Expanding higher education and wage inequality in Chile

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Abstract

Purpose – This study aims to analyse the contribution of the expansion and diversification of higher education to Chile's increase in wage inequality from 1992 to 2000 and its subsequent decrease from 2000 to 2013.

Design/methodology/approach – The wage equation for each year is estimated using data from the national household survey, *Encuesta de Caracterización Socioeconómica Nacional* (CASEN). Employing the method proposed by Firpo *et al.* (2009), the evolution of wage changes is decomposed into composition and wage structure effects of each explanatory variable at different points of the wage distribution.

Findings – Results show that the positive composition effect of higher education, derived from the increasing share of both workers with university degrees and those with vocational degrees, is substantially larger at the upper quantiles and exceeds the negative wage structure effect, thereby contributing to increasing wage inequality from 1992 to 2000. By contrast, the negative wage structure effect of higher education, primarily derived from the decreasing return to university degrees, is substantially larger at the upper quantiles and exceeds the positive composition effect, thereby contributing to decreasing wage inequality from 2000 to 2013.

Originality/value – This study contributes to the literature by showing that the expansion of higher education increased inequality in the 1990s and decreased it in the 2000s while the increasing supply of workers with vocational degrees decreased wage premiums for university degrees in the latter period.

Keywords: higher education; wage inequality; Chile; unconditional quantile regression

JEL classification codes: D31; I23; I24; J31; O15; O54

1. Introduction

Educational expansion is unambiguously one of the most important factors affecting the evolution of income inequality. Human capital models including Knight and Sabot (1983) predict that educational expansion initially increases income inequality; however, it is likely to decrease income inequality later, if accompanied by decreasing wage premiums for educated workers.

Considered among the most successful Latin American countries (LACs) in terms of economic growth and far-reaching economic reforms, Chile has a high level of income inequality, similar to other LACs. However, Chile experienced some improvement in income distribution in the 2000s, after a slight increase in income inequality in the 1990s (Parro and Reyes, 2017). Moreover, the access to higher education improved substantially in this period, mainly due to the establishment of many new private universities and non-university higher education institutions, namely professional institutes (*instituto profesional*, IP) and technical training centres (*centro de formación técnica*, CFT).[1] Such expansion of higher education driven by mass higher educational institutions is a dominant trend in many developing countries (Carnoy 2011; Carnoy *et al*., 2012). Recent studies including Rodríguez *et al*. (2016) and Montoya *et al*. (2017) precisely estimate the returns to the different types of higher education degrees in Chile.

Carnoy (2011) and Carnoy *et al*. (2012) argue that the recent evolution of income distribution in developing countries is mainly attributable to educational expansion, skill-biased technological changes, and government policies including minimum wage policies and trade liberalisation. In the case of Chile, the literature reveals that the sharp increase in inequality from the mid-1970s to the 1980s is attributable to skill-biased technological changes (Gallego, 2012), unilateral trade liberalization (Murakami, 2014) or the deterioration of labour market conditions, including high unemployment and squeeze on real minimum wages (Marcel and

Solimano, 1994). Since Chile had already implemented major trade liberalization by the beginning of the 1990s and enjoyed significant improvements in unemployment and minimum wages in the 1990s and 2000s (Ffrench-Davis, 2010), the increasing supply of workers with higher education is most likely to explain the evolution of income inequality in these periods.

Therefore, the objective of this study is to analyse how the expansion and the diversification of higher education contribute to the changes in wage inequality in the pre-2000 (1992 to 2000) and post-2000 (2000 to 2013) periods in Chile. Accordingly, the wage equation for each year is estimated and wage changes are decomposed into the contribution of each explanatory variable including detailed educational achievements at different points of the wage distribution. For this purpose, this study employs the recently developed method of unconditional quantile regression proposed by Firpo *et al.* (2009). The novelty of this study is to show that the expansion of higher education increased inequality in the 1990s and decreased it in the 2000s. It is shown that the inequality-increasing effect of higher education in the 1990s primarily results from the increasing supply of workers with university and vocational degrees without a sizable decrease in their wage premiums. By contrast, the inequality-decreasing effect in the 2000s primarily results from decreasing return to university education, which has been substituted with vocational education.

The rest of this article is organized as follows. Section 2 briefly discusses the theoretical framework for analysing the relationship between educational expansion and income inequality, and reviews the literature. Section 3 explains the decomposition method using unconditional quantile regression. Section 4 explains the data used in the analysis and presents descriptive statistics. Section 5 presents the estimation results. The final section concludes the paper and provides policy implications.

2. Theoretical framework and literature review

The standard theoretical framework for analysing the relationship between educational expansion and income inequality is the traditional human capital model developed by Chiswick (1974) and others. This model predicts the following human capital earnings function (De Gregorio and Lee, 2002; Lee and Lee, 2018):

$$\log W_s = \log W_0 + \sum_{j=0}^{S} \log(1 + r_j) + u, \quad (1)$$

where W_s represents the level of earnings of an individual with S years of schooling; W_0 is the earnings of an individual with zero formal education; r_j is the rate of return to the *j*-th year of schooling; and u represents other factors that influence earnings independently of education level. The function can be approximated by

$$\log W_s = \log W_0 + rS + u, \quad (2).$$

Taking the variance yields the following earnings distribution function:

$$\mathrm{Var}(\log W_s) = r^2 Var(S) + \bar{S}^2 Var(r) + 2r\bar{S}Cov(r,S) + Var(u). \quad (3)$$

Thus, the model predicts that an increase in educational inequality, $\mathrm{var}(S)$, leads unambiguously to greater earning inequality, keeping other things constant. By contrast, an increase in the average number of years of schooling, $\bar{S}$, has an ambiguous effect on earnings inequality; if $\mathrm{Cov(r,S)} = 0$ or $\mathrm{Cov(r,S)} > 0$, it leads to greater earnings inequality, while if $\mathrm{Cov(r,S)} < 0$ and the impact is sufficiently large, it can reduce inequality.

Knight and Sabot (1983) formalise the two opposing effects of educational expansion on earnings inequality, using the formulation of Oaxaca–Blinder (O-B) decomposition (Blinder, 1973; Oaxaca, 1973). They predict that an increase in the supply of educated workers increases inequality as long as their wage premium remains constant (composition effect). However, after reaching a certain threshold, the increase in the share of educated workers decreases their wage premium, thereby decreasing inequality (wage structure effect). Thus, they predict an inverted-U relationship between educational expansion and inequality in a given country over time, in a similar process predicted by Kuznets (1955) and Adelman and Morris (1973).

Empirical evidence shows that a higher level of education is associated with a decreasing return to education in most developing countries from the 1960s to 1980s (Psacharopoulos and Patrinos, 2004). Aligned with this finding, some studies using cross-section or panel data in this period find that higher level of educational attainment is indeed associated with decreasing income inequality (Adelman and Morris, 1973; Ahluwalia, 1976; Slama, 1978; Papanek and Kyn, 1986; Park, 1996; De Gregorio and Lee, 2002), while other studies find no significant association between educational attainment and inequality (Chiswick, 1974; Ram, 1984, 1989). By contrast, recent evidence suggests that the return to higher education is larger than the return to lower levels of education, and the gap has increased substantially in most developing countries since the 1990s (Colclough *et al.*, 2010; Carnoy, 2011; Carnoy *et al.*, 2012). Although some recent studies using panel data still find no significant association between years of schooling and income inequality (Földvári and van Leeuwen, 2011; Lee and Lee, 2018), Coady and Dizioli (2018) find that average years of schooling was positively associated with inequality especially in developing and emerging countries from 1990 to 2005.

Focusing on LACs including Chile, they experienced a decrease in income inequality in the 2000s, in contrast with the region's previous and global trends (Lustig *et al.*, 2013). Some literature finds that educational expansion has an inequality-increasing effect in most LACs in the 1990s and 2000s (Battistón *et al.*, 2014), and inequality-decreasing effect in some LACs in the 2000s (Sámano-Robles, 2018).

However, there is little consensus on the inverted-U relationship between educational expansion and income inequality for individual LACs in the 1990s and 2000s.

3. Methodology

To reveal the contribution of the expansion and diversification of higher education to the evolution of wage distribution, this study estimates wage equations for the years 1992, 2000, and 2013, respectively. Based on them, this study decomposes the evolution of wage distribution from 1992 to 2000 and 2000 to 2013 into changes attributable to changes in explanatory variables (composition effect) and in the coefficients of explanatory variables (wage structure effect), respectively, based on the Oaxaca–Blinder (O-B) decomposition method. As mentioned in the introduction, this study focuses on the factors that affect changes in wages at different points of the wage distribution. Thus, this study employs the recently developed method proposed by Firpo *et al.* (2009), which enables O-B decomposition of distributional statistics including unconditional quantiles, Gini, and variance. The clear advantage of this method is that it allows subdividing the overall composition and wage structure effects into the contribution of each explanatory variable (Fortin *et al.*, 2011). This method has been applied in studies analysing the evolution of wage distribution in developing countries including LACs (Sámano-Robles, 2018). [2]

The key idea of this method is to replace an observed value of a dependent variable with an estimated value of re-centred influence function (RIF) in the first step, and to estimate an OLS regression of this new dependent variable (unconditional quantile regression) in the second step. The RIF value at the τ-th unconditional quantile of dependent variable y is given by:

$$\mathrm{RIF}\,(y, q^{\tau}) = q^{\tau} + \frac{\tau - 1\{y \le q^{\tau}\}}{f_y(q^{\tau})}, \quad (4)$$

where $q^{\tau}$is the τ-th unconditional quantile of the dependent variable y; $1\{\cdot\}$ is an indicator function; and $f_y(\cdot)$ is the density of the marginal distribution of y. Importantly, since the expected RIF value at the τ-th unconditional quantile is equal to the variable's τ-th unconditional quantile and the law of iterated expectations does apply in the case of RIF values, the estimated coefficients of the unconditional quantile regression indicate the following marginal effect on q^{τ}:

$$q^{\tau} = \mathrm{E}[RIF(y, q^{\tau})] = E[E(RIF(y, q^{\tau}) \mid X)] = \overline{X'}\beta^{\tau}, \ (5)$$

where β represents the coefficients of the unconditional quantile regression and X is a vector of explanatory variables.

The change in the wage distribution between two periods (from 1992 to 2000 and from 2000 to 2013, respectively) at given quantiles (10th, 50th, and 90th quantiles) is decomposed as follows:

$$lnw_1^{\tau} - lnw_0^{\tau} = \overline{X'_1}\beta_1^{\tau} - \overline{X'_0}\beta_0^{\tau} = (\overline{X'_1} - \overline{X'_0})\beta_0^{\tau} + \overline{X'_1}(\beta_1^{\tau} - \beta_0^{\tau}), \ (6)$$

where *0* and *1* index time 0 and 1, respectively; w is hourly wage (deflated by the national consumer price index [December 2008 = 1] sourced from the Central Bank of Chile). The vector X includes dummies for educational achievements (primary education or less, IP/CFT degrees, university degrees, and postgraduate degrees for the wage equations used for the decomposition from 1992 to 2000, and primary education or less, CFT degrees, IP/university degrees, and postgraduate degrees for the corresponding wage equations from 2000 to 2013[3]), years of potential labour experience (age – years of schooling – 6) and its squared term, and other control variables (see the note in Table 2). The first and second terms on the right-hand side of equation (3) represent the composition and wage structure effects.

4. Data and descriptive statistics

The data used for the analysis is sourced from *Encuesta de Caracterización Socioeconómica Nacional* (CASEN), conducted in 1992, 2000, and 2013. [4] CASEN is a nationally representative household survey conducted every two or three years from November to December. The data are repeated cross-sectional and the sample size is substantially large for each year considered in this study with 143,459, 252,748, and 218,491 individuals in 1992, 2000, and 2013, respectively. [5] This study's sample is limited to male workers who are employed full-time (more than 40 hours per week) and are aged between 15 to 64 years, excluding self-employed workers and military personnel.

Table 1 reports the descriptive statistics of the dataset and confirms the expansion of higher education during these periods. As shown, the shares of both workers with university degrees and those with vocational (CFT/ IP) degrees increased from 1992 to 2000. However, the share of workers with CFT degrees increased from 2000 to 2013, while that of workers with IP/university degrees decreased slightly.

The wage inequality is confirmed to have slightly increased in the former period, while it substantially decreased in the latter, as evidenced by the evolution of the variance of log hourly wages and the wage gap between the 10th and 90th quantiles. Wage equalisation in the latter period is evident in the estimated kernel densities of the log hourly wages shown in Figure 1; the whole wage distribution is observed to shift from left to right with a substantially larger wage increase at the bottom of the distribution than at the top.

[Table 1 near here]

[Figure 1 near here]

5. Results

Tables 2 and 3 report the estimation results of unconditional quantile regressions for 1992 and 2000, and 2000 and 2013, respectively. The returns to higher education (relative to secondary education) are revealed to be heterogeneous across different institutions, supporting the findings of Rodríguez *et al.* (2016), and Urzúa (2017), i.e. returns to university degrees are higher than to vocational degrees.

Tables 4 and 5 report the decomposition of the changes in distribution statistics into the composition and wage structure effects of each explanatory variable for the two periods. The findings of the decomposition from 1992 to 2000 are as follows. The composition effects of CFT/IP and university degrees are positive across the whole distribution, and are larger at the upper quantiles. Corresponding wage structure effects are positive at the 10th and 50th quantiles, but negative at the 90th quantile. However, since the positive composition effects exceeded the negative wage structure effects at the 90th quantile, the overall effects (sum of composition and wage structure effects) of CFT/IP and university degrees pushed up wages across the whole distribution. The composition effect of postgraduate degrees is positive across the whole distribution and larger at the upper quantiles. Since the corresponding wage structure effect is positive at the 50th and 90th quantiles, the overall effect of postgraduate degrees pushed up wages at the upper quantiles.

As a result, the composition effect of total higher education is positive across the whole distribution and larger at the upper quantiles. Conversely, the corresponding wage structure effect is negative at the 90th quantile, and positive at the 10th and 50th quantiles. However, the positive composition effect exceeded its negative wage structure effect at the 90th quantile and is substantially larger at the upper quantiles, which increased wage inequality. The difference in the overall effect of total higher education between the 90th and 10th quantiles (0.132) accounts for118.4% of the total increase in the wage gap (0.112). The decomposition of changes in Gini and variance of log hourly wages exhibit quite similar results; although the total and individual composition effects of higher education are positive, the corresponding wage structure effects are negative and the former exceeded the latter. Thus, the expansion and diversification of higher education contributed to the increase in wage inequality from 1992 to 2000.

The findings of the decomposition of wage change from 2000 to 2013 are as follows. The composition effects of CFT and postgraduate degrees are positive throughout and larger at the upper quantiles, while the corresponding wage structure effects are consistently negative. Since the former positive effects exceed the latter negative effects (except for postgraduate degrees at the 10th quantile) and the differences are larger at the upper quantiles, the overall effects of CFT and postgraduate degrees still pushed up wages at the upper quantiles. By contrast, both composition and wage structure effects of IP/university degrees are negative across the whole distribution and larger in magnitude at the upper quantiles; thus, the overall effect of IP/university degrees depressed wages at the upper quantiles substantially.

Hence, the composition effect of total higher education is positive across the whole distribution and larger at the upper quantiles. Conversely, the corresponding wage structure effect is negative and larger in magnitude at the upper quantiles. Moreover, the negative wage structure effect exceeded its positive composition effect with larger differences at the upper quantiles. The difference in the overall negative effect of total higher education between the 90th and 10th quantiles (–0.036) accounts for 11.8% of the total reduction in the wage gap (–0.310). The decomposition of changes in Gini and variance of log wages show similar results; although the composition effect of total higher education is positive, the wage structure effect is negative and the latter exceeded the former. Thus, the expansion and diversification of higher education contributed to the wage equalisation from 2000 to 2013.

The negative association between the increasing supply of workers with vocational degrees and decreasing wage premiums for workers with university degrees in the latter period suggests that vocational education has substituted for university education. Since university education requires longer enrolment periods and higher annual tuition costs, net returns to university degrees are sometimes lower than to vocational degrees (Rodríguez *et al.*, 2016; Montoya *et al.*, 2017). This may primarily explain the recent substitution of vocational education for university education in Chile.

[Tables 2–5 near here]

6. Conclusion

This study analysed the contribution of the expansion and diversification of higher education to Chile's increase in wage inequality from 1992 to 2000 and its subsequent decrease from 2000 to 2013. For this purpose, this study decomposed the wage changes into composition and wage structure effects of each explanatory variable at different points of the wage distribution, by employing the method proposed by Firpo *et al.* (2009). The results show that the positive composition effect of higher education, derived from the increasing share of both workers with university degrees and those with vocational degrees, was substantially larger at the upper quantiles and exceeded the negative wage structure effect, thereby contributing to increasing wage inequality from 1992 to 2000. By contrast, the negative wage structure effect of higher education, primarily derived from the decreasing return to university degrees, was substantially larger at the upper quantiles and exceeded the positive composition effect, thereby contributing to decreasing wage inequality from 2000 to 2013. Thus, this study found the inverted-U relationship between the expansion of higher education and wage inequality, predicted by Knight and Sabot (1983). Moreover, this study highlighted that the substitution of vocational education for university education in the recent period concurs with the latest studies including Rodríguez *et al.* (2016) and Montoya *et al.* (2017), which found net returns to university degrees to sometimes be lower than to vocational degrees, after controlling for economic costs.

The finding that the continued expansion of vocational higher education contributed to the wage equalisation in the 2000s provides some policy implications. Diversification of higher education is important to achieve equitable distribution; thus, higher education policies that favour universities only, might not be justified. Nonetheless, it appears that Chile's higher education policies have favoured universities, especially traditional universities, in terms of public funding and student loans at the expense of vocational schools in which students from disadvantaged backgrounds are more likely to enrol. For example, direct public grant has been limited to traditional universities. Moreover, vocational schools have been de-facto excluded from the indirect public grant as it is assigned based on the enrolled number of best-scoring students in the university admission test, and such students usually enrol in universities (OECD, 2017). The state-subsidised student loan programme has also been limited to disadvantaged students of traditional universities who scored above a threshold score in the university admission test. Thus, vocational school students must instead use the state-guaranteed loan system, which is financed by commercial banks and has higher interest rates and stringent repayment enforceability (Montoya *et al.*, 2017; OECD, 2017). Thus, policies to improve public funding and student loans for vocational schools may be required.

Finally, it should be noted that the decrease in the returns to higher education in Chile in the 2000s may be attributed not only to supply-side but also to demand-side factors. For example, the commodity boom in the 2000s could favour demand for unskilled labour (Pellandra, 2015). Researching the factors explaining the decrease in the returns to higher education is beyond the scope of this study and may be an interesting subject for future research.

Notes

1. IPs provide four-year programs leading to professional degrees; CFTs provide two-year vocational programs leading to technical degrees. Meanwhile, only universities continue to offer five-year programs, leading to both professional and college degrees and allowing graduates to enrol in postgraduate schools (OECD, 2017).The number of higher education institutions (all of which are traditional universities) increased from eight universities in 1980 to 61 universities, 43 IPs, and 48 CFTs in 2017 (http://www.mifuturo.cl/index.php/donde-y-que-estudiar/tipo-de-institucion).

2. Cho and Heshmati (2015) applied another decomposition method proposed by Machado and Mata (2005). However, the method does not decompose the composition effect into the contribution of each explanatory variable (Fortin *et al*., 2011).

3. In both cases, secondary education graduates and dropouts are chosen as the base category. Each higher education category includes workers who enrol but drop out before obtaining a degree. Note that although CFT, IP, and university degrees are separated into different categories in CASEN 2000, CFT and IP degrees are aggregated into the same category in CASEN 1992 while IP and university degrees are aggregated in CASEN 2013.

4. The database is available from http://observatorio.ministeriodesarrollosocial.gob.cl/casen-multidimensional/casen/basedatos.php (accessed on June 6, 2018).

5. The data include sample weights, which are used for all estimations in this study.

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Table 1. Descriptive statistics of the variables

	1992	2000	2013
Observations	20,867	29,752	27,169
Log hourly wage			
Mean	6.702	7.074	7.495
Q10	5.965	6.289	6.884
Q50	6.597	6.937	7.388
Q90	7.753	8.188	8.474
Variance	0.613	0.636	0.479
Experience	19.284	20.415	21.998
Primary education or less	0.395	0.270	0.196
Secondary education graduates and dropouts	0.464	0.496	0.506
Higher education graduates and dropouts	0.141	0.233	0.298
CFT/IP	0.043	0.089	
University	0.094	0.133	
CFT		0.033	0.102
IP/university		0.189	0.170
Postgraduate	0.004	0.012	0.026

Note: Q10, Q50, and Q90 represent the 10th, 50th, and 90th unconditional quantiles, respectively. The number of observations is limited to the target profile described in Section 4 and additionally excludes any samples with missing values for the variables used.

Source: Authors' calculations based on data from CASEN 1992, 2000, and 2013.

Table 2. Estimation results of unconditional quantile regressions (1992 and 2000)

	1992			2000		
Explanatory variables	Q10	Q50	Q90	Q10	Q50	Q90
Primary	-0.199***	-0.308***	-0.360***	-0.149***	-0.413***	-0.214***
	(0.018)	(0.017)	(0.032)	(0.020)	(0.021)	(0.030)
CFT/IP	0.067**	0.369***	1.100***	0.110***	0.470***	0.654***
	(0.026)	(0.034)	(0.128)	(0.017)	(0.031)	(0.109)
University	0.070***	0.494***	3.259***	0.105***	0.650***	3.001***
	(0.012)	(0.018)	(0.105)	(0.012)	(0.019)	(0.122)
Postgraduate	0.102***	0.579***	4.133***	0.075***	0.614***	5.084***
	(0.027)	(0.040)	(0.526)	(0.023)	(0.045)	(0.289)
Experience	0.006***	0.019***	0.043***	0.006***	0.018***	0.029***
	(0.002)	(0.002)	(0.004)	(0.002)	(0.002)	(0.006)
Experience-squared	-0.000**	-0.000***	-0.001***	-0.000***	-0.000***	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Constant	6.016***	6.377***	6.818***	6.327***	6.616***	7.132***
	(0.029)	(0.032)	(0.059)	(0.034)	(0.039)	(0.096)
Observations	20,867	20,867	20,867	29,752	29,752	29,752
R-squared	0.089	0.271	0.351	0.140	0.361	0.375

Note: Numbers in parentheses represent standard errors; ***, **, and * indicate significance at 1%, 5%, and 10% levels, respectively. Demographic dummies (a dummy each for the head of the household and for married workers), industry dummies, informal dummy (a dummy for those working without any contract), firm size dummies, and region dummies are also included as control variables.

Table 3. Estimation results of unconditional quantile regressions (2000 and 2013)

	2000			2013		
Explanatory variables	Q10	Q50	Q90	Q10	Q50	Q90
Primary	-0.149***	-0.415***	-0.247***	-0.100***	-0.208***	-0.078**
	(0.020)	(0.021)	(0.031)	(0.016)	(0.020)	(0.033)
CFT	0.090***	0.430***	0.417**	0.043**	0.327***	0.350***
	(0.026)	(0.043)	(0.173)	(0.019)	(0.025)	(0.061)
IP/University	0.110***	0.604***	2.348***	0.091***	0.502***	2.020***
	(0.012)	(0.020)	(0.106)	(0.014)	(0.021)	(0.083)
Postgraduate	0.075***	0.612***	5.049***	-0.050	0.492***	3.713***
	(0.023)	(0.046)	(0.292)	(0.104)	(0.082)	(0.367)
Experience	0.006***	0.018***	0.036***	0.005***	0.017***	0.042***
	(0.002)	(0.002)	(0.007)	(0.002)	(0.002)	(0.006)
Experience-squared	-0.000***	-0.000***	-0.001***	-0.000**	-0.000***	-0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Constant	6.327***	6.610***	7.056***	6.889***	7.075***	7.286***
	(0.034)	(0.039)	(0.102)	(0.029)	(0.038)	(0.097)
Observations	29,752	29,752	29,752	27,169	27,169	27,169
R-squared	0.140	0.360	0.333	0.096	0.295	0.341

Note: Numbers in parentheses represent standard errors; ***, **, and * indicate significance at 1%, 5%, and 10% levels, respectively. The control variables remain the same as those in Table 2.

Table 4. Decomposition of changes in distribution statistics into composition and wage struc

	Composition effect					Wage structu
Explanatory variables	Q10	Q50	Q90	Gini	Variance	Q10
Primary	0.0248***	0.0382***	0.0447***	0.0002**	0.0052**	0.0134***
	(0.0019)	(0.0020)	(0.0039)	(0.0001)	(0.0025)	(0.0047)
Total higer education	0.0066***	0.0407***	0.2096***	0.0052***	0.1092***	0.0081*
	(0.0018)	(0.0022)	(0.0103)	(0.0003)	(0.0058)	(0.0047)
CFT/IP	0.0031**	0.0170***	0.0507***	0.0011***	0.0202***	0.0038
	(0.0013)	(0.0014)	(0.0035)	(0.0001)	(0.0021)	(0.0028)
University	0.0027***	0.0190***	0.1254***	0.0031***	0.0657***	0.0046
	(0.0008)	(0.0016)	(0.0093)	(0.0002)	(0.0049)	(0.0031)
Postgraduate	0.0008	0.0047***	0.0336***	0.0011***	0.0233***	-0.0003
	(0.0007)	(0.0008)	(0.0035)	(0.0001)	(0.0024)	(0.0011)
Experience	0.0072***	0.0219***	0.0483***	0.0011***	0.0227***	-0.0064
	(0.0020)	(0.0028)	(0.0062)	(0.0002)	(0.0036)	(0.0421)
Experience-squared	-0.0026***	-0.0076***	-0.0169***	-0.0004***	-0.0077***	-0.0143
	(0.0010)	(0.0018)	(0.0040)	(0.0001)	(0.0020)	(0.0221)
Demographic dummies	0.0014*	0.0027***	0.0054***	0.0000	-0.0005	-0.0012
	(0.0007)	(0.0009)	(0.0017)	(0.0000)	(0.0010)	(0.0122)
Industry dummies	0.0035**	0.0111***	0.0118***	-0.0000	-0.0023	0.0062
	(0.0014)	(0.0016)	(0.0034)	(0.0001)	(0.0022)	(0.0180)
Informal dummy	-0.0063***	-0.0031***	-0.0006	0.0003***	0.0042***	-0.0226***
	(0.0009)	(0.0005)	(0.0009)	(0.0000)	(0.0008)	(0.0032)
Firm size dummies	0.0088***	0.0240***	0.0361***	0.0007***	0.0129***	-0.0086
	(0.0016)	(0.0017)	(0.0035)	(0.0001)	(0.0023)	(0.0124)
Region dummies	-0.0004	0.0002	-0.0003	0.0000	0.0013*	-0.0046
	(0.0007)	(0.0010)	(0.0013)	(0.0000)	(0.0008)	(0.0085)
Constant						0.3107***
						(0.0316)
Total	0.0430***	0.1281***	0.338***	0.0072***	0.1451***	0.2808***
	(0.0038)	(0.0048)	(0.0130)	(0.0003)	(0.0071)	(0.0073)
Observations	50,619	50,619	50,619	50,619	50,619	50,619

Note: Numbers in parentheses represent standard errors; ***, **, and * indicate significance at 1%,

ːture effects of each explanatory variable (1992 to 2000)

ure effect			
Q50	Q90	Gini	Variance
-0.0284***	0.0394***	0.0007**	0.0122*
(0.0047)	(0.0106)	(0.0003)	(0.0070)
0.0301***	-0.0625***	-0.0022***	-0.0381***
(0.0045)	(0.0103)	(0.0003)	(0.0068)
0.0090***	-0.0396***	-0.0008***	-0.0176***
(0.0026)	(0.0060)	(0.0002)	(0.0040)
0.0207***	-0.0343***	-0.0013***	-0.0215***
(0.0030)	(0.0068)	(0.0002)	(0.0045)
0.0004	0.0114***	-0.0000	0.0010
(0.0011)	(0.0025)	(0.0001)	(0.0016)
-0.0296	-0.2772***	-0.0060**	-0.0625
(0.0412)	(0.0939)	(0.0028)	(0.0617)
-0.0017	0.1195**	0.0029**	0.0325
(0.0216)	(0.0493)	(0.0014)	(0.0323)
0.0595***	0.0800***	0.0016**	0.0353**
(0.0119)	(0.0272)	(0.0008)	(0.0179)
0.0016	-0.0461	0.0004	0.0155
(0.0177)	(0.0403)	(0.0012)	(0.0264)
-0.0185***	-0.0038	0.0011***	0.0182***
(0.0031)	(0.0071)	(0.0002)	(0.0047)
-0.0189	-0.0210	-0.0005	-0.0134
(0.0122)	(0.0277)	(0.0008)	(0.0182)
-0.0219***	-0.0447**	0.0000	0.0038
(0.0083)	(0.0189)	(0.0006)	(0.0125)
0.2392***	0.3139***	-0.0067***	-0.1253***
(0.0311)	(0.0709)	(0.0021)	(0.0463)
0.2114***	0.0975***	-0.0087***	-0.1217***
(0.0071)	(0.0161)	(0.0005)	(0.0107)
50,619	50,619	50,619	50,619

5%, and 10% levels, respectively.

Table 5. Decomposition of changes in distribution statistics into composition and wage structure e

	Composition effect					Wage structu
Explanatory variables	Q10	Q50	Q90	Gini	Variance	Q10
Primary	0.0111***	0.0309***	0.0184***	0.0000	0.0011	0.0098***
	(0.0010)	(0.0017)	(0.0022)	(0.0001)	(0.0012)	(0.0028)
Total higer education	0.0052***	0.0270***	0.0544***	0.0014***	0.0277***	-0.0114***
	(0.0017)	(0.0028)	(0.0101)	(0.0002)	(0.0055)	(0.0040)
CFT	0.0063***	0.0299***	0.0290***	0.0007***	0.0094***	-0.0048*
	(0.0016)	(0.0019)	(0.0041)	(0.0001)	(0.0024)	(0.0025)
IP/University	-0.0021***	-0.0114***	-0.0442***	-0.0010***	-0.0222***	-0.0033
	(0.0004)	(0.0020)	(0.0076)	(0.0002)	(0.0038)	(0.0024)
Postgraduate	0.0010**	0.0084***	0.0697***	0.0017***	0.0405***	-0.0032***
	(0.0005)	(0.0009)	(0.0059)	(0.0001)	(0.0035)	(0.0011)
Experience	0.0095***	0.0292***	0.0563***	0.0013***	0.0326***	-0.0231
	(0.0020)	(0.0029)	(0.0063)	(0.0002)	(0.0037)	(0.0329)
Experience-squared	-0.0125***	-0.0301***	-0.0518***	-0.0011***	-0.0283***	0.0192
	(0.0025)	(0.0031)	(0.0067)	(0.0002)	(0.0040)	(0.0193)
Demographic dummies	-0.0084***	-0.0306***	-0.0461***	-0.0005***	-0.0064**	-0.0033
	(0.0016)	(0.0020)	(0.0044)	(0.0001)	(0.0025)	(0.0074)
Industry dummies	0.0073***	0.0128***	0.0205***	0.0001	0.0026	0.0199
	(0.0012)	(0.0015)	(0.0034)	(0.0001)	(0.0020)	(0.0126)
Informal dummy	0.0272***	0.0166***	0.0033	-0.0012***	-0.0194***	0.0094***
	(0.0013)	(0.0011)	(0.0020)	(0.0001)	(0.0014)	(0.0014)
Firm size dummies	-0.0025***	-0.0115***	-0.0125***	-0.0003***	-0.0055***	-0.0285***
	(0.0008)	(0.0012)	(0.0020)	(0.0000)	(0.0011)	(0.0090)
Region dummies	0.0026***	0.0036***	0.0019	-0.0001	-0.0006	0.0026
	(0.0007)	(0.0011)	(0.0019)	(0.0000)	(0.0009)	(0.0061)
Constant						0.5617***
						(0.0239)
Total	0.0397***	0.0478***	0.0445***	-0.0003	0.0038	0.5562***
	(0.0038)	(0.0056)	(0.0132)	(0.0003)	(0.0070)	(0.0058)
Observations	56,921	56,921	56,921	56,921	56,921	56,921

Note: Numbers in parentheses represent standard errors; ***, **, and * indicate significance at 1%, 5%, an ffects of each explanatory variable (2000 to 2013)

ıre effect			
Q50	Q90	Gini	Variance
0.0406***	0.0331***	0.0004**	0.0113**
(0.0032)	(0.0076)	(0.0002)	(0.0045)
-0.0309***	-0.0970***	-0.0024***	-0.0823***
(0.0045)	(0.0110)	(0.0003)	(0.0066)
-0.0104***	-0.0068	-0.0001	-0.0024
(0.0028)	(0.0067)	(0.0002)	(0.0040)
-0.0174***	-0.0558***	-0.0015***	-0.0542***
(0.0027)	(0.0066)	(0.0002)	(0.0040)
-0.0031***	-0.0344***	-0.0008***	-0.0256***
(0.0012)	(0.0031)	(0.0001)	(0.0019)
-0.0283	0.1341	0.0043*	0.0216
(0.0369)	(0.0895)	(0.0023)	(0.0530)
-0.0116	-0.1458***	-0.0044***	-0.0563*
(0.0217)	(0.0527)	(0.0014)	(0.0312)
-0.0343***	-0.0001	0.0012**	0.0173
(0.0083)	(0.0201)	(0.0005)	(0.0119)
0.0083	0.0353	-0.0006	0.0091
(0.0141)	(0.0342)	(0.0009)	(0.0203)
0.0075***	0.0044	0.0001	0.0017
(0.0016)	(0.0040)	(0.0001)	(0.0023)
-0.0586***	-0.0157	0.0008	0.0154
(0.0101)	(0.0245)	(0.0006)	(0.0145)
0.0459***	0.0632***	0.0021***	0.0506***
(0.0068)	(0.0166)	(0.0004)	(0.0098)
0.4649***	0.2299***	-0.0131***	-0.1499***
(0.0268)	(0.0649)	(0.0017)	(0.0385)
0.4035***	0.2414***	-0.0117***	-0.1615***
(0.0065)	(0.0157)	(0.0004)	(0.0093)
56,921	56,921	56,921	56,921

ıd 10% levels, respectively.

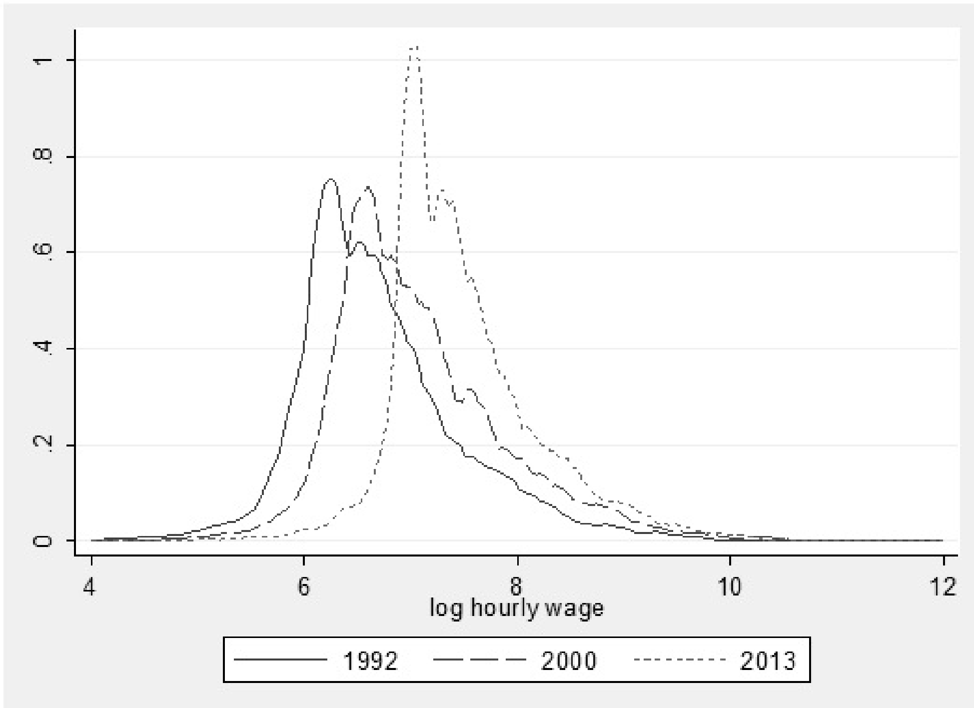

Figure 1. Estimated log wage densities in 1992, 2000, and 2013