INTERGENERATIONAL MOBILITY IN HONG KONG, 1976-2016

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Abstract

Using a large census dataset spanning 40 years, this paper presents the first comprehensive study of intergenerational absolute income mobility in Hong Kong, by employing the copula and marginals approximation method. The main findings indicate a significant decrease in absolute income mobility, declining from 85% in the 1976 cohort to 55% in the 1996 cohort. In 1976, Hong Kong's absolute income mobility(AIM) exceeded that of major higher-income countries, but within 40 years, it converged to the level of the United States and Europe. This decline is primarily attributed to decelerating GDP growth rather than increased income inequality. Our findings remain robust under various alternatives of copula forms and different birth cohorts. Notably, our innovative decomposition of the education factor reveals that education plays a crucial role in mitigating the decline in absolute mobility. We argue that the rapid economic growth of China and the expansion of Hong Kong's tertiary education play important roles in shaping intergenerational income mobility in Hong Kong.

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I Introduction

The aspiration for improved living standards across generations is a common global sentiment. Consequently, the study of intergenerational mobility has been a prominent area of interest for economists and social scientists, who strive to understand the degree of persistence in outcomes between parents and their children.[1] A key distinction in the literature is between absolute and relative mobility: absolute mobility refers to changes in real income across generations, while relative mobility refers to shifts in income ranks. Although relative mobility has been extensively studied, research on absolute mobility has only been expanding in the past decade (see Jäntti and Jenkins (2015) for a recent overview).

The most seminal work in the absolute mobility literature is from Chetty et al. (2017) which documents the fading American dream using the copula and marginals approach and pooled cross-sections of income data for sequential US cohorts born 1940 to 1980. Following Chetty et al. (2017), there has been a consistently expanding body of literature on country-specific estimates of absolute income mobility (AIM), primarily in Europe and North America. However, the findings present a somewhat varied picture (see Chen et al. (2017) for Canada; Blanden (2019) for the UK; Bönke et al. (2024) for Germany; Kennedy and Siminski (2022) for Australia; and Liss et al. (2023) for Sweden). Additionally, these country-specific estimates have recently been complemented by cross-country comparative studies (see Berman (2022); Stockhausen (2021); and Manduca et al. (2024)). These studies indicate that absolute mobility peaked for individuals born around 1940, with 90% surpassing their parents' earnings. However, it declined substantially for those born in the 1980s. Research on Absolute Income Mobility beyond Europe and North America has been limited, primarily due to data constraints.

This paper aims to contribute to the literature by conducting a comprehensive analysis of AIM in Hong Kong, one of the most unequal yet understudied cities in the world. Hong Kong epitomizes the Laissez-Faire economic development model, often heralded

[1] While social scientists, such as sociologists often focus on mobility in occupation, education, or social class, economists emphasize income mobility both within and across generations, known as intergenerational income mobility (for detailed reviews, see Torche (2015) and Cholli and Durlauf (2022)).

as the "Hong Kong miracle," which was once touted as the optimal path for economic growth in underdeveloped Asian economies. Therefore, Hong Kong provides one of the best examples to study evolutions of social mobility and income inequality with minimal government intervention. Much like the American Dream, Hong Kong was envisioned as a land of opportunity where industrious individuals, equipped with academic excellence and entrepreneurial zeal, could transcend the struggles of their upbringing and secure a brighter future. This vision encapsulated the essence of the Hong Kong dream.[2]

However, while the Laissez-Faire economic approach fueled Hong Kong's remarkable economic growth, it also catalyzed the evolution of stark inequalities and complexities in social mobility. The laissez-faire policies, characterized by minimal government intervention in economic affairs, facilitated rapid economic expansion but also created a landscape where wealth and income inequality widened, posing challenges to equitable access to opportunities (Piketty and Yang, 2022). Consequently, while many thrived in Hong Kong's dynamic economic environment, the left found themselves increasingly marginalized, highlighting the dual nature not only of Hong Kong itself but also of the Laissez-Faire economic development model.

The renowned Great Gatsby Curve posits that countries with higher inequality tend to exhibit lower earnings mobility across generations. For instance, the United States, characterized by a high GINI Index of income of approximately 0.4 and a relatively elevated intergenerational elasticity (IGE) coefficient ranging from 0.33 to 0.35, contrasts with Nordic countries with a GINI Index below 0.3 and an IGE of less than 0.2 (Corak, 2013). With the persistent rise in economic inequality in Hong Kong over recent decades – evidence from the income GINI Index reaching as high as 0.6 by 2000 (World Inequality Database, 2023) – has the once-renowned Hong Kong dream now fading, mirroring the decline of the American dream (Chetty et al., 2017)?[3] [4]

To answer the above question, this paper investigates whether Hong Kong is undergoing a decline in absolute income mobility across generations. Moreover, we further seek

[2]Hong Kong has been proud of its free-market economy for a long time. It ranked the world's freest economy in 2024, according to the "Economic Freedom of the World" report published by Fraser Institute (Gwartney et al., 2024).

[3]For insights into the impact of inequality on income mobility, refer to the work of DiPrete (2020).

[4]Interestingly, while Hong Kong grapples with these challenges, mainland China has witnessed a notable rise in the Chinese dream over the same period.

to uncover the factors driving income intergenerational mobility in Hong Kong through the decomposition of absolute mobility, including the income growth factor and income distribution factor through the classical method from Chetty et al. (2017), and other non-income-related factors like education, occupation, industry, and place of birth through our newly developed Mincer equation method.

Typically, absolute income mobility can be expressed as the proportion of children earning more than their parents(Fan et al., 2021). Practically, direct comparisons require long-term panel data that includes parent-child pairs. However, the absence of longitudinal data for Hong Kong has inhibited serious empirical studies on intergenerational income mobility, although researchers have shown much interest in the topic. Vere (2010) used survey data from 2000, 2005, and 2008 to show that sons of fathers in the lowest and second-lowest quintiles had an 82% and 59% chance, respectively, of surpassing their fathers' income. Similarly, Wong and Koo (2016) found, using 1989 and 2007 surveys, that while upward mobility improved overall, sons' mobility in 2007 was more strongly linked to their fathers' occupations than in 1989. In order to overcome the limitations brought by the small sample size, To address small sample size limitations, Peng et al. (2019) used a 5% sample of the 1996, 2006, and 2016 Hong Kong Population By-Censuses to estimate intergenerational earnings mobility. Their findings suggest a decline in intergenerational income elasticity over time, indicating improved average mobility. However, challenges remain, including self-selection bias due to co-residence and the life-cycle bias given the lack of lifetime earnings measures.

To address these challenges, Chetty et al. (2017) developed a copula method that utilizes the distribution of parent and child income ranks, providing a robust framework for analyzing intergenerational mobility without longitudinal panel data. Berman (2022) and Manduca et al. (2024) further confirmed the robustness of this method across several developed countries. Building on the existing literature, this study applies the copula and marginals method to estimate AIM in Hong Kong.

Conceptually, beyond its methodological validity, AIM offers a more nuanced measure of societal progress by integrating both growth and inequality, aligning with Pareto's principle. For instance, in a society with equal income distribution but low or negative growth (like Europe), internal mobility is high, but people's overall well-being doesn't improve. In contrast, a high-growth society with greater inequality (like the U.S.) results in more unequal outcomes, where many fail to benefit from economic growth. Only societies with both high-income growth and more equal distribution can achieve high absolute mobility. Given the drop in income growth rate and the rising inequality happening simultaneously in Hong Kong, this study aims to decompose absolute income mobility trends to quantify the contributions of the growth and distribution factors respectively through counterfactual analysis Chetty et al. (2017), which allows us to quantitatively assess the trade-offs between equality and efficiency.

Several factors contribute to increased absolute income mobility, counteracting the rising Gini coefficient and declining growth rates. Notably, Hong Kong's rapid expansion of tertiary education during our sample period is significant, as education is crucial for equal opportunity and intergenerational mobility. We aim to assess whether Hong Kong's education policy helped mitigate the decline in AIM and sustained mobility. By comparing mobility levels with and without the influence of education using our innovative Mincer equation decomposition approach, we quantify education's role in shaping mobility trends in Hong Kong.

Our paper contributes to the AIM literature in three key ways. First, by estimating AIM in Hong Kong, we provide a unique comparison with Western economies, highlighting both differences and similarities under distinct socio-economic systems. Second, we conduct multiple robustness checks to ensure the reliability of our estimates across different assumptions, copulas, and age measures. Notably, we address limitations in Berman (2022) by using micro-survey data and focusing on a specific cohort rather than the entire population, enhancing the precision of our estimates. Third, we explore the factors influencing AIM fluctuations, particularly the role of education, by estimating AIM based on counterfactual income and controlling for educational impact using the Mincer equation. This approach broadens the scope of research on the factors influencing absolute mobility.

This paper is structured 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 data sources, focusing on the processing of Hong

Kong census data. Section IV presents the empirical results, including decomposition methodologies that extend beyond the baseline findings. Finally, Section V concludes with a discussion of the study's implications.

II Methodology

II.1 Basic Setting

Absolute income mobility (AIM) measures the fraction of children who, upon reaching the same age as their parents, earn more than their parents did. Naturally, the rate of AIM in cohort c, A_c, is conceptually defined as:

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

Where N_c is the number of children in the cohort c; y_{ic}^k and y_{ic}^p denote the income of child i in birth cohort c and his or her parents, respectively.

It's ideal to use the historical panel data to estimate intergenerational mobility. However, such data is rather scarce in many countries or regions including Hong Kong. Fortunately, following Chetty et al. (2017), it is possible to overcome the data limitation by employing the "copula and marginals" approach. This method does not indicate whether a specific child earns more than his or her parents, but instead, it estimates the AIM of the whole generation.

Since A_c can't be estimated directly using cross-sectional data, we can decompose the joint distribution of parent and child income into the marginal distributions of parent and child income and the joint distribution of the ranks (copula):

$$A_c = \int \mathbb{I}\{Q_c^k(r^k) \geq Q_c^p(r^p)\} C_c(r^k, r^p) \mathbf{d}r^k \mathbf{d}r^p \tag{2}$$

Where r_{ic}^k denote the percentile rank of the child i in the income distribution for children in birth cohort c, and r_{ic}^p the percentile rank of the child i's parent in the income distribution of parents with children in cohort c. $Q_c^k(r)$ and $Q_c^p(r)$ denote the rth quantile of the child and parent income distributions respectively, which summarize the marginal distributions of parent and child incomes. And the copula, $C_c(r^k, r^p)$, the probability density function of observing a child with income rank r^k and parent income rank r^p, denotes the joint distribution of parent and child ranks for cohort c. In this paper, we use a 100×100 transition matrix namely copula to give the probability of each child and parent rank pair (r^k, r^p) following Chetty et al. (2017).

II.2 Robustness of Copula Method

Based on the Hong Kong census microdata, obtaining the marginal income distribution for children and parents separately is straightforward. For the copula, we assume copula stability across different cohorts and countries, and the choice of copulas has little to do with the results. The marginal income distributions and a single relative mobility measure(copula) are very reliable when estimating AIM in various countries and cohorts Berman (2022); Chetty et al. (2017); Manduca et al. (2024). Given that empirical copula is limited, we use both the Gumbel, Gaussian, and Clayton synthetic copulas from Berman (2022) and the U.S. empirical 100∗100 percentile cell matrix copula from Chetty et al. (2017) as cross-validation.

However, two significant issues arise in Berman (2022)'s research. First, he employs the method of generalized Pareto curve interpolation to derive marginal income distributions based on the World Inequality Database (WID), which is not micro-level data, unlike the survey data focusing on specific cohorts of interest. Another issue is the representativeness error when the entire population represents a specific cohort of children and parents, which may potentially introduce life-cycle bias that could make the result a downward bias. Correspondingly, when Manduca et al. (2024) applies both methods to their micro-level survey data in the UK, the results are very similar. Therefore, since our paper utilizes micro-level large-scale survey data rather than synthetic data, this method should yield a very reliable result. Although they also show that the choice of population age does not significantly alter the result as long as micro-survey data is used, they still restrict the age used to measure a person's income to the 30s for both parents and children to mitigate life-cycle bias. Therefore, our research measures income both at the entire population level and at people's specific age for less life-cycle bias from 30 to 55.

III Data

The data source comes from the 1976-2016 Hong Kong Population By-census 1%/ 5% Sample Dataset, in which the censuses are conducted every five years. For the 1981 and 1986 data, only 1% population is covered, while for the 1991, 1996, 2001, 2006, 2011, and 2016 data covers 5% of the total population, and 10% is covered in 1976[5].

To ensure a representative sample, individuals with ages below 25 or above 60 have been excluded from the analysis. This decision is motivated by the fact that a significant proportion of the youth population in Hong Kong is engaged in university studies during their early twenties, while individuals tend to retire around the age of 60. No additional restrictions are implemented on population selection.

The primary focus of our analysis is the total income of each individual. In the census, there are three sources of income: (1) Monthly income from main employment [6]; (2) Monthly income from all secondary employment; (3) Other cash income: the total recurrent cash income received by a person which is not remuneration for work, including e.g. capital income [7] and transfer incomes[8]. These three sources are aggregated as the variable "total income". Additionally, the total income for each year is adjusted to the 2010 constant price using the Consumer Price Index obtained from the World Bank database (World Bank Database, 2023).

For high-income individuals, the censuses report a top-coded income of 99,998 Hong Kong Dollars (HKD) for those earning above this threshold in 1981, 1986, and 1991. In subsequent years, the top coding thresholds are raised to 150,000 HKD. To address the issue of top-coding, we apply the method used by Piketty and Yang (2022), which assumes that the upper tail of the wage distribution follows a Pareto distribution (see Appendix A for details).

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[5] Income variables are available only in interval form rather than in raw income form since 2021. Due to the structure change of the data, we did not include the 2021 Census here.

[6] For employers or self-employed persons, this is the amount earned excluding expenses incurred in running their main business. For employees, this is the total amount earned from their main employment including salary or wage, bonus, commission, overtime, housing allowance, tips, and other cash allowances

[7] Such as rent income, interest, dividend

[8] Such as pensions, social security payment, old age allowance, disability allowance, comprehensive social security assistance, education grants (excluding loan), scholarships, the regular contribution from persons outside the household

Within the census data, approximately 10%-25% of individuals report zero income in different census years. Considering this proportion is too large and is not very likely to reflect the real unemployment situation. Therefore 0 income is more likely to be omitted than to be actual 0 income, so we excluded them. Despite this adjustment, a significant portion of the population remains below the poverty line (18.7%), preserving a high level of representativeness for individuals in the lower-income bracket, and very close to the actual poverty ratio of 19.9%, very close to the poverty rate published in the Census and Statistics Department (C&SD, 2021). Such a result also makes it comparable with Berman (2022) since their generated data does not include 0 income population.

Below we explain details for the baseline estimations and other extension estimations that closely mirror them. To facilitate the matching of parent-child pairs with the copula, we restrict the sample size to the sample size of the 1981 census given its least sample size, which has the least observations - 15,392 individuals with positive income. Using 1981 as the baseline, we randomly drew an equal number of cases from other censuses and constructed a 15,392 $*$ 9 matrix, with the columns representing the years from 1976 to 2016. Using copulas on two specific columns, we are able to estimate an absolute income mobility data point. The years gap between two columns is 20 to 40 as we assume there is a 20 to 40-year-old gap between generations. For example, to estimate absolute income mobility for the 1976 population with an assumption of the 30-year-old gap, we paired columns 1976 and 2006, representing parent and child generations, respectively. Then we matched income pairs between 1976 and 2006 based on the copula, which is a 100$*$100 copula matrix showing parents' and children's relative ranks, creating quasi-parent-child pairs. Then the absolute income mobility is calculated through the fraction of children in each cell who earn more than their parents with a specific 100 $*$ 100 copula density. Under the assumption of 30 years old gap, this process was repeated using 1981 and 2011 data for the second point, and 1986 and 2016 data for the third point. Such a process is also repeated for other years-old gaps.

IV Results

IV.1 Absolute Mobility: Baseline Result

Drawing on a range of rank correlation findings from developed countries (Chetty et al. (2014) for the U.S.; Jantti et al. (2006) for the Nordic countries, U.K., and U.S.; and Ueda (2009) for Japan), we estimate our benchmark absolute income mobility series using the Gumbel synthetic copula with rank correlation coefficient equal to 0.3. [9]

Figure1 illustrates the evolution of absolute income mobility across different age gaps between parents and children. Initially, we estimate absolute income mobility using a 30-year age gap, consistent with the approach of Berman (2022). To extend the analysis over a longer period, we also relaxed the age gap to 20 and 25 years(For the full age gap range, see Appendix B1). The results show that reducing the age gap has a minimal effect on the results. For instance, for the 1981 cohort, using age gaps between 20 and 30 years results in mobility levels ranging from 85% to 87%, while for the 1986 cohort, the mobility levels range from 70% to 72%. To present the longest possible series of absolute income mobility with our dataset, we adopt a 20-year gap as the benchmark in subsequent analysis. It is important to note that this age gap reflects our assumption of a generational difference rather than the actual age gap within any particular family.

As shown in Figure 1 absolute income mobility saw a notable decline from 85% for the 1976 cohort to 55% for the 1996 cohort. That is to say, when measuring the income for the entire working-age population, the 1976 generation had approximately an 85% probability of earning more than their parents, while the 1996 generation saw this probability diminish to only half, which is close-to-random probability.[10]

IV.2 Robustness Check: Choice of Copulas

To assess the impact of different copulas on the estimation of intergenerational mobility, we also employed the Gaussian copula and Clayton copula with a rank correlation

[9]These synthetic copulas are obtained through the combination of a mathematical copula and an empirical relative mobility coefficient, for details, refer to Berman (2022)

[10]For details for values in the graph, please refer to Appendix J, same as below

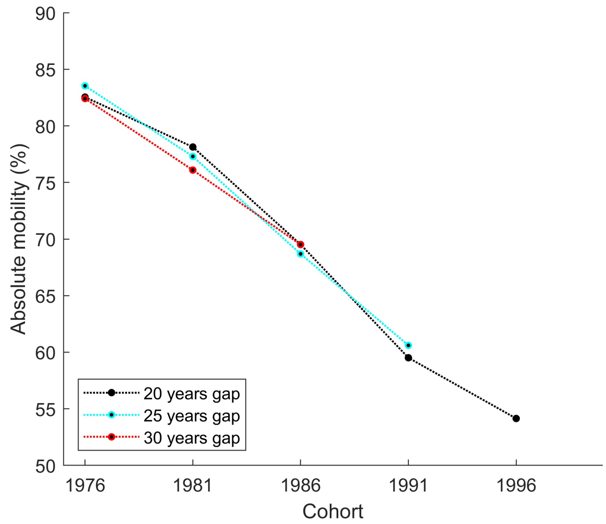
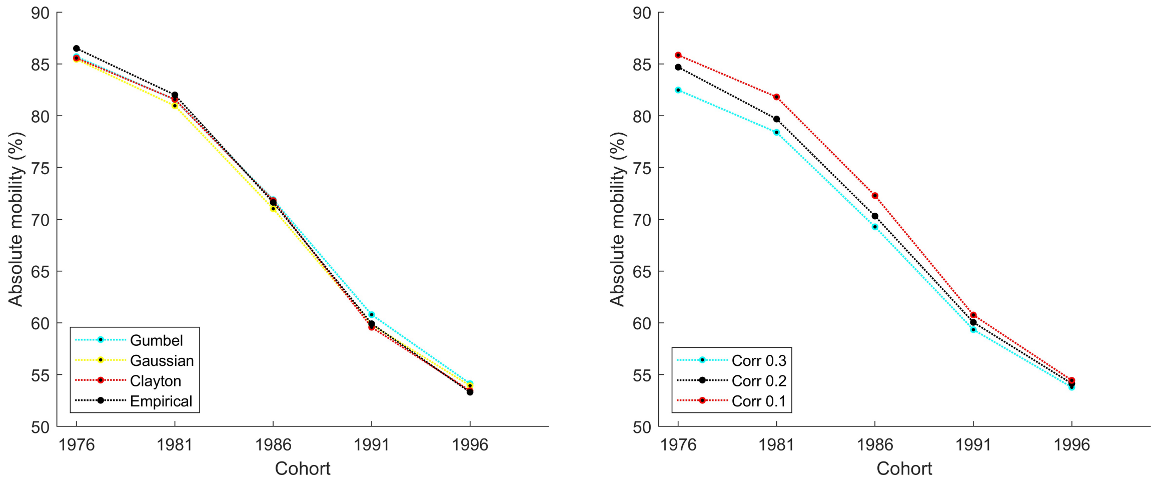


Figure 1: The evolution of absolute intergenerational mobility in Hong Kong using Gumbel copula with rank correlation 0.3

of 0.3, and the empirical copula from the United States (Chetty et al., 2017), aligning with the approach outlined by Berman (2022). From Figure 2a we know all these alternative copulas have no discernible difference in estimating absolute income mobility compared to the benchmark ones. This result suggests that the copulas are structurally similar, and substituting one reliable copula for another has minimal impact on the mobility outcomes, demonstrating their robustness and validity.

Since our estimated relative mobility rates decline from approximately 0.22 to 0.1, we also test rank correlations of 0.2 and 0.1, rather than 0.3, to examine potential variations in the results, as most developed economies exhibit rank correlations between 0.1 and 0.3. As shown in Figure 2b, the results are similar to the result when we choose rank correlation 0.3. Such a result further indicates that the choice of rank correlation parameter is insignificant for the result and the structure of synthetic copula does not vary too much from each other. In conclusion, the absolute income mobility level drops from approximately 85% in 1976 cohort to around 50% in 1996 cohort regardless of the choice of copulas.(For results of fraction of children earning 120%, 150%, or up to 300% more than their parents, see Appendix D)



(a) Different synthetic and empirical copulas (b) Different rank correlations(Gumbel)

Figure 2: The evolution of absolute intergenerational mobility in Hong Kong using different copulas

Note: In Figure 2a, all the empirical copulas have a rank correlation 0.3. In both Figures, the age gap is 20 years

IV.3 Robustness Check: Ages at Which Income is Measured

As noted earlier, using the entire population may not accurately represent a specific cohort, and no single age may perfectly reflect one's lifetime income. However, if there is stability in the mobility rate after a certain age, or if income at an earlier age can reasonably estimate later income, then using income at a certain age for both children and parents could provide a meaningful estimate of absolute income mobility. Therefore, we calculate absolute income mobility using income measured at ages 30, 35, 40, 45, 50, and 55. Since the data is specific to certain ages, we average the income over 5 years, including two years before and after, to represent each age. For example, the 28-32 age group is selected to represent 30-year-olds. Given the rapid expansion of education in Hong Kong, many individuals may still be pursuing higher education, such as a master's degree. Therefore, we do not include the age of 25 when measuring income. If a child's income at age 30 is measured in 1996, then the corresponding birth cohort is 1966.

Figure 3 shows that when the age gap is 20 years(For a 30-year gap, see Appendix C; Also for values of the graph, see Appendix J4), the mobility rates at which ages are measured are very similar to each other. This finding suggests that the choice of

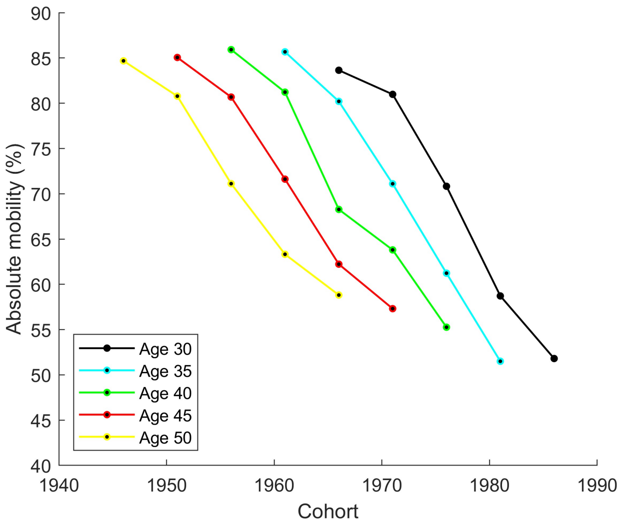


Figure 3: The evolution of absolute mobility by age at which income is measured, 20 years gap

age at which income is measured does not significantly impact the result as long as the age falls within the 30-50 range. Absolute income mobility rates measured at ages 30-50 are generally consistent with results from the entire population. This aligns with the findings of Manduca et al. (2024), who suggested that 35 years old and above is suitable for obtaining results. The similarity in mobility rates across different measured ages, ranging from around 85% to 50%, indicates that the birth cohort does not play a significant role, while the year in which income is measured is the primary determinant. This suggests that the mobility rate is largely influenced by socioeconomic changes over the years rather than increases in an individual's lifetime income through one's promotion and salary increase. Given the smooth downward mobility trend, we do not specifically consider the impact of business cycles or macroeconomic shocks.

This pattern resembles trends observed in countries like Norway and Canada (Manduca et al., 2024), where the trajectory of different age groups shows a similar, overall downward trend. In these economies, the year of measurement is more critical than the age group in determining the trend. This makes sense, as decreasing income growth rates largely explain the decline in absolute income mobility in these economies (Berman, 2022). In other words, the overall growth of the national economy significantly impacts mobility more than individual efforts and job promotions.

IV.4 Country Comparison

To investigate mobility patterns across different market economies with diverse institutional settings and economic structures, we compare our results with those of other developed economies. In Figure 4, the black line shows our results of the absolute income mobility of Hong Kong while other lines are data of other developed economies obtained from Berman (2022). The trend of absolute mobility closely resembles that of other developed economies such as the United States, Japan, and France (Berman, 2022; Chetty et al., 2017). However, the disparity lies in the timing of the trend, with Hong Kong exhibiting a 15 to 20-year lag behind Japan and France and a 25 to 30-year lag behind the United States. The results are compelling and intuitive. As one of the "Four Asian Tigers," Hong Kong's economic development lagged behind Japan by approximately 20 years and even further behind the United States for 30 years or more.

The dramatic speed of declination in absolute income mobility, from 85% to 50% within 15 years in Hong Kong, also coincides perfectly with Japan's trend from 1965 to 1980. Another notable feature is that East Asian economies experience a sharp drop in absolute income mobility, while Western European countries like France and the US undergo a moderate drop. The absolute income mobility of the US has stabilized around 55%, which might be the lower limit of developed economies which we do not fully know yet. Sweden has the least drop over decades, experiencing more than 65% absolute income mobility in 1980. The Nordic countries (especially Sweden, Denmark, and Norway) are one of the few developed economies where absolute income mobility didn't decline to around 50%, indicating that these countries enjoyed equal distribution and high economic growth in the 1970s and 1980s.

In a longer time frame, in contrast, The majority of developed economies experience steady growth of absolute income mobility in the first half of the 20th century. It is worth noting that countries in similar regions yield similar patterns, which are not fully shown here for clarity. This trend suggests that the rise and fall of absolute mobility may be an inevitable phase in the transition from developing to developed economies, providing a framework for understanding national economic transformation. As Eastern Europe and China progress through this transition, their AIM may follow a similar pattern, trailing

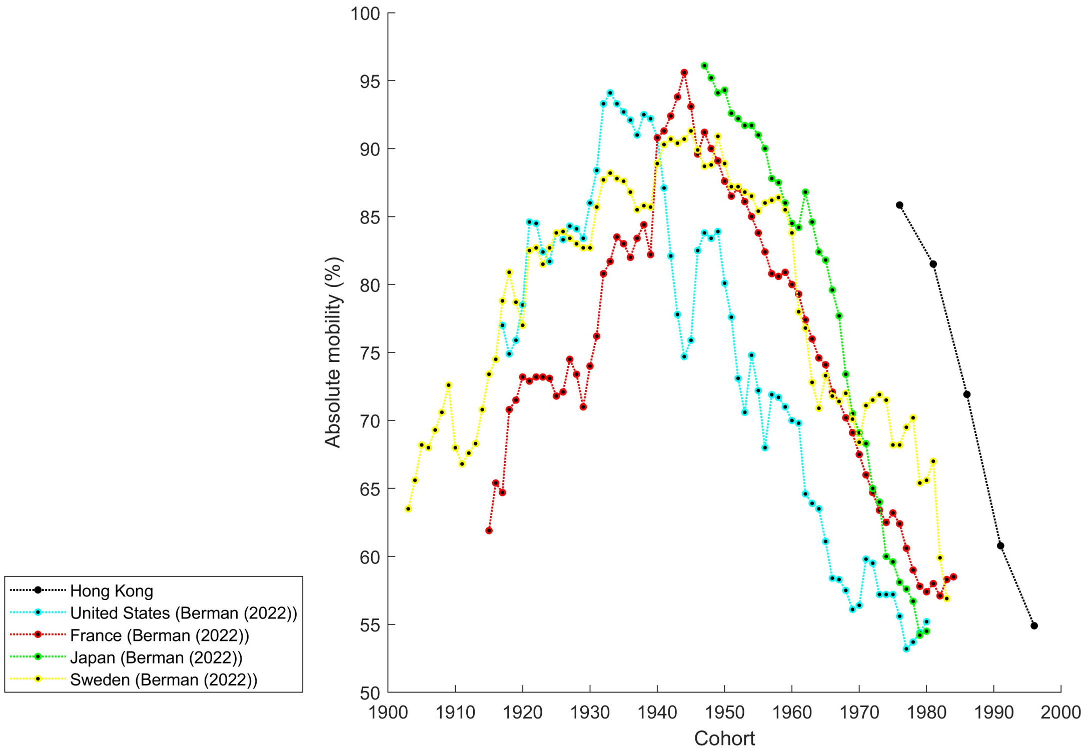


Figure 4: The evolution of absolute intergenerational mobility in five developed economies

Note: The black line represents the baseline result of this study, derived using a Gumbel copula with a rank of 0.3, an age gap of 20 years, and measured across the full population. The primary difference between our series and Berman (2022)'s is the age gap: we use 20 years to estimate AIM over a longer period, while Berman uses 30 years. However, as shown earlier, the trend remains highly consistent regardless of whether a 20- or 30-year age gap is used.

the current developed economies by several decades—a subject for future research.

IV.5 Decomposition of Absolute Mobility

An important question arises regarding the factors driving the observed decline. One potential determinant is the slowdown in GDP growth in Hong Kong in recent decades. In our sample period (1976–2016), the average real growth rate was 4.61% from 1976 to 1996 but fell to 0.67% from 1996 to 2016 (see Figure 5). Another contributing factor is the rise in income inequality. According to our data on the working population, Hong Kong's Gini Index increased from 0.45 in 1976 to 0.51 in 2011. To analyze the impact of these factors, we decomposed absolute income mobility trends to quantify their respective contributions. In examining the first factor, we held income growth constant by setting each year's income growth rate to the 1976–2016 average. For instance, in 1981,

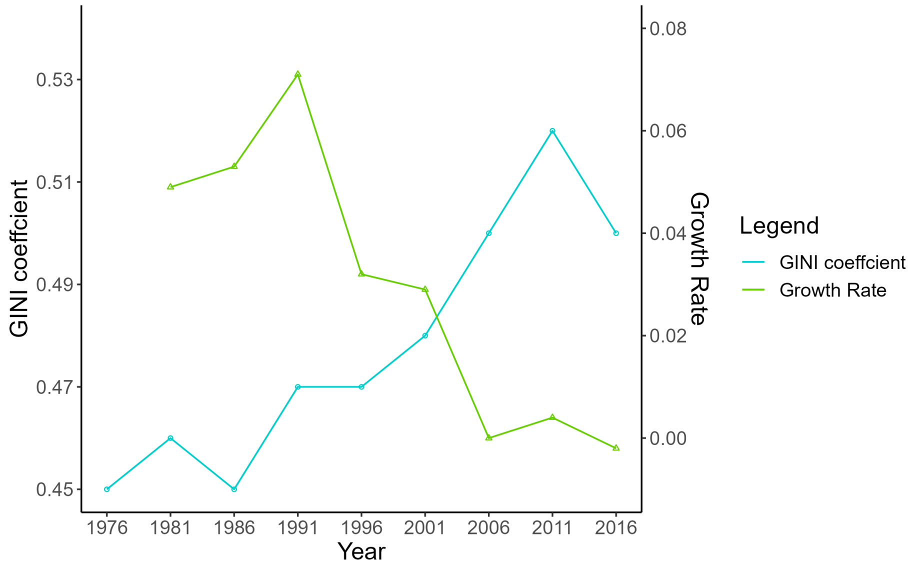


Figure 5: The evolution of GINI Index and real income growth rate in Hong Kong, with working population

$$I_{1981}^{dec\_gr} = \frac{I_{1981}}{mean(I_{1981})} * I_{1976} * (1 + G)^5 \tag{3}$$

Where I_{1981} and I_{1976} denote income in the years 1981 and 1976, respectively, and G represents the average growth rate from 1976 to 2016. By applying the income distribution of 1981, the actual income in 1976, and the five-year growth rate, we obtain the adjusted fixed income growth rate result, $I_{1981}^{dec\_gr}$.

The second factor involves fixing the income distribution by using the 1976 distribution as a baseline and applying it to subsequent years. For example, in the survey year 1981,

$$I_{1981}^{dec\_dis} = \frac{I_{1976}}{mean(I_{1976})} * mean(I_{1981}) \tag{4}$$

Where I_{1981} and I_{1976} denote the income in the years 1981 and 1976. By multiplying the income distribution shape in 1976 and the average income in 1981, we got the fixed distribution result $I_{1981}^{dec\_dis}$.

From Figure 6 we can see that trends in the fixed inequality counterfactual scenario closely align with the baseline estimates (see Appendix E for decomposition results using alternative copulas). Fixing inequality (distribution) has minimal impact on the decline

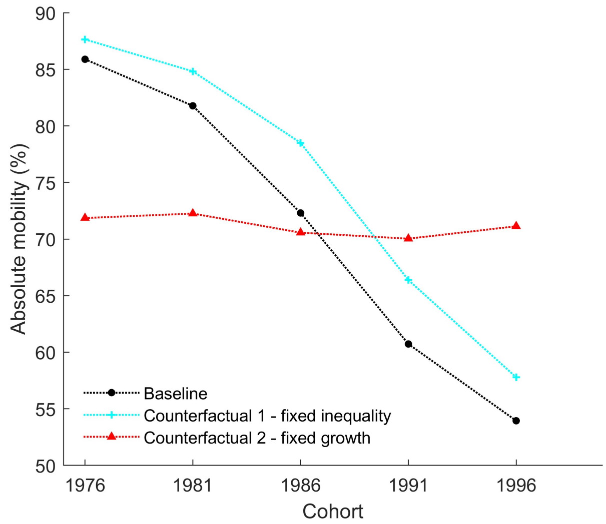


Figure 6: The decomposition of absolute intergenerational mobility in Hong Kong using Gumbel copula

in absolute income mobility. In other words, even if income were distributed as equally as in 1976, absolute income mobility would not significantly increase. Conversely, when holding the income growth rate constant at the 1976–2016 average, absolute income mobility in Hong Kong remained nearly stable at approximately 67%. The rapid drop in income growth rate of the recent decades is the main driver of the decline of AIM in Hong Kong.

Notably, Hong Kong's situation resembles that of Canada, France, Japan, and Nordic countries—especially France—where the decline in absolute income mobility is mainly attributed to slower income growth rates rather than changes in income inequality[11]. This is surprising given that Hong Kong's economic liberalization policies are commonly believed to be similar to those of the United States rather than those of European countries and Canada. One possible reason is that, unlike the U.S., U.K., and Australia, where pronounced income inequality has significantly reduced mobility, Hong Kong's high social inequality has remained relatively stable, especially compared to the slower development resembling the European pattern.

[11]Berman (2022) finds that the decline in absolute income mobility in Australia, the United Kingdom, and the United States is primarily attributed to unequal income distribution. Conversely, in Japan, France, Canada, and Nordic countries, the deceleration of income or GDP growth assumes a more pivotal role.

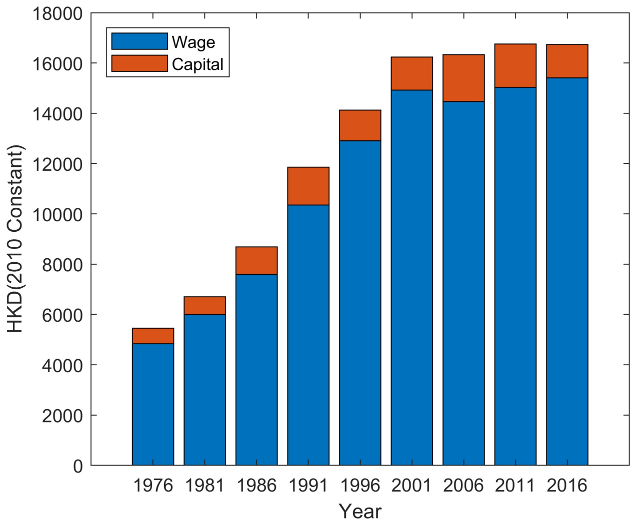


Figure 7: The evolution of average of wage and capital income in Hong Kong

IV.6 Absolute Mobility of Wage and Capital

To examine the roles of wage income and capital/business income in the decline of absolute income mobility, we would like to calculate their contributions separately. First, we provide an overview of their proportions in total income over time. Wage income includes earnings from employment, while capital/business income encompasses rent, dividends, stocks, profits from self-employment or small businesses, and so on. Figure 7 shows trends in average wage and capital income (in inflation-adjusted HKD using the 2010 CPI), highlighting stagnant real income since 2001 and a rising share of capital income. However, the share of capital/business income in our census data is low, likely due to the underreporting issue. Thus, results involving capital income should be interpreted with caution. (For the proportion of the population reporting capital income, see Appendix K1).

Next, we analyze the evolution of the Gini coefficient and the growth rates of total income, wage income, and capital & business income (see Appendix F for the evolution of the income shares of the top 1%, top 10%, middle 40%, and bottom 50%). From Table 1, we observe steady growth in both total and wage income, with a dramatic decline in growth rates for all income types before and after 1996. Given that the proportion of individuals reporting capital or business income is small as stated above, the Gini coefficient remains at a consistently high level. (For full descriptive results, please refer to Appendix K2-K4).

Table 1: GINI Coefficient and Growth Rate of Total, Wage, and Capital Income

GINI coefficient	Total Income	Wage Income	Capital and Business Income
1976	0.45	0.51	0.91
1981	0.46	0.49	0.93
1986	0.45	0.49	0.91
1991	0.47	0.51	0.93
1996	0.47	0.53	0.92
2001	0.48	0.54	0.92
2006	0.5	0.55	0.92
2011	0.51	0.56	0.93
2016	0.5	0.54	0.93
Growth rate 1976-1996	4.60%	5.00%	3.40%
Growth rate 1996-2016	0.70%	0.90%	-0.10%
Growth rate 1976-2016	2.60%	2.90%	1.70%

Then, we examine the absolute income mobility of wage income and capital & business income separately to determine which type of income contributes most to the decline in mobility. Figure 8 shows that absolute income mobility for wage income declines sharply, mirroring the trend for total income. In contrast, capital income remains stable at around 20%, with a slight increase before returning to its initial level. This analysis clarifies that wage income is the primary driver of the decline in absolute income mobility, while the contribution of capital income is minimal due to its low proportion. [12]

Following the method to decompose the impact of inequality and growth on AIM, we adopt similar methods for wage and capital & business income. From Figure 9, we see that the decline in absolute income mobility for wage income primarily results from slow GDP growth, consistent with previous findings. In contrast, the decline in capital & capital income mobility is mainly driven by unequal distribution; the fixed-growth counterfactual closely mirrors the original decline, while mobility remains stable when inequality is held constant. In summary, slow GDP growth predominantly affects

[12] Captial income is "all cash which is not remuneration for work including e.g. rent income, interest, dividend, education grants (excluding loans), regular/monthly pensions, social security payments, old age allowance, disability allowance, comprehensive social security assistance (Formerly known as Public Assistance Scheme), scholarships, the regular contribution from persons outside the household, contribution from charities." Since our sample excludes students and retirees, we have already removed pensions, education grants, and scholarships from consideration. The remaining social security income, aside from that for students and the elderly, is negligible.

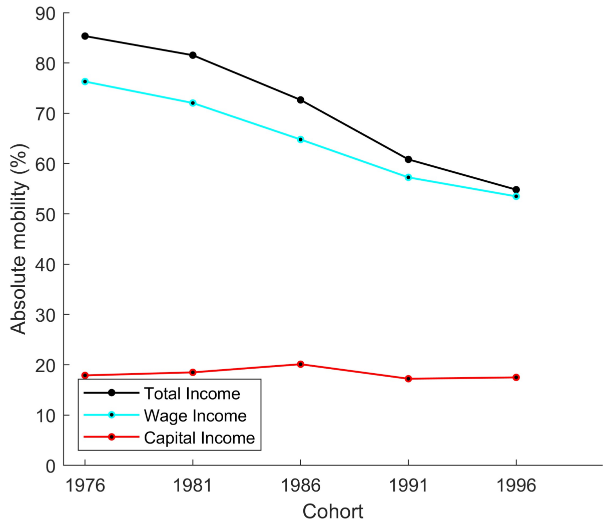
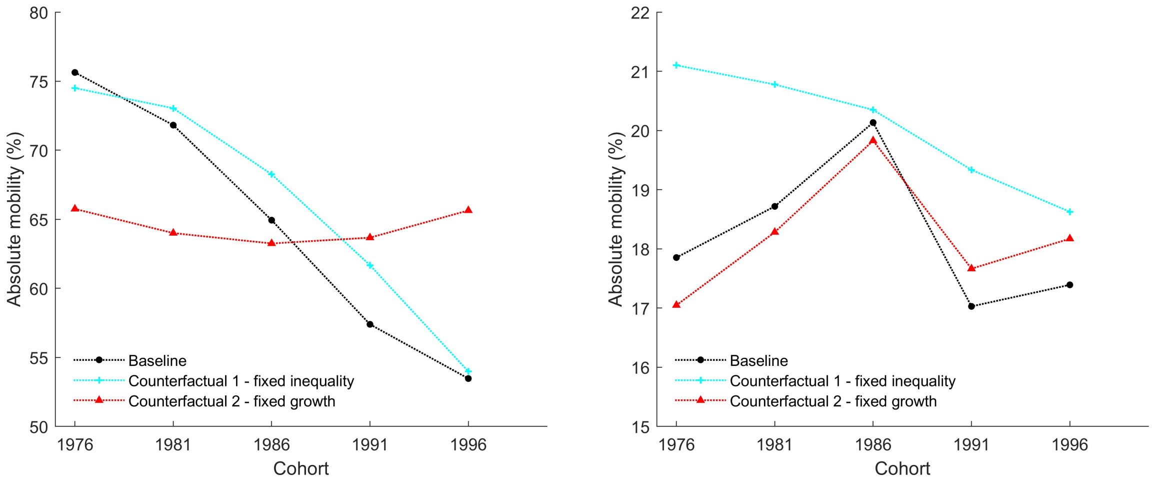


Figure 8: The evolution of absolute intergenerational mobility in Hong Kong by income type

wage income mobility, whereas unequal income distribution drives the decline in capital & business income mobility. Given that wage income constitutes the majority of total income in our census sample, the slow income growth largely accounts for the overall decline in absolute income mobility.

IV.7 Decomposing Influencing Factors using Mincer Equation

It is convenient to decompose our results into growth rate and distribution factors, as this allows us to calculate counterfactual scenarios. However, factors like education, which are not directly reflected in income, are harder to isolate. Fortunately, the rich census data enables us to examine the impact of demographic changes on AIM using an innovative approach based on the Mincer equation Mincer (1974). This method enables us to estimate AIM with and without the education effect by using the Mincer equation, which models wage income as a function of education and experience, allowing us to isolate the education factor through fitted values. Consequently, our analysis focuses on wage income, a key driver of AIM's decline as shown in Section IV.6, making it highly representative. Additionally, we include only individuals with wage income greater than zero, in accordance with the Mincer equation framework (for a comparison of absolute income mobility results between wage income samples with and without zero values, see the appendix G). The approach is outlined as follows:



(a) Wage

(b) Capital

Figure 9: The decomposition of absolute intergenerational mobility in Hong Kong using Gumbel copula, by income type

Given Y_i the wage income of individual i, our Mincer equation would be:

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

Gender is represented as a binary variable indicating whether an individual is male or female, while experience (Exp) and education (Edu) are treated as continuous variables. Education (Edu) is measured in years of schooling, inferred from detailed census information about educational attainment, which includes categories such as lower and upper primary school, each year of middle school, craft and technical training, bachelor's degrees, and graduate school. Therefore this inference regarding years of schooling is robust. Experience (Exp) is calculated as the individual's age minus the years of schooling and the years of preschool. If an individual stops schooling before the age of 15, we subtract 15 instead of the years of schooling. Since our sample comprises individuals older than 15 with non-zero income, we have already excluded those still in school. Additionally, C_i represents a series of controlled variables, including occupation, industry, place of birth, and marital status. All categorical variables have been converted into dummy variables for analysis (for summary statistics, see Appendix L1).

Therefore, our regression result would be(for regression results, see Appendix L2):

$$ln(Y_i) = \hat{\alpha} + \hat{\beta}_1 Gender_i + \hat{\beta}_2 Exp_i + \hat{\beta}_3 Exp_i^2 + \hat{\beta}_4 Edu_i + \sum_{k=5}^{n} \hat{\beta}_k C_i^k + \hat{\epsilon}_i \tag{6}$$

Assuming we want to see the effect of Education on AIM, then we first estimate the fitted value for Y_i when taking the Edu effect out:

$$ln(\hat{Y_i^{-Edu}}) = \hat{\alpha} + \hat{\beta}_1 Gender_i + \hat{\beta}_2 Exp_i + \hat{\beta}_3 Exp_i^2 + \sum_{k=5}^{n} \hat{\beta}_k C_i^k + \hat{\epsilon}_i \tag{7}$$

We can now utilize the new counterfactual scenario $\hat{Y_i^{-Edu}}$ to estimate the adjusted wage absolute income mobility. By comparing the baseline wage AIM using Y_i with our counterfactual wage AIM, we can assess the Contribution of education (Edu) on AIM. Using a similar approach, we can also evaluate the influences of occupation, industry, and place of birth on AIM.

Figure 10 indicates that education plays the most significant role in enhancing absolute income mobility. For children in earlier cohorts, the removal of the education effect results in an approximately 10% drop in AIM each year, demonstrating that education effectively boosts intergenerational mobility by 10 percentage points. For children born in 1991, the impact of education is even more pronounced, raising AIM by nearly 30%. Although the effect diminishes for children born in 1996, it still accounts for about 20% of AIM. This trend aligns with the expansion of higher education in Hong Kong during the 1990s and 2000s (Marginson, 2018) and our findings of consistently high absolute educational mobility (see Appendix I). Thus, the earlier expansion of education significantly improved AIM, although its influence has slightly waned in more recent years.

Figure 10 also reveals that, among factors typically assumed to have a substantial impact on AIM, education remains far more influential. For instance, while one might expect a place of birth to drive down AIM—particularly for Hong Kong residents born in mainland China—this influence is minimal and has even lessened for children born in 1996. Similarly, the effects of occupation and industry on AIM are unclear, with limited mobility between industries and minimal impact of these factors on overall AIM. In other words, facilitating mobility between regions or industries may not significantly impact

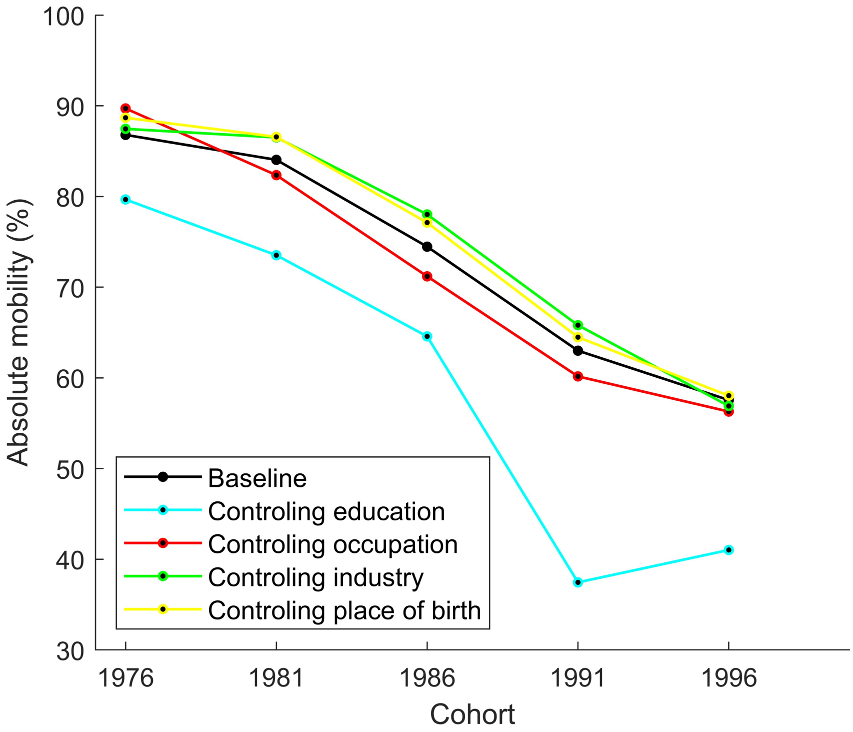


Figure 10: The evolution of absolute intergenerational mobility in Hong Kong while excluding some influencing factors using Mincer equation

absolute income mobility, as mobility remains largely unchanged when everyone shares a similar industry or birthplace. What matters most, and perhaps only, is how much education plays a role in increasing mobility. (for full results excluding other variables such as marital status, experience, gender, and error terms, see Appendix H).

V Concluding Discussion

Our census data reveals a clear trend of real wage stagnation in Hong Kong since 2001. We argue that one of the driving forces of the decline in absolute income mobility in Hong Kong can be partly attributed to the "China shock." Since China joined the WTO in 2001, many manufacturing industries have relocated to mainland China, reducing jobs and economic growth in Hong Kong while shifting its reliance on real estate and finance sectors, which generate fewer job opportunities(Wan et al., 2021). Additionally, competition from highly educated mainland talent has intensified, turning the finance job market into a zero-sum game. Existing research highlights multiple impacts of the China shock: Hsieh and Woo (2005) link outsourcing from Hong Kong to mainland China since the 1980s with rising returns to education favoring skilled workers; Cheng and Zhang (2018) show how mainland immigrants adversely affect local labor markets, particularly for native male earnings; and Weiss et al. (2018) demonstrate how cross-border marriages weaken the bargaining power of native women in both the marriage market and households. Further, Piketty and Yang (2022) documents rising income inequality in Hong Kong from 1981 to 2020, attributing it to a government-business alliance endorsed by the Chinese government. These interconnected dynamics suggest that the China shock significantly shapes intergenerational mobility in Hong Kong, warranting deeper investigation into its relationship with house prices, real estate finance, and education returns.

Another perspective involves the stagnation of higher-level education in Hong Kong after the effective rapid expansion. As our Mincer decomposition result reveals, the expansion of education plays a significant role in mitigating the decline of absolute mobility while the effects subsequently weaken. According to Marginson (2018), East Asian economies, including Hong Kong, witnessed rapid expansion followed by recent stagnation. With wage growth stagnating, many young Hong Kong students discovered their real income lagging behind their similarly educated seniors. Therefore, a comparison of education mobility with other countries according to Van der Weide et al. (2024) is performed to replenish our study of mobility instead of income. This includes both relative mobility and absolute mobility given that the education level in our cross-sectional data does not suffer from life-cycle bias. The data shows that absolute educational mobility increased sharply from 1981 to 1986 and has remained stable since, reflecting the educational expansion of the 1980s. This level is comparable to other top-performing Asian economies. While relative educational mobility increased from 1981 to 1991, it then declined back to 1981 levels, yet still remains among the highest globally. This result aligns closely with our decomposition findings controlling for education, where relative educational mobility peaks and slightly declines, while the role of education in mitigating absolute mobility peaks slightly later, at around the same time. (see Appendix I).

In conclusion, Hong Kong's absolute intergenerational income mobility experienced a sharp decline from 1976 to 1996, from around 85% to 55%. Such declines could mostly be attributed to the stagnation of Hong Kong's income growth rather than the uneven income distribution. Such decline is evenly distributed to any fraction of children who earn more than their parents from 100% to 300%. The decomposition results further indicate that income inequality is not the primary driver of Hong Kong's decline in absolute income mobility; instead, the main factor is the slow income growth rate. Education, on the other hand, played a counterbalancing role by mitigating the decline in AIM.

First, our research is based on the Chetty et al. (2017)'s copula and margins method and Berman (2022)'s empirical method to handle non-panel data. Our usage of synthetic and empirical copula yields similar and robust results, further justifying the validity of the copula method. We also solved two potential issues that Berman (2022)'s method suffers. According to Manduca et al. (2024), we first utilized the micro survey data instead of data generated from the WID, which proved to be a more reliable data source. Secondly, besides the entire population, we measure the income of both parents and children in a specific age, from 30 to 50, to ensure our result is more representative of a specific cohort. An interesting result is that the results do not differ much across different birth cohorts as long as the data is chosen from the same year. This suggests that an individual's rapid wage growth is driven primarily by overall socio-economic progress rather than individual effort, promotion, or wage growth over a lifetime in recent decades in Hong Kong.

Second, from an international point of view, Hong Kong's evolution of income mobility is mostly similar to that of Japan among developed economies. The speed of decline is very sharp in both Japan and Hong Kong while Hong Kong's absolute income mobility declined 15 to 20 years later than Japan's. It is even later than the decline of Western Europe and further than the United States, while faster than them. Such comparison strengthened a belief that absolute income mobility will necessarily decrease as a country has significantly modernized and become a developed country. This enhances our understanding of the social changes accompanying a transition from a developing economy to a developed one.

Third, separating wage income from capital income reveals a clear divergence in the factors driving changes in absolute income mobility for each. In Hong Kong, slower income growth primarily explains the decline in wage income absolute income mobility, while changes in income distribution account for most of the fluctuation in capital income absolute income mobility. Given that wage income constitutes the majority of total income in our census sample, the overall decline in absolute income mobility can largely be attributed to slower income growth in Hong Kong. It is worth noting that wage income is more accessible than capital income, which may lead to an underestimation of the impact of unequal distribution on declining mobility. Future research should focus on improving data reliability and developing better methods for estimating capital income.

Finally, we developed an innovative decomposition method using the Mincer Equation to disentangle the impact of education and other factors on intergenerational absolute income mobility. By estimating the counterfactual income fitted value with the education effect removed, we calculate the absolute income mobility of wage income without the influence of education. To our knowledge, this study is the first to employ this new decomposition approach, demonstrating that education is the primary factor enhancing absolute income mobility compared to other variables. This method could be further applied to future research exploring factors influencing absolute mobility beyond income-related aspects.

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Appendices

A Top-coded Technical

As wage income in the census from 1976 to 2016 is top-coded, it will generate a downward bias at the top of the wage distribution. We then correct the observations with top-coded income, assuming that the top of the wage distribution follows a Pareto distribution.

$$F(x) = 1 - (\frac{c}{x})^{\alpha}, for\, x > c > 0 \tag{8}$$

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 the 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 2016 ($x = -log(1-rank)$, $y = log(inc+1)$). By applying the estimated inverted Pareto coefficient $\hat{b}$ to the threshold, we can estimate the average wage for the observations above the top-coding threshold and assign the average wage to each observation. Finally, we estimate the wage distributional series based on the top-coding-corrected survey.

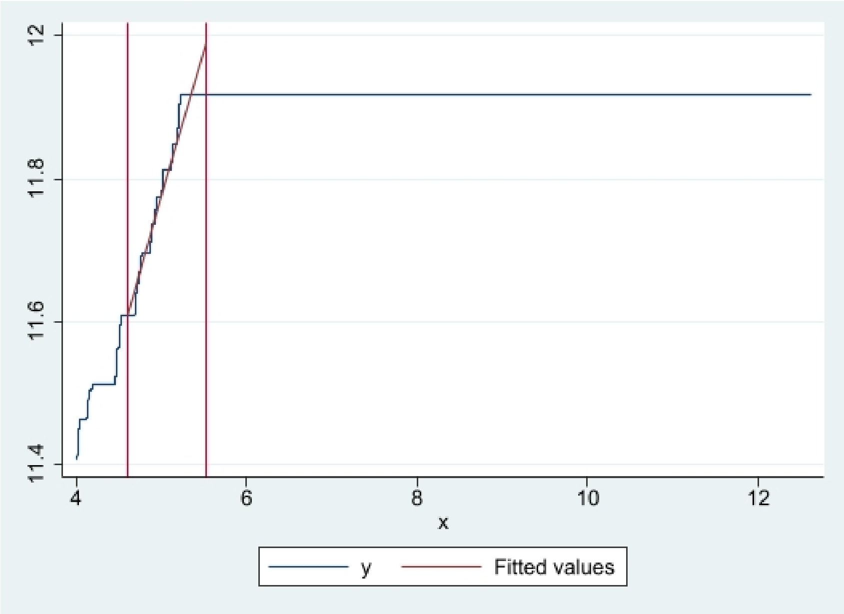


Figure A1: Estimating the Inverted Pareto Coefficient $\hat{b}$

B Absolute Mobility Results with Different Copulas

Figure B1 to B6 display the absolute mobility result using different copulas with a full range of years gap from 20 to 40.

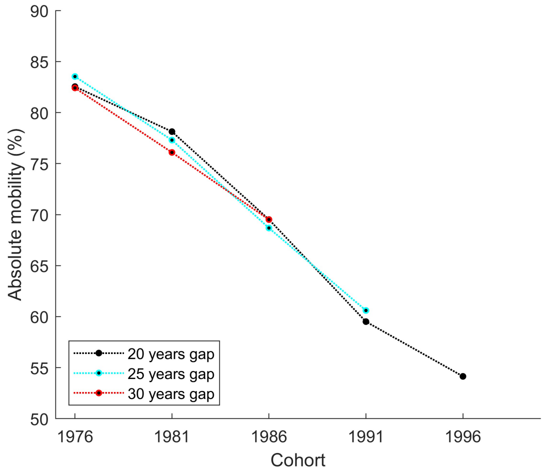


Figure B1: The evolution of absolute intergenerational mobility in Hong Kong using Gumbel copula with rank correlation 0.3 - Full range of years gap

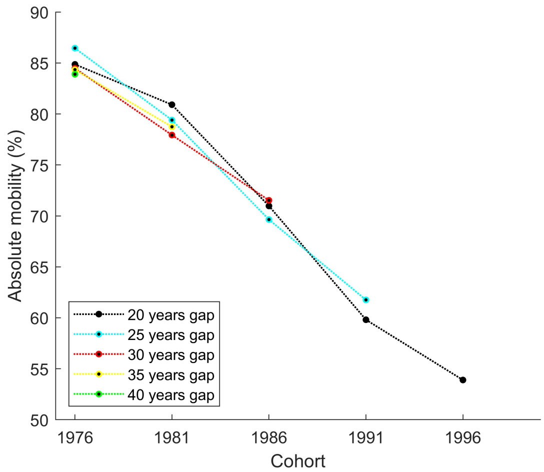


Figure B2: The evolution of absolute intergenerational mobility in Hong Kong using Gaussian copula with rank correlation 0.3 - Full range of years gap

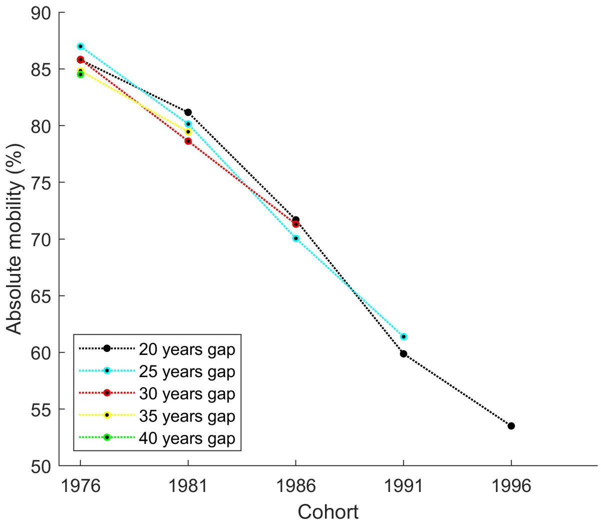


Figure B3: The evolution of absolute intergenerational mobility in Hong Kong using Clayton copula with rank correlation 0.3 - Full range of years gap

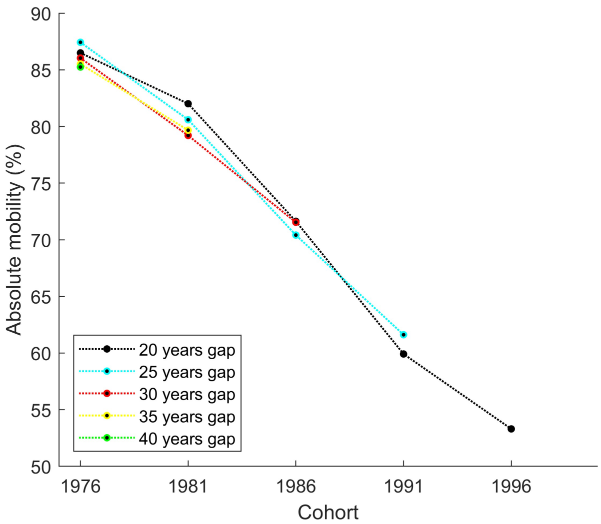


Figure B4: The evolution of absolute intergenerational mobility in Hong Kong using Empirical US copula with rank correlation 0.3 - Full range of years gap

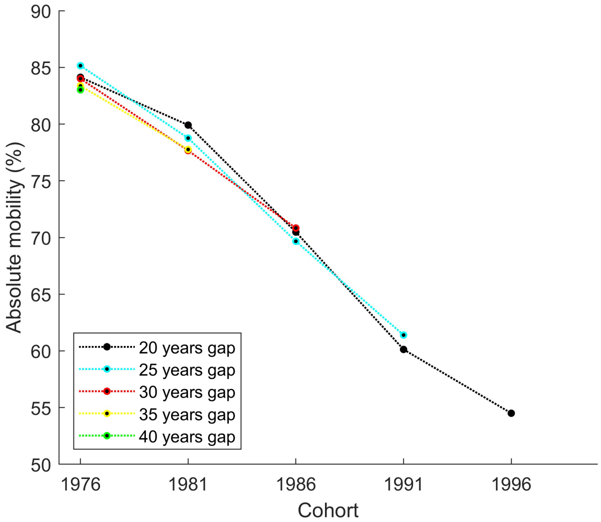


Figure B5: The evolution of absolute intergenerational mobility in Hong Kong using Gumbel copula with rank correlation 0.2 - Full range of years gap

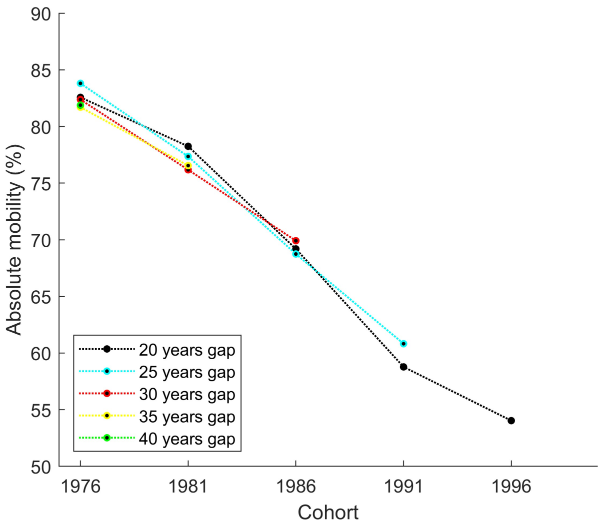


Figure B6: The evolution of absolute intergenerational mobility in Hong Kong using Gumbel copula with rank correlation 0.1 - Full range of years gap

C Absolute Mobility Measured at Different Ages with 30 Years Gap

Figures C1 depict upward mobility when income is measured at different ages, using a 30-year gap as the baseline. 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 Manduca et al. (2024) findings, suggesting that the choice of age for measuring income is not the primary reason for the differences with Berman (2022) results; instead, it is mostly 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.

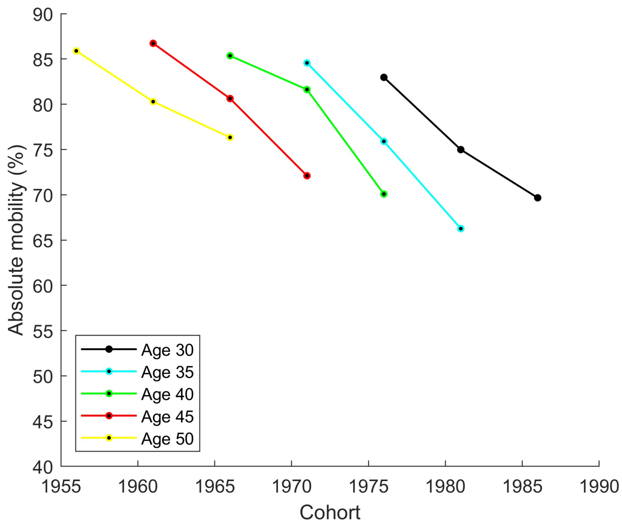
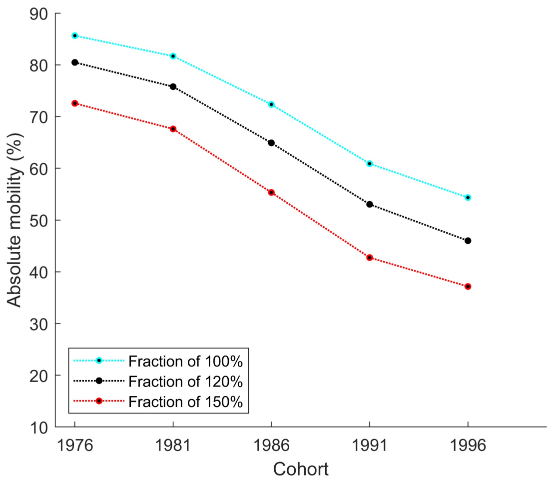


Figure C1: The evolution of absolute mobility by age at which income is measured, 30 years gap

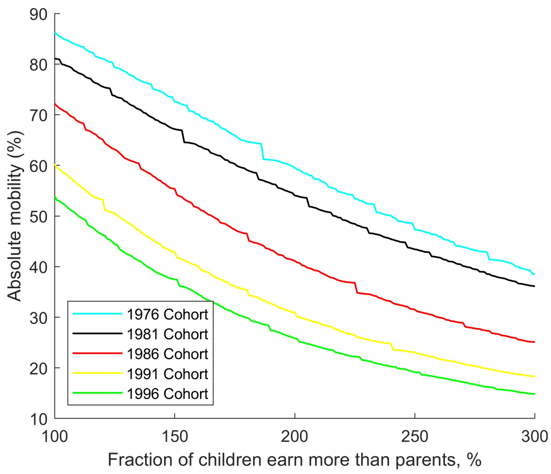
D Fraction of Children Earning More than Their Parents

In addition to displaying the fraction of children's generation earning more than their parents by 100%, we also show percentages of 120% and 150%, reflecting the rapid economic growth in Hong Kong during the late 20th century. Figure D1a demonstrates similar trends whether using 120% or 150%, both showing a decrease in overall mobility. The trend for the 120% fraction is consistently 5% lower than the baseline, while for the 150% fraction, it is 15% lower. There is no significant difference in pattern between the baseline and other trends, suggesting that the decline in absolute income mobility is evenly distributed across all income levels above parents'.

In order to verify that the fraction of children who earn more than their parents is evenly distributed, we also plot the absolute income mobility against the choice of fraction from 100% to 300% in 1% intervals. From Figure D1b we can see that children who earn a fraction more than their parents are steadily decreasing across 100% to 300% without any significant variation. Such a result holds for all birth cohorts. That is to say, absolute income mobility in Hong Kong does not concentrate on a certain level, instead, the chance of earning much more than parents is quite open to the next generation.



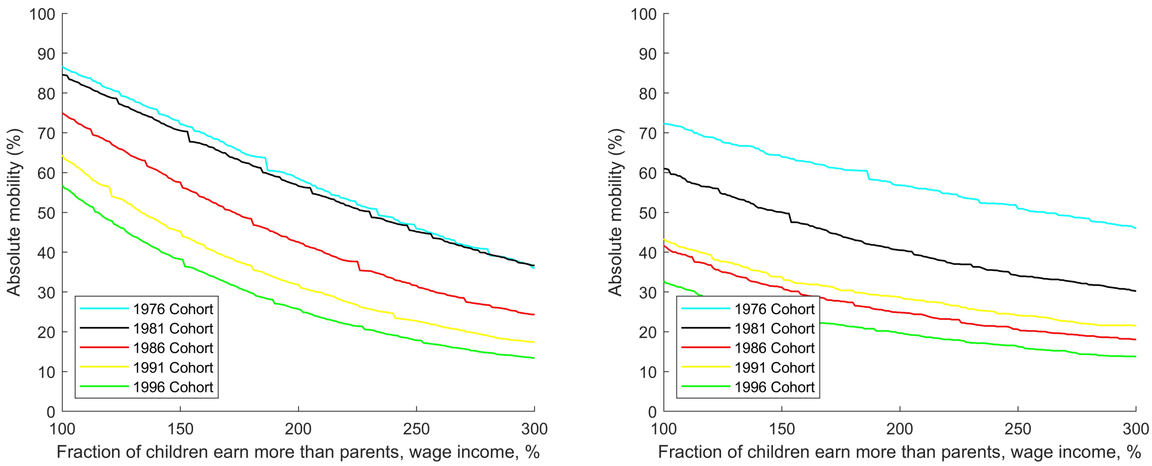
(a) Franction 100, 120, 150



(b) Franction 100 to 300

Figure D1: The evolution of absolute intergenerational mobility with different fractions of children earn more than parents

Figure D2 shows that children earning a multiple of their parents' income are evenly distributed between 100% and 300% for both capital and wage income. The smooth upward curve for capital income suggests that children with capital tend to accumulate significantly more than their parents' generation, with only a 20% or less difference between those earning 100% and 300% of their parents' capital income. This pattern highlights severe wealth concentration, with greater wealth concentrated among a small segment of the population. Additionally, the marked decline in absolute capital income mobility from the 1976 to the 1986 cohort suggests a sharper increase in wealth concentration over this period.



(a) Wage

(b) Capital

Figure D2: The absolute intergenerational mobility by different fractions of children earn more than parents, by income type

E Decomposition of Absolute Mobility Using Various Copulas

Figures E1 to E3 show the decomposition of absolute mobility using other synthetic copulas and empirical copulas. No significant difference is found in the figures. The only disparity is that using the empirical copula generates marginally lower absolute mobility in the fixed growth scenario.

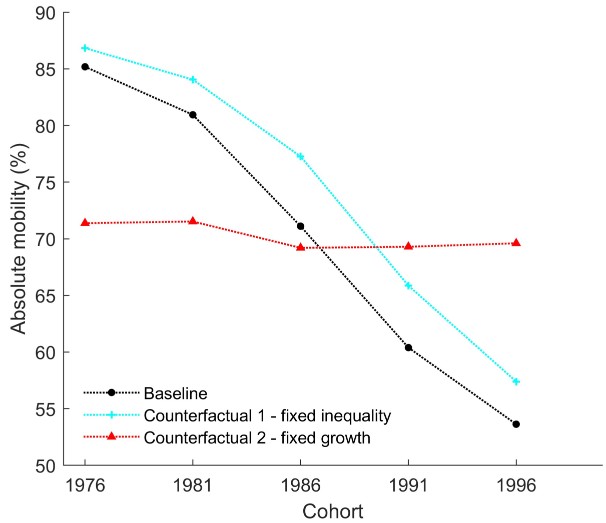


Figure E1: The decomposition of absolute intergenerational mobility in Hong Kong using Gaussian copula

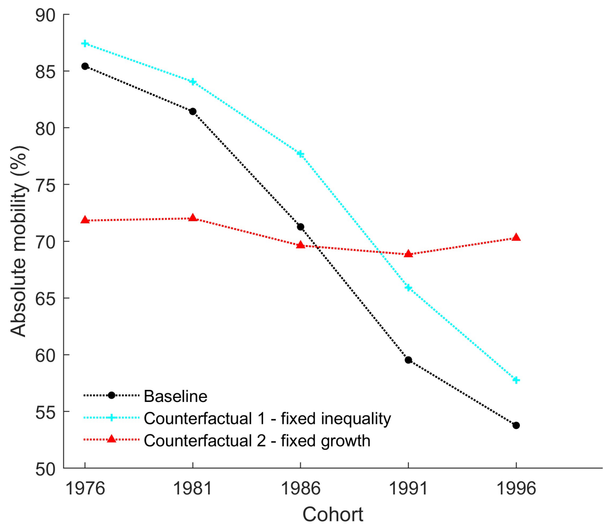


Figure E2: The decomposition of absolute intergenerational mobility in Hong Kong using Clayton copula

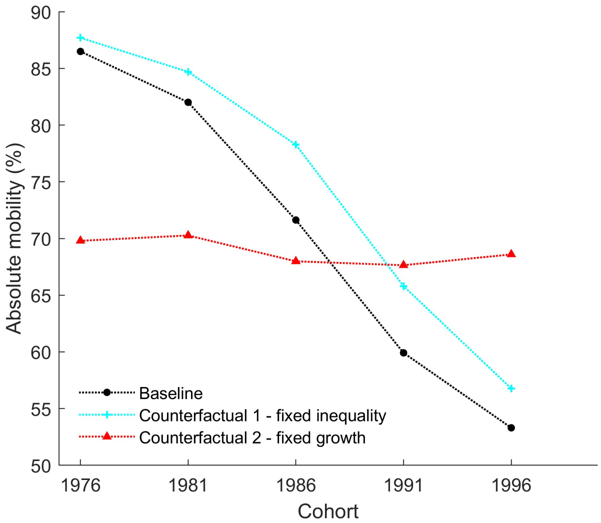
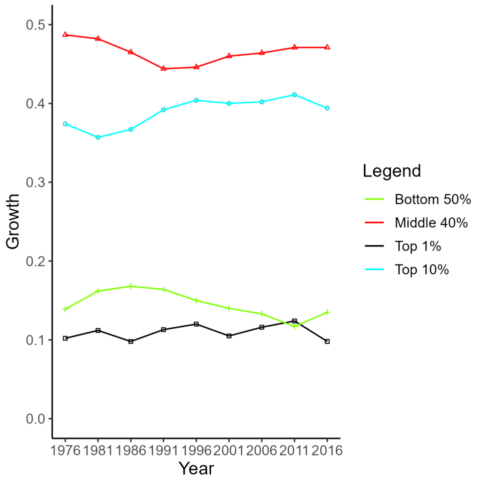


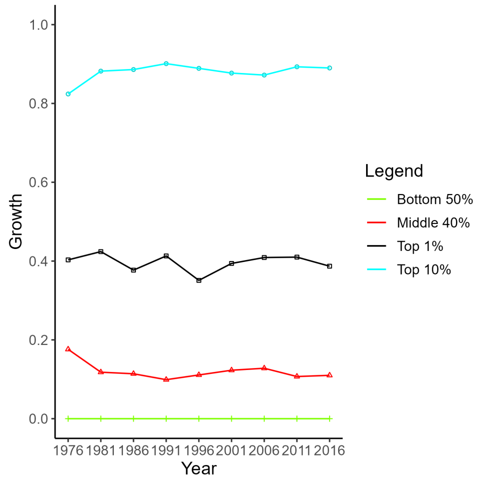
Figure E3: The decomposition of absolute intergenerational mobility in Hong Kong using Empirical copula

F Inequality for total, wage, and capital income

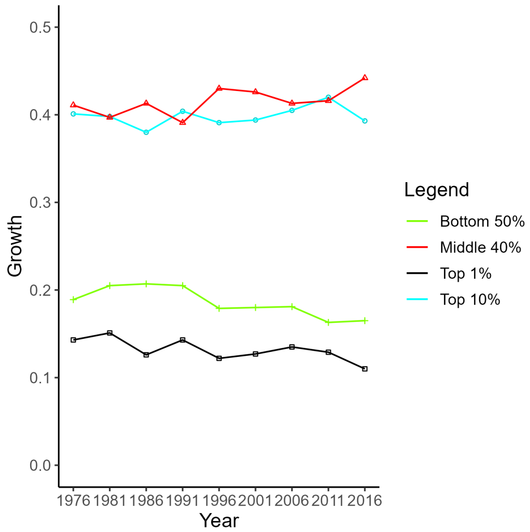
We present income shares—total, wage, and capital—for the top 1%, top 10%, middle 40%, and bottom 50%, providing insights into wage and capital inequality. Figure F1c shows high total income inequality, with the top 1% and 10% shares positioned between those in Europe and the United States. A slight rise in inequality over recent decades appears driven by income gains among the middle 40% and declines for the bottom 50%, independent of changes in the top 1% and 10% shares. Figure F1a indicates that wage income is higher for the middle 40% than for the bottom 50%. Notably, Figure F1b reveals that only about 10% of households report capital income, entirely concentrated within the top 10%, with the top 1% holding half.



(a) Wage income



(b) Capital income



(c) Total income

Figure F1: The evolution of top 1%, top 10%, middle 40%, and bottom 50% share of income

G Absolute Mobility of Wage Income with and without 0 Wage Income

Figure G1 illustrates AIM for wages in both the full sample and the non-zero wage sample. Part *IV.7, "Absolute Mobility of Wage and Capital,"* uses the full sample, while Part *IV.8, "Decomposing Influencing Factors Using the Mincer Equation,"* applies the non-zero wage sample. Both samples exhibit a similar downward trend, consistent with the total income AIM, indicating strong representativeness.

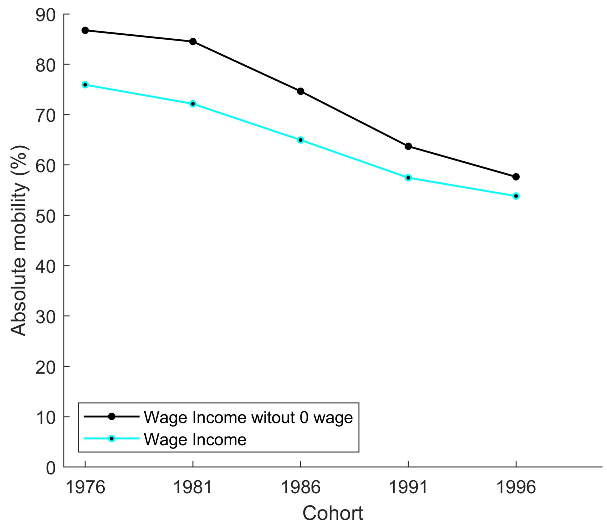


Figure G1: The evolution of absolute intergenerational mobility of wage income with and without 0 wage income in Hong Kong

H Full Result of Mincer Equation Decomposition

Figure H1 presents the full decomposition results of the Mincer equation, illustrating the impact of sequentially removing each explanatory factor. Education remains the primary determinant in increasing AIM.

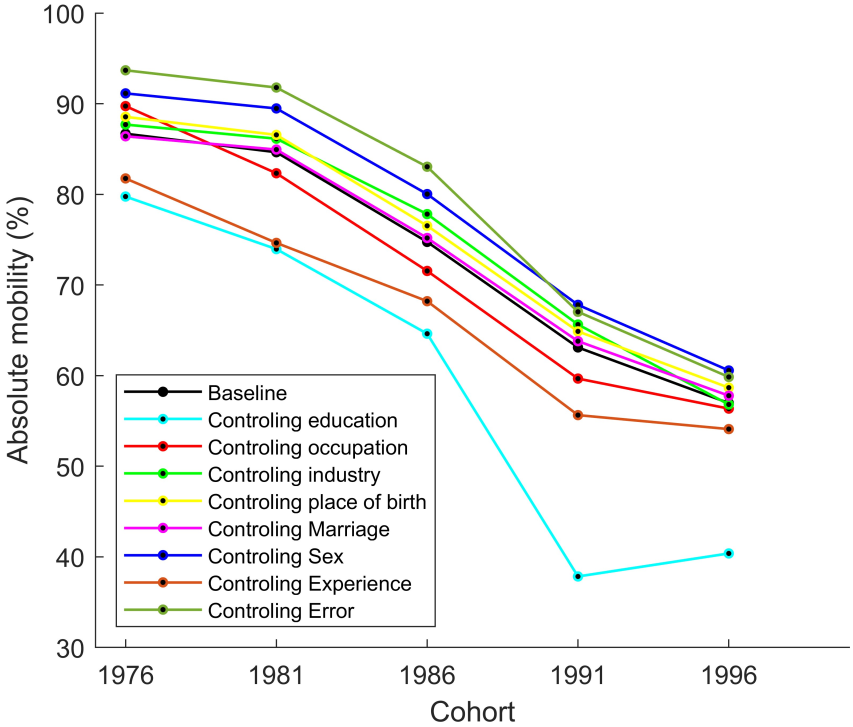


Figure H1: The evolution of absolute intergenerational mobility in Hong Kong while excluding every influencing factor

I Educational Mobility

Figure I1 shows absolute educational mobility, calculated as the percentage of individuals attaining a higher educational level than their parents(Max education of parents). Educational levels are defined according to Van der Weide et al. (2024) and categorized into five levels based on the International Standard Classification of Education (ISCED): (i) less than primary (ISCED 0), (ii) primary (ISCED 1), (iii) lower secondary (ISCED 2), (iv) upper secondary or postsecondary non-tertiary (ISCED 3–4), and (v) tertiary (ISCED 5–8). Parents with tertiary education are excluded because their children cannot achieve upward mobility beyond this level. Therefore, absolute educational mobility is calculated for children whose parents fall into the lower four education categories. We use co-residence data, selecting children aged 21 to 25 who live with their parents, to minimize co-residence bias, as in Van der Weide et al. (2024). The results indicate that absolute educational mobility increased from 0.77 in 1981 to around 0.85 in 1986 and has since stabilized.

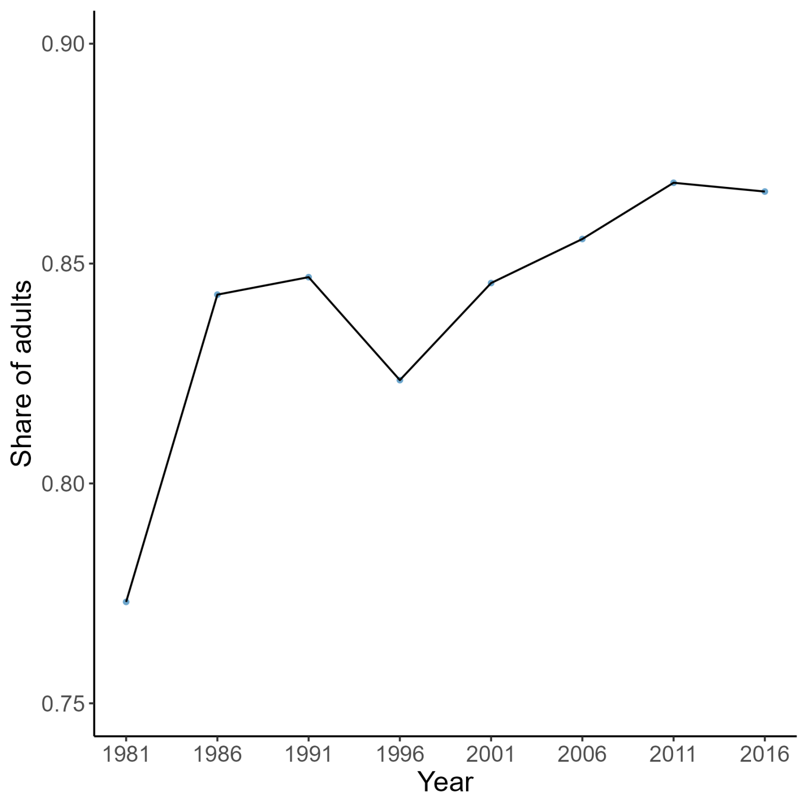


Figure I1: Absolute educational mobility from 1981 to 2016

Figure I2 depicts absolute mobility relative to the education level of parents. As expected, upward mobility decreases from nearly 100% at the less-than-primary level to 0% at the tertiary level. The five colored lines represent data from 1981 to 2016. The most notable change occurred between 2001 and 2011, where absolute mobility significantly decreased for children of parents with upper secondary education while continuously increasing for those with parents at the primary or lower secondary levels.

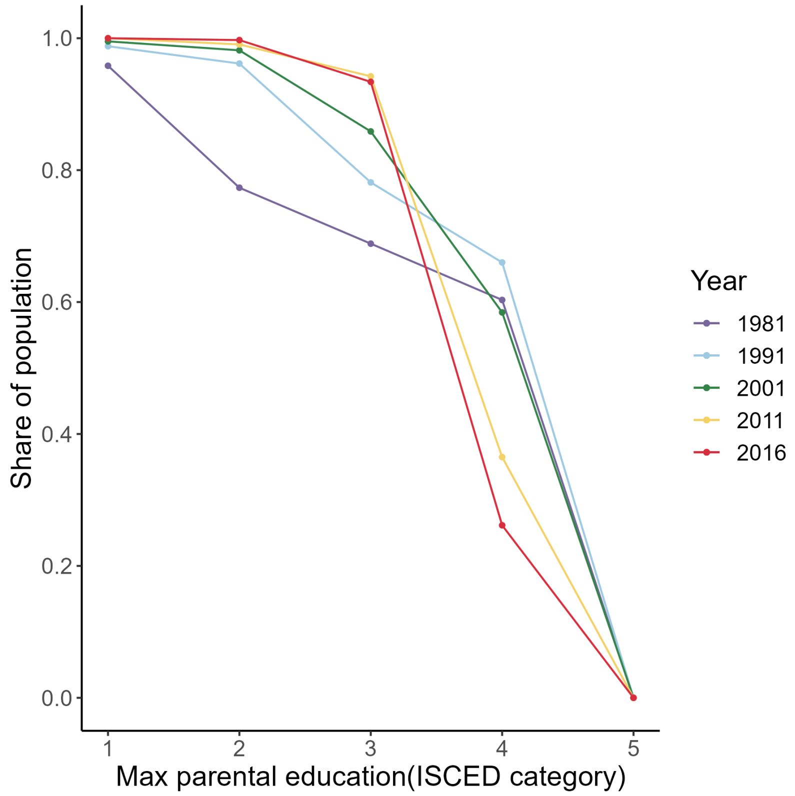


Figure I2: Absolute educational mobility by level of parental education

Figure I3 shows the trend in average relative educational mobility, measured by $1-\beta$, where β is the correlation coefficient between parents' and children's years of education. Since direct measures of years of education are unavailable, we used the extrapolation method from Van der Weide et al. (2024), which maps years of education to ISCED categories as follows: ISCED 1: 6 years; ISCED 2: 9 years; ISCED 3: 12 years; ISCED 4: 13 years; ISCED 5: 15 years; ISCED 6: 16 years; ISCED 7: 18 years; ISCED 8: 21 years. Relative mobility increased from 1981 to 1991, declined back to the 1981 level by 2011, and has stabilized since then.

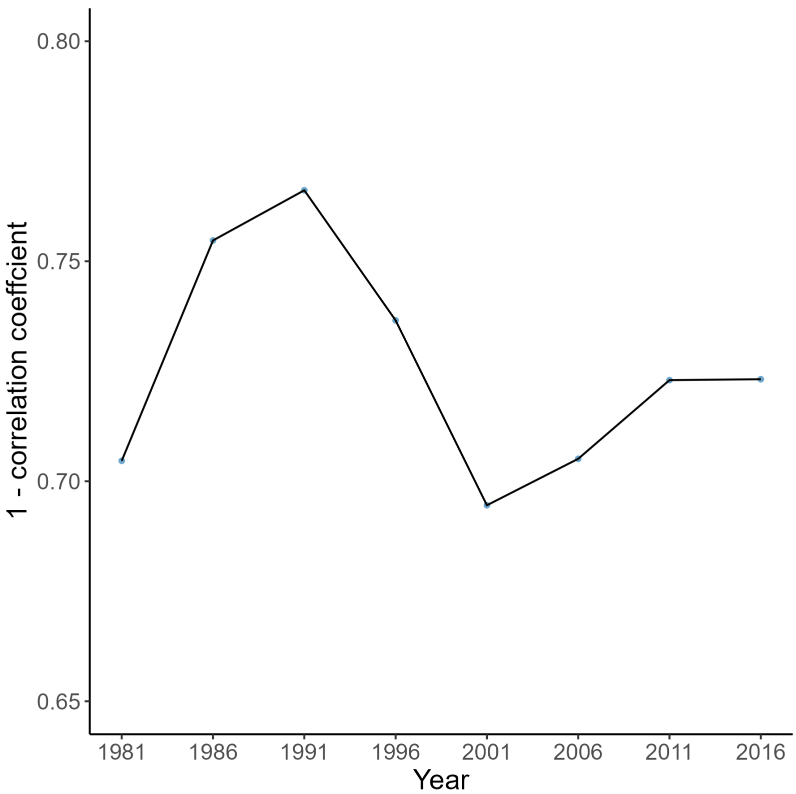


Figure I3: Relative educational mobility from 1981 to 2016

J Tables for the Value of Absolute Mobility

Table J1: Absolute Mobility from 1976 to 2016 - Gumbel copula

Year(income cohort)	1976	1981	1986	1991	1996
Percentage(20 years gap)	85.58	81.70	72.43	59.74	54.86
Percentage(25 years gap)	86.76	80.45	70.00	62.18	
Percentage(30 years gap)	85.41	77.90	72.09		
Percentage(35 years gap)	84.28	79.11			
Percentage(40 years gap)	84.50				

Table J2: Absolute Mobility from 1976 to 2016 - US Copula

Year(birth cohort)	1976	1981	1986	1991	1996
Percentage(20 years gap)	85.99	82.04	71.76	58.78	53.59
Percentage(25 years gap)	87.28	80.70	69.80	61.44	
Percentage(30 years gap)	86.03	78.47	71.42		
Percentage(35 years gap)	84.74	79.40			
Percentage(40 years gap)	84.71				

Table J3: Absolute Mobility from 1976 to 2016 with Gumbel Copula - Income Measured at Different Age, 20 years gap

Year(birth cohort)	1946	1951	1956	1961	1966	1971	1976	1981	1986
Age 30					83.00	82.14	71.44	58.69	49.91
Age 35				85.87	79.96	71.49	60.21	51.89	
Age 40			85.52	79.81	69.12	63.52	55.83		
Age 45		84.03	81.81	71.07	62.98	58.34			
Age 50	84.73	81.49	71.77	64.47	59.86				

Table J4: Absolute Mobility from 1976 to 2016 with Gumbel Copula - Income Measured at Different Age, 30 Years Gap

Year(birth cohort)	1956	1961	1966	1971	1976	1981	1986
Age 30					82.97	75.66	69.27
Age 35				84.27	75.99	66.41	
Age 40			81.58	81.00	70.87		
Age 45		87.05	81.38	71.99			
Age 50	85.17	80.83	74.35				

Table J5: Absolute Mobility with Fractions 100 Percent, 120 Percent, 150 Percent

Year(income cohort)	1976	1981	1986	1991	1996
100 percent	85.58	81.70	72.43	59.74	54.86
120 percent	79.98	76.21	64.75	52.68	46.73
150 percent	71.95	67.61	55.33	42.47	38.16

K Tables for Wage, Capital, and Inequality

Table K1: Proportion of Wage and Capital Income Owner

	1976	1981	1986	1991	1996	2001	2006	2011	2016
Wage	80.6%	83.5%	83.7%	84.3%	84.8%	83.8%	83.1%	83.8%	85.3%
Capital	23.8%	19.7%	21.1%	19.5%	19.4%	21.6%	24.1%	21.7%	22.7%

Table K2: Inequality Level of Total Income

	Top 1%	Top 10%	Middle 40%	Bottom 50%	Total	GINI
1976	14.3%	40.1%	41.1%	18.9%	100.0%	0.45
1981	15.1%	39.8%	39.7%	20.5%	100.0%	0.46
1986	12.6%	38.0%	41.3%	20.7%	100.0%	0.45
1991	14.3%	40.4%	39.1%	20.5%	100.0%	0.47
1996	12.2%	39.1%	43.0%	17.9%	100.0%	0.47
2001	12.7%	39.4%	42.6%	18.0%	100.0%	0.48
2006	13.5%	40.5%	41.3%	18.2%	100.0%	0.5
2011	12.9%	42.1%	41.6%	16.3%	100.0%	0.52
2016	11.1%	39.3%	44.2%	16.5%	100.0%	0.5
	Top 1%	Top 10%	Middle 40%	Bottom 50%	Total	
Growth rate 1976-1996	4.2%	5.1%	4.9%	4.2%	4.6%	
Growth rate 1996-2016	0.3%	0.6%	1.0%	0.2%	0.7%	
Growth rate 1976-2016	2.2%	2.8%	2.9%	2.2%	2.6%	

Table K3: Inequality Level of Wage Income

	Top 1%	Top 10%	Middle 40%	Bottom 50%	Total	GINI
1976	10.2%	37.4%	48.7%	13.9%	100.0%	0.51
1981	11.2%	35.7%	48.2%	16.2%	100.0%	0.49
1986	9.8%	36.7%	46.5%	16.8%	100.0%	0.49
1991	11.3%	39.2%	44.4%	16.4%	100.0%	0.51
1996	12.0%	40.3%	44.7%	15.0%	100.0%	0.53
2001	10.5%	40.0%	46.1%	14.0%	100.0%	0.54
2006	11.6%	40.3%	46.4%	13.3%	100.0%	0.55
2011	12.5%	41.2%	47.1%	11.7%	100.0%	0.56
2016	9.7%	39.3%	47.2%	13.5%	100.0%	0.54
	Top 1%	Top 10%	Middle 40%	Bottom 50%	Total	
Growth rate 1976-1996	5.8%	5.5%	4.8%	5.2%	5.0%	
Growth rate 1996-2016	-0.1%	0.9%	1.2%	0.3%	0.9%	
Growth rate 1976-2016	2.8%	3.2%	3.0%	2.7%	2.9%	

Table K4: Inequality Level of Capital Income

	Top 1%	Top 10%	Middle 40%	Bottom 50%	Total	GINI
1976	40.3%	82.4%	17.6%	0.0%	100.0%	0.91
1981	42.4%	88.2%	11.8%	0.0%	100.0%	0.93
1986	37.7%	88.6%	11.4%	0.0%	100.0%	0.91
1991	41.3%	90.0%	10.0%	0.0%	100.0%	0.93
1996	35.3%	88.9%	11.1%	0.0%	100.0%	0.92
2001	39.4%	87.7%	12.3%	0.0%	100.0%	0.92
2006	40.7%	87.2%	12.8%	0.0%	100.0%	0.92
2011	41.2%	89.4%	10.6%	0.0%	100.0%	0.93
2016	38.9%	89.0%	11.0%	0.0%	100.0%	0.93
	Top 1%	Top 10%	Middle 40%	Bottom 50%	Total	
Growth rate 1976-1996	3.1%	3.6%	1.1%		3.4%	
Growth rate 1996-2016	0.4%	0.1%	-0.2%		-0.1%	
Growth rate 1976-2016	1.7%	1.8%	0.5%		1.7%	

L Tables for Mincer Equation

Table L1: Summary Statistics of Factors in Mincer Equation

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

Table L2: Regression Result for Mincer Equation

Variables	1976	1981	1986	1991	1996	2001	2006	2011	2016
(Intercept)	7.46 ***	7.7 ***	7.7 ***	7.98 ***	7.95 ***	7.89 ***	7.84 ***	7.65 ***	7.75 ***
sex	0.43 ***	0.46 ***	0.38 ***	0.35 ***	0.3 ***	0.31 ***	0.25 ***	0.23 ***	0.23 ***
exp	0.02 ***	0.01 ***	0.02 ***	0.02 ***	0.03 ***	0.03 ***	0.03 ***	0.03 ***	0.03 ***
exp^2	-0.0004 ***	-0.0002 ***	-0.0004 ***	-0.0005 ***	-0.0005 ***	-0.0005 ***	-0.0005 ***	-0.0004 ***	-0.0004 ***
edu	0.04 ***	0.04 ***	0.04 ***	0.04 ***	0.05 ***	0.06 ***	0.06 ***	0.07 ***	0.07 ***
Industry (base: Manufacturing)									
Construction	0.19 ***	0.26 ***	0.06 ***	0.1 ***	0.09 ***	0.13 ***	0.04 ***	0.11 ***	0.15 ***
Wholesale and Retail	0.07 ***	0.1 ***	0.1 ***	0.05 ***	0.02 ***	-0.01	0	0	0.02 *
Restaurant and Hotel	0.14 ***	0.18 ***	0.16 ***	0.15 ***	0.06 ***	0.04 ***	0.01	0.05 ***	0.11 ***
TSC	0.22 ***	0.24 ***	0.19 ***	0.12 ***	0.12 ***	0.09 ***	0.08 ***	0.07 ***	0.06 ***
Financial	0.26 ***	0.28 ***	0.22 ***	0.17 ***	0.15 ***	0.09 ***	0.05 ***	0.09 ***	0.14 ***
Service	0.29 ***	0.28 ***	0.25 ***	0.18 ***	0.13 ***	0.14 ***	0.05 ***	0.04 ***	0.06 ***
Others	0.14 ***	0.15 ***	0.08 *	0.21 ***	0.19 ***	0.2 ***	0.14 ***	0.11 ***	0.11 ***
Occupation (base: Worker)									
Professions	0.61 ***	0.62 ***	0.63 ***	0.64 ***	0.67 ***	0.7 ***	0.72 ***	0.67 ***	0.63 ***
Adm & Managerial	0.92 ***	0.86 ***	0.89 ***	0.96 ***	0.97 ***	1.09 ***	1.17 ***	1.19 ***	1.09 ***
Clericals	0.18 ***	0.23 ***	0.23 ***	0.21 ***	0.22 ***	0.24 ***	0.27 ***	0.18 ***	0.18 ***
Place of Birth (base: HK)									
Mainland China	-0.06 ***	-0.08 ***	-0.12 ***	-0.13 ***	-0.14 ***	-0.14 ***	-0.13 ***	-0.1 ***	-0.08 ***
Other	0.12 ***	0.06 **	-0.06 **	-0.17 ***	-0.32 ***	-0.49 ***	-0.47 ***	-0.52 ***	-0.63 ***
Marital Status (base: Single)									
Married	0.1 ***	0.1 ***	0.11 ***	0.13 ***	0.11 ***	0.12 ***	0.13 ***	0.12 ***	0.1 ***
N	89537	12403	15756	87378	108960	118879	127215	139839	141629
R2	0.48	0.46	0.48	0.49	0.49	0.54	0.53	0.60	0.59
F statistic	4810.5	618.8	843.8	4934.6	6043.8	8372.2	8394.2	12227.1	11835.2

Dependent variable: Wage income. *** $p < 0.001$; ** $p < 0.01$; * $p < 0.05$