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Abstract

Education has long been perceived as a great equalizer, but even with universal rises in schooling years, income distribution worsened world-wide. We propose a method for decomposing the contribution of a variable to the change in inequality into mean, dispersion, and price components. The proposed method is then used to investigate the roles of the education variable in driving down China's wage inequality between 2010 and 2018. We find that (1) education accounted for over 30% of total wage inequality in 2010 and 2018; (2) 70% of the overall decline in wage inequality from 2010 to 2018 can be attributed to education expansion, and (3) the 70% inequality-reducing effect was made up of 95% benign dispersion and price components and 25% malign mean component. The benign components are attributable to an improvement in educational equity and a decrease in the college premium.

Keywords: Education Expansion, Wage Inequality, Rate of Return to Education, China
JEL Classification: I24, I26, J31

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Non-technical summary

FOCUS

Education has long been perceived as a great equalizer, yet income inequality globally has worsened despite universal rises in schooling years. To investigate this inconsistency, we consider the role that education plays in contributing to the level of, particularly to the changes in, income inequality. The rapid expansion of education in China in recent years provides a suitable setting for such research. We ask how education has propelled recent reductions in income inequality in China.

CONTRIBUTION

Previous approaches exhibit methodological shortcomings. We propose a method that decomposes the contribution of a variable to a change in inequality into mean, dispersion, and price components. We then use the proposed method to investigate the roles of the education variable in reducing wage inequality in China between 2010 and 2018. To address the endogeneity issue, we use a major policy shock that occurred in 1999 to identify the causal relationship between wage levels and education in China.

FINDINGS

We find that (1) education accounted for over 30% of total wage inequality in both 2010 and 2018; (2) 70% of the overall decline in wage inequality between 2010 and 2018 was due to education expansion; and (3) the 70% inequality-reducing effect consisted of 95% benign dispersion and price components and 25% malign mean component. The benign components reflect improvement in educational equity and a decrease in college premium. Our findings suggest that education helps promote equality, albeit not in the conventional sense that overlooks the dispersion of the education variable where education expansion is described in terms of increases in average years of schooling. It is therefore crucial when expanding education to prioritize providing support and opportunities to those individuals who are economically disadvantaged, marginalized, or otherwise underprivileged.

1 Introduction

"Education, then, beyond all other devices of human origin, is the great equalizer of the conditions of men, the balance wheel of the social machinery." Horace Mann, 1844

Rising inequality poses a formidable global challenge as it undermines economic growth, social cohesion, political stability, and globalization efforts (Aghion et al. 1999; de la Croix & Doepke 2003; Atkinson et al. 2011; Alesina et al. 2021). National governments, international institutions such as the G20 and OECD, NGOs, and major corporations have responded with measures to promote inclusive growth, as well as initiatives to address various disparities and income gaps. Inequality containment features prominently among the United Nation's Sustainable Development Goals (SDGs). The World Bank announced its Shared Prosperity goal in 2013 to tackle income maldistribution. The research community has also devoted considerable resources in recent year to estimating income inequality, assessing its adverse consequences, uncovering its correlates, and formulating policy recommendations.

Moreover, education's role in driving income distribution was recognized long before Horace Mann, the father of American public education, penned his insight. In 587 AD, Emperor Yang Jian (Sui Dynasty) inaugurated the *Keju* education system to assure the Chinese state of a stable supply of intelligent and competent civil servants. *Keju* was subsequently adopted in Japan, Korea and Vietnam at various times and persisted in China until 1905 when the Qing dynasty found itself hard-pressed to adopt a constitutional system (Chen et al., 2020). *Keju* was seen as a means of enhancing income mobility as it offered every male child the opportunity to become a public official through a rigorous national civil service examination. Modernly, education is generally accepted in policy circles as a means to tackling income inequality (Ram, 1990; Goldin & Katz, 2007; Deming, 2022). The OECD (2017) specifically identifies quality education as a key avenue to improved income distribution, and the World Bank views education as an important driver in reducing inequality[1].

Access to education has clearly expanded. The global literacy rate rose from 45% in 1948 to 95% in 2020, and the proportion of college graduates in the labor force rose from 10% in 1970 to 40% in 2020 (UNESCO, 2021). In the US, the percentage of high school graduates among those aged 25 and over increased from 66% in 1970 to 91% in 2020. In Europe, this percentage increased from 71% in 1973 to 96% in 2020. Education access has also expanded in developing economies.

[1] See: https://www.worldbank.org/en/topic/education/overview#1

India's enrollment rate of upper primary (middle school) students grew from 42% in 1987 to 85% in 2020.[2] In China, the average years of schooling for those aged 15 and over rose from 5.3 in 1982 to 9.6 in 2017 and the average years of schooling of the labor force increased from 6.24 years in 1985 to 10.5 years in 2017 (National Bureau of Statistics of China, 2018).

Technically speaking, a change in the education variable could mean a variation in its mean, its dispersion, or both. Education expansion or increased supply of education, a universal phenomenon and an important policy tool perceived to help improve income distribution as mentioned above, usually means increases in the mean of the education variable coupled with almost inevitable changes in the dispersion of the education variable. The effect of education expansion on income inequality also depends on the coefficient of the education variable in the underlying income or wage function. Knight and Sabot (1983) and Lemieux (2006a) refer to this coefficient as the *price of education*. It is identical to the rate of return to education or schooling in the Mincer model. Thus, conceptually the impact of education on income or wage inequality consists of three distinct components: *a **mean component*** caused by changes or differences in the mean of the education variable only; *a **dispersion component*** caused by changes or differences in the dispersion of the education variable only, and *a **price component*** caused by changes or differences in the price of education or rate of return to education only.

Four methods have been applied to empirically estimate the impact of education on inequality (see Table 1). Using the Mincer function, Knight and Sabot (1983) conduct a counterfactual analysis to estimate the so-called *composition* and *compression* effects. The former is obtained by replacing the current labor force composition by its base-period counterpart and then computing income inequality, holding everything else the same. Thus, the composition effect is the difference between this inequality and actually observed income inequality in the current period. The latter is obtained by replacing the estimated rate of return to schooling in the current period by its base-period counterpart in predicting income using the Mincer model and estimating income inequality, holding everything else the same). The difference between this inequality and actually observed income inequality in the current period is defined as the compression effect. This first methodology has since been utilized by Goldin and Katz (2007). The compression effect is clearly related to the price component, i.e. when increased supply of education leads to reductions in the rate of return to education, the skill premium declines, implying compression of wage or income dispersion or improvement in the wage or income distribution.

[2] CEIC Data Global Database.

In the second approach, Lemieux (2006a), after applying the variance operation on both sides of the random-coefficient version of the Mincer model, performs a counterfactual analysis to gauge the composition effect and the price component.

In the third method, Firpo et al. (2009) use a re-centered influence function (RIF) regression, whereby the marginal impact of an explanatory variable such as education on the distribution of the dependent variable such as wage can be estimated. Building on this basis method, Firpo et al. (2018) expand the Oaxaca-Blinder decomposition framework and decomposed changes in wage inequality into mean and price components.

Fourth, one can simply regress an indicator of income inequality on variables that measure different aspects of the education variable as in Chiswick (1968).

Table 1. Existing methods for estimating inequality impacts of education

Component	Counterfactual		RIF Decomposition	Usual Regression
	Knight and Sabot (1983)	Lemieux (2006a)	Firpo et al. (2018)	
Price (skill premium)	Defined as compression effect	Yes	Yes	Yes
Mean	Lumped in with composition effect		Yes	Yes
Dispersion			No	Yes

As Table 1 indicates, the first two approaches fail to distinguish the dispersion and mean components as the composition effect of Knight and Sabot (1983) and Lemieux (2006a) may be caused by changes in the mean, the dispersion or both of the education variable. The method of Firpo et al. (2018) ignores the dispersion component. Since the mean and dispersion components are highly correlated (Ram 1990), overlooking any of them may lead to biased analytical results. Further, all four methods require estimation of the underlying income or wage equation but relevant applications in the literature fail to consider endogeneity. Also, the two counterfactual approaches of Knight and Sabot (1983) and Firpo et al. (2018) are incomplete as they ignore the residual term when analyzing sources of inequality. That is, inequality contributions of variables not included in the underlying income generating function (often quite substantial) are not considered at all.

In terms of empirical evidence, Knight and Sabot (1983) find that the compression effect of education expansion is negative or inequality-reducing while the composition effect is initially positive or inequality-increasing and later becomes negative or inequality-reducing. More recently, Acemoglu (1998) argues that declining returns due to rising supply of college graduates can cause skill-biased technological progress that raises demand for education, eventually leading to enlargement in the skill premium or wage inequality over the long run. In other words, the price component can switch signs at different time horizons.

According to Lemieux (2006a), the price component and the composition effect are both dis-equalizing, but the price component much more so. Thus, the deteriorating US wage distribution in the 1970s is mainly attributable to rising returns on a college education. Using the RIF of Firpo et al. (2009) to examine US male wage inequality during 1988–2016, Firpo et al. (2018) reveal that both the mean and price components are positive or inequality-increasing.

Finally, by regressing the variance of log-income on the estimated rate of return to, and the mean and variance of, the education variable, Chiswick (1968) finds that the price, mean, and dispersion components are all positive or inequality-increasing. However, most studies adopting the regression approach show that the mean component is equalizing, and the dispersion component is either inequality-increasing (Marin and Psacharopoulos, 1976; Winegarden, 1979; Park, 1996; Gregorio & Lee, 2002) or insignificant (Ram, 1984).

Here, we address the impacts of education on wage inequality and its changes in China, with a special emphasis on recent reductions in income inequality stemming from what Kanbur et al. (2021) have dubbed China's "great turnaround." Our empirical analysis is based on 2010 and 2018 survey data from the China Family Panel Study (CFPS). It is worth noting that little effort has been made to explore the contribution of education to inequality in China. A notable exception is Xu (2010), who, after applying the RIF approach to 1991–2006 data from the China Health and Nutrition Survey, concludes that the negative mean component is outweighed by the positive price component, which is driven by skill-biased technological change and thereby renders education a dis-equalizing contributor to Chinese income inequality.

To accomplish our objective, we propose an analytical framework, quantifying the contributions of a variable to a change in income or wage inequality. Our framework combines the counterfactual analysis with the regression-based inequality decomposition technique of Shorrocks (2013) and Wan (2004) that were designed for inequality accounting. Our framework enables clean estimation of the three components defined above. To address the endogeneity issue, we use a major policy shock that occurred in 1999 to identify the causal relationship between wages and education in China.

Four findings deserve mention. First, a sizable portion of wage inequality is attributable to education. Second, education can explain 70% of the decline in Chinese wage inequality between 2010 and 2018. Third, the equalizing role of education arises from reductions in its dispersion and price components. Finally, the mean component of education is inequality-increasing, contradicting the conventional wisdom set forth by Horace Mann at the start of this section. Our findings support Zhang (2021), who asserts that education plays an important role in affecting China's income distribution and may explain the phenomenon dubbed by Kanbur et al. (2021) as China's "great turnaround". Thus, education can help promote equality, just not in the conventional sense that overlooks the dispersion of the education variable since education expansion is usually measured in terms of increases in average years of schooling.

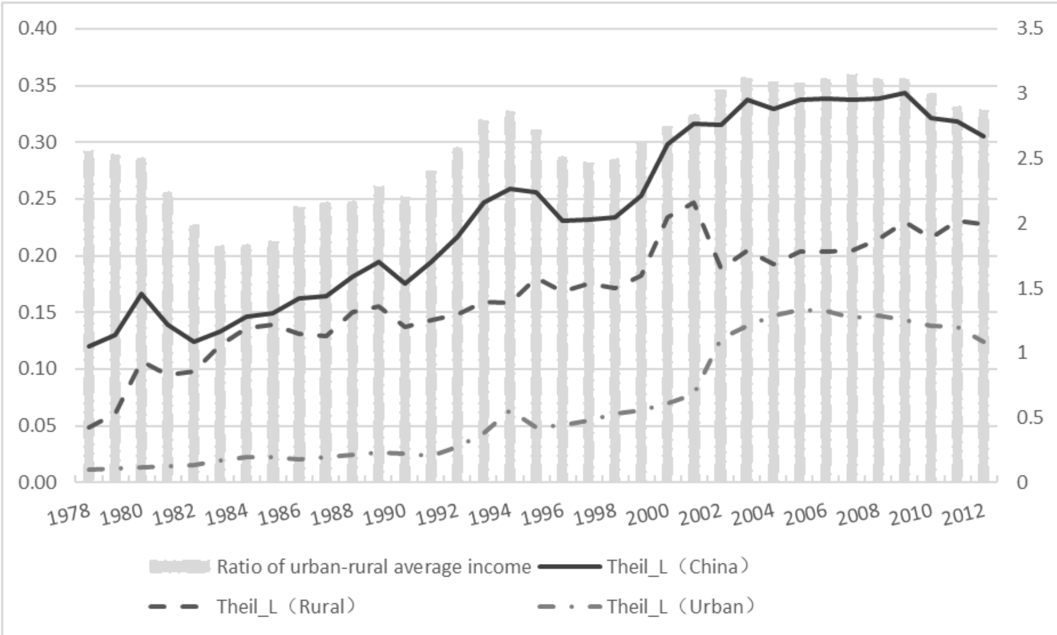
The rest of the paper is organized as follows. Section 2 provides background information on the inequality profile and the 1999 policy shock to the higher education sector in China. Section 3 documents data and preliminary data analyses. Section 4 outlines empirical strategy, followed by presentation and discussions of empirical results in Section 5. Section 6 concludes.

2 China's inequality profile and the 1999 education expansion

Referring to Figure 1 which plots the income Theil index for China as a whole, rural China, urban China, as well the ratio of urban-rural average income,[3] our first stylized fact, contrary to the conventional wisdom (see Kuznets, 1955; Asian Development Bank, 2013), is the rural income inequality in China was higher than its urban counterpart until recently. In the pre-reform period, rural Chinese lived on local resources within the boundary of a production team without social welfare or public re-distribution. A production team typically consisted of several dozen households who cultivated the collectively-owned land and received in-kind payments in harvest seasons based on the work points they had earned. Urban Chinese, in contrast, enjoyed certain forms of social welfare and their wages were set by the central government with little variation across locations (basically, number of years worked, political ranking and technical skillsets to some extent). Thus, it is a misperception to consider pre-reform China as an egalitarian society, particularly given that the rural population was larger than the urban population at the time.

[3] Data from 2013 onwards are not presented as the National Bureau of Statistics of China merged its rural and urban survey teams and changed definitions of some variables including income in 2012.

Figure 1. Income inequality in post-reform China



Source: Authors' calculations based on data from the National Bureau of Statistics of China.

Conceptually, inequality of any country consists of three parts: urban inequality, rural inequality and the urban-rural gap. The gap is usually large in developing economies, especially in China due to the household registration system called *hukou*. *Hukou*, which was embodied in a small booklet similar to an internal passport, strictly prevented any form of migration and population mobility in pre-reform China. Even today, *hukou* still discriminates against rural citizens including rural-to-urban migrants. Segregated by *hukou* status, China's population can be classified into four groups: urban residents with *hukou* status, urban residents without urban *hukou* status, as well as rural residents (almost all with rural *hukou* status) who are engaged or not engaged in a rural form of livelihood. Income gaps between these population groups, largely attributable to *hukou*, account for more than 50% of China's national income inequality (Wan, 2007; Wan et al., 2022). This is the second stylized fact that explains why total inequality moves closely in concert with the urban-rural income ratio in China (see Figure 1). As China's reform was initiated in the rural sector, income inequality declined in the early period. When the reform focus began to shift to the urban sector in the mid-1980s, income distribution had been worsening until 2007-2009.

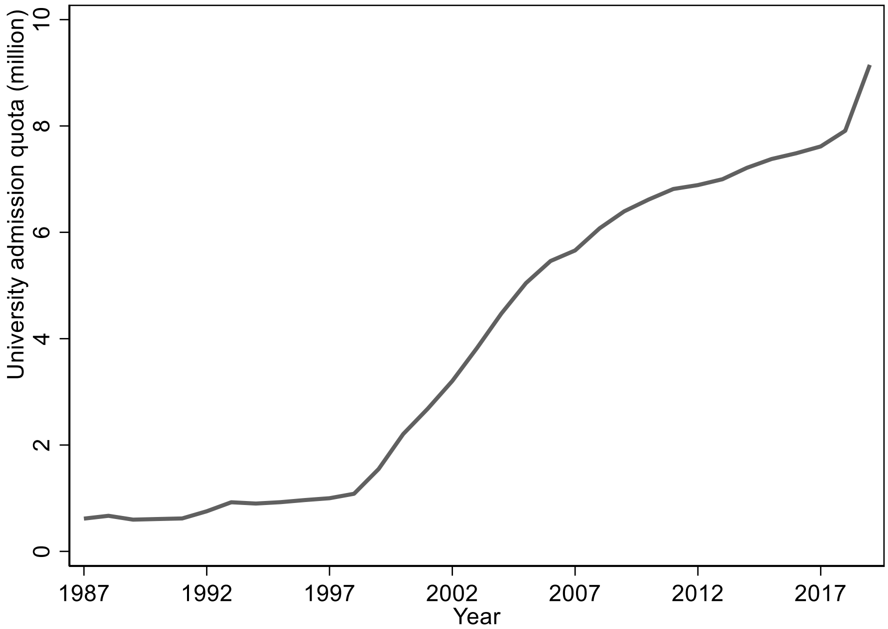
The third stylized fact relates to the recent declines in inequality in China. Dubbed as the great turn-around by Kanbur at al. (2021), the declines attract the attention of researchers and the public (Wan, 2004; Wan et al., 2018; Bai et al., 2020). Several factors may have contributed to these declines, including the elimination of agricultural taxes and emergence of the rural social welfare system around 2006, as well as urbanization (Wan, 2013; Wan et al., 2018). Even so, few attempts have been made at analyzing the role of the 1999 expansion of higher education or the effects on the labor market that would have begun to emerge around 2003.

Rural Chinese could obtain urban *hukou* in three ways: join the army, assume the jobs of their retiring parents if their parents were urban citizens when the *hukou* system was re-introduced in late 1958, or through admission to a college or university. Technically, marriage made it possible for children to obtain urban *hukou* status if the mother had urban *hukou* status at the time of the marriage. For the vast majority of rural youth, however, college admission was (and still is) the only way to obtain coveted urban *hukou* status. A university education grants middle-class or higher status upon graduation, while failure to get into college generally relegates one to a poorer life. Adding to this barrier to middle-class entry is the fact that the education system, and particularly higher education, discriminates against rural youth. For example, rural Chinese accounted for 74% of the national population in 1990, but accounted for only 43% of the college intake (Wang and Chen, 2014). In 1998, urban Chinese accounted for 30.4% of national population, but 70% of the intake at key universities. The latter percentage was as high as 79.3% and 81.5% for the prestigious Tsinghua and Peking universities (Yang, 2006). The intrinsic linkage between *hukou* and educational attainment (thus income) is our fourth stylized fact.

Clearly, *hukou* makes educational disparity (i.e. the dispersion in the education variable) a prominent contributor to income inequality in China. Intuitively, education expansion in China should diminish income inequality as it provides more opportunities to the rural youth. The recent expansion in education began in 1998–1999. On June 16, 1999, the National Planning and Development Commission joined with the Ministry of Education in announcing an increase in the college intake by 337,000. This is in addition to the 220,000 announced in the fall of 1998, raised the total 1999 intake to 1.6 million, a 48% increase from the 1998 level. As Figure 2 shows, the university intake continued to expand thereafter, increasing on average by 340,000 annually. As a consequence, the ratio of college students to those aged between 18 and 22 rose from 9.76% in 1998 to 45.7% in 2017, higher than the average of high-middle income countries (Ministry of Education of the People's Republic of China, 2020). Rural youth benefitted from these expansions. In 2010, the proportion of rural registrants gaining college admission reached 49.2%, 6.2 percentage points higher than in 1990 (Wang and Chen, 2014).

Needless to say, those taking college entrance examinations after 1998 have had a greater chance of receiving a post-secondary education. In 1998, only 34% of the 3.2 million who sat for college entrance exams entered universities. This percentage more than doubled to 75% in 2012. Meanwhile, the expansion was uneven from province to province as provincial governments have much autonomy in allocating enrollment quotas and they naturally have incentive to favor local students (Li & Xing, 2010). Taking 2009 as an example, the quota allocation of Peking University entailed a success rate of 6.68 per 1,000 for Beijing applicants, while national average was only 0.22. In the same year, the chance of Shanghai candidates entering Fudan University was 53 times that of the national average (Liu & Li, 2014). In addition, the strict household registration system prevents students from taking college entrance exams in provinces other than where they are registered. Therefore, students in provinces with greater expansions have benefitted more from the policy shock (Si, 2022).

Figure 2. Enrollment in China's general higher education institutions



Source: National Bureau of Statistics of China.

3 Data, variables and descriptive statistics

3.1 Data sources and key variables

Two data sets will be used in this paper. The first is the widely used China Family Panel Studies (CFPS) survey that provides individual observations on wage, deflated using provincial CPIs (base year = 2018), and personal characteristics such as gender, age, and occupation. It also provides detailed information on education history, enabling estimation of our key independent variable: years of schooling. We limit our analysis to non-agricultural employees aged between 16 and 60, excluding students, retirees and the unemployed. The poorest 1% is also removed to minimize possible outliers in the data. Although there are five waves of CFPS (2010, 2012 2014, 2016 and 2018), we follow Knight and Sabot (1983), Lemieux (2006a), Xu (2010) and Firpo et al. (2018) and use only 2010 and 2018 CFPS (omitting intermittent years) to ensure some variations in the education and inequality variables. In the end, we obtain a sample of 9,095 observations.

The second data set, available from China Education Yearbooks, contains provincial observations on the "number of enrollments in general higher education institutions" and "number of high school graduates." These are used to construct an IV variable that captures the policy shock or college expansion.

As mentioned, China began to expand its higher education sector since 1999. The "massive scale" and "unexpectedness" of the expansion make the policy shock a natural experiment (Wu & Zhao, 2010; Knight et al., 2017; Si, 2022). Although implemented nationwide, the scale of expansion varied across provinces. For example, college enrollment in Guizhou grew by 71% from 1998 to 1999, but only by 14% for Hainan, a difference of 57 percentage points. Following Ou and Zhao (2022), the policy intensity of education expansions (*PIE*) can be measured using the following equation:

$$PIE_{py} = \frac{E_{py}}{HS_{py}} / \frac{E_{p1998}}{HS_{p1998}},$$

where E denotes number of college enrolments and HS denotes number of high school graduates, the first subscript p denotes province and the second subscript y denotes year.

To assess whether and to what extent an individual is affected by the policy shock, it is necessary to work out the year when an individual entered college or took the entrance exams, as well as the province where he or she graduated from high school. The former was estimated using "birth year plus schooling years" by Duflo (2001), Xie and Mo (2014) and Castro Campos et al. (2016). This is problematic as years of schooling the student faced before becoming eligible to sit for college entrance exams varied from 1970s to 1990s when the school system underwent significant changes (Chen et al., 2020). Some student may also have repeated or skipped grades. Fortunately, CFPS provides detailed education history at all levels of schooling, enabling better identification of the year when an individual entered college or graduated from high school.

Regarding the province where an individual graduated from high school, CFPS reports the residential locations of individuals when they were 12 years old. At this age, a typical Chinese would be graduating from a primary school, and unlikely to migrate to other provinces due to the stringent *hukou* system. According to the 2010 census, only 6.44% of migrants emigrated out of their own province (Qiao & Huang, 2013). Moreover, as widely known, most migrant workers left their children and parents behind. In particular, high school graduates must almost without exception sit for their college entrance exams in their *hukou* location. Our approach is similar to Duflo (2001), who uses the birthplace to locate the province where a child attended primary school. It is also similar to Chen et al. (2020), who use the latest residential location to identify the province where an individual received secondary education.

3.2. Descriptive statistics on education and wage variables

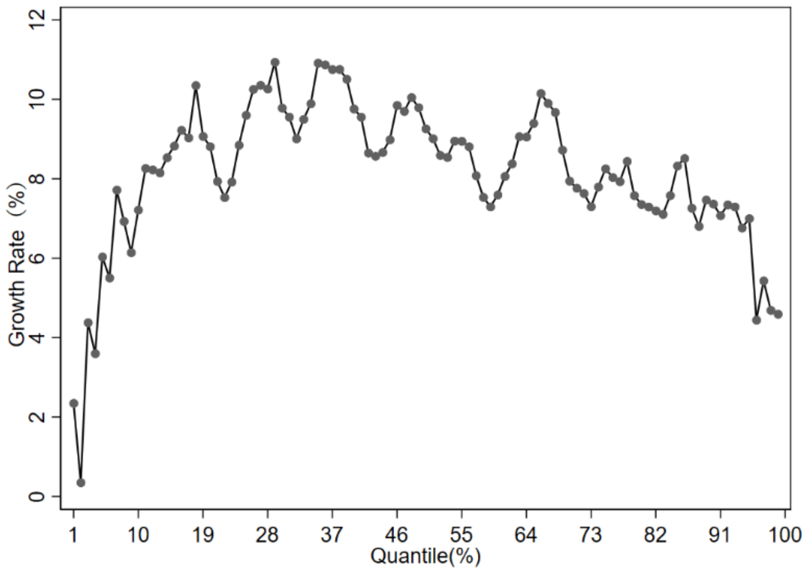
Table 2 reports the summary statistics on wage and education. It is clear that from 2010 to 2018 average wage rose while its dispersion improved. The latter is consistent with the income Theil index in Figure 1. More specifically, the wage gap between the 90th and 10th percentiles remained stable, narrowed between the 90th and 50th percentiles, and worsened between the 50th and 10th percentiles. Figure 3 plots the average growth rate of real wages for different percentiles, showing an inverted “U” shape. Thus, the middle-income group experienced faster wage growth than the high-income and low-income groups, contributing to the decline in income inequality in China. Meanwhile, the average years of schooling expanded from 10.15 years to 10.87, and the educational Gini coefficient decreased from 22.66 to 19.96 (possibly due to the education expansion).

Table 2. Summary statistics of wage and years of schooling

	2010	2018
	Real wage (yuan)	
Mean	25516	43000
Median	19232	36000
Gini (× 100)	40.72	36.94
Wage gap between		
50-10 percentiles	0.97	1.10
90-50 percentiles	0.92	0.80
90-10 percentiles	1.89	1.90
	Years of schooling	
Mean	10.15	10.87
Median	9.00	11.00
Gini (× 100)	22.66	19.96
Observations	4005	5090

Notes: Wage gaps between percentiles are measured by their logarithmic differences.
Source: Authors calculation based on CFPS data.

Figure 3. Average growth rate of real wage at each percentile, 2010–2018



Source: Authors calculation based on CFPS data.

4 Analytical frameworks

4.1 The Mincer wage model

An estimated wage model is required for decomposing wage inequality and quantifying inequality contributions by the education variable. Following the human capital theory, our baseline model is specified as:

$$lnW_{ip} = \alpha_0 + \alpha_1 E_{ip} + \alpha_2 D_i \times E_{ip} + \alpha'_3 Q_{ip} + \alpha'_4 Prov_p + \varepsilon_{ip}\ , \quad (1)$$

where subscript i indexes an individual and p indexes a province. lnW_{ip} is the logarithmic annual wage; E_{ip} denotes years of schooling; D_i is a dummy variable indicating whether an individual obtained college degree. Q_{ip} is a vector of control variables including age and its square, gender, ethnicity, marital status, health condition (self-reported health condition ranging from 1 to 5, with larger values indicating better health) and a dummy variable indicating whether the individual lives in urban areas or not. $Prov_p$ is province fixed effect, and ε_{ip} is the usual disturbance term.

OLS estimation of equation (1) is likely to lead to biased results due to reverse causality, possible measurement errors and omission of variables such as personal ability and family background. Following Duflo (2001) and Si (2022), we use the *PIE* constructed earlier to undertake IV estimations, where the first and second stage equations can be expressed as follows:

$$E_{ip} = \beta_0 + \beta_1(PIE_{py} \times Post_i) + \beta'_2 Q_{ip} + \beta'_3 Prov_p + u_{ip} \quad (2)$$

$$lnW_{ip} = \gamma_0 + \gamma_1 \widehat{E_{ip}} + \gamma_2 D_i \times \widehat{E_{ip}} + \gamma'_3 Q_{ip} + \gamma'_4 Prov_p + \eta_{ip}\ , \quad (3)$$

Where $PIE_{py} \times Post_i$ is the IV for years of schooling, and $Post_i$ is a dummy variable that equals 1 when the individual took the college entrance exam after 1999, and 0 otherwise. $\widehat{E_{ip}}$ is the predicted value of years of schooling from the first stage regression. It is useful to note that γ_1 represents the return to schooling for those without college education, $\gamma_1 + \gamma_2$ represents the return to schooling for college graduates, and the difference γ_2 represents the wage premium for college graduates.

4.2 Decomposition of wage inequality and its changes

4.2.1 Decomposition of wage inequality

After estimating the IV model, we can obtain the wage (not logarithm of wage) generation function as:

$$W_{ip} = EXP\big(\widehat{\gamma_0} + \widehat{\gamma_1}E_{ip} + \widehat{\gamma_2}D_i \times E_{ip} + \widehat{\gamma_3'}Q_{ip} + \widehat{\gamma_4'}Prov_p + \hat{\varepsilon}_{ip}\big)\,. \tag{4}$$

For expository purposes, we drop subscripts and rewrite equation (4) as:

$$W = EXP(AE + B'X + \varepsilon)\,, \tag{5}$$

where $A = \widehat{\gamma_1} + \widehat{\gamma_2}D_i$; X is a $K \times 1$ vector of the constant and control variables; ε is the residual term; and B is the vector containing coefficient estimates for X. Taking inequality on both sides of (5) to obtain:

$$I(W) = I[EXP(AE + B'X + \varepsilon)]\,. \tag{6}$$

The cooperative game theory of Shapley (1953) can then be used to decompose the wage inequality into contributions by X, ε, E, and A (B is the same for all individuals thus does not contribute to inequality) such that

$$I(W) = C(A) + C(E) + \sum_{k=1}^{K} C(X_k) + C(\varepsilon)\,, \tag{7}$$

where X_k is the kth component of X, $C(X_k)$ denotes inequality contributions of X_k. $C(E)$ denotes the inequality contribution of education,$C(A)$ denotes the inequality contribution of the education premium. $C(\varepsilon)$ is the inequality contribution of the residual. For more technical details, see Shorrocks (2013) and Wan (2004).

4.2.2 Decomposition of inequality changes

Equation (7) decomposes a given level of inequality, but here we focus on China's great turnaround or changes in inequality. To decompose an inequality change, we combine (7) with the usual counterfactual analysis. With superscript t indicating year, a change in inequality $\Delta I[W] = I[W^{t_1}] - I[W^{t_0}]$ can be decomposed into the contributions of the independent variables and the residual term based on (7). For example, the contribution of education can be obtained as $COE = C(A^{t_1}E^{t_1}) - C(A^{t_0}E^{t_0})$, which can be further broken down into the mean and price components by conducting the following counterfactual analyses.

Starting from the income generating function for the base period t_0:

$$W^{t_0} = EXP\big(A^{t_0}E^{t_0} + {B'}^{t_0}X^{t_0} + \varepsilon^{t_0}\big)\,. \tag{8}$$

Replacing E^{t_0} in (8) by $E^c = \frac{E^{t_0}}{\mu^{t_0}} \times \mu^{t_1}$ where μ is the mean of the education variable, while holding everything else the same, we can obtain the counterfactual wage income：

$$W^{c_E} = EXP\left(A^{t_0}E^c + B'^{t_0}X^{t_0} + \varepsilon^{t_0}\right). \tag{9}$$

The mean component is simply:

$$Mean\ \ component = I[W^{c_E}] - I[W^{t_0}]. \tag{10}$$

Similarly, replacing A^{t_0} in (8) by A^{t_1} while holding everything else the same, we can obtain the counterfactual wage income：

$$W^{c_A} = EXP\left(A^{t_1}E^{t_0} + B'^{t_0}X^{t_0} + \varepsilon^{t_0}\right). \tag{11}$$

The price component is simply:

$$Price\ component = I[W^{c_A}] - I[W^{t_0}]. \tag{12}$$

Since changing the base period may result in slightly different results (Lemieux, 2006b), adjacent years will be used alternatively as the base period and the averages will be used as the final estimates of the mean and price components. Given the total contribution *COE* and its mean and price components, the dispersion component can be easily computed.

It is useful to note that the advantage of our decomposition lies in its generality. Any inequality index can be used and the underlying wage model can be highly nonlinear or contain interactive terms.

5 Empirical results

5.1 The wage model

5.1.1 Baseline regression results

Table 3 presents the baseline regression results where the *F*-statistics confirm the validity of our IV. It is clear that OLS tends to underestimate the rate of return to education. For instance, in 2010, the OLS estimate of the rate of return to education for individuals without (with) college education is only 4.0% (6.2%), while the IV estimate is 8.6% (13.6%). The latter values are almost twice as large as the former. Indeed, our IV estimates are comparable to those in other countries (Card, 1999) as well as consistent with most recent literature on China using different data and research designs (Liu et al., 2016; Castro Campos et al., 2016; Chen et al., 2020). Therefore, it is advisable to use IV estimates when analyzing the impact of education on income inequality as failure to do so may result in an underestimation of the impact of education, particularly with regard to the price component. The endogeneity of the educational variable, an issue neglected in previous studies on the role of education in driving income inequality, must be addressed.

Table 3 shows that the college premium declined from 2010 to 2018 by as much as 1.2 percentage points (from 5.0% to 3.8%, as indicated by the estimated coefficient for the interaction term $D_i \times E_{ip}$). That is, the rate of return to education for those with college education dropped from 13.6% in 2010 to 12.0% in 2018. This was likely driven by the expansion of education, particularly the increased supply of high-skilled college graduates. As Table 4 reveals, the share of graduates with a college or higher degree from the high-income group declined from 61.42% in 2010 to 55.13% in 2018, but rose for low- and middle-income groups. In other words, access to college education had improved for lower income groups. This is also consistent with the first-stage IV estimation results (see columns (1) and (4) of Table 3): relative to the cohort not affected by the education expansion, doubling the college expansion intensity can lead to an increase in the average years of schooling by approximately 0.9 years.

Table 3. Baseline wage model

	(1)	(2)	(3)	(4)	(5)	(6)
		2010			2018	
	IV Estimates First stage	IV Estimates Second stage	OLS	IV Estimates First stage	IV Estimates Second stage	OLS
Years of education		0.086***	0.040***		0.082***	0.041***
		(0.0243)	(0.0036)		(0.0207)	(0.0046)
$D_i \times E_{ip}$		0.050***	0.022***		0.038***	0.016***
		(0.0024)	(0.0022)		(0.0021)	(0.0023)
$PIE_{py} \times Post_i$	0.959***			0.913***		
	(0.1353)			(0.0968)		
Age	0.454***	0.065***	0.079***	0.058	0.076***	0.072***
	(0.0659)	(0.0093)	(0.0085)	(0.0468)	(0.0087)	(0.0084)
Age squared	-0.006***	-0.001***	-0.001***	-0.001**	-0.001***	-0.001***
	(0.0008)	(0.0001)	(0.0001)	(0.0006)	(0.0001)	(0.0001)
Male	0.023	0.373***	0.369***	0.094	0.447***	0.441***
	(0.1285)	(0.0221)	(0.0217)	(0.1075)	(0.0204)	(0.0203)
Minority	0.056	-0.046	-0.038	-0.594**	0.042	-0.002
	(0.3509)	(0.0624)	(0.0619)	(0.2868)	(0.0562)	(0.0536)
Married	-0.293	0.209***	0.175***	-0.525***	0.144***	0.107***
	(0.2135)	(0.0367)	(0.0348)	(0.1564)	(0.0329)	(0.0318)
Health	0.072	0.051***	0.056***	0.027	0.037***	0.038***
	(0.0959)	(0.0151)	(0.0146)	(0.0496)	(0.0100)	(0.0100)
Urban	2.625***	-0.057	0.118***	1.858***	-0.066	0.058***
	(0.1656)	(0.0679)	(0.0248)	(0.1096)	(0.0446)	(0.0213)
Constant	2.569*	6.948***	7.413***	10.810***	7.750***	8.551***
	(1.3960)	(0.3054)	(0.1927)	(1.0718)	(0.3689)	(0.1758)
N	4005	4005	4005	5090	5090	5090
Adjusted R^2	0.20	0.28	0.31	0.24	0.22	0.24
F statistics	50.17			88.99		

Notes: * p < 0.1, ** p < 0.05, *** p < 0.01. Robust standard errors clustered by province and year of birth are in parentheses. We also control for province fixed effects in each regression.

Table 4. Higher education completion rates by income group

Individuals with a college degree or higher	2010		2018	
	Number	Percentage(%)	Number	Percentage(%)
Low-income group	126	13.39	237	15.80
Middle-income group	237	25.19	436	29.07
High-income group	578	61.42	827	55.13
Total	941	100.00	1500	100.00

Notes: Low-income, middle-income and high-income groups are divided by income tertiles.
Source: Authors calculation based on CFPS data.

5.1.2 Robustness checks

The allocation of university quotas largely depends on educational capacities and financial status of provinces (Li and Xing 2010; Liu and Li 2014). To take these into consideration, we follow Duflo (2001) by interacting the year of birth variable with the 1998 province-level characteristics (denoted by $W'_{p,1998}$) and adding these interactive terms into our baseline model. These characteristics include the number of regular higher education institutions, the number of faculties employed in these institutions, per capita GDP, and per capita fiscal income. The estimation results presented in columns (1) and (2) of Table 5 demonstrate that the coefficient estimates for major variables are close to their counterparts in Table 3.

Moreover, the validity of our IV might be compromised due to unobserved forces that affect wage or education (Stephens & Yang, 2014; Chen et al., 2020). For example, the well-known reform and opening-up strategy favored the coastal provinces in the early years. Thus, different cohorts in different provinces may be affected by different unobservable factors. To see whether this contaminates our estimates, we follow Chen et al. (2020) by interacting the year of birth with province dummies and adding the interactive terms to our model. The estimation results, reported in columns (3) and (4) of Table 5, show that the coefficient estimates for our key variables are quite close to those in Table 3.

Table 5. Robustness checks

	(1) 2010	(2) 2018	(3) 2010	(4) 2018	(5) 2010	(6) 2018
Years of education	0.081***	0.080***	0.081***	0.089***	0.090***	0.084***
	(0.0234)	(0.0206)	(0.0232)	(0.0221)	(0.0227)	(0.0200)
$D \times E$	0.050***	0.038***	0.050***	0.039***	0.049***	0.038***
	(0.0023)	(0.0021)	(0.0023)	(0.0021)	(0.0024)	(0.0021)
$W'_{p,1998} \times Birth\ year$	Yes	Yes	No	No	No	No
Province×Birth year	No	No	Yes	Yes	No	No
LAW_i	No	No	No	No	Yes	Yes
N	4005	5090	4005	5090	4005	5090
Adjusted R^2	0.29	0.23	0.29	0.23	0.28	0.22
F statistics on the instrument	51.21	88.69	54.74	76.02	59.32	96.06

Notes: * p < 0.1, ** p < 0.05, *** p < 0.01. Robust standard errors clustered by province and year of birth are in parentheses. Other control variables include: *age, age squared, male, minority, married, health, urban,* and province dummies.

Additionally, China enacted the Law on Nine-Year Compulsory Education in 1986, affecting individuals born after 1971 (Xie & Mo, 2014) who were likely to graduate from high school after 1989. Could this contaminate our results? Since different provinces implemented the law in different years, we collate the specific years and months of implementation for each province. This enables us to identify individuals affected by this law. A dummy variable (LAW_i) can be defined accordingly and included in the regression. The estimated returns to education, as reported in columns (5) and (6) of Table 5, are similar to our baseline estimates.

Finally, the later an individual is born, the greater the possible benefit due to the improving macroeconomic environment as China deepens its reforms over time. In other words, the time trend may affect education and/or individual earnings (Fang et al., 2012). This can be checked with a placebo test conducted among individuals who took the college entrance examination prior to 1999, in which we assume that the education expansion started in 1988, and not in 1999 when it actually took place. The test results as reported in Table 6 demonstrate that the marginal effect of education became statistically insignificant for individuals both with and without a college degree. It can thus be confirmed that the time trend plays little role in affecting our key estimates.

Table 6. Placebo test

	(1) 2010	(2) 2018
Non-college-educated education returns	0.142	0.085
	(0.2121)	(0.0983)
College-educated education returns	0.202	0.147
	(0.2122)	(0.0985)
N	2905	2404
Adjusted R^2	0.28	0.26
F statistics on the instrument	0.49	3.40

Notes: * p < 0.1, ** p < 0.05, *** p < 0.01. Robust standard errors clustered by province and year of birth are in parentheses. Other control variables include *age, age squared, male, minority, married, health, urban,* and province dummies.

5.2 Decomposition of wage inequality and its change

5.2.1 Decomposition of wage inequality

Several findings can be discerned for the Table 7 presentation of decomposition results. First, as anticipated, the decomposition results using IV and OLS estimates differ significantly. Referring to Panel A in Table 7, about one third of wage inequality is contributed by education and its coefficient, far exceeding contributions by any other variables. Panel B of Table 7 reports the decomposition results based on OLS estimates. The percentage contribution of the education variable and its coefficient is about half of that reported in Panel A. Notably, OLS over-estimates the contribution of the residual term at the expense of the education contribution and its coefficient. In other words, some of the contributions of education is incorrectly included in the residual term if using OLS. It is worth reiterating that previous attempts to explore sources of income or wage inequality almost always use OLS. Two recent examples are Li et al. (2018) and Wicaksono et al. (2017). Applying the decomposition method of Murdoch and Sicular (2002) to 2013 data from China, Li et al. (2018) find that education accounted for 14% of wage inequality. This is nearly the same as the 17% contribution of education to wage inequality as discovered by Wicaksono et al. (2017), who use the decomposition technique of Shorrocks (2013) and Wan (2004) and 2014 Indonesian data. Interestingly, these under-estimated results comport closely with our results in Panel B of Table 7 (about 19% in 2010 and 17% in 2018).

Second, education plays a dominant role in driving inequality in China, contributing 36.39% and 32.97% to total wage inequality in China in 2010 and 2018, respectively. Our findings support Becker and Chiswick (1966) and Lemieux (2006b), who, among others, state that human capital should explain about a third of wage inequality. Moreover, these contributions can be further decomposed into a contribution due to the college premium (corresponding to the "Coefficient of education" in Table 7) and a contribution due to disparities of education attainment among individuals (corresponding to "Years of education" in Table 7). Taking 2010 as an example, the overall contribution of the education variable is as high as 36.39%, out of which the contribution of the college premium is 13.26%. In other words, if the rate of return to education could be made equal for college and non-college groups, the wage Gini index would, *ceteris paribus*, decrease from 40.72 to 35.32.

Finally, both the absolute and relative contributions of education to wage inequality decreased from 2010 to 2018, implying that education acted as an equalizer for China's great turnaround. In passing, it is noted that apart from education, other major drivers of wage inequality include gender and province fixed effects, the latter encompassing cultural, geographical, climate and even governance differences across locations in China.

Table 7. Decomposition of the wage inequality as measured by Gini coefficient

	(1)	(2)	(3)	(4)
	2010		2018	
	Absolute contribution to Gini (× 100)	Relative contribution (%)	Absolute contribution to Gini (× 100)	Relative contribution (%)
	Panel A: Based on IV estimates			
Education	14.82	36.39	12.17	32.97
Coefficient of education	5.40	13.26	4.18	11.33
Years of education	9.42	23.13	7.99	21.64
Age	1.91	4.70	1.08	2.93
Gender	2.52	6.19	3.31	8.96
Ethnicity	0.04	0.09	0.03	0.08
Marriage	0.73	1.79	0.33	0.88
Health	0.32	0.78	0.41	1.10
Urban	0.03	0.07	0.13	0.35
Province	3.20	7.86	2.85	7.73
Residuals	17.15	42.13	16.63	45.01
	Panel B: Based on OLS estimates			
Education	7.54	18.52	6.37	17.26
Coefficient of education	2.53	6.22	1.90	5.15
Years of education	5.01	12.30	4.47	12.11
Age	1.91	4.69	1.53	4.15
Gender	2.68	6.58	3.65	9.88
Ethnicity	0.03	0.08	0.00	0.01
Marriage	0.66	1.63	0.25	0.66
Health	0.36	0.89	0.44	1.20
Urban	0.86	2.12	0.34	0.93
Province	3.53	8.68	3.24	8.76
Residuals	23.13	56.81	21.11	57.14
Wage Gini	40.72	100.00	36.94	100.00

5.2.2 Decomposition of changes in wage inequality

Applying the counterfactual procedure of Section 4, we obtain Table 8, which reports the mean, price and dispersion components associated with the education variable, as well as the overall contributions of control variables to the change in the wage Gini from 2010 to 2018. It can be seen that when OLS estimates are used, nearly all the components would be under-estimated significantly while the non-interpretable residual contribution is over-estimated by 283%.

Turning to the education variable, Table 7 shows that its absolute contribution to wage inequality was 14.82 in 2010 and 12.17 in 2018. Thus, education helped reduce the wage Gini by 2.64. This accounts for 69.93% of the reduction in the wage Gini which decreased by 3.78 from 2010 to 2018 (Table 8). Further, the mean component under the IV estimation is 0.93, implying an inequality-increasing impact. The price component is -2.12 and the dispersion component is -1.45, both making substantial benign contributions to China's great turnaround in income inequality.

Clearly, the overall equalizing effect of education expansion lies in the improvement in its price and dispersion components, which more than offset its malign mean component. This finding corroborates well with the 12% reduction in the education Gini as reported in Table 2, and the spreading of college graduates into the middle and lower-income groups as documented in Table 4. Education expansion not only helped compress the dispersion of the education variable, but also helped reduce the college premium as reflected by the drop in the estimated coefficient for the interactive term in Table 3.

The premium-related price component alone contributed 56.05% to the total decline in wage inequality. This is consistent with Autor (2014), Acemoglu (1998) and Goldin and Katz (2007). The last study finds that increasing the wage premium, particularly the college premium, explains 65% of the increase in US wage inequality (variance) between 1980 and 2005. According to Lemieux (2006a), higher returns to post-secondary education accounts for 46% of increased wage variance among US male workers from 1973 to 2005.

While our positive or inequality-increasing mean component seems counterintuitive, it is in line with earlier studies such as Firpo et al. (2018), who, using an RIF decomposition technique, find that the mean component of education contributed 7.7% to the increase in male wage inequality in the US from 1988 to 2014. It is also consistent with regression results which uncover a positive relationship between average years of education and income inequality using provincial panel data from China (Li et al., 2016) or cross-country data for the period of 1980-2010 (Coady & Dizioli, 2018). Therefore, more equitable education (targeting the dispersion of education, not just bluntly expanding education by raising average years of schooling) is imperative for education to play a benign role in driving income inequality.

Table 8. Contributions to the decrease in wage inequality from 2010 to 2018

	IV estimates		OLS estimates	
	Absolute contribution to Gini (× 100)	Relative contribution (%)	Absolute contribution to Gini (× 100)	Relative contribution (%)
Education	-2.64	69.93	-1.17	30.85
Price component	-2.12	56.05	-0.81	21.41
Mean component	0.93	-24.60	0.42	-11.13
Dispersion component	-1.45	38.47	-0.78	20.56
Age	-0.83	21.96	-0.38	9.97
Gender	0.79	-20.79	0.97	-25.71
Ethnicity	-0.01	0.21	-0.03	0.81
Marriage status	-0.40	10.64	-0.42	11.07
Health	0.09	-2.33	0.08	-2.17
Urban	0.10	-2.71	-0.52	13.76
Province	-0.35	9.13	-0.30	7.83
Residual	-0.53	13.96	-2.03	53.60
Total change	-3.78	100.00	-3.78	100.00

6 Summary and conclusions

The conventional wisdom holds that expanding education reduces income inequality, a hard-to-tackle and an almost universal challenge. In fact, while education has expanded globally in terms of average years of schooling, inequality has continued to rise. To explore these contradicting trends, we applied a rigorous analysis of how education affects income or wage inequality.

Combining the counterfactual approach of many and the regression-based inequality accounting framework of Shorrocks (2013) and Wan (2004), we propose a decomposition framework that disentangles the contributions of a variable to a change in inequality into mean, dispersion and price components. Then, we undertake empirical application using 2010 and 2018 survey data from China Family Panel Studies (CFPS) to account for the consecutive declines in income inequality in China since 2007/2009 – a phenomenon dubbed the “great turnaround” by Kanbur et al. (2021). The significant policy shock that occurred in 1999 is used to identify the causal relationship between wage and education in China.

Major findings of our paper include: (1) education accounted for over 30% of the level of wage inequality in both 2010 and 2018; (2) the education expansion in China, spurred by the policy shock of 1999, was responsible for 70% of the 9% decline in wage inequality between 2010 and 2018; (3) the dispersion and price components of education are inequality-reducing while the mean component is inequality-increasing. More precisely, the dispersion and price components, as a result of the improvement in educational equity and the decrease in college premium from 13.6% to 12.0%, explain about 95% of the decline in income inequality.

Our findings confirm that education can be a great equalizer, but not without distinguishing the various components of the education variable. In many cases, education expansion is measured simply as an increase in average years of schooling. Yet education is actually a dis-equalizer in China as its mean component is inequality-increasing. In other words, successful education expansion policies must include measures that simultaneously reduce educational dispersion by prioritizing assistance and opportunities to the poor, marginalized and otherwise disadvantaged.

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