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Decline in values of degrees and recent evolution of wage inequality: Evidence from Chile

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Abstract

Using the latest available data from nationally representative household surveys, we analyze the association between changes in returns to higher education degrees and the evolution of wage inequality in Chile from 2013–2017. Employing a decomposition method using unconditional quantile regressions, we find that a significant decline in returns to professional degrees especially from new private universities, with a larger magnitude at upper quantiles, is associated with a substantial reduction in wage inequality, especially for younger graduates. The results are robust to the correction for sample selection bias, controlling for workers' occupation categories, and the choice of the analysis period.

Keywords: higher education, returns to degree, wage inequality

JEL classification codes: I23; I24; I26; J31

1. Introduction

Over the past three decades, Latin American countries (LACs) have experienced rapid expansion in higher education. The gross enrollment rate in higher education increased from 17.0% in 1990 to 51.9% in 2017 in LACs, including Caribbean countries.[1] Such educational expansion is likely associated with wage inequality through changes in the proportion of educated workers and the return to education (Knight & Sabot, 1983). Returns to higher education and income inequality slightly increased in LACs during the 1990s. By contrast, the returns to higher education and income inequality sharply decreased during the 2000s (Gasparini et al., 2011; Figures 9 and 10 of Rodríguez-Castelán et al., 2016: 16–17).

The observed reduction in returns to higher education in LACs, which contrasts with the region's previous trend, is a crucial area of research. Such an increase in the share of educated workers decreases wage inequality as long as the return to education is negatively correlated with educational attainment, as predicted by human capital models (Coady & Dizioli, 2018; Murakami & Nomura, 2020). However, the observed reduction in returns to higher education may exceed what the quantity expansion of educated workers predicts. Moreover, the decline in the returns to higher education may not be homogenous across different types of degrees and degree-granting institutions (see Messina & Silva, 2018 for overviews; Camacho et al., 2016 for Colombia; González-Velosa et al., 2015 for Chile and Colombia).

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[1] We sourced the data from CEPALSTAT of Economic Commission for Latin America and the Caribbean (ECLAC) (https://estadisticas.cepal.org/cepalstat/WEB_CEPALSTAT/estadisticasIndicadores.asp?idioma=e, accessed on March 15, 2021).

Considered among the most successful LACs in terms of economic growth as well as far-reaching economic and institutional reforms, Chile, nonetheless, has a similarly high level of income inequality as other LACs and presents an ideal case for analyzing the association between recent changes in returns to degrees and the evolution of wage inequality. Before the reform in 1980, higher education in Chile consisted of two state universities and six private universities, which offered five-year programs leading to college degrees (Brunner, 1993; Cox, 1996). The higher education reform deregulated the country's standards for the establishments and diversified its system. Accordingly, many new private universities and non-university higher education institutions have been established with minimum requirements (Brunner, 1993; Cox, 1996). The latter comprise Professional Institutes (*Institutos Profesionales*, IPs), which provide four-year programs leading to professional degrees (*títulos profesionales*), and Technical Training Centers (*Centros de Formación Técnica*, CFTs), which provide two-year vocational programs leading to technical degrees (*títulos técnicos de nivel superior*). Meanwhile, only universities continue to offer five-year programs leading to professional and college degrees (*licenciaturas*) and allow graduates to enroll in post-graduate schools (Brunner, 1993; Cox, 1996; Espinoza & González, 2013). Moreover, universities in Chile are distinguished into (1) traditional universities, known as the Council of Rectors of Chilean Universities (*Consejo de Rectores de las Universidades Chilenas*, CRUCH), which consist of state and private universities that existed before the 1980 reform and those derived from them, and (2) new private universities founded after 1980 (Cox, 1996; Espinoza & González, 2013).

Based on these diversified higher education systems, Montoya et al. (2017) and Rodríguez et al. (2016) precisely estimate the returns to those different types of higher education degrees (i.e., technical, professional, and college degrees) by addressing the endogeneity issue due to unobserved abilities. González-Velosa et al. (2015) find that technical and professional degrees' returns are substantially heterogeneous across the degree-granting institutions. However, since those studies estimate the returns to degrees in a particular year, they do not analyze their evolution over time. Moreover, the association between the changes in returns to degrees and wage inequality evolution is beyond their analyses.

Therefore, based on the latest available data from household surveys, this study aims to analyze the association between the changes in returns to degrees and the evolution of wage inequality in Chile from 2013 to 2017. For this purpose, this study takes advantage of a method proposed by Firpo et al. (2009). By this method, we can extend the Oaxaca-Blinder (O-B) decomposition (Blinder, 1973; Oaxaca, 1973) and decompose changes in distributional statistics beyond the mean (e.g., quantiles) into a part attributable to changes in average characteristics of the workforce (e.g., an increase in the share of workers with higher education) and a part attributable to changes in returns to the characteristics (e.g., a decrease in returns to higher education degrees).

By employing this method, Fernández and Messina (2018) and Murakami and Nomura (2020) find that a decrease in education premiums, with a larger magnitude at upper quantiles, had a prominent role in decreasing wage inequality among full-time employed workers in Chile from 1990 to 2013 and 2000 to 2013, respectively.

However, Fernández and Messina (2018), who use only years of schooling as the variable indicating educational achievements, do not account for any heterogeneous returns to different types of degrees. Moreover, they include only potential experience (and their quadric terms) and a female dummy as control variables. Therefore, the estimated returns to education may contain bias due to omitted variables, and the contribution of the changes in education premiums to the reduction in wage inequality was likely to be overestimated. Although Murakami and Nomura (2020) find a significant difference between returns to technical and professional degrees, they do not consider within-degree heterogeneity associated with degree-granting institutions. Furthermore, both studies do not deal with any potential bias in the estimated returns to education associated with non-random selection of full-time employed workers.

Consequently, a novel contribution of this study to the literature is identifying the association between changes in returns to different types of degrees and the recent evolution of wage inequality in Chile after including appropriate control variables. We reveal that a significant decrease in returns to professional degrees, especially from new private universities, with a larger magnitude at upper quantiles, is associated with a substantial reduction in wage inequality, especially for younger graduates. Furthermore, we verify that the findings are robust to the correction for the sample selection bias.

This paper is organized as follows. Section 2 explains the data employed in the analysis and presents the descriptive statistics. Section 3 presents the empirical specifications and explains the decomposition method using unconditional quantile regressions. Section 4 presents the estimation results. Section 5 performs robustness checks, and the final section concludes the paper and provides some policy implications.

2. Data and descriptive statistics

The data used for the analysis were sourced from the Socioeconomic Characterization Survey (*Encuesta de Caracterización Socioeconómica Nacional*, CASEN) for 2013 and

2017.[2] CASEN is a cross-sectional household survey conducted every two or three years by the Ministry of Social Development of Chile, collaborating with the National Institute of Statistics (*Instituto Nacional de Estadísticas*, INE) and the Microdata Center of the Department of Economics at the University of Chile.[3] The survey's objectives are to measure the well-being of households in income and other related dimensions and provide necessary information to design and evaluate the country's social policies. Thus, the survey provides detailed information on demographic characteristics, education, employment, sources of income, health, and housing. The survey covered 66,725 and 70,948 households and 218,491 and 216,439 individuals in 2013 and 2017, respectively.

The sample units of the survey are selected in a probabilistic, stratified, and multistage manner so that the sample is representative at national and regional levels and geographical areas (urban and rural). The survey is carried out through face-to-face interviews by trained interviewers. The interviews are conducted with one informant per household who corresponds to the head of the household or a household member older than 18 years. During the interview, no personal information is requested (Ministerio de Desarrollo Social, 2015). The survey's response rates were 77.5% in 2013 and 75.5% in 2017 (Ministerio de Desarrollo Social, 2015: 63; 2018: 111). To minimize problems that arise due to non-responses, the survey provides non-response adjusted expansion weights (expansion factors). By using the weights, the sample is representative for the

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[2] We sourced the data from the Ministry of Social Development and Family of Chile (http://observatorio.ministeriodesarrollosocial.gob.cl/encuesta-casen-2013 and http://observatorio.ministeriodesarrollosocial.gob.cl/encuesta-casen-2017, accessed on October 3, 2015 and October 4, 2019, respectively).

[3] The former has been responsible for the sampling design and elaboration of expansion weights, while the latter has contracted to the implementation of field survey and data processing (Mnisterio de Desarrollo Social, 2015).

country at national, regional, and urban/rural levels (Ministerio de Desarrollo Social, 2015). The expansion weights are used for all estimations in this study.

We define wages as monetary earnings from a principal occupation on a regular basis, deflated by the national consumer price index (December 2008 = 1).[4] Thus, the defined wages do not include any non-regular wages from a principal occupation such as overtime wages, commissions, tips, bonuses, or any additional income from a principal occupation such as housing, transportation, and education allowances. Since the data on income variables had already been corrected and adjusted for non-response and missing income values, we do not apply further data-cleaning, including dropping outliers, to the data on wages.

The sample is limited to full-time (more than 35 hours per week) male and female employed workers aged 18 to 64. We exclude self-employed workers, part-time workers, and military personnel because their income or wages are likely to be determined differently from wages of full-time employed workers. Since this limitation is likely to lead to potential selection bias in estimated returns to degrees, we try to correct this bias using the seminal Heckman two-step procedure (Heckman, 1979) in Section 5-1.

Since the 2013 CASEN, the following surveys report the educational institution from which individuals obtained their final degree for those who attended higher

[4] We sourced the data from the Central Bank of Chile (http://www.bcentral.cl/estadisticas-economicas/series-indicadores/index_p.htm and https://si3.bcentral.cl/Siete/en, accessed on January 1, 2015 December 22, 2020, respectively).

education.[5] Meanwhile, the category of a college degree has been incorporated into the category of a professional degree. Therefore, the available degree types for our analysis are technical, professional, and post-graduate degrees, while the available institution types are CFTs, IPs, new private universities, and traditional universities. While universities can offer the above three types of degrees, IPs can offer only technical and professional degrees, and CFTs can offer only technical degrees. In this study, we set a separate category for those who did not complete a given program and thus did not obtain a degree, irrespective of the type of institution that they attended. To minimize any missing observations, we also set a category for those who did not know the type of institution they attended or did not respond to the question. The resulting degree-institution type combinations are listed in Table 1.

Table 1 presents the descriptive statistics of variables used for our wage equation presented in Section 3. We find that the reduction in wage inequality, which was observed during the 2000s as reported by Fernández and Messina (2018), Murakami and Nomura (2020), and Parro and Reyes (2017), persisted from 2013 to 2017. The log hourly wage gap between the 90th and the 10th quantiles decreased from 1.546 to 1.453. The gap between the 90th and the 50th quantiles decreased from 1.091 to 1.062. We also find that workers with higher education increased from 30.3% in 2013 to 37.0% in 2017. Although the share of any type of higher education degrees and institutions has increased, it is especially evident in workers with professional degrees. We further find an increase in the share of female employment in full-time wage

[5] Although the 2017 CASEN reports more disaggregated classification of the degree-granting institution, we have aggregated some categories such that the results corresponded with the categories in the 2013 CASEN.

workers in this period.

Figure 1 shows the estimated wage distribution for each workers' group classified by educational achievements in 2013 and 2017. The share of workers with professional degrees earning wages above the 90th percentile of the overall wage distribution has declined. Simultaneously, the share of workers with professional degrees earning wages below the 50th percentile of the overall wage distribution has increased. As a result, the wage distribution in 2017 is more symmetric. Similarly, the wage distribution of workers with technical degrees became more right-skewed in 2017. The findings indicate that the observed decrease in wage inequality is likely to be associated with the decrease in the share of higher wage earners among workers with higher education degrees.

3. Empirical specification

3.1. Wage equation

To analyze the association between educational achievements and individual wages, we estimate the wage equation for 2013 and 2017, separately. Given that recent studies find within-degree heterogeneity in the returns to degrees in Chile (González-Velosa et al., 2015; Rodríguez et al., 2016), we consider that the returns to higher education are heterogeneous across different types of degrees and degree-granting institutions (i.e., CFTs, IPs, new private universities, and traditional universities). Thus, we include dummy variables indicating an individual's final educational achievement (i.e., the degree obtained) interacted with dummy variables indicating the educational institution granting the degrees in the wage equation.

We estimate the following wage equation for each year t = 2013 and 2017, separately:

(1) $\ln w_{it} = \sum_{jt} \sum_{kt} \rho_{jkt} I(degree_{it} = j \ \ and \ institution_{it} = k) + \boldsymbol{Z}'_{it}\boldsymbol{\delta}_t + \varepsilon_{it}$,

where w_{it} represents hourly wages. $I(\cdot)$ is the indicator function taking a value of 1 if the condition is satisfied and 0 otherwise. The subscripts *i* indicates individual, *j* type of higher education degree, and *k* type of degree-granting institution. ρ_{jkt} is the return to higher education degree given the type of degree and degree-granting institution, and what we are focusing on in this study. $\boldsymbol{Z}_{it}$ represents other control variables which may affect the wage, and ε_{ijt} is an error term.

The vector of control variables $\boldsymbol{Z}_{it}$ includes years of potential labor experience (age – years of schooling – 6) and its squared term divided by 100. The vector also includes dummy variables for parental final educational achievements categories (based on secondary education as the reference category), male worker, head of the household, married worker, industry classified at the two-digit level of International Standard Industrial Classification (ISIC) Revision 3, worker with a written employment contract, regions, and living in urban areas. Since we evaluate the returns to higher education degrees relative to secondary education, a dummy variable indicating whether the individual's educational achievement is primary education or less is also included. Furthermore, since substantial proportions of individuals did not know their parental education levels or did not respond to the relevant question, as presented in Table 1, we set a separate dummy for this category to avoid dropping observations, as presented in Table 2.

The survey reports a worker's occupation at the four-digit level of the International Standard Classification of Occupations (ISCO)-88. However, we do not include the variable in the wage equation because we consider that the returns to higher education degrees include the increasing opportunities for higher-paying occupations rather than the returns within a given occupation. However, as a robustness check, we show the results controlling for the occupational categories in Section 5-3.

The inclusion of parental education achievements in the equation may require some additional explanations. We assume that an individual's parental education levels, which can be a proxy for individuals' family backgrounds, are likely to be directly correlated with the individual's wages. This argument is based on the finding that people with advantaged family backgrounds, including having educated parents, are likely to enroll in high-quality schools in Chile (Chumacero et al., 2011; Gómez et al., 2012; Hofflinger et al., 2020). Furthermore, they tend to receive significantly higher wages even after controlling for various individual characteristics, including their final educational achievement (Núñez and Gutiérrez, 2004). This is possibly because of productivity-enhancing skills like networking and discrimination (Núñez and Gutiérrez, 2004). Indeed, the dummies on parental education levels explain considerable wage variations; thus, omitting the parental education levels leads to overestimating the returns to degrees (see Table 2), supporting previous studies such as Contreras et al. (1999).[6]

3.2. Decomposition of the wage distribution

To analyze the association between changes in the returns to higher education degrees

[6] We cannot deny the possibility that the association between an individual's parental education levels and their wages arises only through the correlation with their own educational achievements thus the variables should be used as the instruments. Although the Sargan test rejects the exogeneity of the instruments (the result is available upon request), we cannot again deny the possibility that this correlation arises from a possible inclusion of some omitted variables including the individual's unobserved abilities into the error term.

and the evolution of wage inequality, we decompose the evolution of wage distribution from 2013 to 2017 into changes attributable to changes in explanatory variables (i.e., composition effect) and the returns to explanatory variables (i.e., wage structure effect). For this purpose, we employ the method of estimating unconditional quantile regressions proposed by Firpo et al. (2009), which allows the O-B decomposition at any unconditional quantiles. A clear advantage of the method is that it allows the subdivision of the overall composition and wage structure effects into the contribution of each explanatory variable (Fortin et al., 2011). Although the O-B decomposition was initially used for the decomposition between two groups over the same period, the extended O-B decomposition, based on the method by Firpo et al. (2009), is widely used to analyze the changes in wage distribution between two periods, particularly to analyze the association between educational expansion and the evolution of wage inequality (see Firpo et al., 2018).[7]

The key idea of this method is to replace the observed value of a dependent variable with an estimated value of the re-centered influence function (RIF) and regress the RIF value on the covariates (unconditional quantile regression). The RIF value at the τ-th unconditional quantile of the dependent variable $\ln w_{it}$ is given by:

$$(2) \qquad \text{RIF}\,(\ln w_{it}\,, q_t^{\tau}) = q_t^{\tau} + \frac{\tau_t - I\{\ln w_{it} \leq q_t^{\tau}\}}{f_{\ln w_{it}}(q_t^{\tau})} \ ,$$

where q_t^{τ} is the τ-th unconditional quantile of the dependent variable, $\ln w_{it}$. $I(\cdot)$ is an indicator function taking a value of 1 if the condition is satisfied and 0 otherwise.

[7] Other examples are: Fernández and Messina (2018) for Argentina, Brazil, and Chile; Murakami and Nomura (2020) for Chile; Sámano-Robles (2018) for 18 LACs; Seneviratne (2019) for Sri Lanka; Yang and Gao (2018) for China.

$f_{\ln w_{it}}(q_t^\tau)$ is the density of $\ln w_{it}$ evaluated at q_t^τ. Since the expectation of RIF at the τ-th unconditional quantile is equal to the variable's τ-th unconditional quantile and the law of iterated expectations applies in the case of RIF values, the estimated coefficients of the unconditional quantile regression indicate a marginal effect on $\hat{q}_t^\tau$ (see Note 5 and equation (4) of Firpo et al., 2009: 954, 957):

$$(3) \qquad \hat{q}_t^\tau = \mathrm{E}\left[\widehat{RIF}(\ln w_{it}, q_t^\tau)\right] = E\left[E\left(\widehat{RIF}(\ln w_{it}, q_t^\tau)\middle|\boldsymbol{X}_{it}\right)\right] = \overline{\boldsymbol{X}}_{it}'\widehat{\boldsymbol{\beta}}_t^\tau ,$$

where $\boldsymbol{X}_{it}$ is a vector of all explanatory variables in equation (1). The bar over the term denotes the mean. $\widehat{\boldsymbol{\beta}}_t^\tau$ is a vector of the estimated coefficients of the unconditional quantile regression at the τ-th quantile.

Thus, we can write the equivalent of the O-B decomposition for any unconditional quantile as the equation (35) in Fortin et al. (2011: 78). That is, the change in the wage distribution between 2013 and 2017 at the τ-th quantile is decomposed as follows:

$$(4) \qquad \hat{q}_{2017}^\tau - \hat{q}_{2013}^\tau = \overline{\boldsymbol{X}}_{2017}'\widehat{\boldsymbol{\beta}}_{2017}^\tau - \overline{\boldsymbol{X}}_{2013}'\widehat{\boldsymbol{\beta}}_{2013}^\tau$$
$$= (\overline{\boldsymbol{X}}_{2017}' - \overline{\boldsymbol{X}}_{2013}')\widehat{\boldsymbol{\beta}}_{2013}^\tau + \overline{\boldsymbol{X}}_{2017}'\left(\widehat{\boldsymbol{\beta}}_{2017}^\tau - \widehat{\boldsymbol{\beta}}_{2013}^\tau\right) .$$

In equation (4), the first term on the right-hand side represents the composition effect, which captures the change in log hourly wages at the τ-th quantile attributable to changes in the mean of explanatory variables. The second term represents the wage structure effect, which captures the change attributable to changes in returns to explanatory variables.

Finally, based on the result of equation (4), we can decompose the evolution of wage inequality measured by the difference between upper quantile U and lower quantile L (let $\tau \in \{U, L\}$) from 2013 to 2017 as follows (see equation 3.3 of Fernández & Messina, 2018: 560):

(5) $(\hat{q}^{U}_{2017} - \hat{q}^{L}_{2017}) - (\hat{q}^{U}_{2013} - \hat{q}^{L}_{2013})$

$$= \left(\overline{\boldsymbol{X}}'_{2017}\widehat{\boldsymbol{\beta}}^{U}_{2017} - \overline{\boldsymbol{X}}'_{2013}\widehat{\boldsymbol{\beta}}^{U}_{2013}\right) - \left(\overline{\boldsymbol{X}}'_{2017}\widehat{\boldsymbol{\beta}}^{L}_{2017} - \overline{\boldsymbol{X}}'_{2013}\widehat{\boldsymbol{\beta}}^{L}_{2013}\right)$$

$$= (\overline{\boldsymbol{X}}'_{2017} - \overline{\boldsymbol{X}}'_{2013})\left(\widehat{\boldsymbol{\beta}}^{U}_{2013} - \widehat{\boldsymbol{\beta}}^{L}_{2013}\right) + \overline{\boldsymbol{X}}'_{2017}\left[\left(\widehat{\boldsymbol{\beta}}^{U}_{2017} - \widehat{\boldsymbol{\beta}}^{U}_{2013}\right) - \left(\widehat{\boldsymbol{\beta}}^{L}_{2017} - \widehat{\boldsymbol{\beta}}^{L}_{2013}\right)\right].$$

The first term on the right-hand side of equation (5) represents the difference in the composition effects between the upper and lower quantiles, and the second term represents the difference in the wage structure effects between the upper and lower quantiles. Following previous studies analyzing LACs, including Fernández and Messina (2018), we choose *U* as the 90th quantile and *L* as the 50th and 10th quantiles. This choice is based on the findings that income inequality in Chile is fundamentally due to the significant inequality between the wealthiest 10 percent and the rest, while the country's inequality among the rest is relatively small (Núñez & Gutiérrez, 2004).

4. Estimation results

Table 2 reports the estimation results of the mean and unconditional quantile regressions for the selected quantiles in 2013 and 2017, respectively (Table S1 in the Supplemental file provides those for other quantiles). The returns to higher education (relative to secondary education) are heterogeneous across different types of degrees and degree-granting institutions. Expectedly, the returns to professional degrees are substantially higher than to technical degrees, supporting the findings of studies analyzing previous periods in Chile (e.g., González-Velosa et al., 2015; Murakami & Nomura, 2020; Puentes, 2000; Rodríguez et al., 2016; Urzúa, 2017). Furthermore, we find that the degree-granting institutions are an essential source of within-degree heterogeneity in the returns, supporting the finding of González-Velosa et al. (2015). The types of institutions significantly matter in the case of professional degrees: the returns to traditional universities are substantially higher than those to private universities on average, and the gap further widened from 2013 to 2017. Additionally, we find that the returns to higher education, especially technical education, are substantially lower when workers did not complete the given program and thus did not obtain a degree. The returns to higher education degrees decreased from 2013 to 2017. However, the trend is heterogeneous across the different quantiles. It is also different between the types of degrees and degree-granting institutions, as discussed in greater detail below.

Subsequently, we discuss the decomposition results. Table 3 reports the detailed decomposition results of each explanatory variable at the selected quantiles (see Table S-2 in the Supplemental file for other quantiles). We visually summarize the results in Figures 2–4. Figure 2 shows overall wage changes at quantiles from the 5th to the 95th and their decomposition into the composition and wage structure effects. Figure 3 decomposes the overall composition and wage structure effects into the contribution of four groups of explanatory variables (education, experience, gender, and all other variables). Further, Figure 4 reports the detailed composition and wage structure effects of our main interest variables, the higher education degrees. Finally, Table 4 reports each variable's contribution of the difference in the composition and wage structure effects between the selected quantiles to the evolution of wage inequality, as presented by equation (5).

From Figure 2, we find that the composition effect almost monotonically increases when moving from the lower to upper quantiles. In contrast, the opposite trend is observed in the wage structure effect (though there are substantial fluctuations between quantiles): the former effect is 0.005 and 0.083 log points at the 10th and 90th quantiles, respectively, whereas the latter effect is 0.133 and -0.039 log points at the 10th and 90th quantiles, respectively (see Table 3). As a whole, the overall wage increases are particularly more considerable at the lower parts of the distribution (e.g., 0.138 log point at the 10th quantile) and more minor at the upper parts of the distribution (e.g., 0.045 log point at the 90th quantile), thereby indicating the reduction in wage inequality from 2013 to 2017. Additionally, we find that the wage changes are relatively similar in the middle of the distribution (between the 25th and 75th quantiles) except for the 35th and 45th quantiles. Thus, this observed trend of wage changes during the analysis period justifies using log wage gap between the upper (the 90th quantile) and lower (the 10th quantile) ends of the distribution as our inequality measure.

Figure 3 and Table 3 show that the education dummies had a prominent role in the observed upward trend in the composition effect, while the negative wage structure effect of higher education is associated with the observed smaller wage increases at the upper quantiles. Therefore, the findings show that the observed compositional changes toward more workers with higher education degrees, as shown in Table 1, are associated with increasing inequality, whereas the decrease in their returns is associated with decreasing inequality. The finding concurs with those of Fernández and Messina (2018) and Murakami and Nomura (2020). As reported in Table 4, the total wage structure effect of higher education is -0.068, accounting for 73.3% of the decrease in the 90-10 log wage gap.

A novel contribution of this study is the finding that the wage structure effects of higher education are substantially heterogeneous across the types of degrees and degree-granting institutions. We find that higher education's negative wage structure effect, with a larger magnitude at the upper quantiles, is primarily linked to professional degrees, especially from private universities (see Figure 4 and Table 3). Given the degree-institution type combinations, professional degrees from private and traditional universities contribute most significantly to the reduction in wage inequality. The decreases in the returns to those degrees account for 36.7% and 28.7% of the total decrease in the 90-10 log wage gap, respectively (see Table 4). The returns to post-graduate degrees show a similar trend but to a lesser extent (see Figure 4 and Tables 3–4).

Conversely, the returns to technical degrees are relatively stable from 2013 to 2017, and those obtained from IPs increased at the 90th quantile (see Figure 4 and Table 3). Since the new private universities require more extended enrollment periods and higher annual tuition costs than IPs and CFTs, technical degrees are likely to be an alternative to professional degrees, especially for those who cannot gain admittance to traditional universities. Finally, we find that other explanatory variables, such as gender, do not account for the observed reduction in wage inequality because the changes in male premiums are similar among the different quantiles (see Figure 4 and Table 3). In summary, the significant decline in the values of professional degrees, especially from private universities, is primarily associated with the observed reduction in wage inequality from 2013 to 2017.

The revealed decline in the values of professional degrees, especially from private universities, may require further explanations. Although the increase in the relative supply of workers with higher education can explain the observed decline partially, it is not sufficient to account for the entire decline. For example, Murakami (2013) finds the estimated coefficient of the relative supply of college-educated workers to be -0.1652 (i.e., the inverse of the elasticity of substitution between college-educated and unskilled workers) in Chile for the previous period.[8] This estimate predicts that the observed increase in the share of workers with higher education (from 0.303 in 2013 to 0.370 in 2017, see Table 2) leads to a 0.050 log point decrease in the return to higher education. Thus, the actual 0.057 log point decrease in the return is more significant than predicted.[9] Moreover, the quantitative change may not account for the decline in the values of particular types of degrees.

The observed decline in degrees values might be associated with the quality of particular types of higher education. For example, Messina and Silva (2018) point out that the expansion of higher education might have been accompanied by a deterioration in the quality of degrees because of the lower quality of newly created institutions and programs in LACs (see Camacho et al., 2016 for Colombia; González-Velosa et al., 2015 for Chile and Colombia). In this case, the returns to particular degrees are likely to decrease significantly among younger graduates. Further, it is possible that the returns to degrees among older workers significantly decreased because their skills no longer match the current demand and have been replaced by machines (see Campos-Vázquez et al, 2016 for Mexico)

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[8] Note that Table 4.1 of Gasparini et al. (2011: 32) provides similar estimation results from 16 LACs.

[9] Note that the increase in the log of the relative share of workers with higher education from 2013 to 2017 (i.e., log (0.370/ (1 – 0.370)) – log (0.303/ (1 – 0.303)) = 0.300) multiplied by the estimated coefficient -0.1652 yields the value -0.050. Also note that the wage structure effect of overall higher education, -0.021 (see Table 4), divided by the share of workers with higher education in 2017 (0.370), yields the value -0.057.

Considering those possibilities, we analyze the association between the changes in the values of degrees and the evolution of wage inequality across different age groups. We find that the decline in the values of professional degrees from private universities, with a larger magnitude at the 90th quantile, is more evident among younger workers (aged between 18 and 30 years) than the entire sample (see Table S3 and S5 in the Supplemental file). Therefore, the decline in the values of degrees leads to equal wage distribution for the younger aged individuals: the decline in the values of professional degrees accounts for more than 100% of the observed reduction in the 90-10 and 90-50 log wage gaps; the decline in the values of professional degrees from private universities alone accounts for almost 60% of the reductions (see Table 5). Moreover, among younger workers, the values of technical degrees, especially from private universities, show a similar trend to the above but to a lesser extent (see Table 5).

By contrast, among the older workers aged between 51 and 64 years (i.e., born between 1949 and 1966) who enrolled in higher education before the higher education reform in 1980, the returns to degrees do not decline irrespective of the types of degrees and institutions. On the contrary, the values of professional degrees from traditional universities increased on average among this age group, and the increase is more significant in magnitude at the 90th quantile (see Table S4 and S6 in the Supplemental file). Considering that they obtained their technical or professional degrees from new private universities after gaining work experience, and such degrees are more likely to be associated with their professions, the stable returns to those types of degrees are plausible. We note that the decrease in the experience premium primarily accounts for the reduction in wage inequality among this age group (see Table 5).

In summary, we find that the values of professional degrees, especially from private universities, notably declined among younger workers, which might be associated with the lower quality of this particular type of institutions and their programs.

5. Robustness checks

5.1. Selection-bias corrections

The limitation of our sample to full-time employed workers may lead to biased estimates in the returns to degrees, particularly for females, since a larger share of females in this study are non-participants. That is, the female participation share (share of participants to the sum of participants and non-participants) is 0.433 (19,859 out of 45,861) in 2013 and 0.481 (21,650 out of 44,971) in 2017, whereas the male participation share is 0.833 (32,020 out of 38,424) in 2013 and 0.816 (31,087 out of 38,113) in 2017 (see Tables S12 to A14 in the Supplemental file).[10] Since educated individuals are more likely to become full-time employed workers (see Contreras et al., 2011 for the case of Chile), this non-random selection can lead to underestimating the returns to degrees. If this selectivity bias changes over time, our decomposition results can also suffer from the bias. Thus, following Seneviratne (2019), we apply the seminal Heckman two-step approach to our decomposition analysis to address this issue.

[10] Due to very few observations of male post-graduates who did not know their degree-granting institutions or did not respond to this question, we cannot estimate the coefficient for this category of the Probit selection equation (A-1) in 2013. Therefore, we exclude the workers of this category in both 2013 and 2017 in advance. Due to this exclusion, the numbers of observations of male participants decreased from 32,032 to 32,020 in 2013 and from 31,103 to 31,087 in 2017, respectively.

The processes are as follows (see the Appendix for more detail). First, we estimate the Probit selection equation from which the selectivity-correction term (inverse Mills ratio) is estimated for each year. Second, including the correction term, we estimate the wage equation for each year. Since an exclusion restriction variable (the number of children under the age of six years in a given household) is likely to be associated with the participation differently between genders, we separately estimate the selection and wage equations for males and females. Finally, following Neuman and Oaxaca (2004), we decompose all explanatory variables, including the correction term, into the composition and wage structure effects.

We find that workers with higher education degrees are more likely to become full-time employed workers (see Table S12 in the Supplemental file), as expected, and the coefficient on the correction term is positive in 2013 and 2017 (see Tables S13 and S14 in the Supplemental file). Thus, the returns to degrees estimated without the sample selection correction term tend to be underestimated in both years (see Tables S7 and S8 in the Supplemental file for the estimation results of the wage equation without the correction term for males and females, respectively). However, the observed decline in the values of professional degrees, with a larger magnitude at the 90th quantile, is robust to the inclusion of the correction term (see Tables A13 and A14 in the Supplemental file). Moreover, the decline is associated with the reduction in wage inequality, especially for females: the sizable decline accounts for 32.0% and 159.9% of the reduction in the 90-10 log wage gap for males and females, respectively (see Table A1).

5.2. Different analysis period

To confirm that the observed decline in the returns to professional degrees and its association with the reduction in wage inequality are robust to the choice of analysis period and continuous trend, it is helpful to include the data from the 2015 CASEN in our analysis. Considering that the descriptive statistics of 2015 are relatively similar to those of 2013 (see Table S15 in the Supplemental file), we additionally perform the decomposition analysis from 2015 to 2017. Since the 90-50 log wage gap is stable in this period, we only show the contribution to the reduction in the 90-10 log wage gap in Table A2.

As observed in the analysis period from 2013 to 2017, we find that the returns to professional degrees from private and traditional universities substantially declined from 2015 to 2017, with a larger magnitude at the 90th quantile (see Table S17 in the Supplemental file), which is strongly associated with the reduction in wage inequality; the decline accounts for 91.1% of the reduction in the 90-10 log wage gap in this period (see Table A2). The returns of technical and post-graduate degrees also declined in this period (see Table A2). In summary, the observed declines in the returns to degrees and their associations with wage inequality reduction are robust trends that are concentrated in the period from 2015 and 2017.

5.3. Occupation controls

Our final robustness check is to include workers' occupation categories in the wage equation. We find that the inclusion of occupation dummies (the reference category is elementary occupations) provides similar estimation results in the wage equation (see Table S18 in the Supplemental file) and the decomposition analysis (see Table S19 in the Supplemental file). The magnitudes of the contributions of the higher education degrees to the reduction in wage inequality are also similar; the decline in the values of professional degrees accounts for 69.1% of the reduction in the 90-10 log wage gap (see Table A3), which is comparable to the previous results of 76.8% (see Table 4). In other words, the correlation between the final education achievements and the occupation choices was relatively stable in the period from 2013 to 2017.

6. Concluding remarks

After increasing returns to higher education and wage inequality in the 1990s, LACs have experienced a significant reduction in both since the early 2000s. Considering that the recent decline in the returns to higher education degrees may not be homogenous across different types of degrees and degree-granting institutions, an empirical analysis to identify the association between the changes in returns to different types of degrees and the recent evolution of wage inequality is highly required. In this context, Chile presents a fascinating case study because its higher education has experienced significant expansion and diversification.

Thus, this study analyzed this association between changes in returns to degrees and the evolution of wage inequality in Chile from 2013 to 2017 using the latest available data from nationally representative household surveys. For this purpose, this study takes advantage of a method proposed by Firpo et al. (2009), which allowed us to decompose changes in wages at any unconditional quantile into composition and wage structure effects. As observed in the previous period in Chile (e.g., Fernández and Messina, 2018; Murakami & Nomura, 2020), we found that the returns to higher education degrees continuously decreased in general, with a larger magnitude at the upper quantiles, associated with the reduction in wage inequality among full-time employed workers during this period. However, we found that the returns to degrees declined heterogeneously across the types of degrees (i.e., technical, professional, and post-graduate degrees) and degree-granting institutions. We found that the values of professional degrees, especially from new private universities, remarkably declined, and the decline was associated with a substantial part of the reduction in wage inequality. Since the results are more evident among younger workers, the decline might be related to the lower quality of new private universities' programs. Finally, we verified that the findings are robust to the selection of full-time employed workers, controlling for workers' occupation categories, and the choice of the analysis period.

As discussed above, the revealed decline in the values of degrees, especially from private universities, might indicate that these universities have not necessarily succeeded in terms of quality assurance. It is known that higher education policies in Chile have strongly favored traditional universities in terms of accreditation systems, direct public funding, and student loans (see Espinoza & González, 2013; Montoya et al., 2017; Solís, 2017). For example, only students of traditional universities are eligible for the University Credit Solidarity Fund (*Fondo Solidario de Crédito Universitario*, FSCU), and students of new private universities must rely on the State Guaranteed Loan System (*Crédito con Aval del Estado*, CAE), which is the least generous form of financial aid (OECD, 2017). Thus, workers who graduated from low-quality new private universities have low income and job status benefits and have to repay their student loans under poor conditions. Although some issues have been addressed, such a situation may underlie a growing dissatisfaction with the higher education system, which can be at least one of the causes for the recent widespread protests in Chile.

Therefore, policies to ensure the quality of education at the new private universities are required.

Finally, we note that although we controlled for selection bias and as many observable variables as possible, including parental education levels, we still cannot interpret our results as direct causal effects of changes in values of degrees on the reduction in wage inequality because we did not address the endogeneity issue due to individuals' unobserved abilities. Furthermore, to show that the decline in the values of degrees are related to the quality of institutions, we further need to control for individuals' skills before enrolling in higher education institutions. Such an analysis is beyond the scope of this study; however, especially from a policy perspective, it is a interesting subject for future research.

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Appendix

Detailed process of the decomposition with correction for selection bias

First, we estimate a Probit selection equation for the sample of potential wage earners aged between 18 and 64, including unemployed and non-labor force participants except for those who reported that their reasons for not seeking employment were either enrolling in school, own illness or disability, or receiving pensions. The independent variables in the participation equation include all of the explanatory variables in the wage equation except for the current work description (i.e., the industry affiliation and employment contract). We also include the following exclusion restrictions: (1) the sum of an individual's total non-labor income (assets income and transfer income) and income of other family members (in million pesos), and (2) the number of children under the age of six years in the household. Since an individual with a higher non-labor income has a higher reservation wage in general, the individual is less likely to be a full-time employed worker, regardless of their gender.

The number of children under the age of six is likely to be associated with participation differently for each gender. If males tend to be the primary earners in the household and females tend to have more responsibility for childcare, the number of children is likely to correlate positively with full-time labor participation for males but negatively for females. Contreras et al. (2011) find the negative correlation between the number of young children and the labor participation for females and the positive correlation for males in Chile. Considering this gender difference in the exclusion restriction variable, we separately estimate the following selection equation for males and females (see Table S12 in the Supplemental file for the estimation results):

(A-1) $L_{it} = I\{\boldsymbol{H}'_{it}\boldsymbol{\gamma}_t + u_{it} > 0\}$, where L_{it} is a binary variable, taking a value of 1 if an individual *i* becomes a full-time employed worker and 0 otherwise. *H* is a vector of explanatory variables that determine the full-time labor participation. u_{it} is an error term (note that the variance of the error term σ_{ut} is normalized to 1).

The estimation results of the Probit selection equation show that the marital status and the number of children are positively correlated with the full-time labor participation for males, whereas they are negatively correlated for females, as expected. The coefficient of total non-labor income is negative for both males and females but weakly or is not significant (see Table S12 in the Supplemental file).

Second, we include the estimated inverse Mills ratio (the selectivity-correction term) $\hat{\lambda}_{it} = \frac{\phi(\boldsymbol{H}'_{it}\hat{\gamma}_t)}{\Phi(\boldsymbol{H}'_{it}\hat{\gamma}_t)}$ (where $\phi(\cdot)$ and $\Phi(\cdot)$ are the density and cumulative distribution functions of the standard normal distribution, respectively) as an additional variable in the wage equation (1):

(A-2) $\ln(w_{it}) = \boldsymbol{X}'_{it}\boldsymbol{\beta}_t + \theta_t\hat{\lambda}_{it} + \varepsilon_{it}$,

where $\theta_t = \mathrm{cov}(\sigma_{\varepsilon t}, \sigma_{ut}) = \sigma_{\varepsilon ut}$. In the case of adding the correction term, we estimate the wage equation separately for males and females (see Tables S13 and S14 in the Supplemental file for estimation results for males and females, respectively).

Finally, following Neuman and Oaxaca (2004), we decompose the effect of explanatory variables, including the correction term, into the composition and wage structure effect. To apply the O-B decomposition to the correction term, we construct the following counterfactual values of inverse Mills ratios for 2017, where individuals in 2017 would face the same coefficients of the selection equation faced by individuals in 2013:

(A-3) $\hat{\lambda}^0_{i2017} = \frac{\phi(\boldsymbol{H}'_{i2017}\widehat{\boldsymbol{\gamma}}_{2013})}{\Phi(\boldsymbol{H}'_{i2017}\widehat{\boldsymbol{\gamma}}_{2013})}$.

Using the mean value of the counterfactual inverse Mills ratio $\bar{\lambda}^0_{2017}$, we can decompose the change in the mean value of the correction term between t = 2013 and t = 2017 as follows (see equation (8) of Neuman and Oaxaca, 2004: 6):

(A-4)
$$\begin{aligned}\hat{\theta}_{2017}\bar{\lambda}_{2017} - \hat{\theta}_{2013}\bar{\lambda}_{2013} &= \hat{\theta}_{2013}(\bar{\lambda}^0_{2017} - \bar{\lambda}_{2013}) + \hat{\theta}_{2013}(\bar{\lambda}_{2017} - \bar{\lambda}^0_{2017}) \\ &\quad + (\hat{\theta}_{2017} - \hat{\theta}_{2013})\bar{\lambda}_{2017} \\ &= \hat{\theta}_{2013}(\bar{\lambda}^0_{2017} - \bar{\lambda}_{2013}) + \hat{\theta}_{2017}\bar{\lambda}_{2017} - \hat{\theta}_{2013}\bar{\lambda}^0_{2017} .\end{aligned}$$

The first term in the right-hand side of equation (A-4) represents the log wage change attributable to changes in the explanatory variables that determine the selection probability (we refer to the composition effect of the inverse Mills ratio). The last two terms represent the log wage change attributable to changes in the coefficients of explanatory variables in the selection equation and change in the covariance between the selection equation error term and the wage equation error term (we refer to the wage structure effect of the inverse Mills ratio).

Therefore, based on equation (A-4), we can propose the following extension of the decomposition of the wage change from 2013 to 2017 at the τ-th unconditional quantile expressed in equation (4) as follows (see equations (12) and (14) of Neuman and Oaxaca, 2004: 7–8) for the case of mean regression):

(A-5)
$$\begin{aligned}\hat{q}^{\tau}_{2017} - \hat{q}^{\tau}_{2013} &= (\overline{\boldsymbol{X}}'_{2017} - \overline{\boldsymbol{X}}'_{2013})\widehat{\boldsymbol{\beta}}^{\tau}_{2013} + \hat{\theta}^{\tau}_{2013}(\bar{\lambda}^0_{2017} - \bar{\lambda}_{2013}) \\ &\quad + \overline{\boldsymbol{X}}'_{2017}(\widehat{\boldsymbol{\beta}}^{\tau}_{2017} - \widehat{\boldsymbol{\beta}}^{\tau}_{2013}) + \hat{\theta}^{\tau}_{2017}\bar{\lambda}_{2017} - \hat{\theta}^{\tau}_{2013}\bar{\lambda}^0_{2017} .\end{aligned}$$

The decomposition analysis with the sample selection correction term reveals that the negative wage structure effect of the correction term driven by the decline in the covariance between the selection equation error term and the wage equation error term, with a larger magnitude at the 90th quantile (see Tables S13 and S14 in the Supplemental file), is strongly associated with the reduction in wage inequality for both males and females (see Table A1). However, the composition effect of the correction term is associated with increasing and decreasing wage inequality for males and females, respectively (see Table A1).

Table A1. Contribution of the difference in the composition and wage structure effects between selected quantiles to the evolution of wage inequality from 2013 to 2017 for males and females, with the selectivity correction term.

	Male				Female			
	Q90-Q10		Q90-Q50		Q90-Q10		Q90-Q50	
2013	1.5500		1.0533		1.5356		1.0730	
2017	1.4121		0.9948		1.4413		1.0263	
Overall difference	-0.1378	100.00%	-0.0586	100.00%	-0.0943	100.00%	-0.0467	100.00%
Total composition effect	0.0919	-66.71%	0.0759	-129.49%	0.0655	-69.42%	0.0315	-67.36%
Primary education or less	0.0030	-2.17%	0.0007	-1.16%	0.37%	-3.89%	0.22%	-4.61%
Higher education	0.1056	-76.62%	0.0844	-144.05%	12.12%	-128.49%	9.53%	-203.95%
Technical degree	0.0107	-7.80%	0.0050	-8.60%	0.44%	-4.68%	-0.02%	0.39%
CFT	0.0001	-0.08%	-0.0001	0.16%	-0.0039	4.14%	-0.0010	2.09%
IP	0.0033	-2.37%	0.0012	-2.05%	0.0046	-4.85%	0.0020	-4.27%
Private university	0.0031	-2.22%	0.0025	-4.28%	0.0005	-0.56%	-0.0014	2.92%
Traditional university	0.0017	-1.26%	0.0002	-0.40%	0.0038	-4.05%	0.0024	-5.19%
Does not know/Does not respond	0.0017	-1.26%	0.0010	-1.68%	0.0001	-0.13%	0.0000	0.00%
Incomplete	0.0008	-0.60%	0.0002	-0.36%	-0.0007	0.77%	-0.0023	4.84%
Professional degree	0.0697	-50.57%	0.0568	-96.96%	0.0889	-94.24%	0.0709	-151.71%
IP	0.0110	-8.02%	0.0079	-13.53%	0.0140	-14.85%	0.0101	-21.61%
Private university	0.0159	-11.53%	0.0129	-22.05%	0.0234	-24.84%	0.0183	-39.23%
Traditional university	0.0449	-32.61%	0.0386	-65.84%	0.0557	-59.04%	0.0458	-98.00%
Does not know/Does not respond	-0.0044	3.17%	-0.0034	5.84%	-0.0037	3.97%	-0.0031	6.62%
Incomplete	0.0022	-1.59%	0.0008	-1.38%	-0.0005	0.51%	-0.0002	0.50%
Post-graduate degree	0.0251	-18.24%	0.0226	-38.49%	0.0279	-29.56%	0.0246	-52.63%
Private university	0.0067	-4.84%	0.0058	-9.91%	0.0063	-6.66%	0.0054	-11.55%
Traditional university	0.0183	-13.29%	0.0167	-28.44%	0.0212	-22.46%	0.0188	-40.27%
Does not know/Does not respond					-0.0021	2.23%	-0.0019	4.04%
Incomplete	0.0002	-0.12%	0.0001	-0.14%	0.0025	-2.67%	0.0023	-4.85%
Experience	0.0067	-4.87%	0.0060	-10.17%	0.0026	-2.77%	0.0024	-5.06%
Experience-squared	-0.0142	10.27%	-0.0125	21.33%	-0.0081	8.61%	-0.0077	16.48%
Father's educational achievements	-0.0066	4.80%	-0.0063	10.74%	-0.0209	22.11%	-0.0389	83.30%
Mother's educational achievements	-0.0026	1.91%	-0.0036	6.18%	0.0271	-28.69%	0.0392	-83.81%

Demographic dummies	-0.0226	16.42%	-0.0194	33.06%	0.0274	-29.05%	0.0244	-52.22%
Industry dummies	-0.0011	0.81%	0.0017	-2.87%	-0.0081	8.62%	-0.0087	18.62%
Formal	-0.0007	0.48%	-0.0004	0.72%	-0.0014	1.52%	-0.0003	0.74%
Region dummies	-0.0004	0.31%	0.0002	-0.37%	0.0023	-2.43%	0.0019	-3.98%
Urban	-0.0008	0.57%	-0.0011	1.82%	-0.0009	0.94%	-0.0008	1.80%
Inverse Mills ratio	0.0256	-18.61%	0.0262	-44.73%	-0.0793	84.09%	-0.0772	165.33%
Total wage structure effect	-0.2298	166.71%	-0.1345	229.49%	-0.1598	169.42%	-0.0782	167.36%
Primary education or less	-0.0016	1.18%	0.0039	-6.58%	0.0148	-15.65%	0.0124	-26.54%
Higher education	-0.0531	38.51%	-0.0544	92.87%	-0.1799	190.71%	-0.2086	446.63%
Technical degree	-0.0100	7.25%	-0.0084	14.36%	-0.0119	12.57%	-0.0198	42.38%
CFT	0.0035	-2.53%	0.0035	-5.93%	-0.0057	5.99%	-0.0033	6.98%
IP	-0.0056	4.03%	-0.0058	9.87%	-0.0098	10.39%	-0.0210	44.93%
Private university	-0.0077	5.56%	-0.0068	11.63%	0.0031	-3.26%	0.0046	-9.87%
Traditional university	0.0035	-2.56%	0.0035	-5.94%	-0.0049	5.16%	-0.0044	9.36%
Does not know/Does not respond	-0.0029	2.08%	-0.0022	3.69%	0.0010	-1.03%	0.0005	-0.98%
Incomplete	-0.0009	0.66%	-0.0006	1.04%	0.0044	-4.68%	0.0038	-8.03%
Professional degree	-0.0441	32.02%	-0.0460	78.56%	-0.1508	159.87%	-0.1674	358.40%
IP	-0.0012	0.87%	-0.0016	2.66%	-0.0124	13.18%	-0.0148	31.73%
Private university	-0.0246	17.84%	-0.0236	40.36%	-0.0638	67.67%	-0.0621	132.85%
Traditional university	-0.0190	13.75%	-0.0240	41.04%	-0.0631	66.91%	-0.0796	170.31%
Does not know/Does not respond	-0.0002	0.15%	-0.0003	0.47%	-0.0042	4.42%	-0.0056	11.97%
Incomplete	0.0008	-0.59%	0.0035	-5.97%	-0.0073	7.68%	-0.0054	11.54%
Post-graduate degree	0.0011	-0.77%	0.0000	-0.05%	-0.0172	18.27%	-0.0214	45.85%
Private university	0.0020	-1.44%	0.0020	-3.40%	-0.0018	1.93%	-0.0029	6.11%
Traditional university	-0.0042	3.05%	-0.0053	9.07%	-0.0100	10.63%	-0.0123	26.31%
Does not know/Does not respond					-0.0006	0.66%	-0.0007	1.52%
Incomplete	0.0033	-2.37%	0.0034	-5.72%	-0.0048	5.05%	-0.0056	11.91%
Experience	-0.2610	189.38%	-0.2729	465.74%	-0.0425	45.08%	-0.1054	225.60%
Experience-squared	0.1355	-98.30%	0.1276	-217.76%	0.0473	-50.09%	0.0902	-193.04%
Father's educational achievements	-0.1299	94.22%	-0.1697	289.62%	0.0670	-70.99%	0.0627	-134.25%
Mother's educational achievements	0.0276	-20.00%	0.0511	-87.23%	-0.0586	62.11%	-0.0824	176.47%
Demographic dummies	-0.0717	52.04%	-0.0762	130.05%	0.0527	-55.83%	0.0599	-128.28%
Industry dummies	-0.0373	27.09%	-0.0632	107.79%	0.1289	-136.67%	0.0934	-199.87%
Formal	0.0887	-64.38%	0.0238	-40.55%	0.1303	-138.15%	-0.0114	24.37%
Region dummies	0.0148	-10.76%	0.0255	-43.54%	0.0432	-45.74%	0.0499	-106.82%

Urban	0.0147	-10.66%	0.0379	-64.72%	-0.1727	183.07%	-0.1663	355.90%
Constant	0.3237	-234.88%	0.5069	-865.12%	0.1717	-181.97%	0.4826	-1033.14%
Inverse Mills ratio	-0.2802	203.27%	-0.2748	468.93%	-0.3619	383.55%	-0.3552	760.34%

Note: % indicates the contribution of the respective variable to the evolution of wage inequality between the selected quantiles.

Table A2. Contribution of the difference in the composition and wage structure effects between selected quantiles to the evolution of wage inequality from 2015 to 2017.

	All workers (18-64)	
	Q90-Q10	
2015	1.5073	
2017	1.4528	
Overall difference	-0.0545	100.00%
Total composition effect	0.0234	-42.97%
Primary education or less	-0.0004	0.76%
Higher education	0.0702	-128.76%
Technical degree	0.0038	-6.92%
CFT	-0.0010	1.80%
IP	0.0021	-3.80%
Private university	0.0006	-1.16%
Traditional university	0.0011	-2.07%
Does not know/Does not respond	0.0008	-1.53%
Incomplete	0.0001	-0.16%
Professional degree	0.0431	-79.15%
IP	0.0030	-5.46%
Private university	-0.0019	3.44%
Traditional university	0.0385	-70.56%
Does not know/Does not respond	0.0026	-4.85%
Incomplete	0.0009	-1.72%
Post-graduate degree	0.0233	-42.69%
Private university	0.0031	-5.64%
Traditional university	0.0192	-35.22%
Does not know/Does not respond	0.0023	-4.16%
Incomplete	-0.0013	2.33%
Experience	-0.0036	6.65%
Experience-squared	0.0006	-1.17%
Father's educational achievements	-0.0073	13.36%
Mother's educational achievements	-0.0255	46.88%
Male	-0.0006	1.03%
Demographic dummies	-0.0046	8.43%
Industry dummies	-0.0087	16.00%
Formal	0.0029	-5.38%

Region dummies	0.0006	-1.08%
Urban	-0.0002	0.31%
Total wage structure effect	-0.0779	142.97%
Primary education or less	-0.0086	15.70%
Higher education	-0.0646	118.63%
Technical degree	-0.0027	4.90%
CFT	-0.0004	0.67%
IP	-0.0045	8.32%
Private university	0.0001	-0.16%
Traditional university	0.0007	-1.22%
Does not know/Does not respond	-0.0004	0.66%
Incomplete	0.0018	-3.37%
Professional degree	-0.0497	91.13%
IP	0.0003	-0.62%
Private university	-0.0260	47.80%
Traditional university	-0.0287	52.70%
Does not know/Does not respond	0.0034	-6.16%
Incomplete	0.0014	-2.59%
Post-graduate degree	-0.0123	22.59%
Private university	-0.0001	0.20%
Traditional university	-0.0081	14.86%
Does not know/Does not respond	-0.0021	3.84%
Incomplete	-0.0020	3.69%
Experience	0.1759	-322.72%
Experience-squared	-0.0781	143.27%
Father's educational achievements	-0.0667	122.43%
Mother's educational achievements	0.0243	-44.63%
Male	0.0185	-33.94%
Demographic dummies	-0.0660	121.02%
Industry dummies	-0.0208	38.11%
Formal	0.2197	-403.22%
Region dummies	-0.0301	55.17%
Urban	-0.0100	18.32%
Constant	-0.1716	314.83%

Note: % indicates the contribution of the respective variable to the evolution of wage inequality between the selected quantiles.

Table A3. Contribution of the difference in the composition and wage structure effects between selected quantiles to the evolution of wage inequality from 2013 to 2017, with occupation dummies.

	All workers (18-64)			
	Q90-Q10		Q90-Q50	
2013	1.5461		1.0907	
2017	1.4528		1.0618	
Overall difference	-0.0934	100.00%	-0.0289	100.00%
Total composition effect	0.0681	-72.92%	0.0496	-171.38%
Primary education or less	-0.0005	0.58%	-0.0019	6.55%
Higher education	0.0556	-59.56%	0.0371	-128.35%
Technical degree	0.0014	-1.53%	-0.0031	10.87%
CFT	0.0001	-0.08%	0.0007	-2.34%
IP	-0.0012	1.24%	-0.0032	10.90%
Private university	0.0017	-1.80%	0.0009	-3.03%
Traditional university	0.0016	-1.74%	0.0004	-1.39%
Does not know/Does not respond	-0.0002	0.19%	-0.0004	1.28%
Incomplete	-0.0006	0.65%	-0.0016	5.46%
Professional degree	0.0390	-41.72%	0.0271	-93.63%
IP	0.0043	-4.65%	0.0016	-5.53%
Private university	0.0087	-9.37%	0.0057	-19.62%
Traditional university	0.0267	-28.64%	0.0206	-71.37%
Does not know/Does not respond	-0.0015	1.60%	-0.0008	2.91%
Incomplete	0.0006	-0.66%	0.0000	-0.03%
Post-graduate degree	0.0152	-16.31%	0.0132	-45.59%
Private university	0.0038	-4.11%	0.0031	-10.89%
Traditional university	0.0118	-12.68%	0.0105	-36.31%
Does not know/Does not respond	-0.0011	1.21%	-0.0010	3.56%
Incomplete	0.0007	-0.73%	0.0006	-1.96%
Experience	0.0008	-0.81%	0.0004	-1.40%
Experience-squared	-0.0023	2.45%	-0.0011	3.71%
Father's educational achievements	-0.0163	17.42%	-0.0180	62.40%
Mother's educational achievements	0.0024	-2.53%	0.0040	-13.84%
Male	-0.0029	3.16%	-0.0014	4.74%
Demographic dummies	-0.0001	0.09%	0.0011	-3.81%
Occupation dummies	0.0445	-47.64%	0.0387	-133.70%

Industry dummies	-0.0124	13.27%	-0.0095	32.76%
Formal	-0.0011	1.19%	-0.0005	1.78%
Region dummies	0.0005	-0.55%	0.0008	-2.65%
Urban	0.0000	0.04%	-0.0001	0.43%
Total wage structure effect	-0.1614	172.92%	-0.0785	271.38%
Primary education or less	-0.0048	5.17%	0.0005	-1.60%
Higher education	-0.0634	67.94%	-0.0317	109.57%
Technical degree	0.0091	-9.70%	0.0167	-57.63%
CFT	0.0018	-1.90%	0.0046	-15.99%
IP	0.0069	-7.37%	0.0081	-27.92%
Private university	-0.0028	3.03%	-0.0017	5.82%
Traditional university	-0.0002	0.24%	0.0004	-1.32%
Does not know/Does not respond	0.0003	-0.29%	0.0005	-1.56%
Incomplete	0.0032	-3.42%	0.0048	-16.66%
Professional degree	-0.0645	69.05%	-0.0422	145.88%
IP	-0.0033	3.56%	-0.0015	5.23%
Private university	-0.0268	28.72%	-0.0179	61.87%
Traditional university	-0.0298	31.94%	-0.0223	77.11%
Does not know/Does not respond	-0.0007	0.71%	-0.0003	0.95%
Incomplete	-0.0038	4.12%	-0.0002	0.72%
Post-graduate degree	-0.0080	8.59%	-0.0062	21.33%
Private university	-0.0003	0.31%	0.0004	-1.25%
Traditional university	-0.0057	6.06%	-0.0045	15.56%
Does not know/Does not respond	-0.0012	1.26%	-0.0012	4.14%
Incomplete	-0.0009	0.96%	-0.0008	2.88%
Experience	0.1612	-172.72%	0.1973	-682.35%
Experience-squared	-0.0822	88.03%	-0.1100	380.51%
Father's educational achievements	-0.0350	37.48%	-0.0722	249.82%
Mother's educational achievements	-0.0644	68.99%	-0.0617	213.28%
Male	0.0032	-3.48%	0.0017	-6.00%
Demographic dummies	-0.0207	22.14%	-0.0288	99.67%
Occupation dummies	-0.0184	19.74%	-0.0620	214.43%
Industry dummies	0.0276	-29.57%	0.0215	-74.42%
Formal	0.1190	-127.44%	0.0428	-147.84%
Region dummies	-0.0098	10.51%	0.0079	-27.47%
Urban	-0.0447	47.88%	-0.0256	88.58%
Constant	-0.1291	138.25%	0.0419	-144.81%

Note: % indicates the contribution of the respective variable to the evolution of wage inequality between the selected quantiles.

Table 1. Descriptive statistics of the variables in 2013 and 2017.

	2013	2017
Observations	51,891	52,753
Log hourly wage		
Mean	7.440	7.530
Q10	6.849	6.987
Q50	7.304	7.378
Q90	8.395	8.439
Primary education or less	0.179	0.151
Secondary education	0.517	0.479
Humanities school (old system)	0.007	0.004
Scientific-Humanistic school	0.371	0.357
Technical-Vocational school (old system)	0.004	0.002
Technical-Vocational school	0.136	0.116
Higher education	0.303	0.370
Technical degree	0.108	0.131
CFT	0.029	0.027
IP	0.053	0.064
Private university	0.004	0.008
Traditional university	0.002	0.005
Does not know/Does not respond	0.003	0.005
Incomplete	0.018	0.023
Professional degree	0.177	0.214
IP	0.012	0.021
Private university	0.048	0.057
Traditional university	0.079	0.099
Does not know/Does not respond	0.008	0.005
Incomplete	0.029	0.032
Post-graduate degree	0.019	0.025
Private university	0.004	0.006
Traditional university	0.011	0.016
Does not know/Does not respond	0.001	0.001
Incomplete	0.002	0.003
Experience	22.103	22.142
Father's educational achievements		
Primary education or less	0.294	0.174
Secondary education	0.179	0.114
Humanities school (old system)	0.075	0.053
Scientific-Humanistic school	0.075	0.041
Technical-Vocational school (old system)	0.019	0.011
Technical-Vocational school	0.010	0.009
Higher education	0.063	0.051
Technical degree	0.015	0.011
Professional degree	0.045	0.038
Post-graduate degree	0.002	0.002
Does not know/Does not respond	0.464	0.661

Mother's educational achievements		
Primary education or less	0.352	0.217
Secondary education	0.198	0.129
Humanities school (old system)	0.081	0.057
Scientific-Humanistic school	0.093	0.052
Technical-Vocational school (old system)	0.013	0.011
Technical-Vocational school	0.011	0.009
Higher education	0.044	0.045
Technical degree	0.012	0.010
Professional degree	0.031	0.033
Post-graduate degree	0.001	0.001
Does not know/Does not respond	0.405	0.609
Male	0.603	0.580
Head of the household	0.491	0.488
Married	0.375	0.339
Formal	0.895	0.898
Urban	0.890	0.893

Note: Q10, Q50, and Q90 represent the 10th, 50th, and 90th unconditional quantiles of log hourly wages, respectively.

Source: Authors' calculations based on data from CASEN 2013 and 2017.

Table 2. Estimation results of the mean and unconditional quantile regressions for log hourly wages in 2013 and 2017.

	2013					2017				
Explanatory variables	Mean	Mean	Q10	Q50	Q90	Mean	Mean	Q10	Q50	Q90
Primary	-0.167***	-0.157***	-0.124***	-0.196***	-0.116***	-0.130***	-0.122***	-0.065***	-0.174***	-0.088***
	(0.006)	(0.006)	(0.019)	(0.015)	(0.024)	(0.007)	(0.007)	(0.010)	(0.011)	(0.013)
Technical degree										
CFT	0.300***	0.277***	0.093***	0.412***	0.264***	0.281***	0.267***	0.072***	0.323***	0.298***
	(0.012)	(0.012)	(0.027)	(0.031)	(0.065)	(0.012)	(0.012)	(0.014)	(0.027)	(0.057)
IP	0.348***	0.311***	0.134***	0.403***	0.252***	0.294***	0.281***	0.066***	0.367***	0.322***
	(0.010)	(0.009)	(0.020)	(0.029)	(0.073)	(0.008)	(0.008)	(0.009)	(0.020)	(0.046)
Private university	0.423***	0.400***	0.101***	0.417***	0.864**	0.217***	0.196***	0.066*	0.209**	0.322***
	(0.034)	(0.034)	(0.035)	(0.048)	(0.391)	(0.023)	(0.023)	(0.037)	(0.091)	(0.092)
Traditional university	0.529***	0.495***	0.112**	0.569***	0.847***	0.504***	0.476***	0.101***	0.474***	0.804***
	(0.051)	(0.050)	(0.046)	(0.056)	(0.327)	(0.027)	(0.027)	(0.024)	(0.037)	(0.142)
Does not know/Does not respond	0.276***	0.257***	0.146***	0.332***	0.268**	0.208***	0.201***	0.065**	0.248***	0.215**
	(0.035)	(0.034)	(0.041)	(0.063)	(0.116)	(0.027)	(0.027)	(0.030)	(0.044)	(0.103)
Incomplete	0.120***	0.102***	-0.022	0.213***	-0.016	0.170***	0.161***	0.026	0.216***	0.166***
	(0.016)	(0.016)	(0.062)	(0.046)	(0.053)	(0.013)	(0.013)	(0.019)	(0.025)	(0.042)
Professional degree										
IP	0.708***	0.672***	0.138***	0.612***	1.357***	0.606***	0.583***	0.100***	0.561***	1.118***
	(0.019)	(0.019)	(0.022)	(0.029)	(0.187)	(0.014)	(0.014)	(0.013)	(0.024)	(0.097)
Private university	0.915***	0.848***	0.128***	0.654***	2.008***	0.696***	0.662***	0.104***	0.525***	1.386***
	(0.010)	(0.010)	(0.018)	(0.024)	(0.135)	(0.009)	(0.009)	(0.013)	(0.033)	(0.088)
Traditional university	1.069***	0.994***	0.157***	0.682***	2.562***	1.001***	0.961***	0.116***	0.669***	2.249***
	(0.008)	(0.009)	(0.017)	(0.020)	(0.126)	(0.007)	(0.007)	(0.009)	(0.017)	(0.091)
Does not know/Does not respond	0.914***	0.853***	0.187***	0.674***	1.799***	0.789***	0.762***	0.137***	0.636***	1.547***
	(0.024)	(0.023)	(0.027)	(0.033)	(0.247)	(0.027)	(0.026)	(0.012)	(0.030)	(0.152)
Incomplete	0.413***	0.370***	0.051	0.389***	0.654***	0.309***	0.293***	0.054***	0.299***	0.489***

	(0.012)	(0.012)	(0.038)	(0.028)	(0.137)	(0.011)	(0.011)	(0.014)	(0.024)	(0.058)
Post-graduate degree										
Private university	1.253***	1.127***	0.037	0.604***	3.118***	1.367***	1.286***	0.123***	0.690***	3.215***
	(0.032)	(0.032)	(0.080)	(0.055)	(0.385)	(0.025)	(0.025)	(0.016)	(0.025)	(0.223)
Traditional university	1.433***	1.306***	0.140***	0.645***	3.820***	1.407***	1.333***	0.109***	0.657***	3.532***
	(0.020)	(0.020)	(0.019)	(0.027)	(0.251)	(0.016)	(0.017)	(0.011)	(0.019)	(0.153)
Does not know/Does not respond	1.540***	1.374***	0.226***	0.648***	3.674***	0.839***	0.801***	-0.010	0.443***	1.431**
	(0.059)	(0.059)	(0.052)	(0.058)	(0.429)	(0.074)	(0.073)	(0.078)	(0.151)	(0.636)
Incomplete	1.517***	1.350***	0.146***	0.654***	3.061***	1.069***	1.023***	0.128***	0.709***	2.679***
	(0.044)	(0.044)	(0.029)	(0.046)	(0.692)	(0.039)	(0.039)	(0.012)	(0.030)	(0.310)
Experience	0.013***	0.013***	0.003*	0.012***	0.023***	0.017***	0.017***	0.004***	0.013***	0.035***
	(0.001)	(0.001)	(0.002)	(0.001)	(0.003)	(0.001)	(0.001)	(0.001)	(0.001)	(0.003)
Experience-squared	-0.023***	-0.022***	-0.006*	-0.021***	-0.034***	-0.030***	-0.029***	-0.009***	-0.022***	-0.056***
	(0.001)	(0.001)	(0.003)	(0.003)	(0.007)	(0.001)	(0.001)	(0.002)	(0.002)	(0.005)
Father's educational achievements										
Primary education or less		-0.067***	0.012	-0.089***	-0.134**		-0.066***	-0.017	-0.040**	-0.167***
		(0.007)	(0.014)	(0.017)	(0.054)		(0.009)	(0.011)	(0.019)	(0.040)
Technical degree		0.057***	-0.077	-0.038	0.242		0.033	-0.009	0.011	0.191
		(0.018)	(0.063)	(0.038)	(0.162)		(0.020)	(0.016)	(0.026)	(0.141)
Professional degree		0.190***	0.028	0.003	0.627***		0.090***	0.003	-0.030	0.324***
		(0.012)	(0.017)	(0.028)	(0.150)		(0.013)	(0.012)	(0.026)	(0.098)
Post-graduate degree		0.224***	-0.014	-0.027	0.485		0.158***	0.026	0.048	0.268
		(0.048)	(0.062)	(0.054)	(0.470)		(0.045)	(0.031)	(0.049)	(0.400)
Does not know/Does not respond		-0.078***	-0.019	-0.072***	-0.157***		-0.064***	-0.015	-0.040	-0.189***
		(0.009)	(0.018)	(0.022)	(0.054)		(0.009)	(0.012)	(0.026)	(0.041)
Mother's educational achievements										
Primary education or less		-0.040***	-0.007	-0.023	-0.070		-0.045***	0.005	-0.011	-0.159***
		(0.007)	(0.015)	(0.018)	(0.048)		(0.008)	(0.010)	(0.019)	(0.040)
Technical degree		-0.015	0.059*	0.002	0.170		0.117***	-0.010	0.008	0.508***

		(0.020)	(0.034)	(0.036)	(0.206)		(0.021)	(0.018)	(0.030)	(0.136)
Professional degree		0.054***	-0.019	-0.037	0.340**		0.045***	-0.017	0.002	0.143
		(0.014)	(0.021)	(0.031)	(0.149)		(0.014)	(0.015)	(0.027)	(0.098)
Post-graduate degree		0.298***	-0.004	-0.021	1.042*		-0.010	-0.035	-0.048	-0.019
		(0.058)	(0.047)	(0.055)	(0.617)		(0.054)	(0.072)	(0.085)	(0.412)
Does not know/Does not respond		-0.034***	-0.004	-0.025	-0.037		-0.063***	-0.001	-0.032	-0.140***
		(0.009)	(0.019)	(0.024)	(0.049)		(0.010)	(0.014)	(0.028)	(0.042)
Male	0.136***	0.148***	0.093***	0.160***	0.211***	0.114***	0.114***	0.053***	0.124***	0.166***
	(0.005)	(0.005)	(0.015)	(0.013)	(0.036)	(0.005)	(0.005)	(0.007)	(0.010)	(0.021)
Head of the household	0.089***	0.065***	-0.006	0.059***	0.168***	0.088***	0.019***	0.001	0.068***	-0.023
	(0.005)	(0.005)	(0.012)	(0.012)	(0.033)	(0.004)	(0.007)	(0.010)	(0.014)	(0.022)
Married	0.070***	0.062***	0.032***	0.068***	0.030	0.093***	0.096***	0.014**	0.077***	0.216***
	(0.005)	(0.005)	(0.010)	(0.011)	(0.031)	(0.004)	(0.004)	(0.006)	(0.008)	(0.021)
Formal	0.217***	0.218***	0.381***	0.184***	0.004	0.205***	0.205***	0.272***	0.162***	0.033
	(0.007)	(0.007)	(0.041)	(0.016)	(0.029)	(0.007)	(0.007)	(0.026)	(0.014)	(0.020)
Urban	0.036***	0.029***	0.009	0.053***	-0.006	0.025***	0.023***	0.024***	0.040***	-0.044**
	(0.008)	(0.008)	(0.016)	(0.010)	(0.017)	(0.007)	(0.007)	(0.009)	(0.009)	(0.020)
Constant	6.674***	6.770***	6.360***	6.658***	7.672***	6.760***	6.889***	6.606***	6.749***	7.794***
	(0.013)	(0.014)	(0.072)	(0.031)	(0.073)	(0.013)	(0.016)	(0.044)	(0.032)	(0.063)
Observations	51,891	51,891	51,891	51,891	51,891	52,753	52,753	52,753	52,753	52,753
R-squared	0.530	0.540	0.114	0.347	0.398	0.517	0.523	0.106	0.309	0.384

Note: Numbers in parentheses represent standard errors. ***, **, and * indicate significance at 1%, 5%, and 10% levels, respectively. The standard errors of the unconditional quantile regressions are calculated via bootstrap with 500 replications. Industry dummies and region dummies are also included.

Table 3. Decomposition of wage changes from 2013 to 2017 into composition and wage structure effects of each explanatory variable.

	Composition effect				Wage structure effect			
Explanatory variables	Mean	Q10	Q50	Q90	Mean	Q10	Q50	Q90
Overall	0.0333***	0.0053**	0.0285***	0.0833***	0.0565***	0.1326***	0.0450***	-0.0387***
	(0.0033)	(0.0021)	(0.0029)	(0.0077)	(0.0030)	(0.0038)	(0.0038)	(0.0088)
Primary	0.0044***	0.0035***	0.0055***	0.0033***	0.0054***	0.0089***	0.0032*	0.0043
	(0.0004)	(0.0004)	(0.0005)	(0.0006)	(0.0014)	(0.0017)	(0.0017)	(0.0040)
Higher education	0.0471***	0.0080***	0.0369***	0.1096***	-0.0212***	-0.0112***	-0.0192***	-0.0796***
	(0.0023)	(0.0008)	(0.0017)	(0.0060)	(0.0027)	(0.0034)	(0.0034)	(0.0079)
Technical degree	0.0070***	0.0022***	0.0087***	0.0089***	-0.0028**	-0.0045***	-0.0072***	0.0049
	(0.0006)	(0.0004)	(0.0008)	(0.0010)	(0.0013)	(0.0016)	(0.0016)	(0.0036)
CFT	-0.0007**	-0.0002**	-0.0011**	-0.0007**	-0.0003	-0.0006	-0.0024***	0.0009
	(0.0003)	(0.0001)	(0.0004)	(0.0003)	(0.0005)	(0.0006)	(0.0006)	(0.0013)
IP	0.0034***	0.0015***	0.0044***	0.0027***	-0.0019**	-0.0043***	-0.0023**	0.0044*
	(0.0005)	(0.0002)	(0.0006)	(0.0005)	(0.0008)	(0.0010)	(0.0010)	(0.0023)
Private university	0.0016***	0.0004**	0.0016***	0.0033***	-0.0015***	-0.0003	-0.0016***	-0.0041***
	(0.0002)	(0.0002)	(0.0003)	(0.0006)	(0.0003)	(0.0004)	(0.0004)	(0.0009)
Traditional university	0.0018***	0.0004	0.0020***	0.0030***	-0.0001	-0.0001	-0.0005	-0.0002
	(0.0003)	(0.0003)	(0.0003)	(0.0006)	(0.0003)	(0.0004)	(0.0004)	(0.0009)
Does not know/Does not respond	0.0005***	0.0003**	0.0006***	0.0005**	-0.0003	-0.0004	-0.0004	-0.0003
	(0.0001)	(0.0001)	(0.0002)	(0.0002)	(0.0002)	(0.0003)	(0.0003)	(0.0007)
Incomplete	0.0005***	-0.0001	0.0011***	-0.0001	0.0013***	0.0011*	0.0001	0.0041***
	(0.0001)	(0.0001)	(0.0002)	(0.0002)	(0.0005)	(0.0006)	(0.0006)	(0.0013)
Professional degree	0.0319***	0.0051***	0.0240***	0.0775***	-0.0186***	-0.0065***	-0.0128***	-0.0781***
	(0.0021)	(0.0005)	(0.0016)	(0.0053)	(0.0019)	(0.0023)	(0.0023)	(0.0054)
IP	0.0059***	0.0012***	0.0054***	0.0120***	-0.0019***	-0.0008	-0.0011*	-0.0050***
	(0.0006)	(0.0003)	(0.0005)	(0.0012)	(0.0005)	(0.0006)	(0.0006)	(0.0014)
Private university	0.0078***	0.0012***	0.0060***	0.0185***	-0.0106***	-0.0014	-0.0074***	-0.0357***
	(0.0012)	(0.0002)	(0.0009)	(0.0028)	(0.0008)	(0.0010)	(0.0010)	(0.0024)
Traditional university	0.0191***	0.0030***	0.0131***	0.0493***	-0.0032***	-0.0041***	-0.0013	-0.0309***
	(0.0018)	(0.0004)	(0.0012)	(0.0045)	(0.0011)	(0.0014)	(0.0014)	(0.0033)
Does not know/Does not respond	-0.0019***	-0.0004***	-0.0015***	-0.0039***	-0.0005**	-0.0003	-0.0002	-0.0014**
	(0.0004)	(0.0001)	(0.0003)	(0.0009)	(0.0002)	(0.0002)	(0.0002)	(0.0006)

Incomplete	0.0009**	0.0001*	0.0010**	0.0016**	-0.0025***	0.0001	-0.0028***	-0.0052***
	(0.0004)	(0.0001)	(0.0004)	(0.0007)	(0.0005)	(0.0006)	(0.0007)	(0.0015)
Post-graduate degree	0.0081***	0.0007***	0.0041***	0.0233***	0.0002	-0.0001	0.0007	-0.0064***
	(0.0012)	(0.0002)	(0.0006)	(0.0032)	(0.0005)	(0.0007)	(0.0007)	(0.0016)
Private university	0.0022***	0.0001	0.0012***	0.0061***	0.0010***	0.0005*	0.0005*	0.0006
	(0.0005)	(0.0001)	(0.0003)	(0.0014)	(0.0003)	(0.0003)	(0.0003)	(0.0007)
Traditional university	0.0061***	0.0007***	0.0030***	0.0178***	0.0004	-0.0005	0.0002	-0.0045***
	(0.0009)	(0.0002)	(0.0005)	(0.0027)	(0.0004)	(0.0005)	(0.0005)	(0.0012)
Does not know/Does not respond	-0.0007***	-0.0001*	-0.0003**	-0.0018***	-0.0004***	-0.0002**	-0.0001*	-0.0016***
	(0.0003)	(0.0001)	(0.0001)	(0.0007)	(0.0001)	(0.0001)	(0.0001)	(0.0003)
Incomplete	0.0005	0.0001	0.0003	0.0012	-0.0008***	-0.0000	0.0001	-0.0010**
	(0.0004)	(0.0000)	(0.0002)	(0.0009)	(0.0002)	(0.0002)	(0.0002)	(0.0004)
Experience	0.0005	0.0001	0.0005	0.0009	0.0946***	0.0316	0.0205	0.2812***
	(0.0011)	(0.0002)	(0.0010)	(0.0019)	(0.0186)	(0.0225)	(0.0233)	(0.0535)
Experience-squared	-0.0019**	-0.0006*	-0.0018**	-0.0030**	-0.0500***	-0.0215	-0.0059	-0.1439***
	(0.0009)	(0.0003)	(0.0008)	(0.0014)	(0.0112)	(0.0135)	(0.0141)	(0.0322)
Father's educational achievements	-0.0089***	-0.0052***	-0.0034*	-0.0202***	0.0053	-0.0025	0.0296**	-0.0397
	(0.0015)	(0.0020)	(0.0018)	(0.0043)	(0.0099)	(0.0117)	(0.0125)	(0.0286)
Mother's educational achievements	-0.0013	-0.0002	-0.0022	0.0024	-0.0180*	0.0041	-0.0004	-0.0864***
	(0.0015)	(0.0021)	(0.0019)	(0.0045)	(0.0099)	(0.0116)	(0.0125)	(0.0284)
Male	-0.0034***	-0.0021***	-0.0036***	-0.0048***	-0.0201***	-0.0228***	-0.0206***	-0.0264**
	(0.0005)	(0.0003)	(0.0005)	(0.0007)	(0.0040)	(0.0049)	(0.0050)	(0.0115)
Demographic dummies	-0.0024***	-0.0011***	-0.0026***	-0.0015**	-0.0109**	-0.0032	0.0073	-0.0301**
	(0.0003)	(0.0003)	(0.0004)	(0.0007)	(0.0047)	(0.0054)	(0.0059)	(0.0134)
Industry dummies	-0.0012	0.0022***	-0.0007	-0.0035*	-0.0318***	-0.0304**	-0.0294**	-0.0367
	(0.0008)	(0.0008)	(0.0009)	(0.0019)	(0.0112)	(0.0136)	(0.0141)	(0.0323)
Formal	0.0006	0.0011	0.0005	0.0000	-0.0119	-0.0975***	-0.0199*	0.0259
	(0.0004)	(0.0007)	(0.0003)	(0.0001)	(0.0085)	(0.0103)	(0.0107)	(0.0245)
Region dummies	-0.0005	-0.0005	-0.0007	0.0002	0.0024	0.0176***	-0.0001	0.0048
	(0.0005)	(0.0004)	(0.0005)	(0.0007)	(0.0033)	(0.0040)	(0.0042)	(0.0096)
Urban	0.0001	0.0000	0.0001	-0.0000	-0.0055	0.0137	-0.0115	-0.0338
	(0.0001)	(0.0000)	(0.0001)	(0.0001)	(0.0092)	(0.0112)	(0.0115)	(0.0265)
Constant					0.1181***	0.2457***	0.0914***	0.1218**
					(0.0212)	(0.0251)	(0.0267)	(0.0610)
Observations	104,644	104,644	104,644	104,644	104,644	104,644	104,644	104,644

Note: Numbers in parentheses represent standard errors. ***, **, and * indicate significance at 1%, 5%, and 10% levels, respectively.

Table 4. Contribution of the difference in the composition and wage structure effects between selected quantiles to the evolution of wage inequality from 2013 to 2017.

	All workers (18-64)			
	Q90-Q10		Q90-Q50	
2013	1.5461		1.0907	
2017	1.4528		1.0618	
Overall difference	-0.0934	100%	-0.0289	100%
Total composition effect	0.0780	-83.51%	0.0547	-189.25%
Primary education or less	-0.0002	0.22%	-0.0023	7.78%
Higher education	0.1016	-108.83%	0.0727	-251.51%
Technical degree	0.0067	-7.16%	0.0001	-0.51%
CFT	-0.0004	0.47%	0.0004	-1.32%
IP	0.0013	-1.37%	-0.0016	5.67%
Private university	0.0030	-3.17%	0.0017	-5.99%
Traditional university	0.0026	-2.81%	0.0010	-3.44%
Does not know/Does not respond	0.0002	-0.25%	-0.0001	0.42%
Incomplete	0.0000	-0.03%	-0.0012	4.14%
Professional degree	0.0723	-77.48%	0.0534	-184.83%
IP	0.0108	-11.52%	0.0066	-22.72%
Private university	0.0174	-18.59%	0.0125	-43.23%
Traditional university	0.0463	-49.58%	0.0362	-125.17%
Does not know/Does not respond	-0.0035	3.79%	-0.0025	8.54%
Incomplete	0.0015	-1.58%	0.0006	-2.25%
Post-graduate degree	0.0226	-24.19%	0.0191	-66.17%
Private university	0.0060	-6.44%	0.0049	-16.96%
Traditional university	0.0171	-18.37%	0.0148	-51.16%
Does not know/Does not respond	-0.0017	1.85%	-0.0015	5.24%
Incomplete	0.0012	-1.24%	0.0010	-3.30%
Experience	0.0008	-0.84%	0.0004	-1.50%
Experience-squared	-0.0025	2.66%	-0.0012	4.19%
Father's educational achievements	-0.0150	16.07%	-0.0168	58.07%
Mother's educational achievements	0.0026	-2.75%	0.0046	-15.85%
Male	-0.0027	2.89%	-0.0012	4.05%
Demographic dummies	-0.0004	0.43%	0.0011	-3.72%
Industry dummies	-0.0057	6.12%	-0.0028	9.85%
Formal	-0.0011	1.19%	-0.0005	1.84%

Region dummies	0.0007	-0.72%	0.0009	-2.99%
Urban	0.0000	0.04%	-0.0002	0.54%
Total wage structure effect	-0.1713	183.51%	-0.0836	289.25%
Primary education or less	-0.0046	4.97%	0.0010	-3.61%
Higher education	-0.0684	73.32%	-0.0604	208.78%
Technical degree	0.0095	-10.14%	0.0121	-41.83%
CFT	0.0015	-1.58%	0.0033	-11.51%
IP	0.0088	-9.39%	0.0068	-23.37%
Private university	-0.0038	4.09%	-0.0025	8.69%
Traditional university	-0.0002	0.18%	0.0003	-0.92%
Does not know/Does not respond	0.0001	-0.16%	0.0002	-0.57%
Incomplete	0.0031	-3.27%	0.0041	-14.14%
Professional degree	-0.0717	76.78%	-0.0654	226.06%
IP	-0.0042	4.52%	-0.0039	13.62%
Private university	-0.0343	36.71%	-0.0283	97.84%
Traditional university	-0.0268	28.66%	-0.0296	102.31%
Does not know/Does not respond	-0.0011	1.18%	-0.0012	4.05%
Incomplete	-0.0053	5.71%	-0.0024	8.25%
Post-graduate degree	-0.0062	6.68%	-0.0071	24.55%
Private university	0.0001	-0.08%	0.0001	-0.24%
Traditional university	-0.0040	4.28%	-0.0046	16.07%
Does not know/Does not respond	-0.0014	1.50%	-0.0014	4.91%
Incomplete	-0.0009	0.98%	-0.0011	3.81%
Experience	0.2496	-267.39%	0.2608	-901.84%
Experience-squared	-0.1224	131.07%	-0.1380	477.15%
Father's educational achievements	-0.0372	39.82%	-0.0693	239.67%
Mother's educational achievements	-0.0905	96.98%	-0.0860	297.46%
Male	-0.0037	3.92%	-0.0059	20.24%
Demographic dummies	-0.0269	28.82%	-0.0374	129.29%
Industry dummies	-0.0063	6.72%	-0.0073	25.16%
Formal	0.1234	-132.17%	0.0459	-158.59%
Region dummies	-0.0128	13.74%	0.0049	-16.93%
Urban	-0.0475	50.90%	-0.0224	77.30%
Constant	-0.1240	132.81%	0.0303	-104.82%

Note: % indicates the contribution of the respective variables to the evolution of wage inequality between the selected quantiles.

Table 5. Contribution of the difference in the composition and wage structure effects between selected quantiles to the evolution of wage inequality from 2013 to 2017 among different age groups.

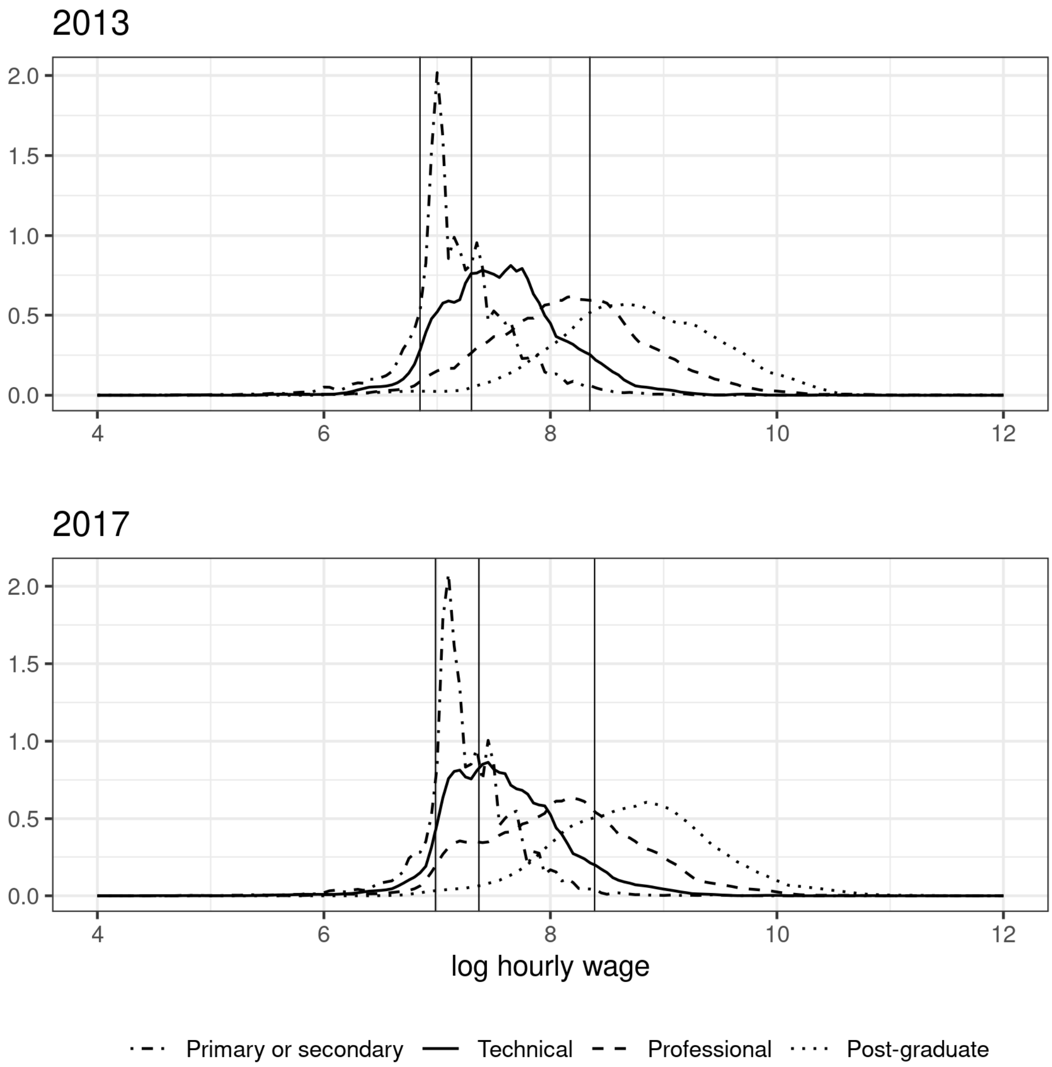
	Younger workers (18-30)				Older workers (51-64)			
	Q90-Q10		Q90-Q50		Q90-Q10		Q90-Q50	
2013	1.2976		0.9341		1.6381		1.1449	
2017	1.1733		0.8210		1.4908		1.0442	
Overall difference	-0.1243	100%	-0.1131	100%	-0.1474	100%	-0.1007	100%
Total composition effect	0.1309	-105.31%	0.1042	-92.12%	-0.0396	26.90%	-0.0506	50.29%
Primary education or less	0.0003	-0.28%	-0.0017	1.49%	0.12%	-0.0080	-0.64%	6.36%
Higher education	0.1357	-109.20%	0.1011	-89.38%	-0.67%	0.0457	-1.25%	12.46%
Technical degree	0.0216	-17.35%	0.0131	-11.55%	0.24%	-0.0165	-0.35%	3.44%
CFT	0.0000	0.00%	0.0000	-0.02%	0.0001	-0.05%	0.0000	0.00%
IP	0.0041	-3.29%	0.0011	-0.98%	0.0005	-0.34%	-0.0007	0.72%
Private university	0.0111	-8.89%	0.0081	-7.19%	0.0004	-0.26%	0.0003	-0.33%
Traditional university	0.0045	-3.64%	0.0032	-2.86%	0.0021	-1.45%	0.0006	-0.60%
Does not know/Does not respond	0.0007	-0.57%	0.0001	-0.12%	-0.0002	0.13%	-0.0006	0.62%
Incomplete	0.0012	-0.96%	0.0004	-0.37%	-0.0005	0.33%	-0.0030	3.03%
Professional degree	0.1103	-88.76%	0.0847	-74.91%	0.0025	-1.67%	0.0018	-1.78%
IP	0.0165	-13.24%	0.0105	-9.24%	0.0039	-2.65%	0.0027	-2.65%
Private university	0.0323	-26.00%	0.0251	-22.17%	-0.0043	2.95%	-0.0033	3.27%
Traditional university	0.0640	-51.47%	0.0517	-45.69%	0.0136	-9.24%	0.0110	-10.97%
Does not know/Does not respond	-0.0028	2.26%	-0.0018	1.59%	-0.0070	4.75%	-0.0061	6.03%
Incomplete	0.0004	-0.31%	-0.0007	0.60%	-0.0037	2.53%	-0.0026	2.54%
Post-graduate degree	0.0038	-3.09%	0.0033	-2.93%	-0.0116	7.88%	-0.0109	10.80%
Private university	0.0036	-2.90%	0.0031	-2.71%	-0.0016	1.09%	-0.0013	1.26%
Traditional university	-0.0001	0.09%	-0.0001	0.09%	0.0077	-5.19%	0.0068	-6.72%
Does not know/Does not respond	-0.0022	1.76%	-0.0019	1.66%	-0.0101	6.84%	-0.0095	9.44%
Incomplete	0.0025	-2.04%	0.0022	-1.97%	-0.0076	5.15%	-0.0069	6.83%
Experience	0.0005	-0.44%	0.0006	-0.53%	0.0068	-4.61%	0.0078	-7.75%
Experience-squared	0.0005	-0.40%	0.0007	-0.59%	-0.0087	5.88%	-0.0105	10.38%
Father's educational achievements	-0.0106	8.54%	-0.0069	6.14%	-0.0120	8.14%	-0.0163	16.16%
Mother's educational achievements	-0.0016	1.27%	0.0015	-1.37%	-0.0040	2.68%	-0.0044	4.37%
Male	-0.0007	0.58%	0.0003	-0.29%	-0.0029	1.96%	-0.0030	3.00%

Demographic dummies	0.0033	-2.65%	0.0026	-2.33%	0.0006	-0.39%	0.0019	-1.91%
Industry dummies	0.0005	-0.44%	0.0023	-1.99%	-0.0133	9.01%	-0.0074	7.36%
Formal	-0.0026	2.07%	-0.0014	1.23%	-0.0016	1.11%	-0.0008	0.84%
Region dummies	0.0056	-4.53%	0.0054	-4.73%	0.0011	-0.78%	0.0011	-1.05%
Urban	-0.0002	0.16%	-0.0003	0.25%	-0.0002	0.12%	-0.0001	0.06%
Total wage structure effect	-0.2552	205.31%	-0.2174	192.12%	-0.1077	73.10%	-0.0500	49.71%
Primary education or less	0.0049	-3.95%	0.0038	-3.39%	0.0198	-13.42%	-0.0073	7.28%
Higher education	-0.1637	131.71%	-0.1520	134.39%	0.0372	-25.27%	0.0385	-38.25%
Technical degree	-0.0341	27.44%	-0.0319	28.23%	0.0159	-10.78%	0.0189	-18.80%
CFT	0.0018	-1.46%	0.0009	-0.82%	0.0007	-0.44%	0.0008	-0.78%
IP	-0.0106	8.54%	-0.0141	12.49%	0.0085	-5.76%	0.0085	-8.47%
Private university	-0.0135	10.88%	-0.0093	8.24%	-0.0077	5.22%	-0.0068	6.78%
Traditional university	-0.0043	3.43%	-0.0044	3.85%	0.0066	-4.46%	0.0070	-6.94%
Does not know/Does not respond	-0.0027	2.19%	-0.0019	1.71%	0.0034	-2.33%	0.0030	-2.96%
Incomplete	-0.0048	3.86%	-0.0031	2.76%	0.0044	-3.02%	0.0065	-6.44%
Professional degree	-0.1265	101.78%	-0.1172	103.57%	0.0209	-14.18%	0.0201	-19.96%
IP	-0.0107	8.65%	-0.0120	10.61%	0.0041	-2.75%	0.0039	-3.84%
Private university	-0.0705	56.71%	-0.0639	56.45%	0.0004	-0.24%	0.0022	-2.21%
Traditional university	-0.0460	37.04%	-0.0485	42.87%	0.0117	-7.92%	0.0111	-11.04%
Does not know/Does not respond	0.0003	-0.24%	0.0005	-0.40%	-0.0002	0.15%	-0.0006	0.60%
Incomplete	0.0005	-0.39%	0.0067	-5.95%	0.0050	-3.42%	0.0035	-3.45%
Post-graduate degree	-0.0031	2.50%	-0.0029	2.59%	0.0005	-0.31%	-0.0005	0.51%
Private university	-0.0002	0.20%	-0.0004	0.35%	0.0036	-2.47%	0.0037	-3.69%
Traditional university	-0.0014	1.10%	-0.0009	0.80%	0.0006	-0.41%	-0.0001	0.08%
Does not know/Does not respond	0.0001	-0.08%	0.0001	-0.07%	-0.0009	0.63%	-0.0012	1.17%
Incomplete	-0.0016	1.27%	-0.0017	1.50%	-0.0029	1.95%	-0.0030	2.95%
Experience	0.0496	-39.90%	-0.0918	81.14%	-0.9462	642.08%	-1.4418	1432.04%
Experience-squared	-0.0152	12.26%	0.0554	-48.96%	0.4038	-274.01%	0.5937	-589.72%
Father's educational achievements	-0.0330	26.52%	-0.0922	81.54%	0.0094	-6.35%	-0.0141	13.98%
Mother's educational achievements	-0.0752	60.46%	-0.0651	57.53%	-0.0722	49.01%	-0.1052	104.50%
Male	0.0317	-25.51%	0.0198	-17.51%	-0.0450	30.51%	-0.0924	91.82%
Demographic dummies	-0.0268	21.58%	-0.0227	20.07%	0.0619	-42.02%	0.0404	-40.12%
Industry dummies	-0.0110	8.86%	0.0496	-43.88%	0.0409	-27.74%	-0.0047	4.66%
Formal	0.1112	-89.48%	0.0585	-51.73%	0.0354	-24.02%	0.0028	-2.82%
Region dummies	0.0590	-47.46%	0.0742	-65.62%	-0.1028	69.77%	-0.0549	54.57%

Urban	0.0415	-33.42%	0.0245	-21.63%	-0.1524	103.42%	-0.0946	93.95%
Constant	-0.2283	183.62%	-0.0794	70.17%	0.6025	-408.86%	1.0896	-1082.17%

Note: % indicates the contribution of the respective variable to the evolution of wage inequality between the selected quantiles.

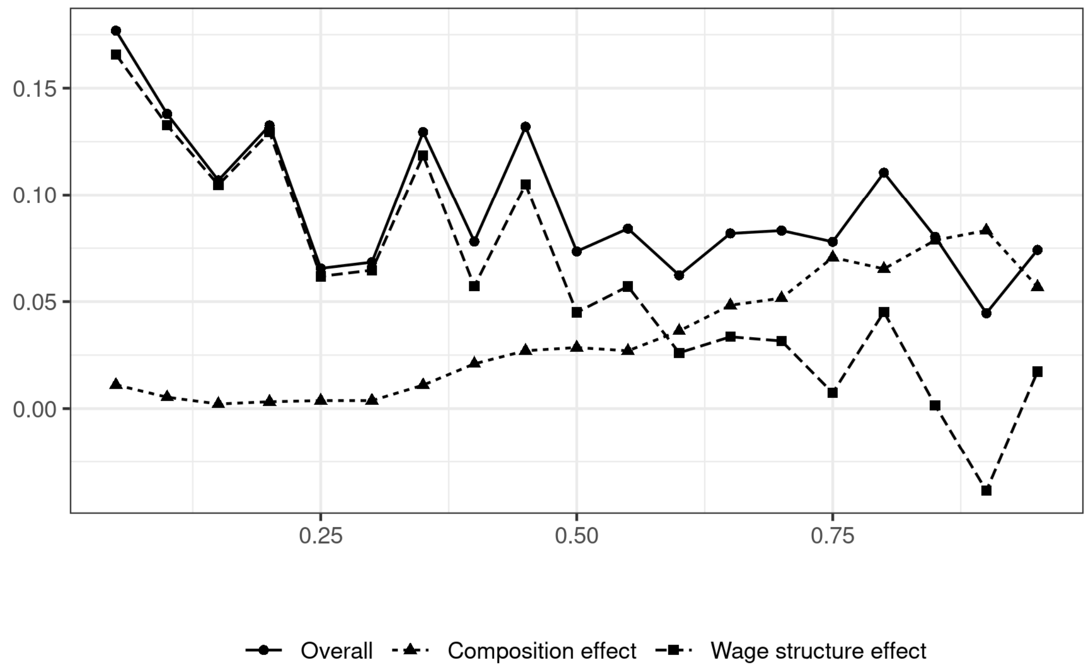
Figure 1. Estimated log hourly wage distribution in 2013 and 2017, classified by educational achievements.



Note: The vertical lines show the 10th, 50th, and 90th quantiles of the overall wage distribution for each year.

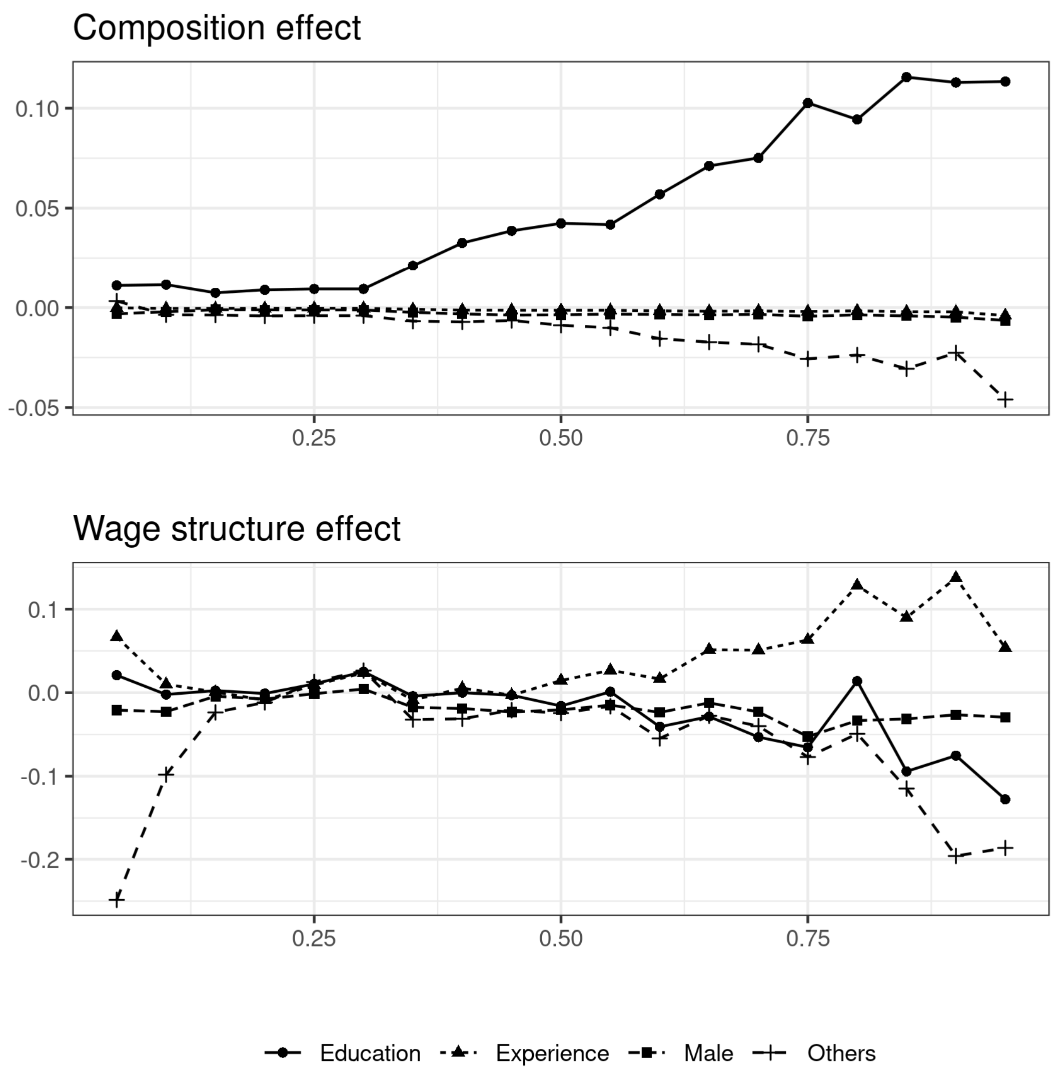
Source: Authors' calculations based on data from the 2013 and 2017 CASEN.

Figure 2. Decomposition of overall wage changes into composition and wage structure effects.



Source: Authors' calculations based on data from the 2013 and 2017 CASEN.

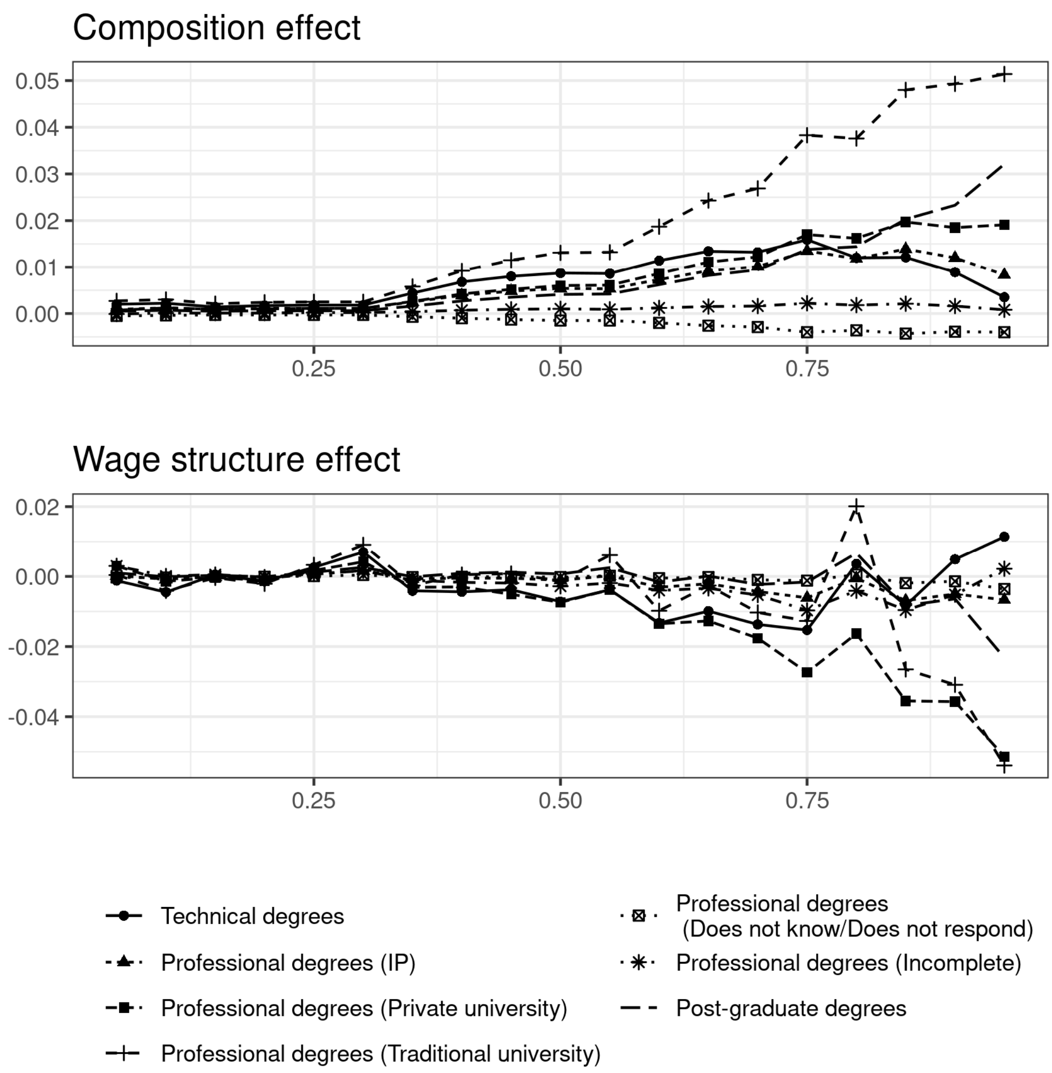
Figure 3. Decomposition of overall composition and wage structure effects into four groups of explanatory variables.



Note: Education is the sum of dummies on educational achievements; Experience is the sum of years of potential labor experience and its squared term; Male is the dummy for male worker; and Others is the sum of all other explanatory variables except for the constant term.

Source: Authors' calculations based on data from the 2013 and 2017 CASEN.

Figure 4. Detailed composition and wage structure effects of higher education degrees.



Note: The wage structure effects of technical and post-graduate degrees are not disaggregated into degree-granting institutions. The degree-granting institutions of professional degrees are represented in parentheses.

Source: Authors' calculations based on data from CASEN 2013 and 2017.