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DISCUSSION PAPER

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From Lion Rock to Locked Gates: The Decline of Upward Mobility in Hong Kong

From Lion Rock to Locked Gates: The Decline of Upward Mobility in Hong Kong *

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Abstract

Using Hong Kong census data from 1976 to 2021, this paper provides the first comprehensive analysis of absolute intergenerational mobility (AIM) in a transitioning Asian economy. We introduce two innovations: decomposing AIM by factor income (labor component vs. capital component) and a Mincer-based counterfactual framework isolating education, birthplace, and other sociodemographic factors. AIM declined sharply from 85% for the 1976 cohort to 49% for the 2001 cohort, driven primarily by slower income growth rather than rising inequality, which is similar to France or Sweden, but lagging Western economies by one to two decades. Labor component mobility drove the entire decline (75% to 49%), while capital component mobility remained low and stable (17–20%). Education expansion temporarily boosted AIM by up to 18 percentage points for the 1991 cohort, coinciding with Hong Kong's post-1989 tertiary enrollment surge. Instrumental variable estimates using the 1978 compulsory education reform are consistent with the OLS-based estimates and support their validity. Our replicable framework offers insights for transitioning economies facing similar structural shifts.

Keywords: Absolute intergenerational mobility, education expansion, labor component vs capital component, Hong Kong.
JEL Codes: D31, J62, O15, O53.

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1. Introduction

Intergenerational mobility has become an increasingly prominent focus in academic research (see the review in Cholli and Durlauf 2022). Although most studies emphasize relative intergenerational mobility (RIM), absolute intergenerational mobility (AIM), the proportion of children surpassing their parents' income, has gained traction only in the past decade.[1] The seminal work by Chetty et al. (2017) documented the decline of the "American Dream" using a "copula-and-marginals" approach on U.S. cross-sectional income data for cohorts born 1940–1980. Berman (2018, 2022) and Manduca et al. (2024) further validated the method across developed economies and identifies two primary drivers for this downward trend: rising income inequality and slower economic growth. Existing research reveals substantial variation in AIM levels and trends across European countries and the United States.[2] Yet, AIM remains underexplored beyond these regions and its underlying drivers are poorly understood. Furthermore, previous studies, relying largely on long-term macroeconomic series or microlevel fiscal data (e.g., Chetty et al. 2017; Berman 2022 and Manduca et al. 2024), offer limited insight into income composition or sociodemographic heterogeneity, hindering explanations of the evolution of AIM.

Leveraging Hong Kong Census data (1976–2021), this study breaks new ground in two folds. First, the census data provide detailed information on different sources of income, allowing us to decompose total income into labor and capital components. This enables us to estimate and analyze absolute intergenerational mobility (AIM) not only for total income, but also separately by factor income sources. Second, we advance the literature by introducing a novel Mincer-equation-based approach to construct counterfactual AIM measures while controlling for key sociodemographic characteristics, such as educational attainment and immigration status. This framework enables us to quantify the contribution of different factors to changes in AIM, thereby providing more granular insights into the mechanisms underlying intergenerational mobility and opening a new avenue for examining the multidimensional determinants of

[1]See Chetty et al. (2017) for the US; Acciari et al. (2022) for Italy; Blanden (2019) for the UK; Bönke et al. (2024) for Germany; Chen et al. (2017) for Canada; Liss et al. (2023) for Sweden; and Kennedy and Siminski (2022) for Australia. Recent country-specific comparisons include Berman 2022; Stockhausen 2021 and Manduca et al. 2024.

[2]The United States exhibits lower AIM than several European countries, such as Norway, with most, including the US and UK, experiencing declining trends since the 1980s.

AIM. Figure 1 summarizes the contributions of this paper, with the boxed region highlighting our novel AIM decompositions.

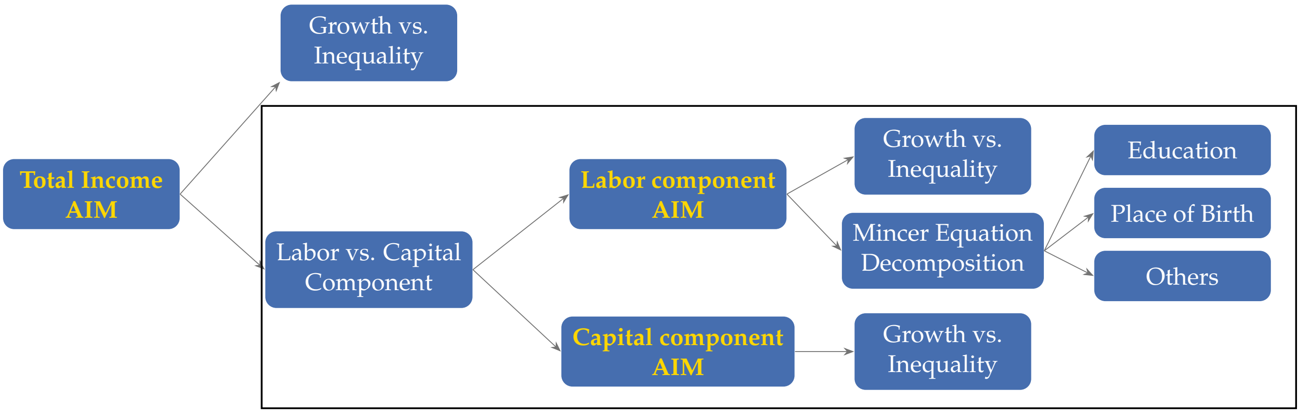


Figure 1: Analytical overview: the paper's mechanisms and contributions to the literature.

Note: The boxed region indicates this paper's novel decompositions of AIM.

Beyond the advantage of high-quality census data enabling exploration of AIM's drivers in Hong Kong, several compelling reasons justify focusing on this case study. As one of the world's most dynamic capitalist economies with minimal government intervention, Hong Kong offers a unique lens for examining social mobility evolution under laissez-faire conditions. Furthermore recent social and political upheavals, particularly the 2019–2020 protests, have intensified the scrutiny of the city's long-standing economic model, raising fundamental questions about the sustainability and inclusivity of its development trajectory. At the core is whether the vaunted "Hong Kong Dream", also known as the "Lion Rock spirit" and embodying the meritocratic promise of upward mobility through effort, is eroding, akin to the "American Dream" (Chetty et al., 2017).[3] Despite these concerns, empirical research on long-term intergenerational income mobility remains sparse, mainly constrained by data limitations.[4] Thus, mobility challenges during this transitional era remain underexplored.[5]

[3]The parallels are evident: both ideals rest on opportunity through individual merit, yet both encounter growing doubt amid structural barriers and wealth concentration that hinder progress for disadvantaged groups.

[4]This research gap stems largely from the absence of long-term panel surveys or administrative records essential for rigorous mobility studies. Hong Kong lacked a comprehensive and representative household panel until 2011 (Wu, 2016), unlike established ones such as PSID (US, 1968–present), SOEP (Germany, 1984–present) or KLIPS (South Korea, 1998–present). This data scarcity may reflect Hong Kong's laissez-faire ethos, as illustrated by Milton Friedman's 1963 anecdote: When asking Financial Secretary John Cowperthwaite about limited statistics, he reportedly replied, "If I let them compute those statistics, they'll want to use them for planning" (Friedman, 1998).

[5]Due to data constraints, prior Hong Kong studies largely focused on measuring upward mobility using fixed

This paper aims to fill this gap by systematically addressing three key questions. First, given the sharp rise in inequality since the 1980s and the slowdown in economic growth since the 2000s (Piketty and Yang, 2022), how have these trends shaped the trajectory of absolute intergenerational mobility (AIM) in Hong Kong? Second, as a major Asian financial hub, Hong Kong has experienced a substantial increase in the share of capital income since the 1990s, reaching levels that exceed those observed in most high-income economies. How, therefore, has AIM evolved differently across labor and capital incomes? Third, in the context of major structural transformations since the 1990s, including the expansion of tertiary education and the transition from manufacturing to services following China's accession to the WTO in 2001, what role have these changes played in shaping AIM dynamics?

Our findings can be summarized in three key points. First, we document a sharp decline in absolute intergenerational mobility (AIM) in Hong Kong, from 85% for the 1976 cohort to 49% for the 2001 cohort, driven primarily by slower income growth rates rather than increasing inequality. This pattern mirrors trends in industrialized economies but lags by 10–20 years, aligning with Hong Kong's later industrialization. Comparing AIM trajectories when countries reach the same GDP per capita levels, Hong Kong's AIM aligns closely with France, the United States and Sweden, while markedly surpassing Japan and the United Kingdom.[6] Underlying drivers further align Hong Kong with France, Japan, and Sweden (growth-dominated declines) over the United States and the United Kingdom (inequality-driven). These baseline results are robust across a comprehensive set of specification checks: alternative copula families (Gumbel, Gaussian, Clayton, and the empirical US copula from Chetty et al. 2014), alternative rank correlation coefficients (0.1, 0.2, and 0.3), multiple generational gaps (20–30 years), income measured at ages 30, 35, 40, and 45, and alternative earnings thresholds requiring children to earn 120%, 150%, or up to 300% of parental income, as well as control for migration background. Nonparametric bootstrap confidence intervals confirm that the estimated decline is precisely estimated and statistically significant throughout. Findings are further robust to Pareto top-coding corrections and to the selective migration pressures operating through both the emigration of high-skilled residents and continuous inward immigration from mainland China.

threshold-based approaches (Vere, 2010; Office of Economic Analysis, F. S. O. and Business and Finance Unit, 2015; Liu et al., 2023) or relative mobility analyzes (Peng et al., 2019).

[6] Measured for the children's cohorts.

Second, decomposing total income into labor and capital components shows that the decline in AIM stems largely from falling absolute mobility of the labor component, which dropped from 75% for the 1976 cohort to 49% for the 2001 cohort. By contrast, capital component mobility remained consistently low and stable, fluctuating between 17% and 20% across cohorts. Labor component mobility primarily follows macroeconomic growth patterns, while capital component mobility is mainly shaped by distributional inequality. To our knowledge, this is the first study in the AIM literature to decompose absolute intergenerational mobility by factor income source. Prior work (Chetty et al., 2017; Berman, 2022; Manduca et al., 2024) measures AIM using total or earnings income without distinguishing labor from capital components; our high-quality census data, which separately records primary employment income, secondary employment income, and other cash income (including rents, interest, and dividends), uniquely enables this disaggregation and reveals that the two components follow entirely different dynamics and are governed by different macroeconomic forces.

Third, our innovative Mincer equation-based decomposition estimates counterfactual AIM by isolating specific factors, revealing education as the most significant mitigator of the decline. This effect peaks for the 1991 cohort (boosting AIM by 18 percentage points), but weakens thereafter (11 points in 1996; 10 points in 2001), mirroring Hong Kong's tertiary education expansion and subsequent plateau. Examining counterfactual AIM across income measurement ages (25–45) reinforces this finding: the education channel operates most powerfully for younger workers, who entered the labour market precisely when tertiary enrolment surged, with education-removed AIM falling as low as 25–35% for the youngest age groups at the 1991 cohort. To address potential endogeneity in the education coefficient, we instrument years of schooling with Hong Kong's 1978 compulsory education reform, which raised the minimum school-leaving age to nine years. First-stage F-statistics exceed the conventional threshold of 10 in all census years, confirming instrument strength, and the 2SLS estimates closely mirror OLS coefficients across all periods, indicating that OLS-based counterfactuals provide a reliable approximation of the true causal return to education. Together, these results are consistent with the interpretation that Hong Kong's post-1989 tertiary education expansion was a pivotal force in sustaining intergenerational mobility during this period. This temporarily offset the structural forces of slower growth and rising inequality that would otherwise have depressed AIM further. While factors such as birthplace, industry, and occupation have negligible impact, the education channel highlights that human capital investment can serve as an effective policy lever for restoring intergenerational mobility in transitioning economies. We conclude by examining mainland China's economic rise and its implications for Hong Kong's AIM evolution.

The remainder of the paper is organized as follows. Section II provides an overview of the copula method introduced by Chetty et al. (2017) and discusses subsequent enhancements to its validity. Section III describes the Hong Kong census data and processing steps. Section IV presents the baseline empirical findings on AIM. Section V develops the decomposition of AIM by income components and sociodemographic factors. Section VI examines the mechanism behind the education-driven AIM peak observed for the 1991 cohort, linking it to the timing of Hong Kong's tertiary expansion and the intergenerational premium gap. Finally, Section VII concludes and discusses the broader implications of the study, including policy insights and directions for future research.

2. Methodology

Absolute intergenerational mobility (AIM), defined as the proportion of children earning more than their parents at a comparable age (Fan et al., 2021), ideally requires longitudinal panel data linking parent-child pairs over time for accurate measurement. For cohort c, AIM (A_c) is conceptually:

$$A_c = \frac{1}{N_c} \sum_i \mathbb{I}\{y_{ic}^k > y_{ic}^p\}$$

where N_c is the number of children in cohort c, y_{ic}^p denotes the parents' income of child i at a certain age, and y_{ic}^k denotes child i's income when he or she reaches the same certain age as the parents.

However, the lack of large-scale longitudinal datasets has hindered rigorous analysis of intergenerational income mobility. To address this, the "copula and marginals" method by Chetty et al. (2017) estimates AIM using income distributions of parents and children derived from repeated cross-sectional data. It decomposes the joint parent-child income distribution into marginals and a copula capturing rank dependencies:

$$A_c = \int \mathbb{I}\{Q_c^k(r^k) \geq Q_c^p(r^p)\} C_c(r^k, r^p)\, \mathrm{d}r^k\, \mathrm{d}r^p$$

where $Q_c^k(r)$ and $Q_c^p(r)$ are the r-th quantiles of the child for the cohort c and the parent income distributions, respectively, summarizing the marginal distributions of their incomes. r_{ic}^k denotes the percentile rank of the child i in the income distribution of children in cohort c and r_{ic}^p the percentile rank of the parents of the child i in the income distribution of parents whose children belong to cohort c. Furthermore, $C_c(r^k, r^p)$ denotes the copula, which is the probability density function of observing a child with income rank r^k and a parent with income rank r^p—the joint distribution of parent and child ranks for cohort c.

Chetty et al. (2017) demonstrate that copulas are remarkably stable across cohorts, with subsequent studies (Manduca et al., 2024; Berman, 2022) affirming the robustness of AIM estimates to copula selection in developed countries. Building on this literature, we apply synthetic copulas (Gumbel, Gaussian, Clayton) from Berman (2022) and empirical ones from Chetty et al. (2014) and Manduca et al. (2024) for cross-validation.[7]

3. Data

Our data source is the 1976–2021 Hong Kong Population By-Census Sample Dataset, comprising census data collected at 5-year intervals. It covers 10% of the population in 1976; 1% in 1981 and 1986; and 5% in 1991, 1996, 2001, 2006, 2011, 2016, and 2021. To ensure a representative sample, we restrict the sample to individuals aged 25–60, as many young adults in Hong Kong pursue university studies into their early 20s (Marginson, 2018), while retirement typically occurs between ages 60 and 65. No further restrictions are applied to the sample.

Individuals' total income is derived from three sources in the census: Monthly income from primary employment;[8] Monthly income from all secondary employment; Other cash income not tied to work, such as capital income (e.g., rents, interest, dividends) and transfer income (e.g., pensions and social security). From these components, we can further decompose total income into labor components (i.e., wages) and capital components (i.e., capital income and

[7]Following Chetty et al. (2017), we employ a transition matrix of 100×100, or copula, to calculate the probability of each parent-child rank pair (r^k, r^p). Using higher resolutions for estimating the copula can make the AIM derived from the "copula and marginals" approximation method more closely align with results obtained from linked parent-child data (Manduca et al., 2024). Given the availability of a large-scale microcensus dataset in Hong Kong, we opt to use 100 fractiles to represent the copula.

[8]For employers or self-employed persons, this represents profit (excluding expenses) from their main business; for employees, it includes base salary/wages, bonuses, commissions, overtime, housing allowances, tips, and other cash allowances.

business profit).[9] All income values are adjusted to constant 2010 prices using the Consumer Price Index from the World Bank Database (World Bank Database, 2023).

To address top-coding biases in the census wage income data, we apply a Pareto distribution correction following Piketty and Yang (2022). Specifically, income is topcoded at 99,998 Hong Kong Dollars (HKD) for those earning that amount or more in 1981, 1986, and 1991, with the threshold increased to 150,000 HKD in later years. This method of Piketty and Yang (2022) assumes that the upper tail of the wage distribution follows a Pareto form, mitigating downward bias at the top (see Appendix A for details).

To address zero-income reports in the census data, we exclude them, as they likely represent data omissions rather than true zero earnings. Across census years, 10–25% of individuals report zero income, a proportion far exceeding realistic unemployment levels. After exclusion, 18.7% of the sample remains below the poverty line, closely aligning with the official 19.9% rate of the Census and Statistics Department (C&SD, 2021) and confirming the strong representativeness for the low-income brackets. This adjustment mirrors the practices of previous AIM studies from developed countries (Berman, 2022; Bönke et al., 2024; Kennedy and Siminski, 2022; Manduca et al., 2024).

After adjusting the sample, we build a balanced sample of positive-income individuals and pair parent-child generations across census years. In particular, starting with the 1976 sample as a baseline, we randomly draw an equal number of observations (15,392) from each census to form a matrix of $15,392 \times 10$, with columns representing years 1976–2021. For each generational gap (20–30 years), we apply copulas to two columns to generate an AIM estimate. For instance, assuming a 20-year gap for the 1976 cohort, we pair the 1976 column (parents) with 1996 (children), matching incomes via a 100×100 copula matrix of relative ranks to create quasi-parent-child pairs. AIM is then the fraction of children exceeding their parents' income, weighted by copula densities. We repeat this for subsequent pairs (e.g., 1981–2001, 1986–2006, 1991–2011) and other gaps (25 and 30 years).

A final consideration concerns migration. Hong Kong experienced both outward emigration of high-skilled residents (around the 1997 handover and after 2019) and continuous inward

[9] In the census data, capital income includes all non-labor streams, such as rental income, interest, dividends, pensions, social security payments, old age/disability allowances, scholarships, education grants (excluding loans), regular contributions from outside the household, and charitable donations. As our sample excludes students and retirees, we omit pensions, grants, and scholarships.

low-skilled immigration from mainland China under the One-Way Permit scheme. Both forces selectively depress the child income distribution relative to the parent distribution, implying that our AIM estimates represent a lower bound of the true intergenerational mobility for the native population. We provide a detailed robustness analysis of this migration channel in Section 4.4.

4. Results

4.1. *Absolute Intergenerational Mobility (AIM): Baseline Result*

Drawing on rank correlation estimates from developed countries, namely Chetty et al. (2014) for the US, Jantti et al. (2006) for the Nordic countries, UK, and US, and Ueda (2009) for Japan, we estimate our benchmark AIM series using the Gumbel synthetic copula with a rank correlation coefficient of 0.3.[10]

Figure 2 illustrates the evolution of AIM across varying generational gaps between parents and children. We initially estimate AIM with a 30-year gap, but extend the series by relaxing generational gaps to 40 years. We find that assumptions on generational gaps have minimal impact on trends or levels of AIM. For example, the 1981 cohort shows AIMs ranging from 85% to 87% across these gaps, while the 1986 cohort produces 70% to 72%. To maximize the time span covered by our dataset, we adopt a 20-year gap as a benchmark. Note that this gap reflects a general generational assumption rather than actual family-specific intervals. The figure reveals a substantial decline in AIM from 85% for the 1976 cohort to 49% for the 2001 cohort. In other words, the probability of children earning more than their parents dropped from about 85% in 1976 to less than half by 2001, when measured in the working-age population.[11]

Because our AIM estimates are constructed by combining two independent cross-sectional income distributions via a synthetic copula rather than from directly linked parent–child records, it is important to verify that the results are not driven by sampling variation or simulation noise. We address this concern through a nonparametric bootstrap procedure: in each of 500 replications we resample the income data with replacement, re-pair the parent and child distri-

[10]The synthetic copula is obtained through the combination of a mathematical copula and an empirical relative mobility coefficient. Please refer to Berman (2022) for the details.

[11]Appendix F provides detailed values of all AIMs estimations.

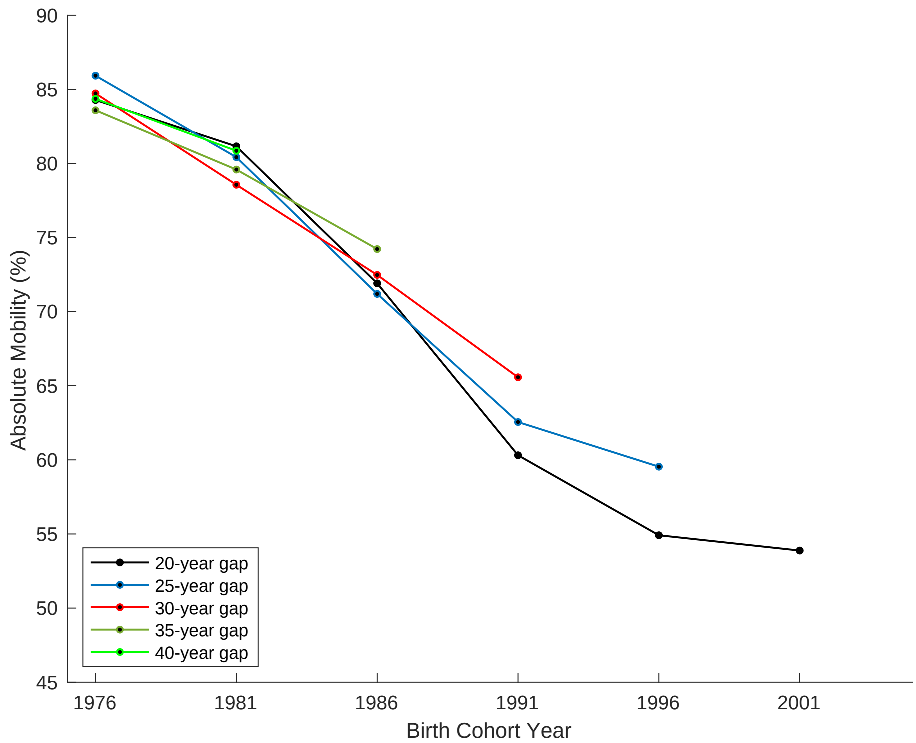


Figure 2: Absolute intergenerational mobility in Hong Kong using Gumbel copulas with a rank correlation 0.3

Note: The horizontal axis shows the parent generation's census year (birth cohort). Each point represents the AIM estimate for the cohort whose parents were observed in that census year.

butions using the Gumbel copula, and recompute AIM. The resulting 95% confidence intervals, reported in Appendix B, are narrow throughout the sample period, confirming that the estimated AIM series is precisely estimated. In particular, the steep decline between the 1986 and 1991 cohorts and the continued downward trend through the 2001 cohort are statistically significant, ruling out the possibility that the observed pattern is an artifact of estimation uncertainty.

We perform extensive robustness checks to confirm these baseline results, as detailed below.

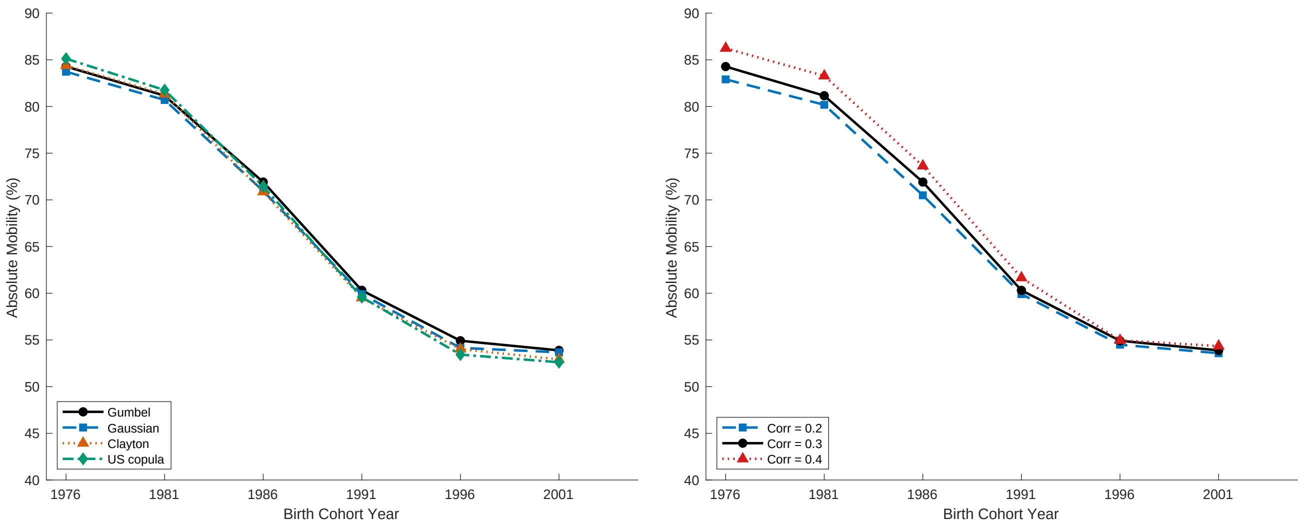
4.2. *Robustness Check: Choice of Copulas and Rank Correlation Coefficients*

Our findings remain robust to alternative copula assumptions. Figure 3a presents AIM estimates derived from various copulas, including the Gaussian copula, the Clayton copula, and an empirical copula based on US intergenerational income data (Chetty et al., 2017). These results closely match our benchmark Gumbel series, affirming the validity of the methodology. Furthermore, given that relative mobility rates in developed economies typically range from

0.1 to 0.3, we also estimate AIM using alternative rank correlation coefficients of 0.2 and 0.1. As shown in Figure 3b, this choice minimally affects the results, with synthetic copula structures remaining consistent between different parameter values.

As an additional robustness check, we examine whether the observed decline in AIM is sensitive to the definition of upward mobility. While our baseline measure defines upward mobility as children earning at least 100% of their parents' income, Appendix D reports results using higher thresholds of 120% and 150%.[12] The trends remain remarkably consistent: the 120% threshold yields AIM values approximately 5 percentage points lower than the baseline, while the 150% threshold is about 15 percentage points lower. Crucially, both alternative measures replicate the same downward trajectory over time, suggesting that the decline in absolute mobility is evenly distributed across all children who outearn their parents, regardless of the margin by which they do so.

Overall, our AIM estimates exhibit strong robustness across copulas, rank correlations, and thresholds for children's earnings relative to their parents.



(a) Different copulas

(b) Different rank correlations

Figure 3: Absolute Intergenerational Mobility in Hong Kong Using Different Copulas

Note: In the left panel, all empirical copulas assume a rank correlation of 0.3. In both panels, the generational gap is 20 years. The solid black line is our benchmark result using a Gumbel copula with rank correlation 0.3.

[12]For a similar analysis, see Fan et al. (2021).

4.3. *Robustness Check: Proxies of Lifetime Income*

In estimating absolute intergenerational mobility (AIM), the primary focus is on capturing lifetime income, although it is inherently difficult to observe directly. If income ranks stabilize after a certain age or early-age earnings reliably predict future income, measuring income at a specific age for both parents and children offers a valid approximation. As Manduca et al. (2024) suggest, incomes for individuals aged 35 and above serve as effective proxies for lifetime income in AIM estimates. To assess robustness across different proxies, we calculate AIM using incomes measured at ages $30, 35, 40$, and 45, averaging over a five-year window centered on each age (e.g., ages 28–32 for age 30).[13] For instance, if a child's income at age 30 is measured in 1996, the corresponding birth cohort is 1966.

Figure 4 depicts AIM trends using incomes measured at different ages.[14] For comparison, the dashed gray line shows the benchmark AIM using the full population (all ages combined), which is identical to the baseline result in Figure 2. The age-specific lines closely track the benchmark, with the consistent decline across ages, from approximately 85% to 50%, indicating that birth cohorts play a minor role, with the income measurement year as the primary driver. This mirrors patterns in Norway and Canada (Manduca et al., 2024), where the measurement year outweighs the age group in determining trends. In general, these findings underscore that macroeconomic growth exerts a far greater influence on aggregate mobility than individual efforts or career advancements.

Furthermore, we verify that our results are robust to the assumed rank correlation between parent and child income. Appendix E examines AIM series under various copulas (Gumbel, Gaussian, Clayton, US Copula) and rank correlation values (0.2, 0.3, and 0.4) across all four income measurement ages. The results indicate that the choice of copula and rank correlation has only a minor effect, around 5 percentage points, within each income measurement age. Importantly, the shape and timing of the secular decline remain unchanged. The pronounced

[13]Given Hong Kong's rapid education expansion starting from 1990 onward with a third university, the education attainment level of post-secondary education has increased from 4% to nearly 60% for the period 1980 to 2025. Therefore, many individuals may still pursue higher education into their mid-20s (Marginson, 2018); age 25 is retained in the main estimation sample (ages 25–60, inclusive), but excluded from the age-specific income measurement proxies below, as it is less likely to reflect stable lifetime earnings.

[14]We use a 20-year generational gap as the benchmark; results with a 30-year gap are similar across age groups (see Appendix C).

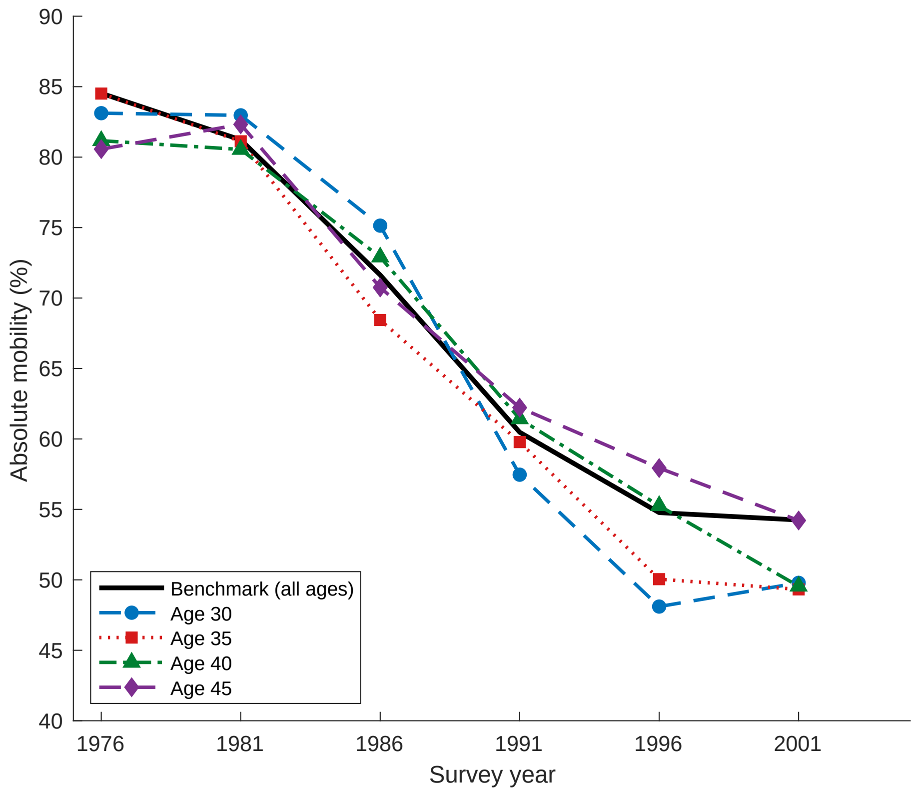


Figure 4: Absolute Intergenerational Mobility in Hong Kong by Age of Income Measurement (20-Year Generational Gap)

Note: Income is measured at ages 30, 35, 40, and 45, respectively, using a five-year window centered on each age (e.g., ages 28–32 for age 30). The dashed gray line shows the benchmark AIM using the full population (all ages combined, identical to Figure 2). The generational gap is 20 years throughout.

drop between the 1986 and 1991 cohorts persists regardless of the assumed correlation, confirming that our main conclusions are robust to the precise calibration of intergenerational income dependence.

4.4. Robustness Check: Migration and the Lower-Bound Interpretation

Our AIM estimate for cohort c compares the *child* income distribution measured at census year $t + 20$ against the *parent* income distribution measured at census year t. Any force that selectively lowers the child distribution relative to the parent distribution will therefore reduce measured AIM below the level that would prevail for a stable population of native Hong Kong residents. Two migration flows produce exactly this pattern.

Outward emigration of high-skilled residents. Hong Kong experienced recurrent waves of high-skilled emigration, most notably in the years surrounding the 1997 handover and again after

2019, directed primarily to Canada, the United Kingdom, Australia, and the United States (Lam and Fong, 2025). These emigrants were disproportionately high-educated and high-earning (Chong et al., 2024). The critical observation is that their *parents* were resident in Hong Kong during the earlier census rounds (e.g. 1976–1986) and are therefore captured in the parent distribution, whereas the emigrants themselves had already left by the time the corresponding child census round was conducted (e.g. 1996–2006) and are thus *absent* from the child distribution. We therefore observe the high-income parents who raised these emigrants but do not observe the high-income children they produced. Under the copula framework, the high-ranked parent positions are matched to children drawn from a distribution that excludes these high earners, systematically understating the income of children at the upper end of the distribution. Since it is precisely these high-earning children who would most likely have outearned their parents, their absence reduces measured AIM (see Lam, 2000; Wong and Salaff, 1998, for evidence on the positive selection of Hong Kong emigrants). The theoretical basis for this selection mechanism is formalized in Borjas (1987), with recent empirical confirmation in Borjas et al. (2019).

Inward low-skilled immigration. Mainland China's One-Way Permit scheme admitted a continuous inflow of immigrants to Hong Kong, where the quota is 75 persons per day before 1995 and 150 persons per day after 1995, the majority of whom were low-skilled workers with earnings well below the native median (Sautman, 2004). Because this inflow accumulated over time, the later census rounds (which serve as our *child* distributions, e.g. 1996–2021) contain a substantially larger share of low-income immigrants than the earlier rounds (which serve as our *parent* distributions, e.g. 1976–2001). This asymmetry shifts the child income distribution downward relative to the parent distribution. In the copula framework, a lower child income distribution means that, for any given parent rank, the matched child income is lower than it would be in a native-only sample, reducing the fraction of children who outearn their parents and thereby reducing measured AIM.

Both forces act through the same channel: they selectively depress the child income distribution relative to the parent income distribution. Outward emigration removes high earners from the child distribution; inward immigration adds low earners to it. Their combined effect is to shift the child distribution down, which mechanically reduces the fraction of children who outearn their parents. Our AIM estimates should therefore be interpreted as a *lower bound* of the true intergenerational mobility for the native Hong Kong population. The true decline in mobility is at least as large as we document, and the substantive conclusion of this paper, that the Hong Kong Dream has faded significantly, is if anything understated by our estimates.

Figure 5 provides direct evidence for this lower-bound interpretation. The green dashed line restricts both the parent and child samples to Hong Kong–born individuals, thereby removing the compositional effect of immigrant inflows on the child distribution. Across all cohorts the Hong Kong–born AIM series lies above the baseline (black solid line), consistent with the prediction that low-skilled immigration depresses measured AIM. The gap between the two series widens over time, mirroring the acceleration of One-Way Permit inflows after 1995. Importantly, both series display the same secular decline, indicating that the downward trend in mobility is not driven by changing migrant composition but reflects a genuine deterioration in the economic prospects of successive Hong Kong–born cohorts.

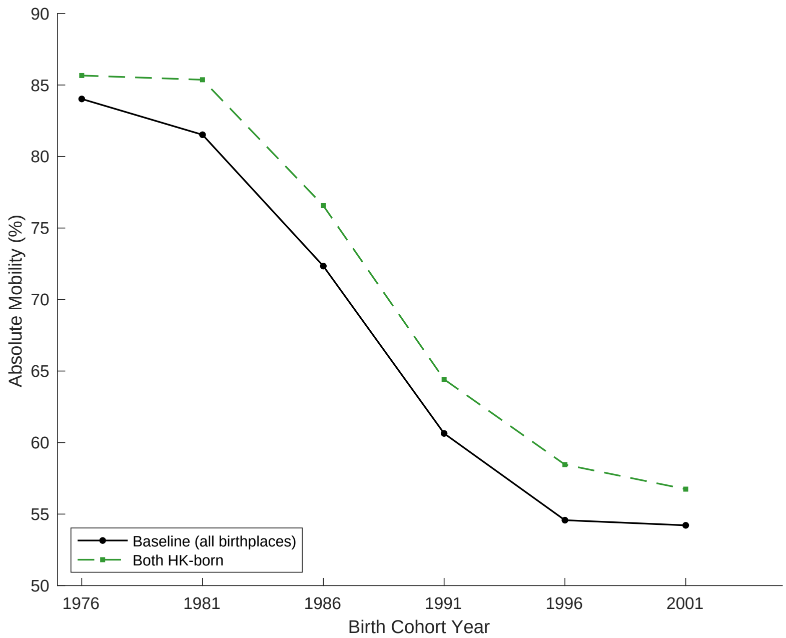


Figure 5: Absolute intergenerational mobility by birthplace: baseline (all birthplaces) versus Hong Kong–born only, Gumbel copula with rank correlation 0.3, 20-year generational gap

Note: The black solid line shows the benchmark AIM series using the full census sample (all birthplaces). The green dashed line restricts both parent and child distributions to individuals born in Hong Kong. Both series use the Gumbel copula with rank correlation 0.3 and a 20-year generational gap.

4.5. *Country Comparison*

To investigate intergenerational mobility patterns across diverse market economies, we compare our Hong Kong results with those of other developed countries. In Figure 6, the black line represents our estimates of absolute income mobility (AIM) in Hong Kong, while the other lines represent trends in selected advanced economies drawn from Berman (2022). Hong Kong's AIM trajectory closely parallels those of France, Japan and the United States (Berman, 2022; Chetty et al., 2017), reflecting the shared dynamics of economic maturation. However, a clear divergence emerges in the timing of the downward trend. Hong Kong lags approximately 15–20 years behind Japan and France, and 25–30 years behind the United States. This delay is both compelling and intuitive, aligning with Hong Kong's developmental path as one of the "Asian Tigers", where rapid industrialization trailed Japan's by about 20 years and the United States' by 30 years or more. In particular, Hong Kong's steep decline in AIM, from 85% to around 50% over roughly 20 years, mirrors Japan's trajectory from 1965 to 1980. A striking observation is that AIM in Hong Kong falls even lower than in these developed economies for the most recent cohort (2001).

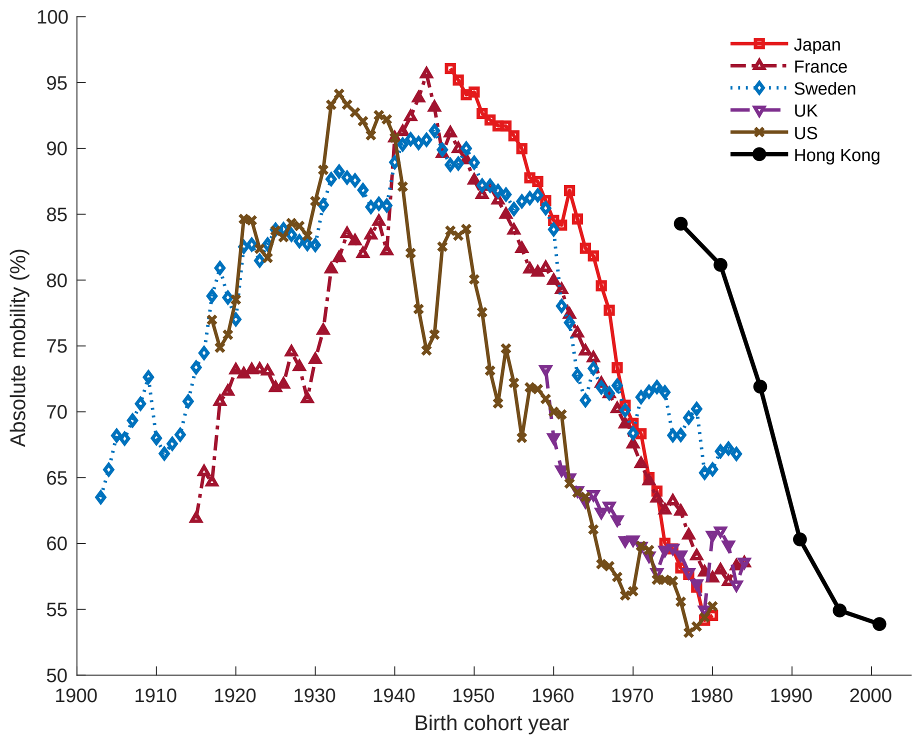


Figure 6: Absolute intergenerational mobility in six developed economies

Note: The black line represents the baseline result of this study, derived using a Gumbel copula with a rank of 0.3, a generational gap of 20 years, and measured across the full population. Data for all other countries were obtained from Berman (2022).

Looking back to the first half of the twentieth century, when AIM rose consistently across most developed economies, one might ask: Does this rise and fall represent an inevitable transition as economies evolve from developing to developed status? To explore this question, we map AIM trajectories against national development stages, using adjusted net national income per capita (GNI minus fixed capital consumption and natural resource depletion) as our metric. As Figure 7 illustrates, a broadly convergent pattern emerges: Most advanced economies, including Hong Kong, the US, France, and Sweden, exhibit broadly similar AIM levels once per capita income exceeds certain thresholds. Japan and the UK deviate slightly, showing lower AIM than their peers at comparable income levels, possibly due to unique socioeconomic factors. However, the overall pattern remains the same: AIM predictably decreases as per capita income (PPP) increases from $\$5,000$ to $\$35,000$, reflecting the shift from developing to developed economies.

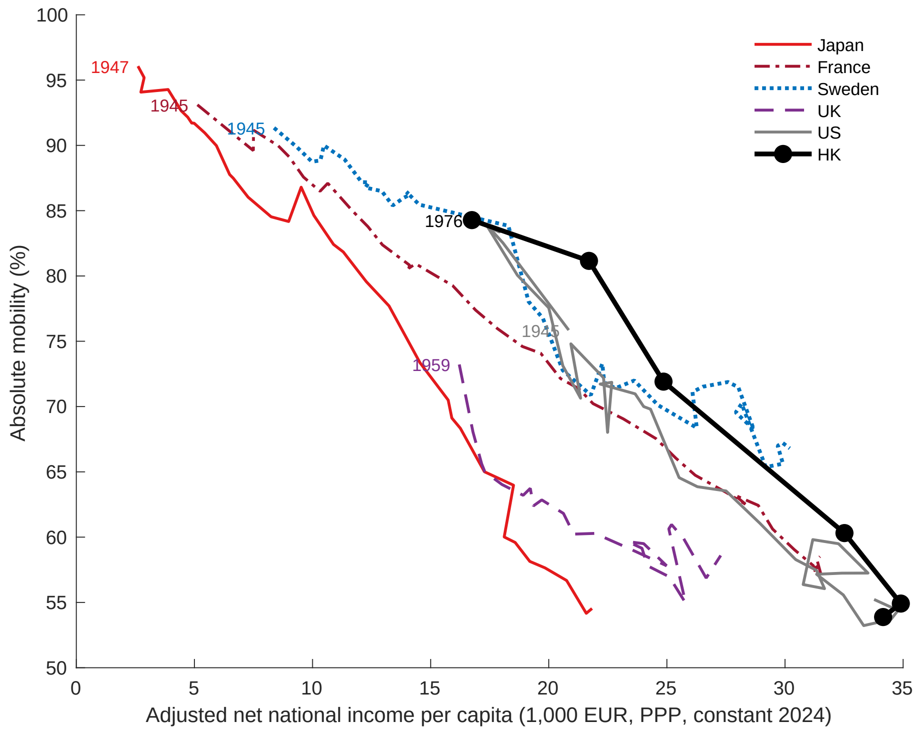


Figure 7: Absolute intergenerational mobility in six developed economies against adjusted net national income per capita

Note: The black line is our baseline result for Hong Kong, derived using a Gumbel copula with a rank of 0.3, a generational gap of 20 years, and measured across the full population. Data for all other countries were obtained from Berman (2022). The PPP-adjusted net national income per capita in constant 2023 US dollars was obtained from the World Inequality Database (World Inequality Database, 2023), which has the longest trend in the existing database. The starting year is marked in the graph for each country, to ease comparison.

5. Decomposition of Absolute Intergenerational Mobility

5.1. *Counterfactual Decomposition: Growth and Inequality*

Conceptually, absolute intergenerational mobility (AIM) provides a nuanced gauge of societal well-being by integrating both economic growth and income inequality, highlighting inherent trade-offs akin to Pareto efficiency principles. For instance, in societies with equitable income distribution but stagnant or negative growth (e.g., parts of Europe), relative mobility may be high, yet overall well-being stagnates. Conversely, in high-growth but unequal contexts (e.g., the US), expansion often yields uneven benefits, excluding many from prosperity. True high AIM emerges only in economies that balance robust growth with equitable distribution. Amid Hong Kong's slowing income growth and rising inequality (see Figure 8), a key question arises: To what extent does the observed decline in AIM stem from reduced growth versus increased inequality?

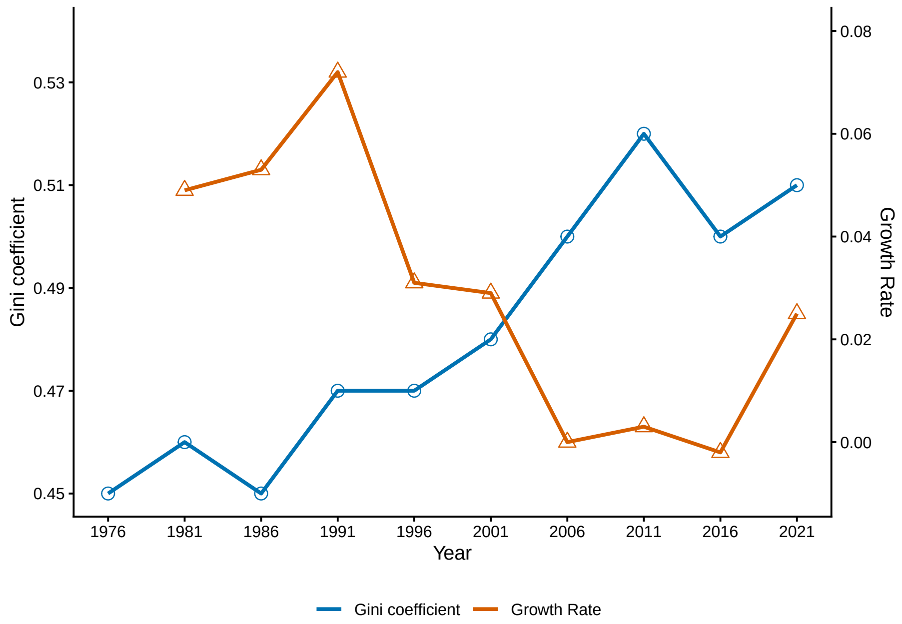


Figure 8: GINI index and real income growth rate in Hong Kong for working population

To address this question, following the algorithm of Berman (2022) and Manduca et al. (2024), we construct counterfactual scenarios by holding either income growth or inequality levels constant, isolating their respective impacts on observed AIM trends. First, to assess inequality's (distributional) effect, we fix the growth rate at the 1976–2021 average ($\approx$ 2.6%), while retaining each year's actual distribution.

$$I_t^{\text{fixed\_gr}} = \frac{I_t}{\text{mean}(I_t)} \times \text{mean}(I_{1976}) \times (1+G)^{t-1976}$$

where I_t denotes real income in year t, and G represents the average annual growth rate from 1976 to 2021. This normalizes the distribution in year t (via division by its mean) by scaling it to the mean income of 1976, and applies average growth, yielding the fixed-growth counterfactual.

Conversely, to isolate growth's effect, we fix the distribution at 1976 levels while applying subsequent years' actual mean incomes.

$$I_t^{\text{fixed\_dis}} = \frac{I_{1976}}{\text{mean}(I_{1976})} \times \text{mean}(I_t)$$

which normalizes 1976's distribution and scales it to average income in year t.

As shown in Figure 9, the fixed inequality counterfactual closely tracks the baseline estimates. This indicates that preserving inequality at 1976 levels has minimal impact on AIM. Even with such equity, mobility would not rise substantially. Conversely, fixing growth at the 1976–2021 average (2.6% annually) yields stable AIM at approximately 67%. Thus, Hong Kong's AIM decline stems primarily from slower income growth. This pattern aligns with Canada, France, Japan, and Nordic countries, where growth slowdowns drive mobility erosion, unlike Australia, the UK, and US, where rising inequality predominates (Berman, 2022).

5.2. *Income Decomposition: Labor and Capital Components*

Due to data availability constraints, the existing literature on absolute intergenerational mobility (AIM) focuses predominantly on total income, leaving trends by income type largely unexplored. Yet, disaggregating income growth by type is essential for a nuanced understanding of mobility drivers. To this end, we analyze AIM by income components, distinguishing the labor component (employment income: wages, salaries, and employer or self-employment earnings) from the capital component (non-labor cash income: capital income such as rents,

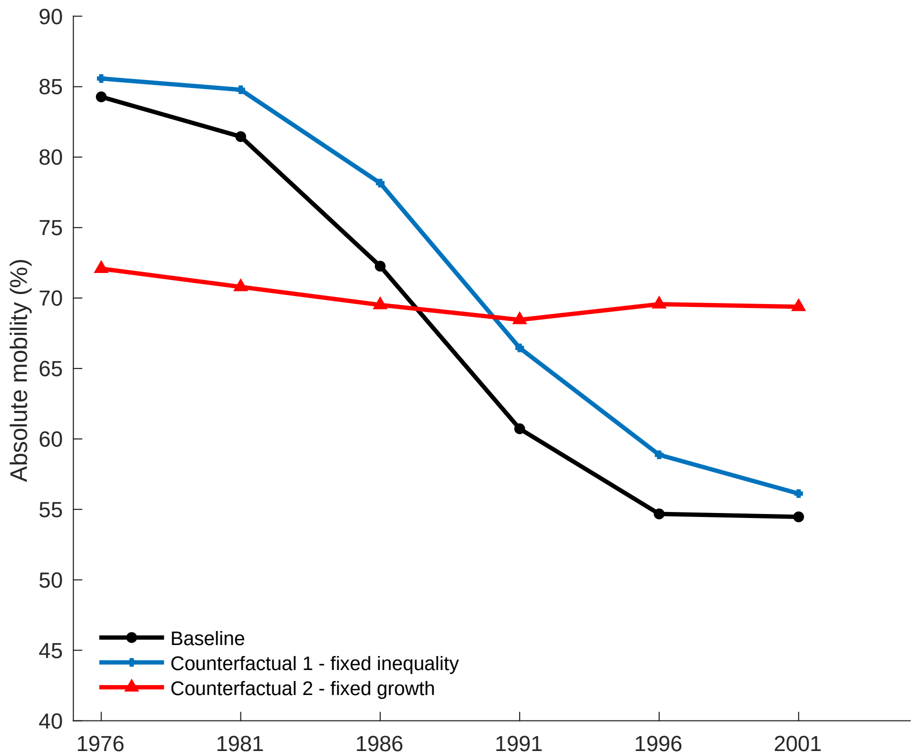


Figure 9: Decomposition of absolute intergenerational mobility in Hong Kong

Note: The horizontal axis shows the parent generation's census year (birth cohort).

dividends, and interest, plus business profit).[15] The sample for the wage and capital AIM estimates is identical to the total income sample: the same set of individuals (aged 25–60, excluding students and retirees) appears in all three series, with only the income measure varying. Individuals with zero wage income are included in the wage AIM calculation, and likewise for zero capital income. For the 2021 census, we apply a total income floor of HKD 1,000 per month (with HKD 500 as a robustness check) to filter out income observations inflated by one-off government COVID-19 relief transfers.[16]

We begin by examining average wage and capital/business income growth over time (in

[15]In the census data, capital income includes all non-labor streams, such as rental income, interest, dividends, pensions, social security payments, old age/disability allowances, scholarships, education grants (excluding loans), regular contributions from outside the household, and charitable donations. As our sample excludes students and retirees, we omit pensions, grants, and scholarships.

[16]During the 2021 census reference period, the Hong Kong government disbursed a universal HKD 10,000 cash payout to all permanent residents aged 18 or above (HKSAR Government, 2020) and launched a HKD 5,000 electronic Consumption Voucher Scheme covering approximately 7.2 million residents (HKSAR Government, 2021). These transfers, recorded as "other cash income" in the census, would otherwise distort the income distribution by inflating non-labor income for individuals with little or no genuine market income.

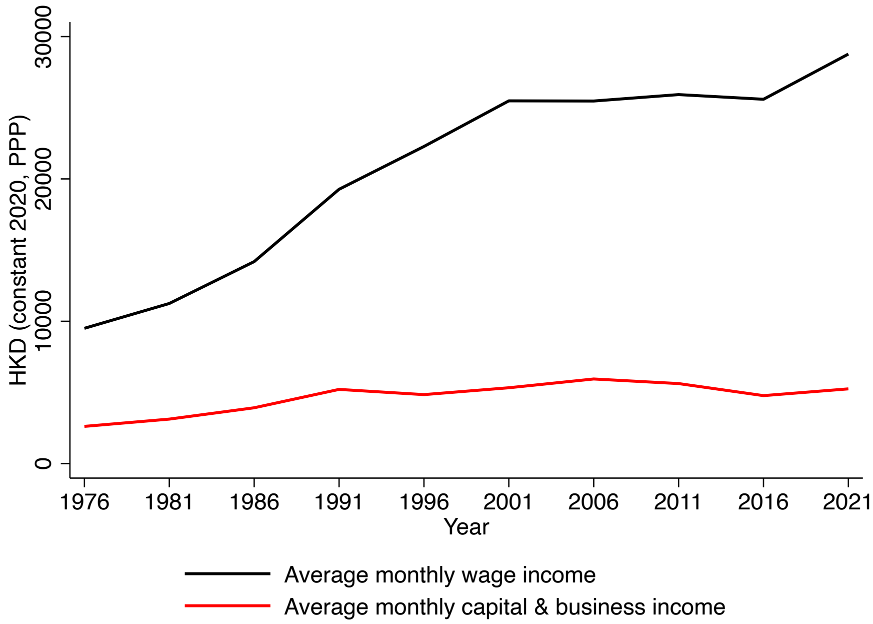


Figure 10: The evolution of average wage income and capital & business income in Hong Kong

2023 PPP USD). Figure 10 shows that both components grew robustly through 2006, but by 2021, wages had stagnated, while capital and business income reverted to 1986 levels.[17] Figure 11 further illustrates AIM by income component: labor component mobility declines sharply from 75% for the 1976 cohort to 49% for the 2001 cohort, mirroring total income trends albeit less steeply, while capital component mobility remains stable at under 20%.[18]

Figure 12 documents the income participation rates underlying each series. Workers with positive employment income account for approximately 81–86% of the sample throughout the period. Capital component recipients, by contrast, constitute a persistently small minority of roughly 20–27%. Notably, the share with zero capital component income remains remarkably stable across all ten census waves, an extensive-margin stability that is central to the low-and-flat profile of capital component AIM. This concentrated participation is central to understanding why capital component mobility is structurally lower than labor component mobility across all cohorts.

[17]For detailed distributional series and growth rates by component, see Appendix G. Note that capital and business income shares appear low in census data, likely due to under-reporting. As a result, our related findings should be interpreted with caution.

[18]Since only 20% of the population possesses capital component income in our sample, a substantial proportion reports zero values across both cohorts. This accounts for the low observed mobility rate, with the central implication being that the mobility of capital and business income exhibits no substantial change.

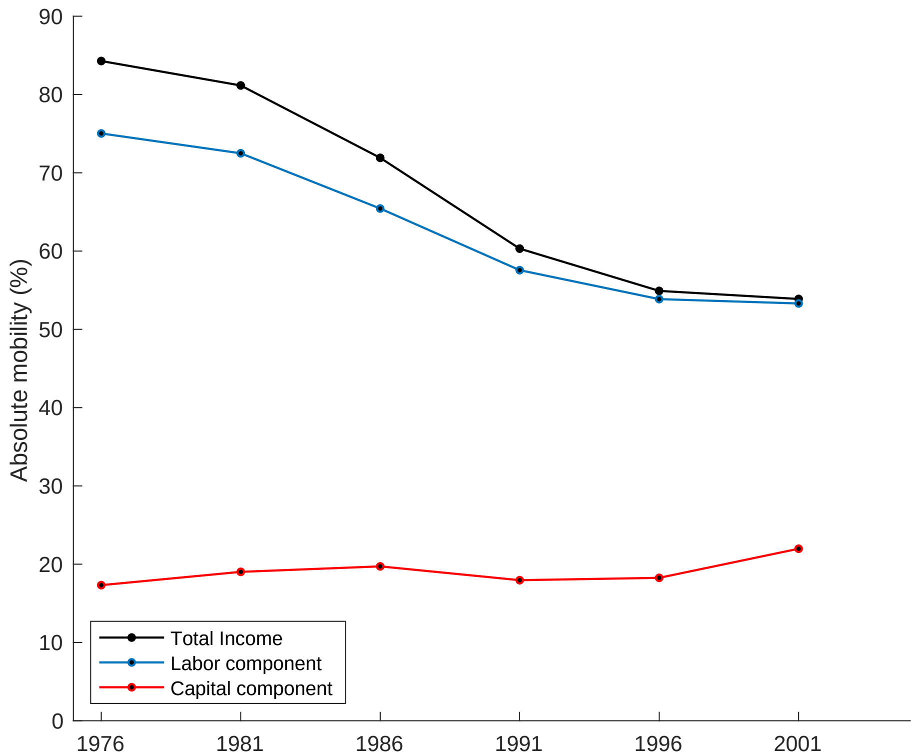


Figure 11: Absolute intergenerational mobility in Hong Kong by income component

Note: The horizontal axis shows the parent generation's census year (birth cohort). Labor component = employment income; capital component = capital income and business profit.

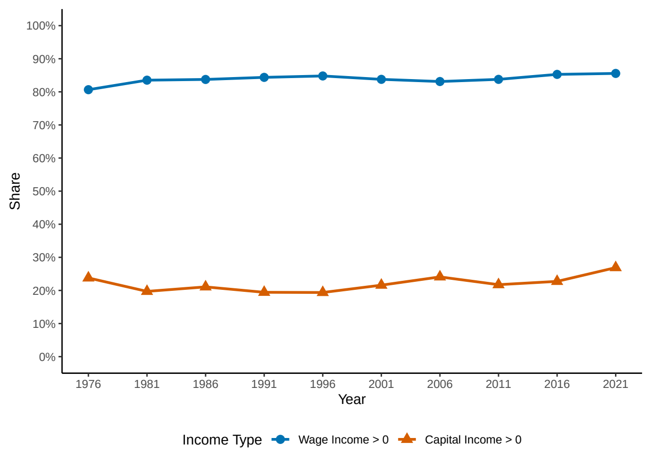


Figure 12: Share of working-age individuals with positive wage income and positive capital income in Hong Kong, 1976–2021

We apply the same growth-versus-inequality decomposition used for total income (Section 5.1) separately to wage income and capital & business income. The two counterfactuals are constructed identically: Counterfactual 1 (fixed inequality) rescales the 1976 distribution to match each subsequent year's mean, while Counterfactual 2 (fixed growth) applies the period-average annual growth rate to the actual distribution of each year. AIM is computed under each scenario using the Gumbel copula with rank correlation 0.3 and a 20-year generational gap.

Labor component. Figure 13 presents the decomposition for the labor component. The fixed-inequality counterfactual (cyan) tracks the baseline (black) closely throughout the period, indicating that changes in labor component inequality have a limited independent effect on labor component mobility. By contrast, the fixed-growth counterfactual (red) maintains AIM at approximately 63–66%, well above the baseline for later cohorts. This pattern mirrors the total income decomposition and confirms that the sharp decline in labor component AIM, from roughly 75% for the 1976 cohort to 53% for the 2001 cohort, is driven primarily by the slowdown in real wage growth rather than by widening inequality.

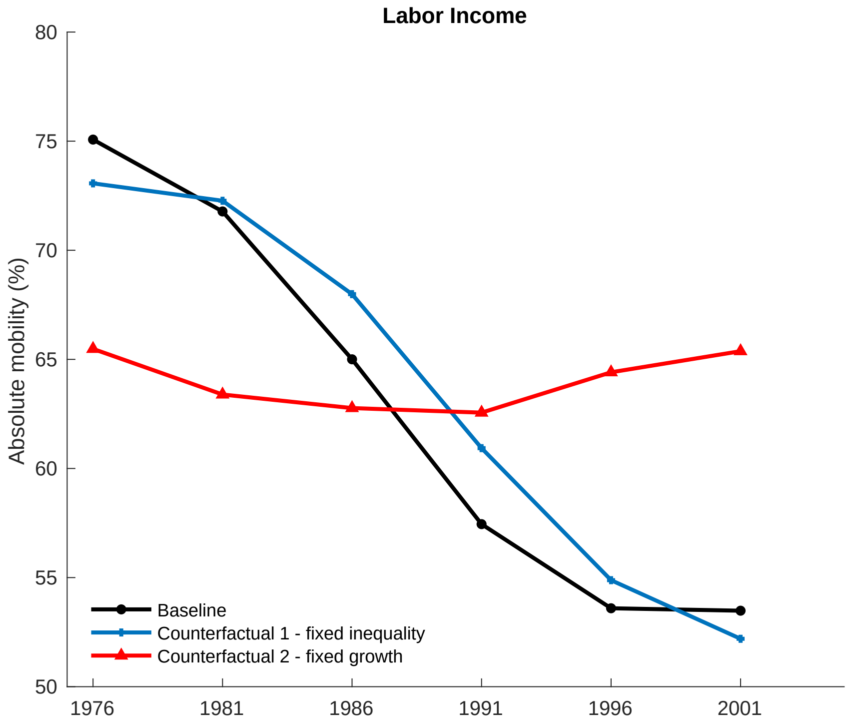


Figure 13: Decomposition of absolute intergenerational mobility: labor component

Note: The horizontal axis shows the parent generation's census year (birth cohort).

Capital component. Figure 14 presents the corresponding decomposition for the capital component. Here the pattern is markedly different. The fixed-growth counterfactual (red) rises from roughly 17% to 23%, closely tracking or exceeding the baseline, suggesting that mean capital component growth alone would have raised mobility. The fixed-inequality counterfactual (cyan), however, declines from approximately 21% to 19% over the period, diverging below the baseline for later cohorts. This indicates that rising inequality in the capital component, reflecting the increasing concentration of asset ownership, rental income, and investment returns among a small segment of the population, is the primary force suppressing capital component mobility. The result is consistent with Berman and Milanovic (2024), who document that capital income is far more unequally distributed than labor income, with returns disproportionately accruing to high-income households.

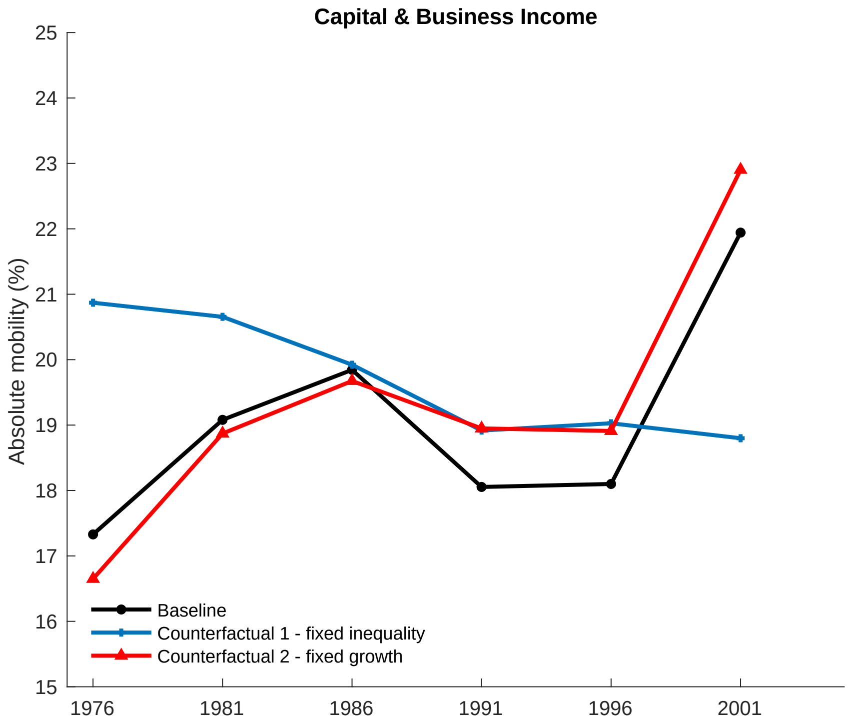


Figure 14: Decomposition of absolute intergenerational mobility: capital component

Note: The horizontal axis shows the parent generation's census year (birth cohort).

Taken together, the two decompositions reveal a structural asymmetry: labor component mobility declines because real wages stopped growing, while capital component mobility remains low because capital returns are increasingly concentrated. This dual mechanism underscores the importance of disaggregating income by type when analysing AIM dynamics, and highlights that the forces shaping intergenerational mobility differ fundamentally across the income distribution.

5.3. *Mincer Equation-Based Decomposition Framework*

From research and policy perspectives, it is essential to deepen our understanding of how demographic factors, such as education, gender, and immigration background, shape the evolution of absolute intergenerational mobility (AIM), as they significantly influence economic trajectories and upward mobility potential. However, the existing AIM literature focuses mainly on measuring overall trends, with limited attention to the underlying socioeconomic mechanisms, leaving demographic impacts on mobility outcomes underexplored. To bridge this gap, we introduce a novel Mincer equation-based decomposition framework for systematically analyzing the influence of these factors on AIM dynamics. By estimating counterfactual AIM trends that isolate effects of key sociodemographic variables (e.g., educational attainment, gender, and immigration background), we quantify their relative contributions and uncover new insights into the mechanisms driving intergenerational mobility.

5.3.1. *Benchmark: OLS Results*

Below, we demonstrate the Mincer equation-based decomposition using wage income. The corresponding results based on total income (wage plus capital income) are presented in Appendix Figure A6, confirming the robustness of our findings.

The Mincer equation is presented below:

$$\ln(Y_i) = \alpha + \beta_1 Gender_i + \beta_2 Exp_i + \beta_3 Exp_i^2 + \beta_4 Edu_i + \sum_{k=5}^{n} \beta_k C_i^k + \epsilon_i$$

where Y_i denotes the wage income of individual i, $Gender_i$ is a binary indicator for male, Exp_i represents work experience (calculated as age minus years of schooling minus preschool years),[19] and Edu_i is years of schooling inferred from census categories (e.g., primary levels, middle school years, technical training, bachelor's and graduate degrees).[20] The summation $\sum \beta_k C_i^k$ incorporates controls for occupation, industry, birthplace, and marital status, all encoded as dummy variables.[21]

[19]If schooling ends before age 15, we subtract 15 instead. Our sample excludes individuals under 15 years of age or with zero income, thus omitting current students.

[20]Years of schooling are derived from detailed educational attainment, including lower/upper primary, each middle school year, craft/technical training, bachelor's degrees, and graduate school.

[21]For summary statistics, see Appendix H.

Therefore, our estimated regression can be expressed as follows:

$$\ln(\hat{Y}_i) = \hat{\alpha} + \hat{\beta}_1 Gender_i + \hat{\beta}_2 Exp_i + \hat{\beta}_3 Exp_i^2 + \hat{\beta}_4 Edu_i + \sum_{k=5}^{n} \hat{\beta}_k C_i^k + \hat{\epsilon}_i.$$

To construct the education-removed counterfactual, we define residual-preserving counterfactual income $Y_i^{(-Edu)}$ by omitting only the fitted education component while retaining all other fitted components and the individual residual:

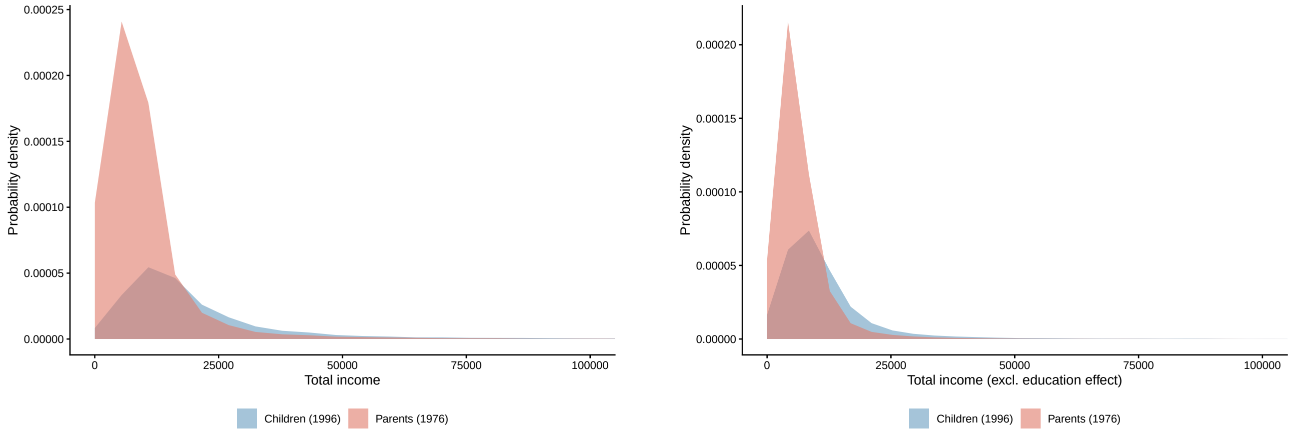
$$\ln\left(\hat{Y}_i^{(-Edu)}\right) = \hat{\alpha} + \hat{\beta}_1 Gender_i + \hat{\beta}_2 Exp_i + \hat{\beta}_3 Exp_i^2 + \sum_{k=5}^{n} \hat{\beta}_k C_i^k + \hat{\epsilon}_i.$$

This is not a fitted value in the conventional sense (which would exclude $\hat{\epsilon}_i$); rather, it is a *residual-preserving counterfactual*: the individual residual $\hat{\epsilon}_i$ is retained so that all unobserved heterogeneity not captured by the Mincer covariates is preserved.[22] We then use this counterfactual income $\hat{Y}_i^{(-Edu)}$ to compute the adjusted wage AIM, which allows us to isolate the specific contribution of education and clarify its role in mobility dynamics. By extending this framework, we can assess the impacts of other socioeconomic factors on AIM, such as occupation, industry, and place of birth.

Figure 15 illustrates the income distributions of parents (1976) and children (1996) before and after controlling for education. Panel (a) shows that the children's distribution shifts substantially to the right relative to the parents', reflecting higher real incomes. Panel (b) removes the contribution of education from predicted income: the rightward shift narrows considerably, indicating that a substantial portion of the intergenerational income gain is attributable to educational expansion.

Panel (a) of Figure 16 illustrates counterfactual wage AIM trajectories across all decomposition factors. Each curve represents the counterfactual wage AIM trajectory after removing the contribution of a specific factor from the income distribution. The cyan curve isolates the impact of educational attainment; the remaining curves apply the same approach to occupation, industry, place of birth, marriage, sex, and experience. Panel (b) highlights the education

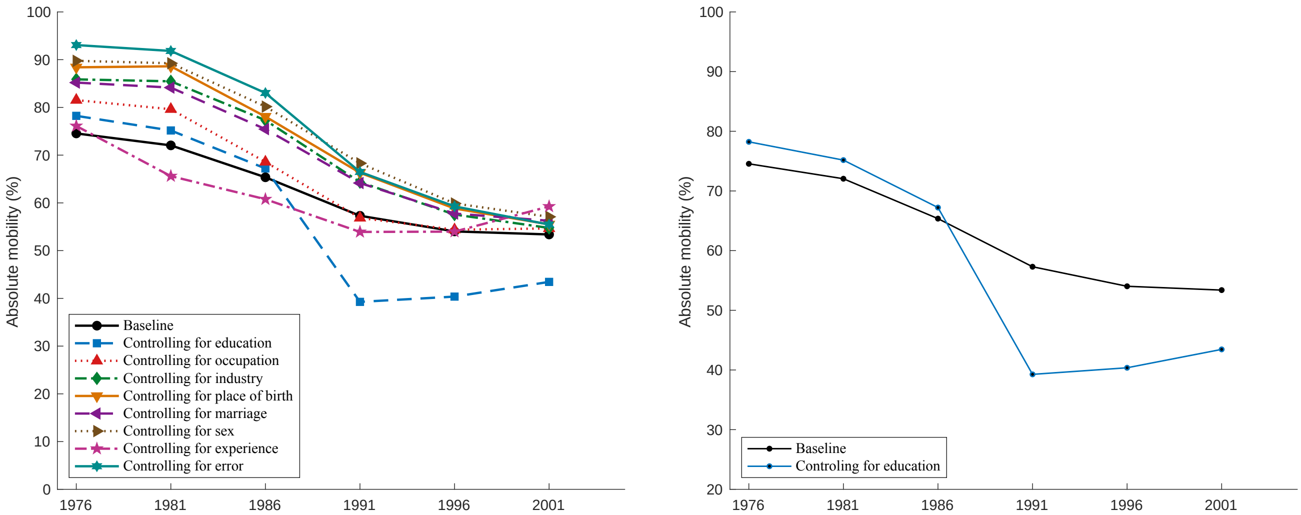
[22]Retaining the residual is essential for the copula-based AIM statistic, because discarding it would replace each worker's actual income rank with a rank derived solely from observable characteristics, thereby conflating the education channel with the residual channel. The approach is equivalent to a partial R^2 decomposition of AIM: we ask how much of the observed intergenerational income difference is attributable to the education component of the Mincer equation, holding everything else, including idiosyncratic earnings differences, constant.



(a) Actual wage income

(b) Wage income excluding education effect

Figure 15: Kernel Density of Wage Income for Parents (1976) and Children (1996): Before and After Controlling for Education



(a) All factors

(b) Baseline and education

Figure 16: Counterfactual Absolute Intergenerational Mobility in Hong Kong Using Mincer Equation Decompositions (Excluding Specific Factors; Based on Wage Income)

channel, showing only the baseline and education-controlled trajectories.

Among all socioeconomic variables, education emerges as by far the most influential factor, though its role reverses over time. For earlier cohorts of children (1976–1986), removing the effect of education actually raises counterfactual wage AIM by approximately 2–4 percentage points, implying that education slightly *reduced* intergenerational mobility during this period. This likely reflects the scarcity premium earned by the small share of highly educated workers, which widened the income distribution and compressed wage AIM. The pattern reverses sharply from the 1991 cohort onward: for the 1991 cohort, education increases wage AIM by nearly 18 percentage points, followed by approximately 11 percentage points for the 1996 cohort and about 10 percentage points for the 2001 cohort. This shift indicates that the rapid expansion of higher education in the late twentieth century transformed education from a source of inequality into a powerful driver of upward mobility, although its wage AIM-enhancing contribution has been gradually diminishing for more recent cohorts as the education premium compressed.

5.3.2. *Robustness Check: IV Results*

A potential concern with the OLS Mincer decomposition is that the education coefficient $\hat{\beta}_4$ may be biased. Ability bias, which arises because unobserved ability is positively correlated with both educational attainment and earnings, tends to overstate the return to schooling, while classical measurement error in self-reported years of education attenuates it.

We use the 1978 nine-year compulsory schooling reform in Hong Kong as the instrument of education. Before 1978, compulsory education in Hong Kong covered only six years of primary school. The government instituted nine-year compulsory education in 1978, extending the mandate by three years of lower-secondary schooling; by the end of the 1980s, secondary education was nearly universal (National Center on Education and the Economy, 2024).[23] We exploit cohort-level variation in exposure to this reform: since primary school in Hong Kong finishes at age 12, individuals born in 1966 or earlier had completed primary school by 1978 and were unaffected, whereas those born in 1967 or later were still in primary school when the reform took effect and were subject to the nine-year mandate. We construct a sharp binary instrument equal to one for cohorts born 1967 or later and zero otherwise. Following Hu and Luo (2026), this instrument requires sufficient workers on both sides of the cutoff. Since the first affected cohort (born 1967) enters the labour market around age 15 in 1982 and reaches prime working age by the mid-1990s, earlier censuses lack meaningful instrument variation: in 1981, 1986 and 1991 all workers aged 25 or above were born before 1967.[24] We therefore apply the compulsory schooling instrument to the six census rounds from 1996 to 2021, in which both pre- and post-reform cohorts are well represented in the workforce.

[23] Free education was later extended from nine to twelve years in 2009, and the university entrance examination was replaced by a unified qualification (HKDSE) in 2012 (National Center on Education and the Economy, 2024). These subsequent reforms do not affect our identification, which relies solely on the 1978 policy change.

[24] The 1976 census is excluded because the reform had not yet occurred.

Table 1 reports the OLS and 2SLS estimates of the education coefficient for each instrumented census year. First-stage F-statistics are well above the conventional threshold of 10 in all years, confirming that the instrument has strong predictive power for educational attainment. In the earlier censuses (1996 and 2001), the IV estimate exceeds the OLS estimate, suggesting that OLS understates the true return to education. From 2006 onward the pattern reverses, with IV estimates falling below OLS, consistent with ability bias becoming the dominant source of OLS bias in more recent cohorts. Across all six census years, the OLS and IV coefficients follow broadly comparable patterns. The 1996 census shows a larger gap (IV/OLS ratio of 1.52), and the 2001 census a more modest gap (ratio of 1.12); from 2006 onward IV falls below OLS, consistent with ability bias. Overall, the proximity of OLS and IV estimates indicates that the OLS-based education decomposition provides a reasonable approximation of the causal return to education.

Table 1: OLS vs. 2SLS estimates of the education coefficient in the Mincer equation

Census year	$\hat{\beta}_{\text{OLS}}$	$\hat{\beta}_{\text{IV}}$	IV/OLS ratio	First-stage F
1996	0.053	0.081	1.52	5,470
2001	0.061	0.069	1.12	15,468
2006	0.061	0.054	0.89	24,933
2011	0.076	0.065	0.86	24,198
2016	0.072	0.059	0.82	23,748
2021	0.070	0.037	0.53	12,371

Note: All years use the 1978 nine-year compulsory schooling reform as a sharp binary instrument (1 if born $\geq$ 1967, 0 otherwise). The dependent variable is log real wage income. All regressions control for gender, experience and its square, occupation, industry, birthplace, and marital status.

Figure 17 translates these IV estimates into counterfactual AIM series. Because AIM is computed from parent–child pairs with a 20-year gap, both the parent and child census years must have IV-estimated counterfactuals for a clean comparison. IV estimates are available for the 1996–2021 censuses, so only the 1996 and 2001 cohorts (parent 1996/child 2016 and parent 2001/child 2021) satisfy this requirement. The orange line plots AIM for these two cohorts using IV-based no-education counterfactual income, while the blue line shows the OLS-based series across all cohorts. The IV and OLS counterfactual AIM series show broadly similar patterns for both cohorts; the 2001 cohort exhibits a somewhat larger IV–OLS gap (consistent with Table 1), though both series point in the same direction. This provides broad support for the finding of education as the primary driver of AIM improvement.

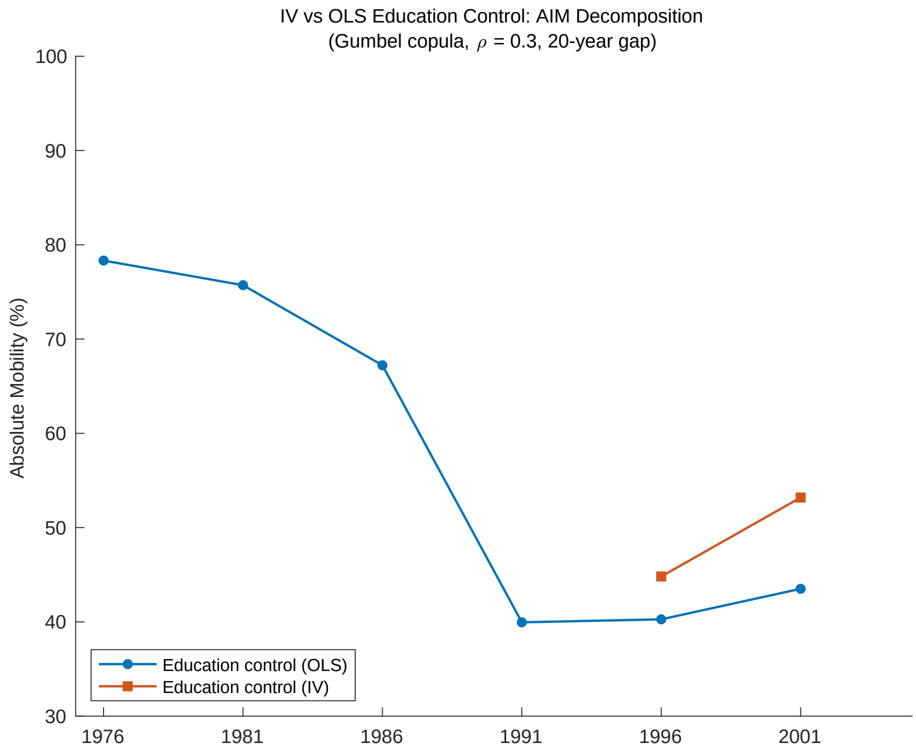


Figure 17: IV vs. OLS education control: counterfactual AIM decomposition (Gumbel copula, rank correlation 0.3, 20-year gap)

Note: The blue line removes the education component using OLS Mincer coefficients for all six cohorts. The orange line removes it using 2SLS coefficients (compulsory schooling instrument) and is shown only for the 1996 and 2001 cohorts, where both the parent and child census years have IV-estimated counterfactuals. All series use the Gumbel copula with rank correlation 0.3 and a 20-year generational gap.

5.3.3. *The mechanism behind the education-driven AIM peak*

Having established that the OLS-based decomposition provides a reliable approximation of the causal return to education and identified the intergenerational premium gap as an amplifying mechanism, we now turn to the economic conditions underlying the 1991 cohort peak. To understand why the education effect peaks for the 1991 cohort, it is important to consider the timing of Hong Kong's tertiary expansion relative to the generational structure of our analysis. In our analysis, each cohort label refers to the census year in which parents' incomes are observed; children's incomes are measured 20 years later under the baseline generational gap. For the 1991 cohort, children are observed in the 2011 census and include workers born in the late 1960s through the 1980s. This is precisely the generation that entered university during or shortly after Hong Kong's rapid tertiary expansion beginning in 1989.[25] Their parents, observed in the 1991 census, largely entered the workforce before the expansion, when tertiary attainment was rare. This intergenerational asymmetry in educational attainment, where children benefited massively from expanded university access while their parents did not, creates the maximum education effect on AIM for this cohort. For subsequent cohorts (1996 and 2001), parents' generations also become increasingly educated, narrowing the intergenerational education gap, while the education premium itself begins to compress. As Hong Kong's economy became increasingly reliant on high-skilled sectors like finance and technology, the demand for advanced and specialized skills grew, potentially leaving behind those with general or lower-tier qualifications. This highlights the need for ongoing reforms in the educational system to adapt to evolving labour market demands and to restore its role as a driver of intergenerational mobility.

Figure 18 confirms this interpretation by plotting the estimated Mincer return to education across birth cohorts. To clarify the construction: for each five-year birth cohort (1917–1921, 1922–1926, etc.), we pool all working-age observations from the ten census rounds (1976–2021) into a single sample and estimate a separate Mincer wage regression. Because the censuses are independent cross-sections rather than a panel, individuals observed in multiple rounds enter as multiple observations within their cohort regression. Each point in the figure plots the resulting cohort-specific coefficient on years of schooling. These birth-cohort-specific returns reveal a secular upward trend: the premium rises steadily from approximately 0.02 for the oldest birth cohorts (born 1917–1921) to around 0.095 for cohorts born in 1982–1986, before declining slightly for the 1987–1991 and 1992–1996 birth cohorts. This temporal pattern is critical for interpreting the AIM peak at the 1991 cohort, which compares parents observed in the 1991 census to children observed in the 2011 census. The parent distribution (1991 census) comprises predominantly older birth cohorts (e.g., born 1940s–1960s) who faced relatively low education returns early in the secular rise, while the child distribution (2011 census) comprises younger birth cohorts (e.g., born 1960s–1980s) who entered the labour market precisely when education returns peaked. This intergenerational divergence in returns, combined with the concurrent

[25] As noted by Marginson (2018), East Asian economies, including Hong Kong, experienced a phase of rapid expansion of higher education in the late twentieth century, which later plateaued. Van der Weide et al. (2024) provides a comprehensive international comparison of educational mobility trends, highlighting similar patterns across other economies.

expansion in tertiary attainment, maximizes the education effect on measured AIM for the 1991 cohort. For the 1996 and 2001 cohorts, the compression of education returns among the most recent birth cohorts (1987–1996) is consistent with the diminishing education effect observed in the Mincer decomposition.

Beyond estimating education return by birth cohort, comparing the Mincer education coefficient across census years provides a more direct measure of the intergenerational premium gap—the difference between the return earned by children and the return earned by their parents. Since each cohort pairs the children's census (year C) with the parents' census 20 years earlier (year $C - 20$), we compute $\Delta\hat{\beta} = \hat{\beta}^{C}_{\text{eduyr}} - \hat{\beta}^{C-20}_{\text{eduyr}}$ for each cohort. Using the OLS Mincer estimates of return on education reported in Appendix Table A11, the intergenerational premium gap is 0.01 for the 1976 cohort (0.05 − 0.04), 0.02 for 1981, 0.01 for 1986, 0.03 for the 1991 cohort, 0.02 for 1996, and 0.01 for 2001. The 1991 cohort exhibits the largest gap: each year of schooling yielded 0.03 more log-points in children's labour market than in parents'. This "premium gap" amplifies the AIM effect of education beyond the shift in attainment alone. Even holding the distribution of education fixed, the higher return in the children's generation concentrates income gains among the well-educated, compressing upward mobility for those without tertiary qualifications. Together with the tertiary expansion that widened the education distribution between generations, this premium gap provides a complementary explanation for the sharp 18 percentage-point drop in AIM observed when education is controlled for the 1991 cohort.

Figure 19 reinforces this interpretation by showing AIM at different income measurement ages (25–45) before and after controlling for education. Panel (a) displays the baseline AIM, which declines gradually and relatively uniformly across all age groups. Panel (b) removes the education premium: AIM drops sharply at the 1991 cohort, with the largest declines among younger workers (age 25 and 30, falling to approximately 25–35%). This age gradient is consistent with younger workers being the primary beneficiaries of the education expansion, as they entered the labour market precisely when tertiary attainment surged. The dramatic cliff at 1991 in Panel (b) confirms that the education channel is the key factor sustaining measured AIM for the post-expansion cohorts.

It is important to distinguish the role of the 1978 nine-year compulsory schooling reform instrument from the mechanism underlying the peak of education effect on AIM in the 1991

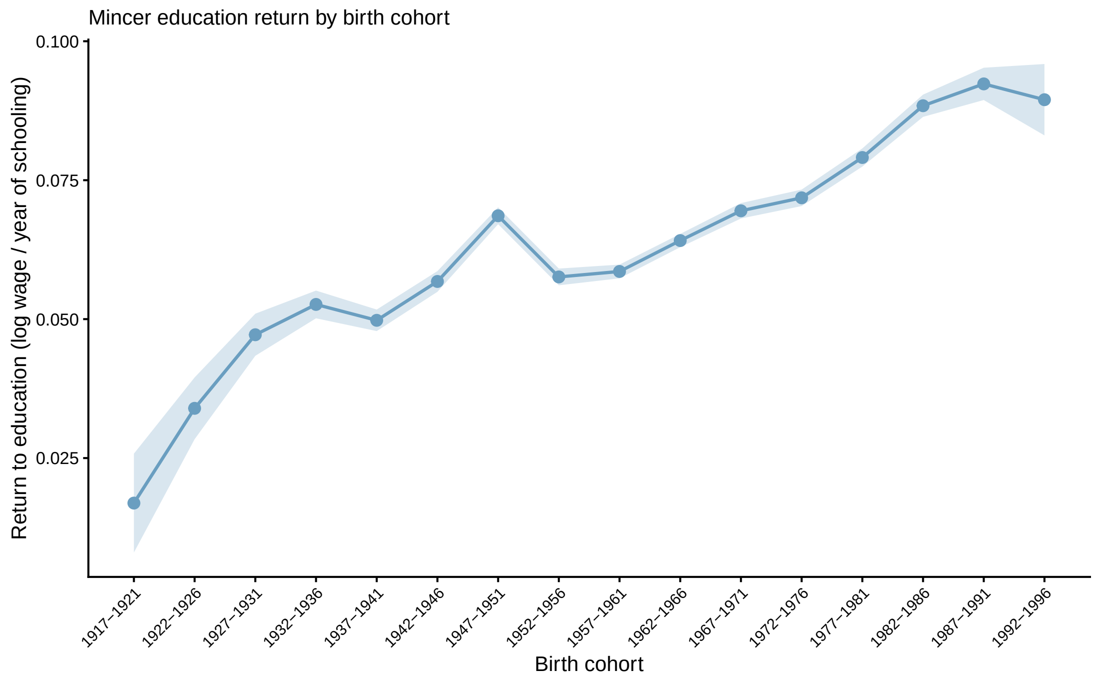


Figure 18: Mincer education return by birth cohort

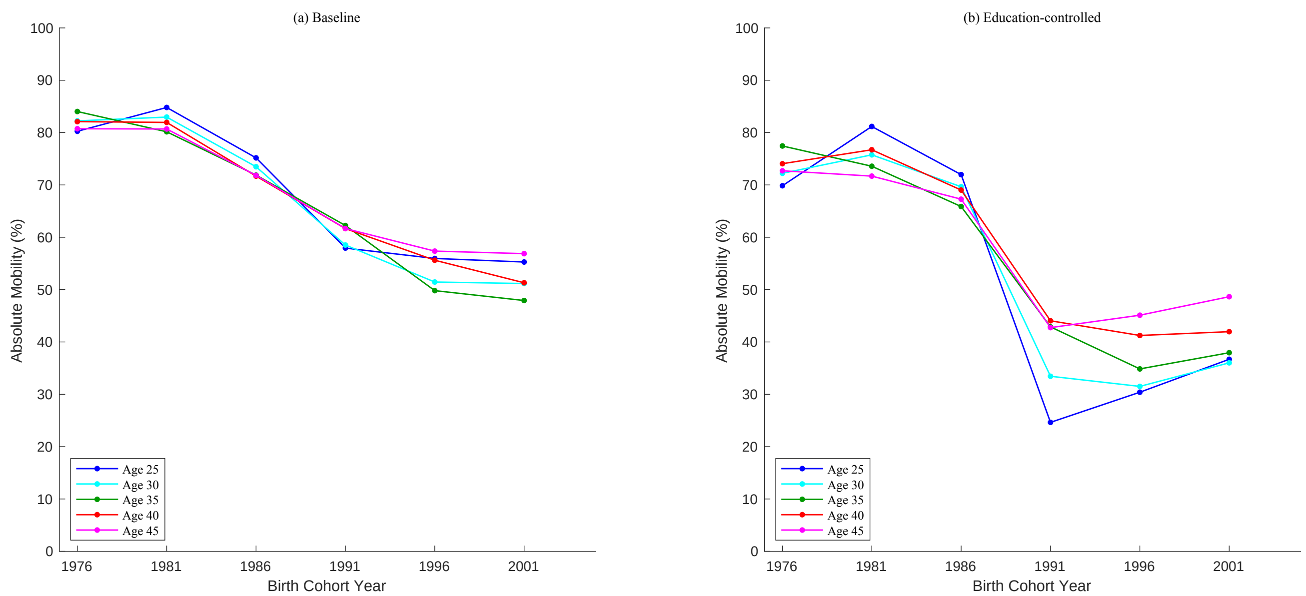


Figure 19: Absolute Intergenerational Mobility by Income Measurement Age: Baseline and Education-Controlled

cohort. The 1989 tertiary education expansion explains the education effect on AIM by fundamentally changing the *distribution* of educational attainment across generations: children of the 1991 cohort benefited from a massive increase in university places that their parents' generation did not experience. The instrumental variable, by contrast, serves a narrower purpose: it provides exogenous variation in years of schooling that allows us to verify the *causal return* to education in the Mincer equation. Even though the two reforms operate at different margins of the education distribution, namely compulsory secondary schooling versus tertiary access, the similarity between the OLS and IV estimates confirms that the linear Mincer specification provides a reliable approximation of the education premium.[26]

6. Conclusion

Our research provides the first comprehensive examination of absolute intergenerational mobility (AIM) in Hong Kong, illuminating its long-term trajectory. We find that Hong Kong's decline in AIM lagged other advanced economies, such as Japan, by 10–20 years, reflecting its later industrialization, with mobility dropping sharply from 85% for the 1976 birth cohort to 49% for the 2001 cohort. This decline stems primarily from stagnant income growth rather than rising inequality, aligning more with patterns in France, Japan, and Sweden than in the US and UK. Furthermore, decomposing total income into labor and capital components shows that the overall decline in AIM is mainly driven by the decreasing mobility of the labor component (from 75% for the 1976 cohort to 48% for the 2001 cohort), while capital component mobility remained low and stable, ranging between 17% and 20% across cohorts. We also find that labor component mobility trends are largely shaped by stagnant growth, while capital component AIM is primarily influenced by rising inequality in its distribution. Finally, our novel Mincer equation-based decomposition allows us to estimate counterfactual AIM by isolating the contributions of specific factors. The results highlight education as the primary promoter of AIM. By elucidating these mechanisms, our study advances methodological tools for mobility analysis,

[26] A natural question is whether the 1989 tertiary expansion itself could serve as a complementary instrument, since it operates at the tertiary margin that drives the AIM mechanism. In principle, one could define cohort-level exposure as the share of university places available when a cohort reached university entrance age and use this as a continuous instrument alongside the 1978 binary instrument; an over-identification test would then provide a direct check on whether the return to schooling is approximately constant across margins. In practice, however, the tertiary expansion presents several challenges as an instrument. Unlike the compulsory reform, which universally forced all post-1967 cohorts to complete nine years, the tertiary expansion only created additional university places while admission remained competitive, so selection into treatment is partly driven by unobserved ability. Moreover, the expansion was gradual (university places roughly tripled between 1989 and 1994) and lacked a single sharp cutoff, weakening the first stage. Finally, the government's decision to expand higher education was partly endogenous to economic conditions—including demand for skilled labour and anticipation of the 1997 handover—which may independently affect earnings. We therefore rely on the cleaner compulsory schooling instrument and note that the consistency of OLS and IV estimates across census years provides indirect support for the reliability of the linear Mincer specification at both schooling margins.

bridges a key gap in Hong Kong's context, and offers a replicable framework for investigating AIM dynamics worldwide.

It is essential to mention that mainland China's economic growth had a profound impact on the evolution of Hong Kong's AIM. Following China's accession to the World Trade Organization (WTO) in 2001, manufacturing industries increasingly relocated from Hong Kong to the mainland, drawn by lower production costs and favorable policies. This shift marked a pivotal transformation in Hong Kong's economic development, leading to higher unemployment, decelerated growth, and greater reliance on the real estate and finance sectors (Wan et al., 2021). Furthermore, the handover of Hong Kong in 1997 led to an influx of immigrants from mainland China, exacerbating the economic situation by driving down wages, particularly for native male workers (Cheng and Zhang, 2018). These interconnected factors indicate that the rise of China has had a major impact on Hong Kong's long-term economic development and, by extension, on intergenerational mobility trends, which should be further studied in the future.

Declaration of generative AI and AI-assisted technologies in the manuscript preparation process

During the preparation of this work the authors used ChatGPT (OpenAI) and Claude (Anthropic) in order to improve the language, readability, and stylistic consistency of the manuscript, and to assist with formatting LaTeX tables and figure-generation scripts. After using these tools, the authors reviewed and edited the content as needed and take full responsibility for the content of the published article.

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Appendix

A. Top-coded Technical

As wage income in the census from 1976 to 2021 is top-coded, it will generate a downward bias at the top of the wage distribution. Therefore, we correct the observations with top-coded income, assuming that the top of the wage distribution follows a Pareto distribution.

$$F(x) = 1 - \left(\frac{c}{x}\right)^{\alpha}, \text{ for } x > c > 0$$

A property that characterizes the Pareto distribution is that the average income of individuals above any income threshold, divided by that threshold, is constant and equal to the inverted Pareto coefficient $b = \alpha/(1-\alpha)$. Using observations near the top-coding threshold, we can estimate the inverted Pareto coefficient $\hat{b}$ (see Blanchet et al. (2022a,b)). Figure A1 presents the log (wage) and its fitted value in the range between the top 1% and top 0.4% wage earners in 2021($x = -\log(1 - rank), y = \log(inc + 1)$). Applying the estimated inverted Pareto coefficient $\hat{b}$ to the threshold, we can estimate the average wage for observations above the top-coding threshold and assign the average wage to each observation. Finally, we estimate the wage distribution series based on the top-coding corrected survey.

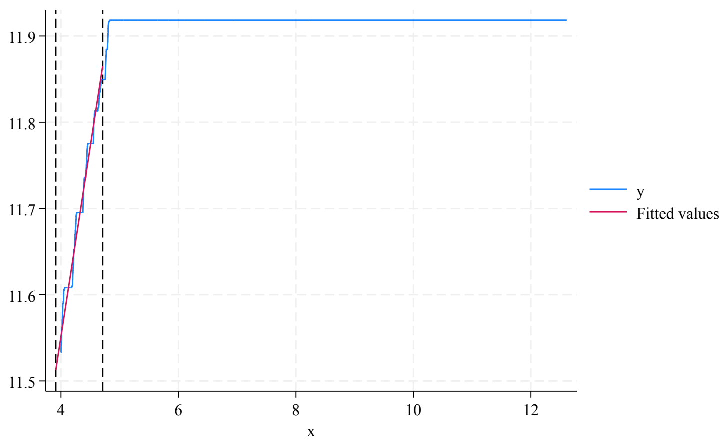


Figure A1: Estimating the Inverted Pareto Coefficient $\hat{\beta}$

B. Bootstrap Confidence Intervals for Absolute Intergenerational Mobility

Figure A2 presents the main absolute intergenerational mobility (AIM) results for Hong Kong alongside bootstrap 95% confidence intervals. The confidence bands are narrow throughout the sample period, confirming that the estimated AIM series is precisely estimated and not driven by sampling variation. The broad downward trend from 1976 to 2021 remains statistically significant, providing additional support for the robustness of our main findings.

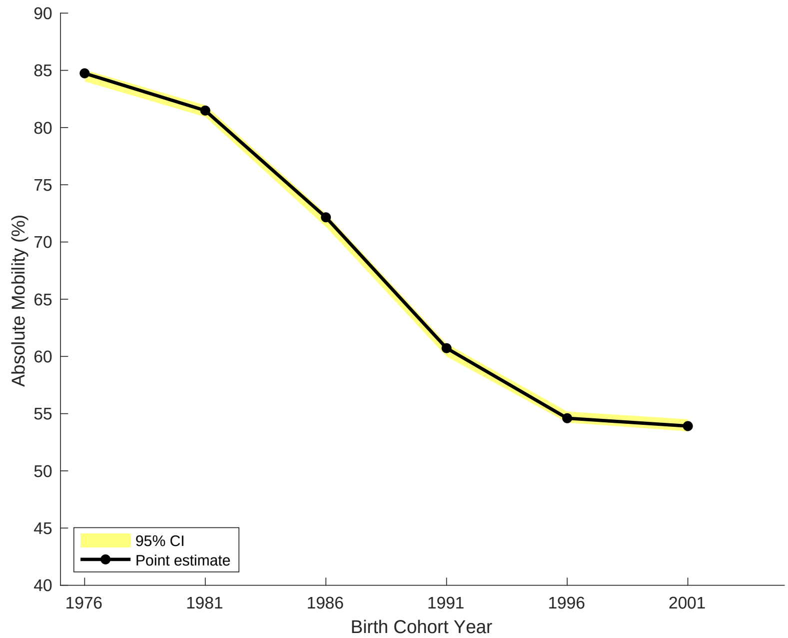


Figure A2: Absolute intergenerational mobility in Hong Kong with bootstrap 95% confidence intervals

C. Absolute Mobility Measured at Different Ages with 30 Year Gap

Figure A3 depicts upward mobility when income is measured at different ages, using a 30-year generational gap. Consistent patterns are observed across all age groups, indicating a higher mobility rate in specific years compared to previous results. This further underscores that the choice of age at which income is measured is not crucial for the mobility rate; rather, the specific year of income measurement is the determining factor. This aligns with the findings of Manduca et al. (2024), suggesting that the choice of age to measure income is not the primary reason for the differences with Berman (2022) results; instead, it is primarily attributed to the use of survey data. In conclusion, utilizing the entire population from a specific year is quite robust, even if it may seem unrepresentative at first glance.

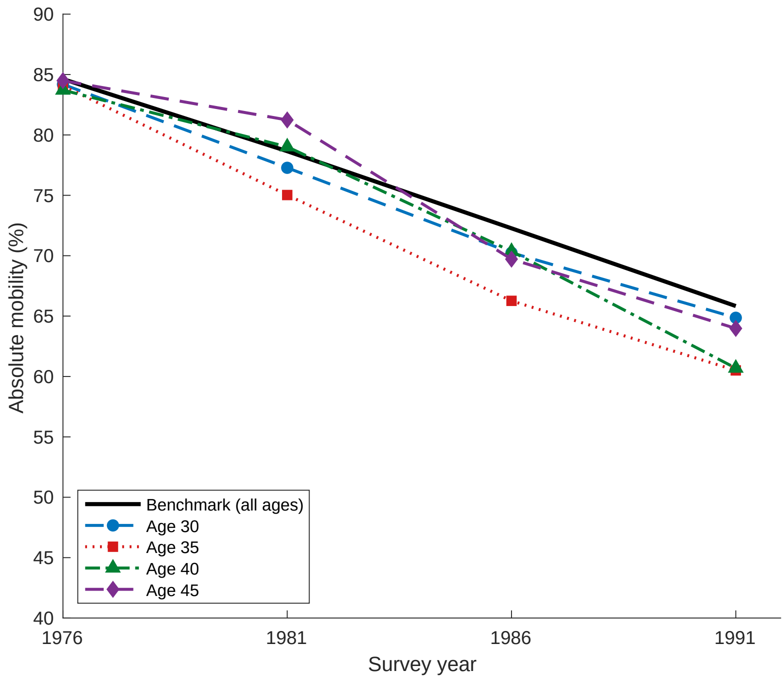


Figure A3: Absolute mobility by age at which income is measured; 30-year gap

D. Fraction of Children Earning More than Their Parents

In addition to showing the share of children who earn more than 100% than their parents, we also show the share of children who earn more than their parents by 120% and 150%. Figure A4 shows similar trends for the 120% or 150% share, showing an overall decrease in mobility. The trend for the 120% fraction is consistently 5 percentage points lower than the baseline, while the 150% fraction is 15 percentage points lower. There are no significant differences in the pattern between the baseline and other trends, suggesting that the decline in AIM is evenly distributed across all children who outearn their parents.

E. Copula Robustness by Age of Income Measurement

Figure A5 jointly examines sensitivity to the copula family and the assumed rank correlation across all four income measurement ages. The figure is arranged as a 4 $\times$ 4 grid: rows correspond to copula type (Gumbel, Gaussian, Clayton, and US empirical) and columns to income measurement age (30, 35, 40, 45). Within the first three rows, three lines show AIM series under

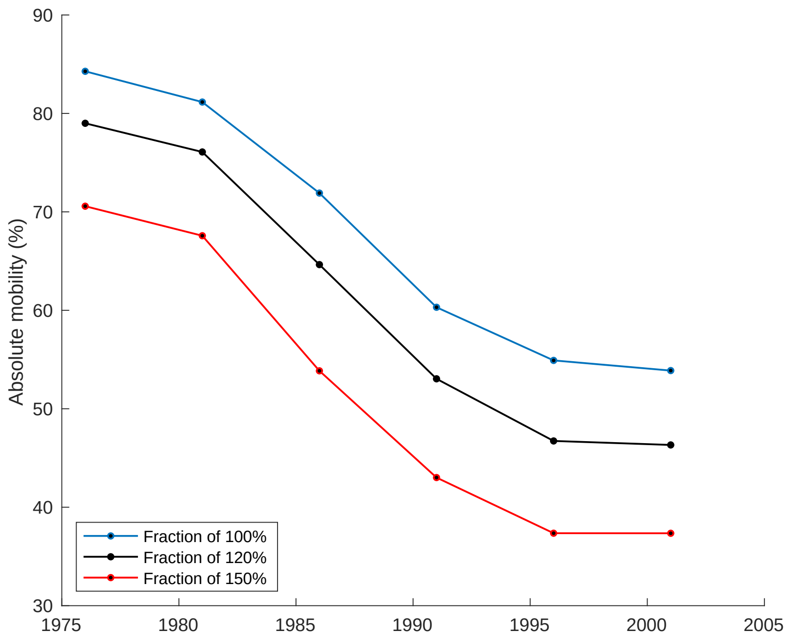


Figure A4: Absolute intergenerational mobility by different fractions of children earning more than parents

rank correlations 0.2 (cyan), 0.3 (black, baseline), and 0.4 (red), all with a 20-year generational gap. The fourth row uses the US empirical copula estimated from PSID data, which embeds a fixed dependence structure and therefore shows a single line per panel.

Two patterns emerge. First, within any given parametric-copula row the three rank-correlation lines are approximately parallel: a higher ρ shifts the AIM series upward by roughly 3–6 percentage points while a lower ρ shifts it downward by a similar margin, but the shape and timing of the secular decline are preserved. Second, comparing across rows at the same age and ρ, the three parametric copulas produce virtually identical AIM trajectories; level differences between copula families are negligible (typically within 1–2 percentage points). The US empirical copula yields AIM levels close to the parametric baseline (0.3), further confirming that the results are not driven by functional-form assumptions about the dependence structure. The pronounced drop between the 1986 and 1991 cohorts is replicated under every combination of copula and rank correlation, ruling out any specification-specific explanation for this discontinuity. These results hold at every income measurement age, confirming that the downward trend in Hong Kong's absolute intergenerational mobility is robust to the joint choice of dependence structure and rank correlation, and that the Gumbel copula with 0.3 used as the benchmark in the main text is representative of a broad class of specifications.

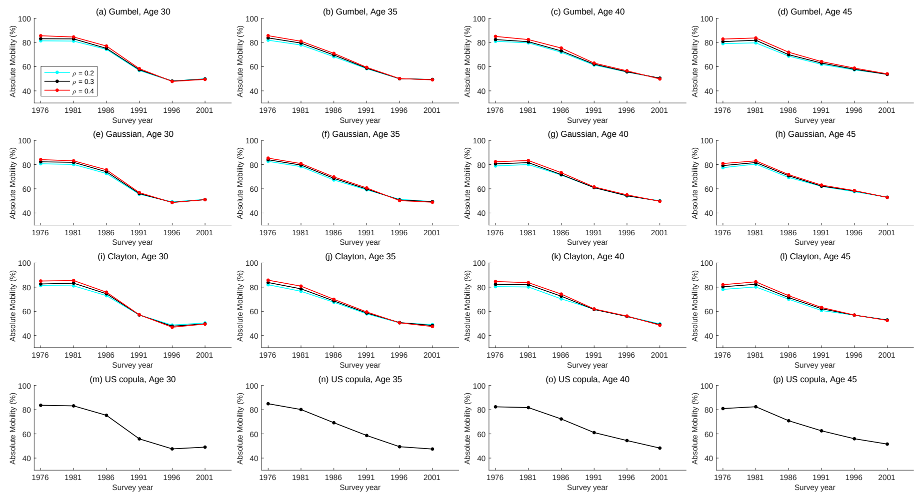


Figure A5: Joint copula and rank-correlation robustness check by income measurement age. Rows: Gumbel, Gaussian, Clayton, and US empirical copulas. Columns: ages 30, 35, 40, 45. Rows 1–3: lines show 0.2, 0.3, 0.4. Row 4: single line (empirical copula). 20-year generational gap

Note: Each panel shows absolute intergenerational mobility (AIM) computed from age-specific income distributions. Rows vary the copula family (Gumbel, Gaussian, Clayton, US empirical); columns vary the income measurement age (30, 35, 40, 45). In the first three rows, three lines correspond to rank correlations 0.2 (cyan), 0.3 (black, baseline), and 0.4 (red). The fourth row shows a single line per panel because the US empirical copula embeds a fixed dependence structure with no free rank-correlation parameter. All panels use a 20-year generational gap.

F. Tables: Absolute Mobility Values

This appendix presents the complete numerical results underlying the figures in the main text. Table A1 and Table A2 provide the baseline AIM values under the Gumbel and US copula assumptions, respectively. Tables A3 and A4 document AIM at five income measurement ages under 20- and 30-year generational gaps. Table A5 reports robustness to alternative earnings thresholds. Table A6 provides the numerical counterparts to the growth–inequality decomposition in Figure 9. Table A7 disaggregates AIM by income type, and Table A8 reports counterfactual AIM from the Mincer-equation decomposition.

Table A1 confirms the sharp decline in AIM from approximately 85% for the 1976 birth cohort to under 50% for the 2001 cohort across all generational gaps (20–40 years), with higher gaps generally producing similar or slightly higher AIM levels.

Table A1: Absolute mobility from 1976 to 2021 — Gumbel copula

Year	1976	1981	1986	1991	1996	2001
Percentage (20-year gap)	85.58	81.66	72.25	60.12	54.92	49.09
Percentage (25-year gap)	87.05	80.27	70.47	62.32	54.07	
Percentage (30-year gap)	85.38	78.30	72.36	60.13		
Percentage (35-year gap)	84.02	79.52	69.19			
Percentage (40-year gap)	84.65	75.42				

Note: Absolute intergenerational mobility (AIM) is measured as the share of children earning more than their parents (in percent). Parental income is proxied by drawing from the income distribution 20, 25, 30, 35, or 40 years earlier. The Gumbel copula is used to model the joint distribution of parent and child income, with a rank correlation of 0.3.

Table A2 replicates the baseline analysis using the US copula from Chetty et al. (2014), yielding nearly identical estimates (85.97% in 1976 to 47.66% in 2001 for the 20-year gap). The close agreement between the Gumbel and US copula results confirms that AIM estimates are robust to the choice of rank-dependence structure.

Table A2: Absolute mobility from 1976 to 2021 — US copula

Year	1976	1981	1986	1991	1996	2001
Percentage (20-year gap)	85.97	82.19	71.74	58.90	53.80	47.66
Percentage (25-year gap)	87.53	80.50	69.91	61.67	52.75	
Percentage (30-year gap)	85.85	78.63	71.79	59.37		
Percentage (35-year gap)	84.79	79.79	68.50			
Percentage (40-year gap)	85.03	75.45				

Note: Absolute intergenerational mobility (AIM) is measured as the share of children earning more than their parents (in percent). The US copula, estimated from the US intergenerational income distribution, is used to model the joint distribution of parent and child income.

Table A3 examines whether the baseline results depend on the age at which incomes are measured. AIM values at ages 30–50 are broadly similar for the 1976 cohort (83–85%), confirming that the choice of measurement age does not drive the baseline estimates. In later cohorts the age profiles diverge moderately, with incomes measured at older ages (45–50) tending to yield somewhat higher AIM, consistent with continued life-cycle returns to experience.

Table A3: Absolute mobility from 1976 to 2021 with Gumbel copula — income measured at different ages, 20-year gap

Year	1976	1981	1986	1991	1996	2001
Age 30	83.12	82.97	75.14	57.46	48.10	49.79
Age 35	84.51	81.12	68.44	59.78	50.05	49.32
Age 40	81.17	80.54	72.91	61.43	55.26	49.55
Age 45	80.57	82.33	70.75	62.22	57.93	54.21
Age 50	78.04	81.68	71.36	65.12	61.75	59.05

Note: Absolute intergenerational mobility (AIM) is measured as the share of children earning more than their parents (in percent). Income is measured at specific ages (30, 35, 40, 45, 50) using a 20-year generational gap. Year refers to the birth cohort year of the parent generation. The Gumbel copula is used with a rank correlation of 0.3.

Table A4 repeats the exercise under a 30-year generational gap, with parent census years 1976–1991. The decline from the 1976 to the 1991 cohort mirrors the pattern observed under the 20-year gap, supporting the conclusion that the downward trend in AIM is not an artefact of the assumed generation length.

Table A4: Absolute mobility from 1976 to 2021 with Gumbel copula — income measured at different ages, 30-year gap

Year	1976	1981	1986	1991
Age 30	84.19	77.28	70.24	64.86
Age 35	84.08	75.02	66.26	60.50
Age 40	83.71	79.02	70.36	60.69
Age 45	84.50	81.24	69.72	63.98
Age 50	79.36	83.55	78.20	68.38

Note: Absolute intergenerational mobility (AIM) is measured as the share of children earning more than their parents (in percent). Each column corresponds to a parent census year (birth cohort); child income is measured 30 years later at the age shown in each row. The Gumbel copula is used with a rank correlation of 0.3.

Table A5 tests sensitivity to the income threshold used to define upward mobility. Raising the threshold from 100% to 120% or 150% uniformly lowers AIM levels, from 85.41%, 80.17%, and 71.54% in 1976 to 48.96%, 41.97%, and 33.35% in 2001, respectively, but leaves the downward trend intact, indicating that the decline in AIM is not sensitive to where the bar is set.

Table A5: Absolute mobility from 1976 to 2021 with Gumbel copula — fraction thresholds of 100%, 120%, and 150%

Year	1976	1981	1986	1991	1996	2001
100 percent	85.41	81.82	71.94	60.28	55.42	48.96
120 percent	80.17	76.62	65.11	52.73	47.11	41.97
150 percent	71.54	67.66	55.04	42.22	37.38	33.35

Note: AIM is reported for three income thresholds: 100% (child earns at least as much as parents), 120% (child earns at least 20% more), and 150% (child earns at least 50% more). A 20-year generational gap is used. The Gumbel copula is used with a rank correlation of 0.3.

Table A6 provides the numerical counterparts to the growth–inequality decomposition in Figure 9. The baseline series declines from 85.30% in 1976 to 49.12% in 2001, a fall of 36 percentage points. The *inequality-held-constant* counterfactual, which fixes the income distribution at its 1976 level while allowing mean income growth to vary, tracks the baseline closely throughout: 87.42% in 1976, falling to 52.03% in 2001, only 3 percentage points above the actual baseline. This small gap confirms that changes in the shape of the income distribution (inequality) account for only a minor fraction of the observed decline. By contrast, the *growth-held-constant* counterfactual, which fixes income growth at the 1976–2021 average of approximately 2.6% while retaining each year's actual distribution, maintains AIM in a narrow band of 65–70% across all cohorts: 69.72% in 1976, 68.24% in 1986, 66.81% in 1991, and 65.69% in 2001, a total decline of fewer than 5 percentage points. The gap between this counterfactual and the actual baseline widens sharply over time, from just 16 percentage points in 1976 to over 16 percentage points by 2001, pinpointing the post-1986 growth slowdown as the dominant driver of the mobility erosion.

Table A6: Decomposition of absolute mobility from 1976 to 2021 with Gumbel copula

Year	1976	1981	1986	1991	1996	2001
Baseline	85.30	81.82	72.15	60.04	54.98	49.12
Inequality held constant	87.42	84.82	77.98	65.99	58.06	52.03
Growth held constant	69.72	69.52	68.24	66.81	68.34	65.69

Note: AIM decomposition following Manduca et al. (2020). "Inequality held constant" fixes the income distribution at the 1976 level while allowing income growth to vary. "Growth held constant" fixes income growth at the 1976 level while allowing inequality to vary. A 20-year generational gap and the Gumbel copula with rank correlation 0.3 are used.

Table A7 disaggregates AIM by income source. *Total income* AIM follows the well-documented baseline pattern, declining from 85.35% in 1976 to 81.70% in 1981, 71.90% in 1986, 60.27% in

1991, 54.99% in 1996, and 48.84% in 2001, a cumulative fall of 36.5 percentage points over the period. *Labor component* AIM tracks this trend closely but at a lower level, falling from 74.84% in 1976 to 71.76% in 1981, 66.22% in 1986, 57.63% in 1991, 54.02% in 1996, and 48.36% in 2001, a decline of 26.5 percentage points. The gap between total and wage AIM is largest in the early years, at 10.5 percentage points in 1976, and narrows to under 1 percentage point by 2001, reflecting the diminishing weight of capital income in total earnings as wage and capital income trends diverged. *Capital component* AIM is persistently low and nearly flat throughout: 16.90% in 1976, rising marginally to a peak of 18.80% in 1986 before settling at 16.82% in 1991, 17.01% in 1996, and 17.65% in 2001. The near-zero trend in capital income AIM reflects the highly concentrated distribution of asset ownership in Hong Kong, where only 20–27% of the working-age population reports any capital income in a given census year, so the bulk of participants face near-zero probability of outearning their parents on this component.

Table A7: Absolute mobility from 1976 to 2021 with Gumbel copula — total, labor component, and capital component

Year	1976	1981	1986	1991	1996	2001
Total Income	85.35	81.70	71.90	60.27	54.99	48.84
Wage Income	74.84	71.76	66.22	57.63	54.02	48.36
Capital Income	16.90	17.63	18.80	16.82	17.01	17.65

Note: AIM is computed separately for total income, labor component only, and capital component only. A 20-year generational gap and the Gumbel copula with rank correlation 0.3 are used. All incomes are CPI-deflated to a common base year.

Table A8 reports the full set of Mincer-equation counterfactual AIM values for wage income across all sociodemographic controls.

Education produces by far the largest and most distinctive shift. For earlier cohorts (1976–1986), removing the education premium slightly raises AIM (e.g., from 74.55% to 78.23% in 1976), reflecting the scarcity premium earned by a small educated elite that compressed the income distribution from below. The pattern reverses sharply from 1991 onward: education-controlled AIM falls to 39.26% against a baseline of 57.30%, a gap of nearly 18 percentage points, confirming that the tertiary expansion created a large intergenerational asymmetry that boosted measured mobility. By 2001 the gap narrows to 10 percentage points (43.45% versus 53.38%), as parents' cohorts became increasingly educated and the education premium began to compress.

Occupation, industry, place of birth, marriage, and sex all produce upward shifts relative to the baseline, indicating that controlling for these factors raises counterfactual AIM above the unadjusted level. The effects are largest for the 1991 cohort: removing sex raises AIM to 68.30%, place of birth to 66.31%, industry to 64.36%, and marriage to 64.16%, each well above the 57.30% baseline. Occupation produces a smaller adjustment (56.85% in 1991). By 2001 these gaps narrow considerably, with all five controls clustering between 54% and 57% against a baseline of 53.38%, suggesting that the structural influence of these characteristics on income distribution diminished as the labour market matured.

Experience follows a distinct trajectory. It substantially depresses AIM for the 1981 cohort (65.61% versus a baseline of 72.05%), when steep experience–earnings profiles concentrated income gains among older workers and thereby compressed intergenerational mobility. The experience effect weakens through the 1990s and reverses by 2001, where experience-controlled AIM exceeds the baseline (59.25% versus 53.38%), reflecting the flattening of experience premiums as the economy shifted toward knowledge-intensive sectors.

Error tracks the baseline closely but consistently above it across all cohorts (e.g., 66.48% versus 57.30% in 1991; 55.46% versus 53.38% in 2001), confirming that residual variation in the Mincer regression does not systematically distort the counterfactual estimates and that the decomposition captures the relevant observable factors.

Table A8: Absolute mobility from 1976 to 2021 with Gumbel copula — Mincer equation decomposition

Cohort	1976	1981	1986	1991	1996	2001
Baseline	74.55	72.05	65.36	57.30	54.03	53.38
Education (control)	78.23	75.17	67.22	39.26	40.37	43.45
Occupation (control)	81.53	79.62	68.57	56.85	54.38	54.65
Industry (control)	85.87	85.46	77.31	64.36	57.56	54.75
Place of birth (control)	88.40	88.61	78.08	66.31	58.82	55.50
Marriage (control)	85.20	84.15	75.45	64.16	57.77	56.25
Sex (control)	89.76	89.24	80.17	68.30	59.88	57.08
Experience (control)	76.11	65.61	60.77	53.91	53.98	59.25
Error (control)	93.06	91.82	83.02	66.48	59.27	55.46

Note: AIM is the share of children earning more than their parents (in percent), computed from wage income. Each row removes the contribution of one Mincer factor from the wage income distribution via rank-by-rank scaling before recomputing AIM. "Baseline" uses the unadjusted wage income distribution. A 20-year generational gap and the Gumbel copula with rank correlation 0.3 are used throughout.

G. Tables for Wage, Capital, and Inequality

This appendix reports detailed inequality statistics and income-recipient shares. Table A9 shows that the share of individuals with positive wage income is broadly stable at around 81–86%

throughout the period. The share with positive capital and business income is considerably lower, ranging from 19.4% to 26.9%, with a trough in the mid-1990s and a recovery to 26.9% by 2021.

Table A9: Proportion of labor component and capital component recipients

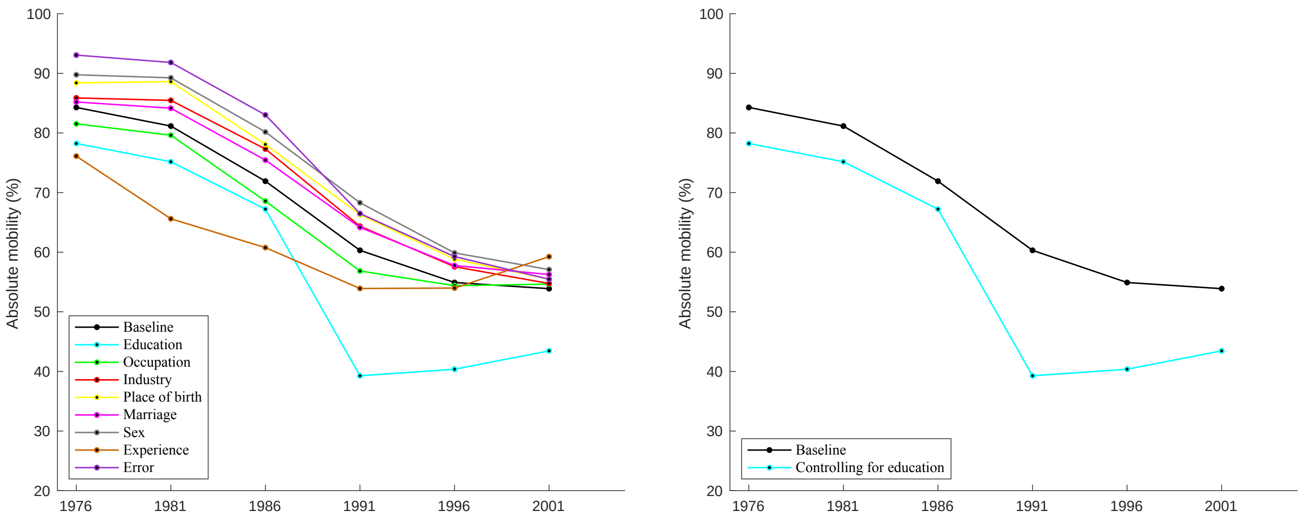
	1976	1981	1986	1991	1996	2001	2006	2011	2016	2021
Labor component	80.6%	83.5%	83.7%	84.4%	84.8%	83.8%	83.1%	83.8%	85.3%	85.6%
Capital component	23.8%	19.7%	21.1%	19.4%	19.4%	21.6%	24.1%	21.7%	22.7%	26.9%

Note: Proportion of individuals with positive labor component income (Labor component) and positive capital component income (Capital component) in each census year. Computed from the top-coded census microdata.

H. Tables for Mincer Equation

This appendix presents the Mincer equation estimates that underpin the counterfactual AIM decomposition in the main text. Table A10 reports summary statistics for the Mincer estimation sample and Table A11 presents the full set of coefficient estimates by census year.

The Mincer decomposition presented in the main text (Figure 16) is based on wage income only, as the Mincer equation framework is designed to explain labor earnings through human capital and demographic characteristics. Figure A6 replicates the analysis using total income (wage plus capital income) as the baseline. The results are qualitatively identical to those obtained using wage income alone. Education remains the dominant factor, and the temporal pattern is preserved: education slightly reduces AIM for earlier cohorts (1976–1986) and substantially increases it for later cohorts (1991–2001), with the peak effect observed for the 1991 cohort. The magnitudes of the education effect are nearly identical across the two specifications, confirming that the Mincer decomposition results are robust to the inclusion of capital income and that the education channel operates primarily through the wage component of total income.



(a) All factors

(b) Baseline and education

Figure A6: Counterfactual Absolute Intergenerational Mobility in Hong Kong Using Mincer Equation Decompositions (Excluding Specific Factors; Based on Total Income)

Note: This figure replicates Figure 16 using total income (wage plus capital income) instead of wage income only. Each line represents the counterfactual AIM trajectory after removing the contribution of a specific factor from the income distribution. The baseline uses the actual total income distribution. All series use the Gumbel copula with rank correlation 0.3 and a 20-year generational gap.

Table A10 summarises the key characteristics of the Mincer sample. The share of workers with tertiary education rises substantially across census years, consistent with Hong Kong's rapid higher education expansion after 1991, which underpins the education channel identified in the Mincer decomposition.

Table A10: Summary Statistics of Factors in the Mincer Equation

	1976	1981	1986	1991	1996	2001	2006	2011	2016	2021
Gender										
Male	72.0%	66.9%	62.9%	61.4%	58.2%	53.2%	51.1%	48.0%	46.3%	44.9%
Female	28.0%	33.1%	37.1%	38.6%	41.8%	46.8%	48.9%	52.0%	53.7%	55.1%
Place of Birth										
Hong Kong	29.0%	37.4%	51.8%	56.1%	59.8%	61.9%	65.2%	64.2%	61.1%	60.7%
Mainland China	67.2%	57.9%	43.2%	37.0%	30.8%	28.3%	25.5%	23.7%	24.1%	23.9%
Other	3.8%	4.7%	5.0%	6.9%	9.4%	9.9%	9.4%	12.2%	14.8%	15.5%
Industry										
Manufacturing	40.8%	41.0%	37.9%	29.3%	19.1%	12.5%	9.8%	4.8%	3.7%	3.1%
Construction	7.7%	10.0%	7.0%	7.7%	8.8%	7.7%	7.3%	7.5%	8.0%	7.9%
Wholesale & Retail	9.8%	8.8%	10.3%	11.1%	13.7%	15.7%	17.0%	20.5%	17.0%	15.0%
Restaurants & Hotels	6.8%	6.8%	7.1%	8.1%	8.2%	8.3%	7.5%	7.2%	7.8%	6.9%
Transport, Storage & Comm.	9.7%	9.1%	8.6%	10.2%	10.9%	10.9%	11.3%	10.4%	12.0%	11.0%
Finance	3.9%	4.7%	6.9%	10.6%	13.9%	16.8%	17.6%	18.1%	18.1%	19.3%
Community & Personal Services	20.0%	18.1%	20.6%	21.7%	24.4%	27.2%	28.8%	30.8%	32.8%	36.1%
Other	1.2%	1.5%	1.5%	1.3%	1.0%	0.8%	0.6%	0.7%	0.5%	0.6%
Occupation										
Workers	78.3%	77.7%	70.6%	63.2%	55.7%	52.1%	50.7%	47.1%	46.9%	43.8%
Professionals	7.4%	7.0%	10.1%	15.9%	19.1%	22.7%	24.2%	26.3%	28.5%	31.6%
Admin. & Managers	3.5%	3.4%	4.7%	5.6%	8.7%	8.5%	7.8%	9.3%	9.3%	9.8%
Clerical	10.9%	11.9%	14.7%	15.3%	16.6%	16.7%	17.3%	17.3%	15.2%	14.8%
Marital Status										
Single	26.5%	27.3%	33.1%	31.3%	31.6%	32.9%	36.0%	37.3%	37.3%	40.9%
Married	73.5%	72.7%	66.9%	68.7%	68.4%	67.1%	64.0%	62.7%	62.7%	59.1%

Note: Sample restricted to working-age individuals (25–60) with positive income. Percentages may not sum to 100% due to rounding or minor categories omitted for brevity.

Table A11 presents the Mincer equation estimates by census year. Returns to education are positive and statistically significant throughout the sample period, and the education premium evolves in a pattern consistent with Hong Kong's tertiary education expansion after 1991. These coefficients form the basis for the counterfactual income distributions used to compute the AIM values in Table A8.

Table A11: Mincer Equation Estimates by Census Year

	1976	1981	1986	1991	1996	2001	2006	2011	2016	2021
Male	0.425***	0.455***	0.376***	0.348***	0.295***	0.307***	0.248***	0.231***	0.229***	0.221***
Experience	0.009***	0.003	0.015***	0.015***	0.020***	0.022***	0.027***	0.022***	0.021***	0.017***
Experience^2/100	−0.000***	−0.000*	−0.000***	−0.000***	−0.000***	−0.000***	−0.000***	−0.000***	−0.000***	−0.000***
Years of schooling	0.038***	0.042***	0.050***	0.047***	0.053***	0.061***	0.061***	0.076***	0.072***	0.070***
Industry fixed effects (base: Manufacturing)										
Construction	0.191***	0.271***	0.065***	0.105***	0.093***	0.131***	0.043***	0.109***	0.156***	0.194***
Wholesale & retail	0.069***	0.095***	0.093***	0.047***	0.021***	−0.013**	0.005	−0.000	0.022***	−0.015
Restaurants & hotels	0.135***	0.183***	0.161***	0.152***	0.065***	0.046***	0.007	0.047***	0.106***	0.099***
Transport & comm.	0.225***	0.243***	0.196***	0.120***	0.116***	0.092***	0.079***	0.066***	0.057***	0.087***
Finance	0.255***	0.271***	0.206***	0.164***	0.139***	0.082***	0.042***	0.085***	0.136***	0.174***
Services	0.289***	0.272***	0.248***	0.172***	0.125***	0.140***	0.049***	0.033***	0.052***	0.080***
Other industry	0.143***	0.150***	0.083**	0.209***	0.187***	0.195***	0.142***	0.105***	0.109***	0.170***
Occupation fixed effects (base: Workers)										
Professionals	0.589***	0.585***	0.593***	0.609***	0.657***	0.685***	0.716***	0.660***	0.615***	0.606***
Admin. & managers	0.903***	0.832***	0.862***	0.935***	0.958***	1.078***	1.154***	1.174***	1.065***	1.014***
Clerical	0.188***	0.214***	0.213***	0.200***	0.223***	0.250***	0.276***	0.188***	0.182***	0.188***
Born in Mainland China	−0.062***	−0.082***	−0.126***	−0.135***	−0.155***	−0.156***	−0.139***	−0.111***	−0.083***	−0.038***
Born elsewhere	0.109***	0.052*	−0.082***	−0.188***	−0.341***	−0.503***	−0.481***	−0.527***	−0.631***	−0.644***
Married	0.108***	0.103***	0.118***	0.136***	0.114***	0.123***	0.129***	0.122***	0.097***	0.107***
Observations	89.537	12.403	15.756	87.378	108.960	118.879	127.215	139.839	141.629	139.500
R^2	0.48	0.46	0.48	0.49	0.49	0.55	0.53	0.60	0.59	0.56

Note: Dependent variable is log monthly wage income (labor component). Robust standard errors. $***\ p < 0.01$, $^{**}\ p < 0.05$, $^{*}\ p < 0.1$. All regressions include a constant.

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