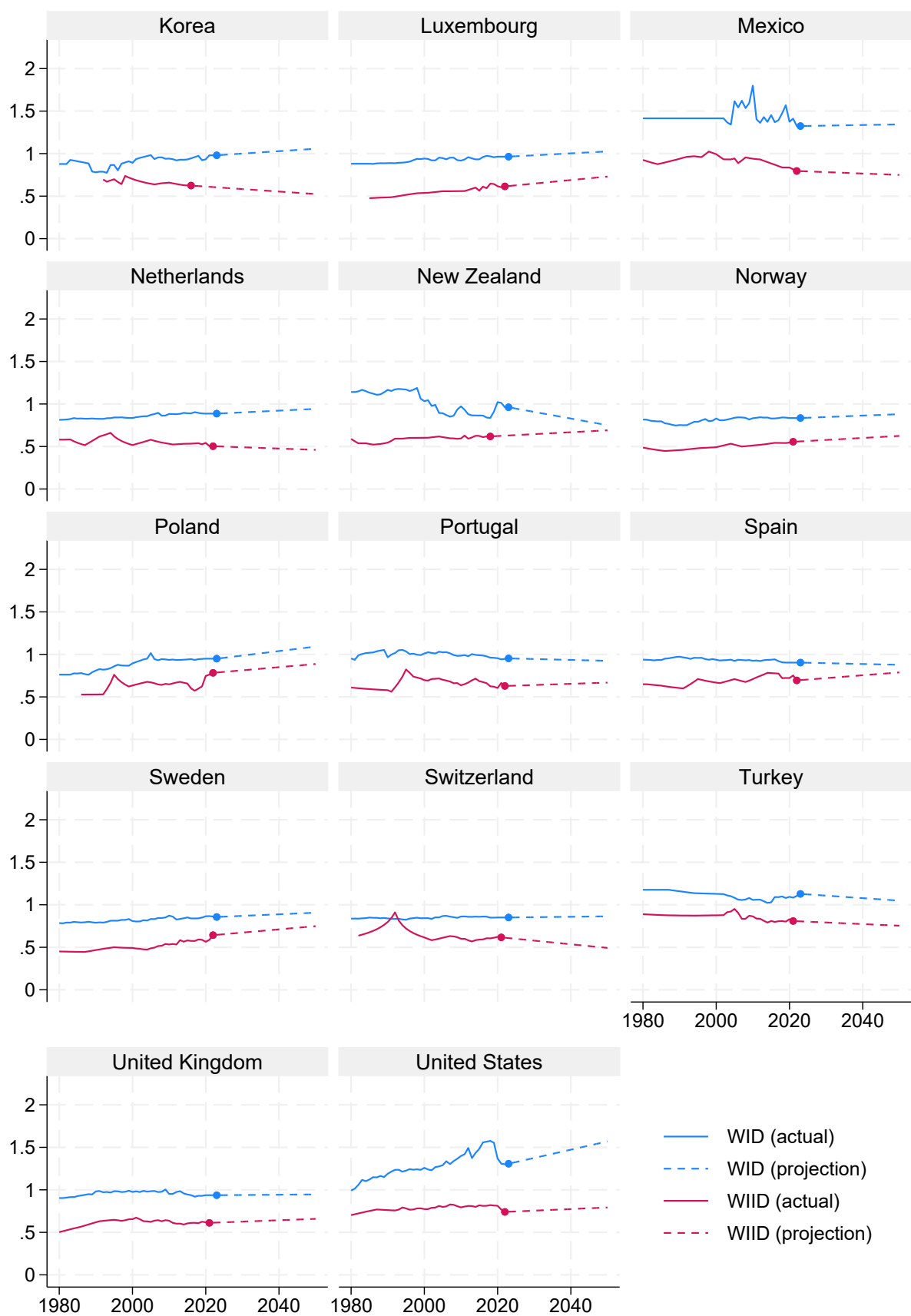


Figure 2 (cont.): Inequality extrapolation (1980-2050)

Note: Dots indicate where projections begin.

increases (e.g., Germany and Korea), while others remained relatively stable. Countries with high initial inequality (above 1.00), such as Italy, the United States, and Mexico, exhibited the sharpest divergences. Italy experienced the most pronounced increase in inequality from 1.32 in 1980 to 1.92 in 2023, followed by the United States, which rose from 0.99 to 1.31. Conversely, some countries—most notably Iceland and New Zealand—recorded declines in inequality during this period.

When comparing changes between 1980 and 2023, Italy, the United States, Poland, and Canada experienced substantial increases in inequality, whereas Iceland, New Zealand, Austria, and Spain saw inequality decrease or stabilize.

Since our inequality projections are simply extrapolations, the projected trends follow the observed trends. Hence most countries are projected to see further modest increases in inequality by 2050, with sharper rises expected in Italy, the United States, Poland, and Germany.

WIID Inequality is almost always much lower in WIID than in WID. This is expected, due to the different income concepts, especially since WIID uses after-tax income. However, for 20 of these 28 countries, the inequality trends are reasonably similar in WIID as they are for WID. The eight main exceptions are all countries where the inequality trends in WIID and WID are in opposite directions. These are Switzerland, Portugal, the Netherlands, Austria, New Zealand, Spain, Ireland and Korea.

4.4 Absolute Mobility Trends and Projections

We now present the main results - actual and projected absolute intergenerational mobility estimates. These are shown in Figure 3.

4.4.1 Historical Mobility Patterns

The Great Mobility Decline in Advanced Economies The historical analysis using both WID (pre-tax) and WIID (post-tax) data reveals a consistent decline in absolute mobility across most advanced economies between the 1950s and 1990s birth cohorts. Us-

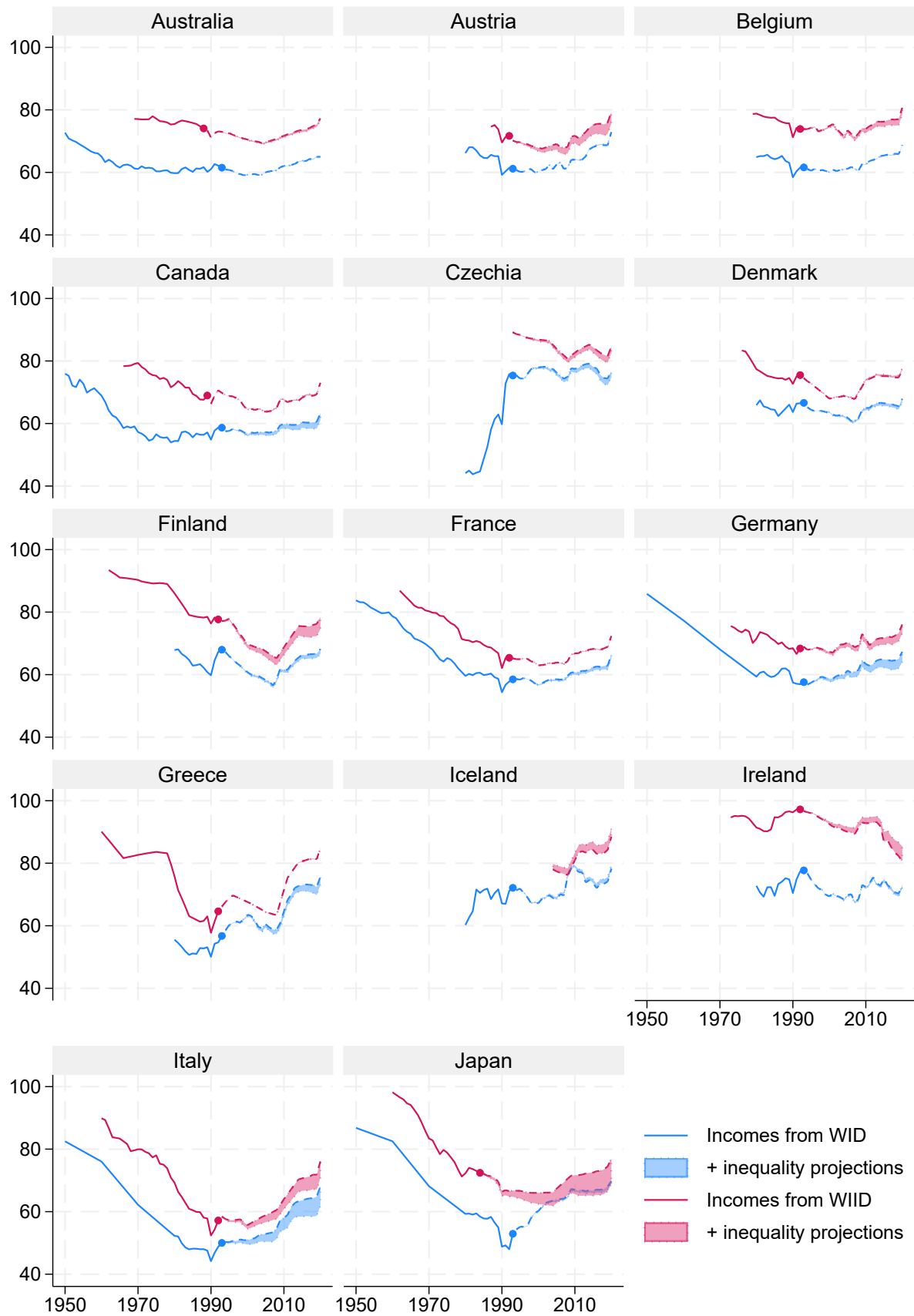


Figure 3: Absolute mobility projections by child birth year (1950-2020)

Note: Dots indicate where projections begin. Czechia, Iceland and Korea do not have long enough WIID series to observe absolute mobility for any birth cohort—all estimates rely on projected incomes. We censor observations below 40% for readability (affecting Luxembourg).

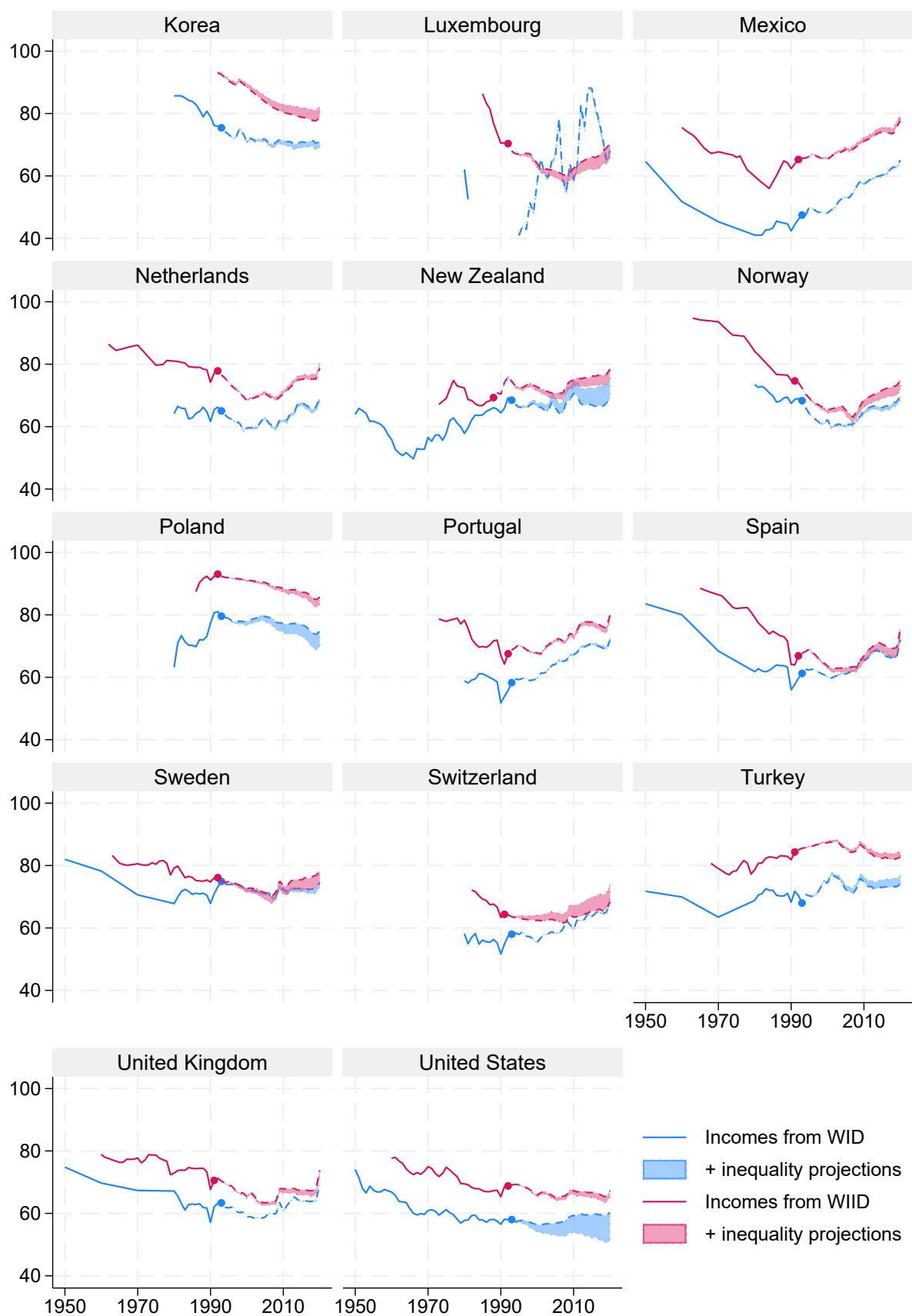


Figure 3 (cont.): Absolute mobility projections by child birth year (1950-2020)

Note: Dots indicate where projections begin. Czechia, Iceland and Korea do not have long enough WIID series to observe absolute mobility for any birth cohort—all estimates rely on projected incomes. We censor observations below 40% for readability (affecting Luxembourg).

ing WID data, the largest declines exceed 25 percentage points, including Japan (-44 pp), Italy (-33 pp), Luxembourg (-29 pp), Germany (-28 pp), and France (-25 pp). The WIID data yield quite similar findings for this set of countries.

Islands of Resilience and Growth Contrasting sharply with the dominant pattern of decline, several economies demonstrated remarkable resilience or outright improvement in mobility outcomes. The Czech Republic emerges as the most dramatic success story, with a 31 percentage point gain under WID data, reflecting the substantial catch-up growth during its post-communist transition. Poland similarly recorded significant gains (+16 pp), while Iceland (+12 pp), New Zealand (+5 pp), and Ireland (+5 pp) also improved, reflecting the economic transformation and catch-up growth these countries experienced at various times over recent decades.

4.4.2 Projected Mobility Trajectories: Growth, Inequality, and Interactions

The Recovery Scenario Under Constant Inequality The projections from the 1990s to the 2020 birth cohort suggest a potential reversal of historical mobility declines for many countries. Italy and Greece are both projected to experience substantial improvements in absolute mobility (around 18 pp each assuming constant inequality, using either WID or WIID).

The results are qualitatively similar for many nations, with thirteen countries projected to have double-digit gains under constant inequality assumptions using WIID data. These are Greece, Italy, Mexico, Portugal, Iceland, Austria, Spain, France, Belgium, Canada, New Zealand, and the Netherlands. The projections for Luxembourg again differ markedly between the WID and WIID series, suggesting care with interpretation. And a different story is seen for Korea and Poland, where moderating growth will start to weigh on current high levels of absolute mobility.

The widespread recovery reflects a projected return to trend growth following the weakness that accompanied the GFC. This is most clearly seen for countries that experienced sharp downturns. Because this measure of absolute mobility is anchored to a single year of observation (income at age 30), the sharp fall observed after a significant economic

contraction is mirrored by a sharp rebound when it is the *parents* being observed in that year. For example, Greece saw a sharp fall in absolute mobility for those born in 1980, whose incomes were observed just after the contraction due to the sovereign debt crisis that followed the GFC. Those born a few years earlier were observed with significantly higher incomes, just before the crisis hit. But the flip side is that children of the 1980s cohort will find it easier to surpass their parents' incomes at age 30.

The sensitivity of absolute mobility to the economic cycle is the downside of the features that make it so easy to measure (and, as we show, project). The use of single-year cross-sectional data has allowed significant empirical progress. However, it is not obvious that lifetime incomes would be better for a measure designed to target a 'salient' concept of mobility. And early career experiences of both generations might well be more pertinent to how people experience mobility.

The Inequality Effect: Systematic Attenuation of Gains The projections change if inequality trends are also incorporated, although typically only modestly. The shaded areas near the projections in Figure 3 show the impact of inequality trends. For most countries, inequality is trending upwards which, if continued, reduces future mobility. This is strongest for the United States, for which a projected increase in absolute mobility (+3 pp) turns into a decline (-6 pp) when inequality trends are incorporated, resulting in a 9 percentage point discrepancy for the 2020 cohort, using WID data.

This inequality effect can be seen with both WID and WIID data, for all countries where inequality trending upwards (and hence is projected to increase here). In WID projections, Canada and Finland see their projected mobility increases nearly halved when inequality evolves. Germany, Portugal, Denmark, Sweden, and the United Kingdom have moderate projected increases in mobility assuming no change in inequality, which diminish when inequality trends are incorporated. The magnitude of the inequality effect varies, reflecting heterogeneous distributional trajectories and institutional contexts.

For the smaller set of countries where inequality is trending downwards—Switzerland, Ireland, Iceland, Mexico, the Netherlands, Turkey, Denmark, and Canada under WIID projections—mobility projections are of course higher when inequality trends are incor-

porated.

5 Conclusion

This paper outlines a new approach to project absolute intergenerational income mobility. Since parental income distributions for future cohorts are already observed, we need only model children’s income. Adopting the copula-and-marginals approach, this task is reduced to projecting the marginal income distribution for future years.

We have demonstrated this approach by implementing it for 28 OECD countries using widely available databases. We have also shown historical absolute mobility estimates for the same countries. To our knowledge, this includes the first estimates for 16 countries—Austria, Belgium, Czechia, Greece, Iceland, Ireland, Italy, Korea, Luxembourg, Mexico, New Zealand, Poland, Portugal, Spain, Switzerland, and Türkiye.¹⁰

For triangulation, our projections draw on two complementary income distribution databases—WID and WIID. And they consider two scenarios: one based on OECD/UN projections of per capita income growth only, and another that combines projected income growth with extrapolations of existing inequality trends.¹¹

We present several key findings. First, we confirm that absolute mobility has declined substantially across most advanced economies. The dominant factor is slower income growth in many countries, which has reduced the opportunity for younger generations to surpass their parents’ living standards. The magnitude of these declines is large, exceeding 30 percentage points in countries like Japan and Italy. This widespread decline shows the fragility of the high rates of post-WW2 absolute mobility. Second, the projections suggest that a strong recovery of mobility is possible under scenarios where mean income grows in line with GDP per capita forecasts, especially when inequality is held constant. Many countries, especially Greece and Italy, could be poised for significant rebounds, if OECD

¹⁰Chetty et al. (2017) focused on the United States; Berman (2022) examined ten advanced economies (Australia, Canada, Denmark, Finland, France, Japan, Norway, Sweden, the United Kingdom, and the United States); and Manduca et al. (2024) studied Canada, Finland, the Netherlands, Norway, and Sweden, the United States and Germany.

¹¹Of course there are many factors—including technological disruption, wars and political transitions, and natural disasters—which may cause trends in growth and inequality to diverge from current projections.

growth forecasts are realised. Third, as previously established with historical data, rising inequality may attenuate projected increases in mobility in many countries. The United States provides the starkest illustration: a projected increase in absolute mobility of 3 percentage points reverses to a decline of 6 percentage points if inequality continues on current trends. This 9 percentage point differential underscores how rising inequality can completely negate the mobility-enhancing effects of economic growth.

This empirical application illustrates the ease of applying our approach. International and national agencies routinely produce long-run economic and fiscal projections to understand long-run prosperity and fiscal sustainability prospects for nations. It is also common to explore how these vary with different assumptions, for example, around productivity growth. With our method, policymakers can now also relate these projections to a salient measure of intergenerational mobility—the probability of children growing up to have higher real incomes than their parents did at a similar age.

Declaration of Generative AI Use

During the preparation of this manuscript, the authors used Generative AI (ChatGPT and Claude) for copy-editing and English-language refinement. All substantive content, including the research design, methodology, analysis, interpretation of results, arguments, and conclusions, was developed by the authors. The authors critically reviewed and revised all AI-assisted edits and take full responsibility for the content of the manuscript.

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A Appendix: Data Quality & Supplementary Results

A.1 Data quality and cross-country comparability caveats by country

This appendix documents data quality considerations for the two primary sources used in this study: the World Inequality Database (WID) and the World Income Inequality Database (WIID) across 28 OECD countries, focusing on methodological differences, documented limitations, and cross-country comparability.

The WID provides Distributional National Accounts (DINA) estimates following [Piketty et al. \(2018\)](#). It reports income distribution series based on pre-tax national income—labour income, capital income, and mixed income—before taxes and transfers. The unit of analysis is equal-split adults: income is divided equally between partners within couples. The database covers 100 per cent of national income by integrating tax microdata, household surveys, and national accounts. We rely on the official WID DINA series and do not make country-specific adjustments beyond those already documented.

The WIID Companion provides standardised income distribution series following [Gradín \(2021a\)](#) and [Gradín \(2021b\)](#). We use per capita net income expressed in 2017 PPP U.S. dollars. The income concept is post-tax, post-transfer (net) income, measured on a per capita basis. Data sources include the Luxembourg Income Study (LIS), Eurostat’s EU-SILC, the OECD Income Distribution Database, and national household surveys.

A.1.1 WID Quality Grading Framework

The WID assigns each distributional income series a quality grade from 0 (lowest) to 5 (highest). The 2025 DINA Guidelines introduce an explicit time dimension, allowing grades to vary annually within a country. This lets users track data-infrastructure improvements and compare reliability across countries and time.

Grade 5 denotes fully integrated tax and survey microdata; Grade 4 indicates both sources are present but at least one is tabulated rather than micro-level; Grade 3 relies on survey data alone (income or consumption); Grade 2 represents mechanically interpo-

lated values between benchmarks; Grade 1 uses carry-forward/backward imputation for short gaps; and Grade 0 imputes regional averages where no country-specific data exist. Grades are reported alongside each series in the WID database. They are also aggregated into the **Inequality Transparency Index**, which incentivises improvements in national distributional statistics.

The *Inequality Transparency Index* provides a cross-country measure of the availability, accessibility, and quality of data used to measure income and wealth inequality. Developed by the World Inequality Lab in collaboration with the United Nations Development Programme, the index evaluates the extent to which national statistical systems produce transparent and accessible distributional data on income and wealth (Burq and Chancel, 2020). The index ranges from 0 to 20, with higher values indicating greater transparency and better data availability. It combines information from several sources, including household income surveys, administrative income tax records, wealth surveys, and wealth tax data. Each source is evaluated according to criteria such as data quality, frequency of publication, and public accessibility.

A score close to 20 reflects an environment in which countries regularly publish detailed distributional accounts that integrate survey and administrative data, allowing researchers to measure inequality accurately across the entire distribution, including top income and wealth groups. Lower scores indicate limited availability of reliable distributional data, often requiring researchers to rely on indirect estimation methods or regional imputations. The index is updated annually alongside the World Inequality Database and serves as a benchmark for comparing the transparency of inequality statistics across countries (Burq and Chancel, 2020; United Nations, 2019). The Data Quality Scores and Inequality Transparency Index Scores are presented in Table A.1.

Countries with Advanced Administrative Data for Distributional Accounts

Few countries possess the fully integrated tax and survey microdata required for Grade 5; these represent the pilot DINA implementations.

The United States is the benchmark case, with tax micro-files since 1962 and extensive survey integration. Piketty et al. (2018) constructed synthetic microfiles covering nearly

Table A.1: Data Quality Scores and Inequality Transparency Index Scores from WID

Country	Data Quality Score (out of 5)	Inequality Transparency Index (out of 20)		
		Income Score	Wealth Score	Weighted Transparency Score (out of 20)
Australia	3	6.0	3.0	9.0
Austria	4	8.0	2.5	10.0
Belgium	3	7.5	2.5	10.0
Canada	3	6.0	3.0	9.0
Czechia	3	5.0	0.0	4.5
Denmark	4	8.5	5.0	13.0
Finland	4	8.5	2.5	10.5
France	5	8.0	7.0	15.0
Germany	4	8.0	5.5	13.0
Greece	3	6.0	2.5	8.5
Iceland	4	8.0	0.0	7.0
Ireland	4	8.0	2.5	10.0
Italy	4	8.0	5.5	13.0
Japan	3	3.5	2.5	6.0
KoreaRep	3	6.5	5.0	11.5
Luxembourg	3	5.0	2.5	7.5
Mexico	4	6.0	3.0	8.5
Netherlands	4	7.5	7.0	14.5
NewZealand	3	8.0	3.0	10.5
Norway	4	8.5	9.0	17.5
Poland	4	7.0	2.0	8.5
Portugal	4	8.0	2.5	10.0
Spain	4	8.0	8.0	16.0
Sweden	4	8.5	6.0	14.5
Switzerland	4	7.5	4.5	12.0
Turkiye	2	3.5	0.0	3.0
UnitedKingdom	4	8.0	7.5	15.5
UnitedStates	5	8.0	7.5	15.5

Note: The Data Quality Score (0–5) is retrieved from WID metadata associated with the relevant income distribution series (field `quality`); in practice, this can be obtained by downloading the series with metadata enabled (e.g., using the WID Stata tool with the `metadata` option) and then extracting the reported `quality` values for each country. The Inequality Transparency Index (2023) is obtained from the World Inequality Database transparency project. Detailed information on the construction of the index and its methodology is available at <https://wid.world/transparency/>.

the entire population under a narrow equal-split tax-units framework. France is the second pilot, with tax micro-files since 1970 and high-quality wealth surveys (Bozio et al., 2020; Garbinti et al., 2018, 2020). France also applies narrow equal-split under joint taxation.

Germany provides triennial tax micro-files since 1992 (Bach et al., 2020). Its data exclude individuals below the basic tax allowance, requiring imputation of low-income earners and pensioners; a dual income tax introduced in 2009 further excludes certain capital income from the tax base. The United Kingdom benefits from individual taxation microdata (Alvaredo et al., 2018), but the shift from joint to individual taxation in 1990 introduces a structural break.

Several additional economies—including the Nordic countries, the Netherlands, Spain, Australia, Canada, and New Zealand—possess strong administrative infrastructures and are covered in regional DINA estimates, but their microdata are not documented as thoroughly as for the pilot cases.

Regional Patterns in Data Quality North America and Oceania exhibit the highest quality, driven by tax microdata and strong administrative systems. Western Europe generally achieves Grade 4 or 5, while Eastern Europe is heterogeneous. East Asia typically ranges between Grades 3 and 4: Japan and South Korea possess strong administrative data, whereas China relies more heavily on survey-based corrections.

The grading framework reveals substantial heterogeneity in the empirical foundations of `ptinc` series, with the highest reliability concentrated in a group of advanced economies. All pre-tax results rely on WID `ptinc` and all post-tax results rely on WIID Companion `shareseries` = 1.

A.1.2 WIID Companion: Interpolation, Extrapolation, and Country Coverage

The WIID Companion is constructed as a balanced annual panel by (i) linearly interpolating percentile income shares between survey years and (ii) holding the distribution constant before the first and after the last observed survey for each country. In particular,

for countries with late first-survey years, inequality is assumed to be unchanged before the first included survey. [Gradín \(2021c\)](#) notes that this procedure may understate inequality changes before 1980. The dataset includes an `interpolate` flag indicating whether an observation is from a survey year, is interpolated, or is extrapolated.

Table [A.2](#) summarises the first survey year, final survey year, total number of survey-year observations (N), and an approximate survey density for all countries in the analytical sample, compiled directly from the WIID data (downloaded on 2 March 2025) used in this study, updating Table A1 in [Gradín \(2021c\)](#). Surveys are only included in this table if they include the mean incomes for each percentile, which we draw on in our main analysis. Survey density is defined as N divided by the length of the observed span (final year minus first year plus one), and ranges from 0 to 1; a value closer to 1 indicates that nearly every year in the span has a survey observation, implying minimal interpolation, whereas a lower value indicates longer gaps between surveys and heavier reliance on interpolation. The global dataset covers 1950–2022. ([Gradín, 2021c](#)).

Coverage varies considerably across countries. The United States has the highest N (62 observations, density 0.816), indicating a nearly continuous series with limited interpolation. Germany (density 0.840), Iceland (0.733), Austria (0.639), Portugal (0.620), New Zealand (0.609) and Canada (0.593) also have high survey density within their observed spans. By contrast, Greece (density 0.212), Norway (0.288), Spain (0.293), and Finland (0.311) have sparser coverage, implying longer interpolated gaps. Observations before the first survey year are extrapolated (within-country inequality held constant at the earliest observed level), and observations after the final survey year are similarly extrapolated at the last observed level. The earliest included surveys are much later for some countries than for others. Iceland’s first included survey was in 2004, the latest in the sample. The first surveys are also relatively late for Czechia (1993) and Poland (1986). The extrapolation approach that is used for earlier years may not fully capture the sharp distributional shifts of the transition era ([Gradín, 2021c](#)). Several countries have final survey years before 2022—notably Japan (2014) and Korea (2016), meaning post-final-survey years in the global dataset are extrapolated (with within-country inequality held

constant at the last observed level).

Cross-Country Comparability. Cross-country comparability is strongest after 1990, when survey coverage reaches approximately 98 per cent of world population ([Gradín, 2021c](#)). Earlier within-country changes are understated where first-survey years are late or survey density is low. Researchers can restrict analysis to survey years only, using the `interpolate` flag, to avoid interpolated or extrapolated observations.

Table A.2: WIID survey coverage for selected countries

Country	First Survey Year	Final Survey Year	N (Surveys)	Survey Density ^a
Australia	1969	2018	16	0.320
Austria	1987	2022	23	0.639
Belgium	1979	2022	26	0.591
Canada	1966	2019	32	0.593
Czechia	1993	2022	13	0.433
Denmark	1976	2022	16	0.340
Finland	1962	2022	19	0.311
France	1962	2022	33	0.541
Germany	1973	2022	42	0.840
Greece	1957	2022	14	0.212
Iceland	2004	2018	11	0.733
Ireland	1973	2022	27	0.540
Italy	1948	2022	36	0.480
Japan	1956	2014	26	0.441
KoreaRep	1992	2016	11	0.440
Luxembourg	1985	2022	17	0.447
Mexico	1950	2022	25	0.342
Netherlands	1962	2022	19	0.311
New Zealand	1973	2018	28	0.609
Norway	1963	2021	17	0.288
Poland	1986	2022	23	0.622
Portugal	1973	2022	31	0.620
Spain	1965	2022	17	0.293
Sweden	1963	2022	30	0.500
Switzerland	1982	2021	20	0.500
Turkiye	1968	2021	24	0.444
United Kingdom	1960	2021	34	0.548
United States	1947	2022	62	0.816

Notes: This table updates [Gradín \(2021c\)](#)’s summary Table A1 using the WIID data (downloaded on 2 March 2025) used in this study. Surveys are only included in this table if they include the mean incomes for each percentile, which we draw on in our main analysis. ^aSurvey density is computed as $N/(\text{final year} - \text{first year} + 1)$ and reflects the proportion of calendar years within the observed span that contain a survey observation. A value closer to 1 implies minimal interpolation; a lower value implies longer gaps between surveys and heavier reliance on linear interpolation.