Changes in Earnings Inequality in Hong Kong: 1981-2021

by

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Measures of Inequality

A common measure of earnings inequality is the Gini coefficient. In a graph which plots the cumulative percent of the population versus the cumulative percent of their earnings in a Lorenz curve (Lorenz, 1905), it is the ratio of the area between the Lorenz curve and the diagonal, taking the value of zero if there is perfect equality and the value of unity if there is perfect inequality with one person holding the entire earnings of the population. The main advantage of the Gini coefficient is that it is intuitive. The inequality of an entire earnings distribution is represented by one summary statistic which is simple but therein lies its shortcoming. It tells us little about the inequality between different segments of the population. For instance, when the Gini increases, it just indicates that the overall inequality has increased but it is not informative as to whether the increased inequality is more due to a widening differential between the high earnings and the middle earnings or between the middle and the low end of the distribution.

An alternative and more informative measure is the log earnings differential between different percentiles of the distribution. A commonly used measure of inequality is the log earnings differential between the 90th percentile and the 10th percentile of the distribution. An over time increase in this differential represents the percentage increase in the earnings differential between the 90th and 10th percentile. We can decompose the 90th-10th percentile differential into the 90th-50th percentile differential and the 50th -10th percentile differential. This enables us to make inference on the contribution of the upper half of the earnings distribution (90th-50th) as compared to the lower half of the distribution (50th-10th) to the overall inequality (90th-10th). In fact, inequality between any two points in the earnings distribution

[*] The opinions expressed herein are those of the authors and do not necessarily reflect the views of the Institute.

can be easily derived. In this paper we will mainly rely on the log earnings differential as the measure of earnings inequality with occasional reference to the Gini coefficient.

Trends in Earnings Inequality in Hong Kong

Figure 1 shows the trend of earnings inequality in Hong Kong from 1981 to 2021 for males age 20-60 as measured by the 90-10 log earnings differential as well as the Gini coefficient of their earnings using census/by-census datasets. For comparison, we also show the Gini coefficient of household earnings reported by the Department of Census and Statistics. Our analysis is on earnings inequality instead of wage inequality because there is no information on the hours of work in the Hong Kong censuses.[1]

Several features are salient. First, the trends as represented by the two measures of inequality for males are similar in shape with the 90-10 differential trend exhibiting sharper rises and falls than the Gini coefficient trend. Second, there has been a continuous increase in inequality for three decades from 1981 to 2011. Third, the sharpest increase in inequality appears in the two 5-year periods, 1981-1986 and 1991-1996. Fourth, there has been a reduction in inequality in 2011-2016 according to the 90-10 differential, and in 2011-2021 according to the Gini coefficient. Besides these 5-years periods, there has been a continuous but more moderate increase in inequality from 1981 to 2021.

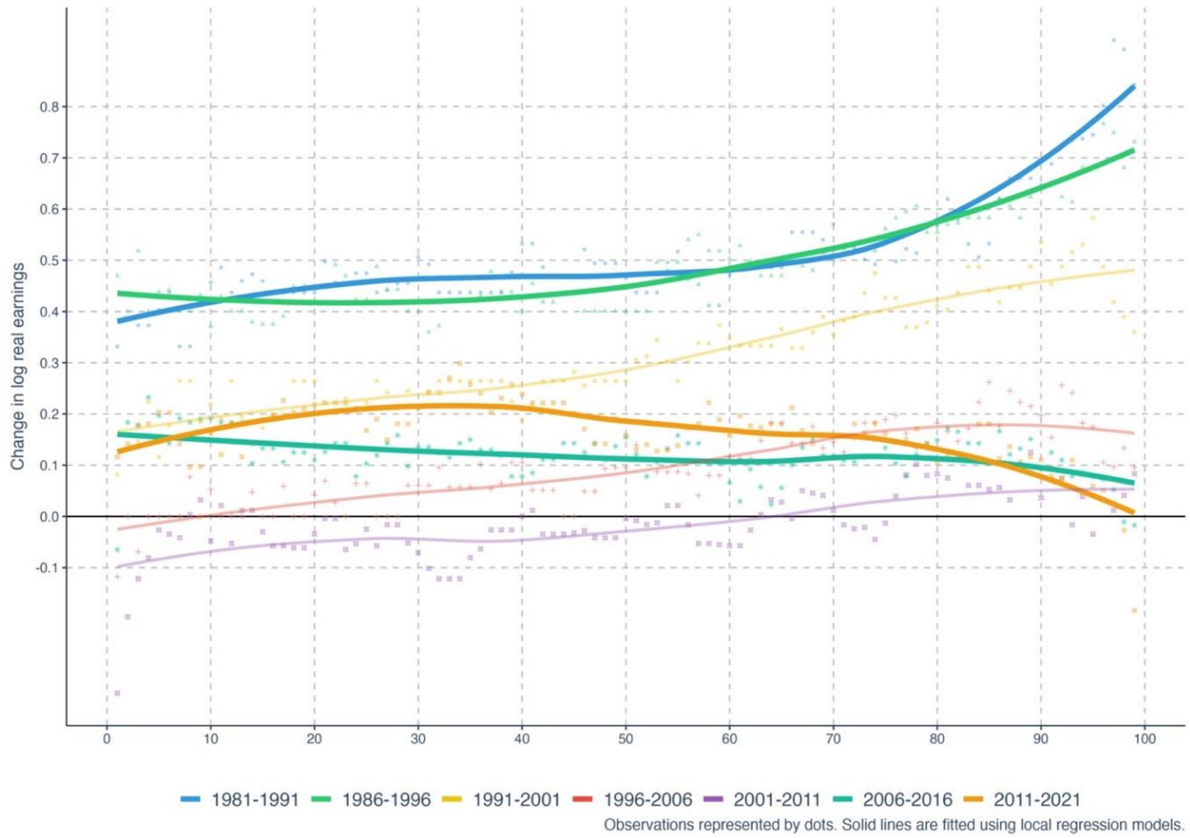
[1] By focusing our analysis on males age 20-60 we eliminate earnings differences due to different hours of work because the percentage of male workers in this prime age bracket who work part time is small in Hong Kong.

Figure 1: Gini Coefficient vs 90-10 Log Earnings Differential (Male Only)

Note: Calculated gini coefficients and 90-10 log differentials are based on male employees aged 20-60 whereas official data covers economically active households.

Figure 2 shows the over time change in log earnings at every percentile of the distribution in 10-year overlapping intercensal periods. The fluctuations in the change in log real earnings at different percentiles are smoothed out by a regression model to give the percentile log earnings curve. A rising curve indicates that the increase in log real earnings in the higher percentiles is greater than in the lower percentiles, resulting in a widening of the 90-10 log earnings differential and hence greater earnings inequality. Figure 2 shows that the percentile log earnings curve has the sharpest slope in 1981-1991 and 1986-1996, consistent with the observation in Figure 1 that earnings inequality increases the most in 1981-1986 and 1991-1996. In 2011-2021 the percentile log earnings curve becomes downward-sloping above the 40th percentile, indicating that the log earnings in the upper end of the earnings distribution actually increase slower than in the middle and the lower end of the distribution, resulting in a reduction in earnings inequality during this period.

Figure 2: Log Real Main Earnings – Changes by Percentile, 1981-2021 (Male Only)



There are a few other notable features of the percentile log earnings curves. First, the 2001-2011 curve up to the 60th percentile is in the negative zone, indicating a decline in the low and middle real earnings in that 10-year period. This is a reflection of the negative impact on the economy of the burst of the dotcom bubble in 2001, the ravage of the SARS epidemic on the housing market and the economy in 2003, and the global financial crisis in 2008-2009. Real earnings of the lower and middle classes decline in the decade while those of the high earnings class increase moderately. Earnings inequality nevertheless increases. Second, the percentile curves are remarkably flat in the lower half of the distribution, say from the 10th to the 50th percentile. This suggests that the widening of the earnings differential, in particular in 1981-1991, 1986-1996 and 1991-2001, happens mostly in the upper half of distribution, between those with high earnings and those with middle earnings. In other words, the worsening of inequality over time is largely due to the much more rapid growth of high earnings than the middle earnings.

We summarize the salient features of the changes in earnings inequality in Hong Kong from 1981 to 2021 measured by changes in the log earnings differential as follows:

1. The sharpest increases in earnings inequality are in 1981-1986 and 1991-1996.
2. Earnings inequality actually declines in 2011-2021.
3. Except 2001-2011, the increase in inequality between the upper end and the middle range of the earnings distribution is much larger than the increase in inequality between the middle range and the lower end of the distribution.
4. In 2001-2011, low and middle real earnings actually decline while upper earnings increase moderately. The increase in inequality between the middle and the low earnings is actually larger than the increase between the high and middle earnings.

Explaining Changes in Earnings inequality Based on Skills and Their Prices

The starting point of the theoretical explanation is a simple earnings model in which earnings is loglinear in skills and their prices as in Lam and Liu (2011) where skills are dichotomized into observed skills and unobserved (or unmeasured) skills.

$$Log\ y_i = P_o Q_{oi} + P_u Q_{ui} \qquad (1)$$

where y_i, Q_{oi} and Q_{ui} are the earnings, quantity of observed skills and unobserved skills respectively of the i^{th} individual. P_o and P_u are the prices of observed and unobserved skills. The log earnings differential between the 90^{th} and 10^{th} percentile is given by

$$Log\ y^{90} - Log\ y^{10} = P_o(Q^{90} - Q^{10}) + P_u(Q^{90} - Q^{10}) \qquad (2)$$

It follows that the 90-10 log earnings differential will widen over time if, (1) the quantity of observed and/or unobserved skills possessed by individuals at the 90^{th} percentile increases relative to individuals at the 10^{th} percentile, and (2) the price of observed and/or unobserved skills (or skill premium) increases.

To account for the relative contribution of the change in the distribution of skills and the change of skill price to the change in earnings inequality over time, we make use of the methodology of Juhn, Murphy and Pierce (1993). For empirical estimation we can re-write Equation (1) as

$$Log\ y_{it} = X_{it}\beta_t + u_{it} \qquad (3)$$

where X_{it} is a vector of the i^{th} individual's observable characteristics including schooling, experience, experience squared and the interaction of schooling and the experience terms in time t. X_{it} is therefore the observable skills and β the prices which determine earnings in a Mincerian earnings function. u_{it} is the residual or the component of earnings due to the unobservable skills and their prices. We can quantify the change in log earnings differential of two individuals over two time periods by first estimating β and the distribution of the regression residuals in each time period. We then use the results to reconstruct the earnings distribution with the observable prices and residual distribution fixed at the average of the two periods and attribute the change in log earnings differential over the two periods to changes in the observable quantities. We can then allow both the observable prices and quantities to vary and reconstruct an earnings distribution for each time period, and attribute any additional changes in the log earnings differential to changes in observable prices. Finally, we allow observable prices and quantities and the distribution of residuals to all change over time to recover the actual earnings distribution and attribute any additional change in the differential beyond those accounted for earlier to changes in the distribution of unobservables.

Using this methodology we can decompose the change in log earnings differential between any two percentiles into three components caused by the observed quantity change, the observed price change and the unobserved change. We analyze intercensal changes in inequality over 10-year periods, instead of 5-year periods, to give larger changes over a longer time span. To generate more data points, we look at overlapping 10-year periods. Table 1 shows the decomposition for the 90 -10 percentiles, the 90 - 50 percentiles and the 50 -10 percentiles of males age 20-60 in the Hong Kong censuses and by-censuses from 1981 to 2021. The results are plotted in Figure 3.

Table 1: Decomposing Change in Log Earnings Differential

Statistics	Total Change	Observed Quantity Change	Observed Price Change	Unobserved Change
1981-1991				
diff_9010	0.1891	0.0775	0.0468	0.0647
diff_9050	0.1807	0.0961	0.0531	0.0315
diff_5010	0.0084	-0.0186	-0.0063	0.0332
1986-1996				
diff_9010	0.2744	0.1837	0.0019	0.0888
diff_9050	0.2446	0.1723	-0.0003	0.0726
diff_5010	0.0299	0.0114	0.0023	0.0162
1991-2001				
diff_9010	0.3158	0.2406	-0.0020	0.0773
diff_9050	0.2707	0.2005	0.0194	0.0508
diff_5010	0.0451	0.0401	-0.0214	0.0265
1996-2006				
diff_9010	0.1442	0.1622	-0.0971	0.0792
diff_9050	0.1020	0.1093	-0.0521	0.0448
diff_5010	0.0422	0.0529	-0.0450	0.0344
2001-2011				
diff_9010	0.0841	0.1054	-0.0381	0.0168
diff_9050	0.0404	0.1000	-0.0687	0.0092
diff_5010	0.0437	0.0054	0.0306	0.0077
2006-2016				
diff_9010	-0.0991	0.0800	-0.0917	-0.0875
diff_9050	-0.0610	0.0614	-0.0609	-0.0615
diff_5010	-0.0381	0.0186	-0.0308	-0.0260
2011-2021				
diff_9010	-0.0530	0.1400	-0.2014	0.0084
diff_9050	-0.0476	0.0928	-0.1388	-0.0017
diff_5010	-0.0054	0.0472	-0.0626	0.0101

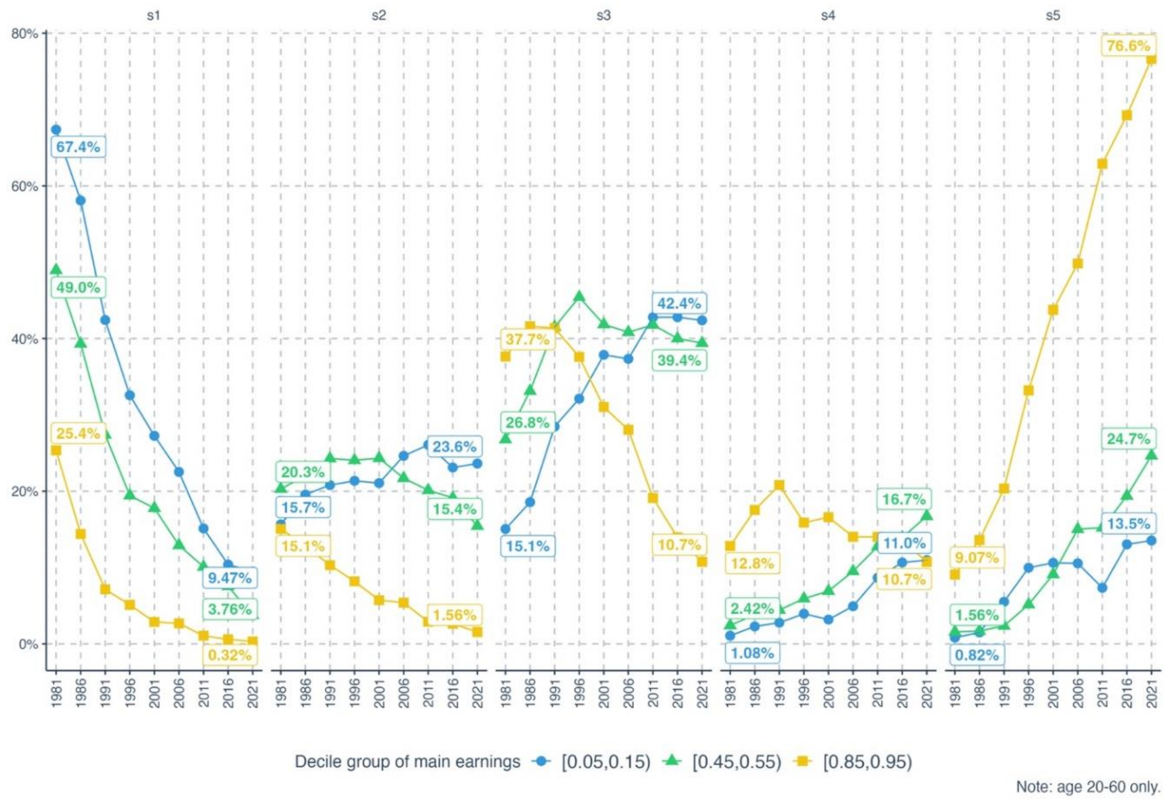
Figure 3: Decomposing Change in Log Earnings Differential

It is clear from Figure 3 that over the entire period 1981-2021, the intercensal change in the 90-10 differential and the 90-50 differential of the 90th and the 50th percentiles track each other rather closely, suggesting that much of the change in earnings inequality (as measured by the 90-10 differential) over time can be accounted for by what happens to the earnings at the upper end and the middle of the earnings distribution. The same observation applies, albeit to a lesser extent, to the contribution of the observed quantity change, the observed price change and the unobserved change to the total change in inequality.

It should be noted that the main contribution to the increase in log earnings differential over time is the larger increase in the observed quantity of skill of the 90th percentile than the 10th percentile. The underlying factor for the increased dispersion of observed skills between the upper end and the lower end of the earnings distribution is paradoxically the expansion of educational opportunity. While the widening access to education is meant to provide a channel of upward mobility which over time should reduce inequality, it also enables a greater concentration of skills as those at the upper end acquire much more schooling, especially at the university level, than those at the lower end. This is evident following the rapid expansion of the university system which started in 1991.[2] Specifically, from 1991 to 1996 the 90–10 differential increases by 24.17% (subject to log approximation), of which 17.19% is due to the larger increase in the observed skills of the 90th percentile over the 10th percentile as a result of the greater dispersion of skills.

Figure 4 illustrates the rapid increase in skill intensity as represented by the percent of university graduates (S5) in the 90th percentile, bracketed by the decile between the 85th and the 95th percentiles. This percent increases rapidly from 9.07% in 1981 to 76.6% in 2021, a total of 67.5 percentage points, whereas for the 10th percentile (bracketed by the decile from the 5th to the 15th percentile), the corresponding increase is only 12.7 percentage points. To the extent that the observed skills are mainly derived from schooling (and experience), increasing disparity in schooling attainment between the upper and the lower end of the distribution is a major driving force for the increase in earnings inequality from 1981 to 2021.

Figure 4: Skill Intensity at the Lowest, Median and Top Deciles of Main Earnings, 1981-2021



[2] For a brief description of this expansion, see Lam and Liu (2011).

From 2011 to 2016, earnings inequality decreases, the only period of decline from 1981 to 2016. This is possibly due to the introduction of the statutory minimum wage of $28 an hour in May 2011. The minimum wage does not only put a floor on the hourly wage but it also induces a ripple effect which increases the wage of workers just above the minimum. This policy-induced wage increase of those with low level of schooling shows up as a reduction in the rate of return to university education and consequently a sizeable negative observed price change in 2006-2016 and 2011-2021. In this connection, it is pertinent to note that since 1991 the observed price change has been negative. This is largely because of the rapid expansion of the educational system at the post-secondary and tertiary levels after 1991. The increase in the supply of the highly educated workers lowers the rate of return to university education, as is evident in the decline in the regression coefficient of the university-educated (S5) over this period shown in the Appendix.

The contribution of the change in the quantity and prices of the unobserved skills to inequality is positive from 1981 to 2006. The factors behind the positive change is more intricate as they involve the unobserved/unmeasured skills. By and large, all skills that cannot be attributed to schooling and experience and/or are not measured are relegated to this category. Liu and Lam (2022) enumerated some of these unobserved/unmeasured skills of Mainland Chinese migrants in Hong Kong which include, inter alia, Putonghua fluency and socio-cultural networking skills that facilitate their interaction with Mainland clients. The demand for these Mainland-relevant skills increases as Mainland Chinese trade, investment and tourism become dominant in Hong Kong and these skills are given a higher premium. Other examples of unobserved/unmeasured skills earning a rising premium are specific skills in the finance industries catering to the international financial markets which are much in demand as Hong Kong becomes an international financial centre and a gateway to Mainland China.

Skill-biased Technological Change, Trade Liberalization, Globalization and Earnings Inequality

There has been a wide literature on the effect of skill-biased technological change, trade liberalization, globalization and outsourcing on earnings inequality. Much of the work is on the differential effect on the wages of the skilled versus the unskilled workers, or the skill premium. Less work is on the impact on the overall earnings distribution. Bound and Johnson (1992) and Acemoglu (2002) argue that the widening wage differential between the skilled and the unskilled is mainly due to skill-biased technological changes. Trade economists, however, tend to emphasize trade liberalization as the cause for increased inequality on the base of the prediction of the Heckscher-Ohlin model and the Stolper-Samuelson theorem. Specifically, international trade increases the skill premium in countries that have a comparative advantage in skill-intensive sectors. Empirically, trade liberalization increases the skill premium in almost all countries (Burstein and Vogel, 2017). Even in developing countries with abundant unskilled labor which globalization is expected to help, unskilled workers are not better off than the skilled workers (Goldberg and Pavcnik, 2007). Trade openness enables outsourcing and offshoring. Increasingly international trade does not only involve trade in final products but also trade in intermediate products and components. Hsieh and Woo (2005) show that the large offshoring of manufacturing activities from Hong Kong to Mainland China causes a decline in the relative demand for less skilled workers and a rise in the skill premium. At the higher end of the skill spectrum, financial globalization, financial openness, liberalized international capital flow and FDI increases the relative demand for skilled workers who have specific skills in the financial services. The higher skill premium in the financial industries leads to a significant increase in inequality (Furceri, Loungani and Ostry, 2019), Financial globalization benefits mainly the top 20% of the population (Jaumotte, Lall and Papageorgiou, 2013).

Against this background in the literature, we can interpret and explain the salient characteristics of the changes in earnings inequality in Hong Kong in 1981-2021. The changes are the outcome of a mix of widening and narrowing effects on earnings differential of different factors. First, skill-biased technological change is not likely to be a major factor driving inequality since Hong Kong is more a follower than an originator of technology. Following the opening up of China in 1979, Hong Kong industrialists relocated their manufacturing operation to Mainland China. The process is by and large complete in the 1990's. With the decline of the local manufacturing industries in Hong Kong, the service industries become ascendant in the economy. The specific technology that most likely enhances efficiency in service industries is information technology adopted over the years. Its impact on the skill premium, at least the premium of observed skills, is not likely to be significant. This is evident from the negative observed price change that prevails since 1991 (Table 1), underscored by a declining university premium over this period (Appendix). It should be pointed out that the declining university premium over this period is not only caused by the demand side factor of a weak technology-biased skill demand but more so by the supply side factor of a large increase in the supply of university graduates following the drastic expansion of the university system after 1991. This increase in supply is also the underlying factor for the greater dispersion of skills between the upper and the lower end of the earnings distribution over this period, resulting in a sizeable observed quantity change mentioned earlier. To summarize, skill premium due to skill-biased technological change may not be an adequate explanation of the increase in inequality.

If skill-biased technological change cannot adequately explain changes in inequality, we should look to trade liberalization and globalization as possible causes. Hong Kong has always been a free trade port which does not levy custom duty on imports from other countries irrespective of whether they adopt a free trade policy. Therefore, the effect of trade liberalization of Hong Kong on inequality is irrelevant as far as Hong Kong is concerned. What may have an impact is trade liberalization of Hong Kong's trading partners. A case in point is the openness to trade and investment of Mainland China after 1979 which facilitates the massive re-location of low-skill manufacturing production from Hong Kong to Mainland China. These offshoring activities are most intense in the 1980's and by and large complete in the 1990's. During this period Hong Kong evolves from being a manufacturing economy to become a service and financial center. In the process there has been a shift in the relative demand for skilled workers over unskilled workers. Unskilled wages are depressed until the service sector expands to eliminate the slack in the unskilled labor market. This may account for the relatively large contribution of the change in observed skill price to the change in earnings differential in 1981-1991 and a smaller contribution in 1986-1996.

As the Hong Kong economy integrates with the Mainland Chinese economy, trade and investment with the Mainland become dominant in Hong Kong. The skill premium of unobserved/unmeasured skills that are productive in servicing the Mainland economy increases, as we have reasoned before. The contribution of the unobserved skill price and quantity is positive in 1981-2011. However, it turns negative in 2006-2016. While the demand for

Mainland-relevant skills has increased, their supply has also increased significantly after 2008 due to the large increase in the intake of Mainland Chinese migrants under the Admission Scheme for Mainland Talents and Professionals and the Immigration Arrangements for Non-local Graduates.[3] Unobserved skill prices may have fallen during this period. This may explain the negative contribution of the change in unobserved prices and quantities in 2006-2016.

Concluding Remarks

Earnings inequality is determined by a host of factors internal and external to the economy. In the case of Hong Kong an important internal factor is the large expansion of the education system at the post-secondary and tertiary levels. The increase in access to higher education is intended to be socially equalizing. However, it induces a greater dispersion of skills between the upper and lower end of the earnings distribution (quantity effect), thus increasing inequality. At the same time educational expansion increases the supply of high-level skills which, ceteris paribus, reduces the skill premium (price effect), thereby mitigating the inequality effect of the greater dispersion of skills.

The role of unobservable/unmeasured skills and their prices on inequality merits more exploration as they account for a sizeable change in inequality. There need to be a better understanding on what these skills are, how they can be measured, how are they generated and how specific are they to different jobs and industries. For instance, we know that the financial service industries have expanded rapidly in Hong Kong and employees in these industries garner higher pay than employees with the same level of education in other industries. Expansion of the financial service industries is expected to increase overall earnings inequality. An in-depth industrial study of the specific skills involved is needed to quantify their skill premium and evaluate their contribution to increasing inequality.

[3] For details of Mainland Chinese migration to Hong Kong under the various schemes, read Chapter 3 of Liu and Lam (2022).

Appendix

Table A1: Regression Output, 1981-1991

	Dependent variable:		
	ln_real_mearn		
	1981	1986	1991
	(1)	(2)	(3)
s2	-0.014 (0.011)	0.034** (0.015)	0.068** (0.028)
s3	0.026*** (0.009)	0.057*** (0.013)	0.165*** (0.025)
s4	0.391*** (0.014)	0.127*** (0.016)	0.263*** (0.029)
s5	1.185*** (0.015)	0.918*** (0.017)	0.688*** (0.028)
exp	0.038*** (0.001)	0.043*** (0.001)	0.042*** (0.002)
exp2	-0.001*** (0.00001)	-0.001*** (0.00002)	-0.001*** (0.00003)
s2:exp	0.009*** (0.001)	0.006*** (0.001)	0.003 (0.002)
s3:exp	0.030*** (0.001)	0.037*** (0.001)	0.024*** (0.002)
s4:exp	0.045*** (0.002)	0.099*** (0.002)	0.077*** (0.003)
s5:exp	-0.028*** (0.002)	0.058*** (0.002)	0.098*** (0.003)
s2:exp2	-0.0001*** (0.00003)	-0.0001* (0.00003)	-0.00002 (0.00005)
s3:exp2	-0.001*** (0.00002)	-0.001*** (0.00003)	-0.0005*** (0.00004)
s4:exp2	-0.001*** (0.0001)	-0.002*** (0.0001)	-0.002*** (0.0001)
s5:exp2	0.0004*** (0.0001)	-0.002*** (0.0001)	-0.003*** (0.0001)
Constant	7.004*** (0.007)	7.024*** (0.011)	7.307*** (0.023)
Observations	202,005	177,791	88,727
R^2	0.234	0.324	0.358
Adjusted R^2	0.234	0.324	0.358
Residual Std. Error	0.465 (df = 201990)	0.503 (df = 177776)	0.505 (df = 88712)
F Statistic	4,401.705*** (df = 14; 201990)	6,096.022*** (df = 14; 177776)	3,532.981*** (df = 14; 88712)

Note: *p<0.1; **p<0.05; ***p<0.01

S1-5 are schooling dummies. S1: Primary; S2: Lower Secondary; S3: Upper Secondary; S4: Post-secondary; S5: University and above. S1 is omitted from the regressions.

Table A2: Regression Output, 1996-2006

	Dependent variable:		
	ln_real_mearn		
	1996	2001	2006
	(1)	(2)	(3)
s2	0.101*** (0.037)	0.068 (0.048)	0.109 (0.068)
s3	0.219*** (0.035)	0.225*** (0.045)	0.218*** (0.065)
s4	0.344*** (0.037)	0.323*** (0.046)	0.302*** (0.065)
s5	0.711*** (0.035)	0.699*** (0.045)	0.697*** (0.065)
exp	0.044*** (0.002)	0.050*** (0.003)	0.050*** (0.004)
exp2	-0.001*** (0.00004)	-0.001*** (0.0001)	-0.001*** (0.0001)
s2:exp	0.0001 (0.003)	0.002 (0.003)	0.001 (0.005)
s3:exp	0.020*** (0.003)	0.018*** (0.003)	0.019*** (0.004)
s4:exp	0.066*** (0.003)	0.058*** (0.004)	0.050*** (0.005)
s5:exp	0.085*** (0.003)	0.082*** (0.003)	0.069*** (0.004)
s2:exp2	0.00003 (0.0001)	-0.00003 (0.0001)	-0.00003 (0.0001)
s3:exp2	-0.0004*** (0.00005)	-0.0003*** (0.0001)	-0.0004*** (0.0001)
s4:exp2	-0.002*** (0.0001)	-0.001*** (0.0001)	-0.001*** (0.0001)
s5:exp2	-0.002*** (0.0001)	-0.002*** (0.0001)	-0.002*** (0.0001)
Constant	7.343*** (0.033)	7.333*** (0.044)	7.186*** (0.064)
Observations	103,374	100,315	102,734
R^2	0.367	0.414	0.357
Adjusted R^2	0.367	0.414	0.357
Residual Std. Error	0.546 (df = 103359)	0.548 (df = 100300)	0.599 (df = 102719)
F Statistic	4,287.696*** (df = 14; 103359)	5,062.783*** (df = 14; 100300)	4,069.201*** (df = 14; 102719)

Note: *p<0.1; **p<0.05; ***p<0.01

S1-5 are schooling dummies. S1: Primary; S2: Lower Secondary; S3: Upper Secondary; S4: Post-secondary; S5: University and above. S1 is omitted from the regressions.

Table A3: Regression Output, 2011-2021

	Dependent variable:		
	ln_real_mearn		
	2011	2016	2021
	(1)	(2)	(3)
s2	0.502^{***} (0.104)	0.431^{***} (0.134)	0.176 (0.154)
s3	0.516^{***} (0.100)	0.570^{***} (0.131)	0.246^{*} (0.148)
s4	0.511^{***} (0.100)	0.538^{***} (0.130)	0.274^{*} (0.148)
s5	1.052^{***} (0.099)	0.833^{***} (0.130)	0.583^{***} (0.147)
exp	0.062^{***} (0.006)	0.049^{***} (0.008)	0.034^{***} (0.010)
exp2	-0.001^{***} (0.0001)	-0.001^{***} (0.0001)	-0.0005^{***} (0.0002)
s2:exp	-0.022^{***} (0.007)	-0.014^{*} (0.009)	0.002 (0.010)
s3:exp	-0.001 (0.006)	-0.005 (0.008)	0.010 (0.010)
s4:exp	0.037^{***} (0.007)	0.025^{***} (0.008)	0.031^{***} (0.010)
s5:exp	0.050^{***} (0.006)	0.056^{***} (0.008)	0.060^{***} (0.010)
s2:exp2	0.0003^{***} (0.0001)	0.0001 (0.0001)	-0.0001 (0.0002)
s3:exp2	-0.0001 (0.0001)	-0.0001 (0.0001)	-0.0003^{*} (0.0002)
s4:exp2	-0.001^{***} (0.0001)	-0.0005^{***} (0.0001)	-0.001^{***} (0.0002)
s5:exp2	-0.001^{***} (0.0001)	-0.001^{***} (0.0001)	-0.001^{***} (0.0002)
Constant	6.876^{***} (0.099)	7.064^{***} (0.130)	7.420^{***} (0.147)
Observations	73,201	71,334	66,543
R^2	0.441	0.386	0.322
Adjusted R^2	0.441	0.386	0.322
Residual Std. Error	0.570 (df = 73186)	0.572 (df = 71319)	0.596 (df = 66528)
F Statistic	$4,129.873^{***}$ (df = 14; 73186)	$3,200.690^{***}$ (df = 14; 71319)	$2,256.586^{***}$ (df = 14; 66528)

Note: $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

S1-5 are schooling dummies. S1: Primary; S2: Lower Secondary; S3: Upper Secondary; S4: Post-secondary; S5: University and above. S1 is omitted from the regressions.

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