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Yoshimichi MURAKAMI
Tomokazu NOMURA

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Research Institute for Economics and Business Administration
Kobe University
2-1 Rokkodai, Nada, Kobe 657-8501 JAPAN

Impact of changes in values of degrees on wage inequality: Evidence from Chile

Yoshimichi Murakami[a]* and Tomokazu Nomura[b]

[a]Research Institute for Economics and Business Administration (RIEB), Kobe University, Kobe, Japan; [b]Faculty of Information Technology and Social Sciences, Osaka University of Economics, Osaka, Japan

Associate Professor, Research Institute for Economics and Business Administration (RIEB), Kobe University, 2-1, Rokkodai, Nada-ku, Kobe 657-8501, Japan. Email: y-murakami@rieb.kobe-u.ac.jp *corresponding author

Abstract

Using the latest available data from nationally representative household surveys, we analyze the impact of changes in returns to higher education degrees on the evolution of wage inequality in Chile from 2013 to 2017. Employing a recently developed decomposition method using unconditional quantile regression and controlling for parental education levels, we find that a significant decrease in returns to professional degrees from new private universities plays a prominent role in reducing wage inequality. The effect is especially evident among younger graduates, thereby supporting the "degraded tertiary" hypothesis.

Keywords: higher education, returns to degree, wage inequality, unconditional quantile regression, Chile

JEL classification codes: I23; I24; I26; J31; O15; O54

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 undoubtedly has affected the evolution of wage inequality through changes in its returns (so-called skill premiums). It has been found that returns to higher education sharply decreased since the early 2000s after a slight increase in the 1990s, which has been closely associated with the evolution of wage inequality in the same direction (Gasparini et al., 2011; Messina & Silva, 2018; Rodríguez-Castelán et al., 2016).

The observed reduction in returns to higher education in LACs, which is in clear contrast with not only the region's previous trend but also the global trend, is a highly important area of research. Obviously, such an increase in the share of educated workers decreases their wage premium as long as the returns to education are sufficiently negatively correlated with years of schooling, as predicted by human capital models, including Knight and Sabot (1983). The relation is formally expressed by the variance of log earnings (see Coady & Dizioli, 2018; Murakami & Nomura, 2020). However, beyond the impact of the simple quantity expansion, it has been argued that the quality of higher education also has played a prominent role in the observed recent reduction in its returns in LACs (Messina & Silva, 2018). For example, the "degraded tertiary" hypothesis argues that the expansion of higher education has degraded the value of its degrees among younger graduates, either because of the lower quality of new

[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).

institutions and/or the quality of marginal students with lower abilities (Campos-Vázquez et al., 2016; Messina & Silva, 2018). Another possibility is that the returns to degrees among older workers decreased because their skills no longer match the current demand for labor and/or are replaced by machines, which forms the crux of the "skill obsolescence" hypothesis (Campos-Vázquez et al., 2016; Messina & Silva, 2018). In line with these two hypotheses, several studies have analyzed recent returns to degrees in LACs. However, their findings remain controversial. González-Velosa et al. (2015) for Chile and Colombia, and Camacho et al. (2016) for Colombia find supportive evidence for the former hypothesis while Campos-Vázquez et al. (2016) for Mexico find supportive evidence for the latter hypothesis. Moreover, these studies do not analyze the impact of recent trends in returns to degrees on wage inequality.

Considered among the most successful LACs in terms of economic growth as well as far-reaching economic and social reforms, Chile, nonetheless, has a similarly high level of income inequality as other LACs and presents a particularly interesting case for analyzing the recent changes in returns to degrees and their impact on the evolution of wage inequality. Before the reform in 1980, higher education in Chile consisted two state 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 establishment 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 both professional and college degrees (*licenciaturas*), and allowing graduates to enroll in postgraduate 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) other new private universities founded after 1980 (Cox, 1996; Espinoza & González, 2013). Based on these diversified higher education systems, recent studies, including 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 ability.[2] However, the distributional aspect of returns to degrees is beyond their analysis.

Therefore, this study aims to analyze the impact of changes in returns to degrees on the evolution of wage inequality in Chile from 2013 to 2017. In this respect, Murakami and Nomura (2020) find that a decrease in returns to professional and college degrees contributed to decreasing wage inequality from 2000 to 2013 in Chile. Nonetheless, this study contributes to the literature by addressing the following three issues: First, this study analyzes the impact of changes in returns to different types of higher education degrees and the institutions from which the degrees are obtained based on the latest available household data, identifying that a significant decrease in returns to professional degrees from new private universities is an important factor to explain

[2] Contreras et al. (2005) also address the endogeneity issue by using panel data. However, since they estimate linear returns to education, they do not consider heterogeneous returns to different types of degrees.

the observed reduction in wage inequality. Second, considering the importance of unobserved inherent ability in the determinants of individual wages, this study controls for parental education levels, which can be a proxy for both an individual's unobserved inherent ability and family background. Third, this study performs the aforementioned analysis across different age groups, confirming the robustness of the "degraded tertiary" hypothesis. This contribution is particularly important because Montoya et al. (2017) and Rodríguez et al. (2016) used detailed administrative data, which only covered recent graduates. The use of data from household surveys enabled us to implement the analysis across different age groups.

The remainder of this paper is organized as follows. Section 2 presents the empirical specifications and explains the decomposition method using unconditional quantile regression. Section 3 explains the data employed in the analysis and presents descriptive statistics. Section 4 presents the estimation results. The final section concludes the paper and provides policy implications.

2. Empirical specification

2.1. Wage equation

To analyze the impact of higher education on individual wages, we separately estimate the wage equation for the years 2013 and 2017. Given that recent studies have found within-degree heterogeneity in the returns to degrees in Chile (González-Velosa et al., 2015; Rodríguez et al., 2016), we consider the heterogeneous returns to different types of higher education degrees and institutions from which the individuals obtained their degrees (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 from which the individual obtained their final degree in our wage equation. According to the "degraded tertiary" hypothesis, we expect that the returns to degrees from new private universities would be substantially lower than those from traditional universities and that the dispersion between them would be greater. We estimate the following wage equation:

(1) $\ln w_i = \boldsymbol{Z}_i'\boldsymbol{\beta} + \sum_j \sum_k \gamma_{jk} D_{ij} * D_{ik} + \varepsilon_i$

where i, j, and k index an individual, types of higher education degrees, and types of higher education institutions, respectively; w represents hourly wages; and vector $\boldsymbol{Z}$ represents other control variables at the individual level, which include years of potential labor experience (age – years of schooling – 6), its squared term, demographic dummies (a dummy each for the head of the household and for married workers), industry dummies classified at the two-digit level of International Standard Industrial Classification (ISIC) Revision 3, and region dummies. Since the returns to higher education degrees are expressed relative to secondary education, a dummy variable indicating whether the individual's educational achievement is primary education or less is also included.

Furthermore, following Contreras et al. (1999), the control variables include dummy variables indicating parental (both father and mother's) education levels based on secondary education as the reference category, assuming that they directly affect the individual's wages. Since parental education level is considered to be positively correlated with both an individual's own wage and educational achievement, the omission of this variable leads to an overestimation of the returns to degrees. Although we can use parental education level as an instrumental variable if it affects individuals' wages only through the effect on one's own educational achievement, we consider that the assumption is not plausible. The reasons for this are as follows: First, if an individual's educational achievement is correlated with family specific ability, which is observable as their parents' educational achievements, but is not correlated with individual-specific ability, parental education can be a proxy for the individual's unobserved inherent ability (Ashenfelter & Zimmerman, 1997). Second, parental education can be a proxy for family background, which directly affects an individual's own wages (Gong, 2019). In the case of Chile, Núñez and Gutiérrez (2004) find that individuals with higher socio-economic backgrounds receive significantly higher wages after controlling for various individual characteristics including their final educational achievement; this could be due to their productivity-enhancing skills, such as social networking skills, and/or simply due to discrimination by their employer. Additionally, Chumacero et al. (2011), Gómez et al. (2012), and Hofflinger et al. (2020) find that students from advantaged family backgrounds including those with educated parents are likely to enroll in high-quality secondary schools instead of geographically nearest ones, which in turn leads to higher wages after controlling for their final educational achievement, as evidenced by Núñez and Gutiérrez (2004). Indeed, following Gong (2019), when we use parental educational levels as instruments for the individual's educational achievement, the Sargan test strongly rejects the exogeneity of the instruments, thereby indicating that they directly affect the individual's wages.[3]

2.2. Decomposition of wage distribution

To analyze the contribution of the changes in the returns to higher education degrees to the evolution of wage inequality, we next decompose the evolution of wage distribution from 2013 to 2017 into changes attributable to changes in explanatory variables (i.e.,

[3] The result is available upon request.

composition effect) and in the returns to explanatory variables (i.e., wage structure effect). For this purpose, we employ a recently developed method of a simple approximation in the estimation of unconditional quantile regressions proposed by Firpo et al. (2009), which enables Oaxaca–Blinder (O-B) decomposition (Blinder, 1973; Oaxaca, 1973) at any unconditional quantiles. The clear advantage of this 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). This method has been applied in studies analyzing the impact of education expansion on the evolution of wage inequality in developing and emerging countries (e.g., Fernández & Messina, 2018 for Argentina, Brazil, and Chile; Murakami & Nomura, 2020 for Chile; Sámano-Robles, 2018 for 18 LACs; Seneviratne, 2019 for Sri Lanka; Yang & Gao, 2018 for China).

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) 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 the dependent variable $\ln w_i$ is given by:

(2) $$\mathrm{RIF}\,(\ln w_i\,, q^\tau) = q^\tau + \frac{\tau - 1\{\ln w_i \leq q^\tau\}}{f_{\ln w_i}(q^\tau)}$$

where q^τ is the τ-th unconditional quantile of the dependent variable $\ln w_i$, $1\{\cdot\}$ is an indicator function, and $f_{\ln w_i}(q^\tau)$ is the density of the marginal distribution of $\ln w_i$ evaluated at q^τ. 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 applies in the case of RIF values, the estimated coefficients of the unconditional quantile regression indicate the following marginal effect on q^τ:

(3) $\quad q^{\tau} = \mathrm{E}[RIF(y, q^{\tau})] = E[E(RIF(y, q^{\tau})|\boldsymbol{X})] = \overline{\boldsymbol{X}'}\boldsymbol{\beta}^{\tau}$

where $\boldsymbol{X}$ is a vector of all explanatory variables represented in wage equation (1), $\boldsymbol{\beta}^{\tau}$ represents a vector of coefficients of the unconditional quantile regression at the τ-th quantile, and the bar over term denotes the mean.

Thus, the change in the wage distribution between the two periods from 2013 to 2017 at selected quantiles is decomposed as follows:

(4) $$\ln w_{2017}^{\tau} - \ln w_{2013}^{\tau} = \overline{\boldsymbol{X}}'_{2017}\boldsymbol{\beta}_{2017}^{\tau} - \overline{\boldsymbol{X}}'_{2013}\boldsymbol{\beta}_{2013}^{\tau}$$
$$= (\overline{\boldsymbol{X}}'_{2017} - \overline{\boldsymbol{X}}'_{2013})\boldsymbol{\beta}_{2013}^{\tau} + \overline{\boldsymbol{X}}'_{2017}(\boldsymbol{\beta}_{2017}^{\tau} - \boldsymbol{\beta}_{2013}^{\tau})$$

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

Finally, based on the result of equation (4), the evolution of wage inequality measured by the difference between upper quantile *U* and lower quantile *L* (let $\tau \in \{U, L\}$) between the two periods is decomposed as follows:

(5) $$(\ln w_{2017}^{U} - \ln w_{2017}^{L}) - (\ln w_{2013}^{U} - \ln w_{2013}^{L})$$
$$= (\overline{\boldsymbol{X}}'_{2017}\boldsymbol{\beta}_{2017}^{U} - \overline{\boldsymbol{X}}'_{2013}\boldsymbol{\beta}_{2013}^{U}) - (\overline{\boldsymbol{X}}'_{2017}\boldsymbol{\beta}_{2017}^{L} - \overline{\boldsymbol{X}}'_{2013}\boldsymbol{\beta}_{2013}^{L})$$
$$= (\overline{\boldsymbol{X}}'_{2017} - \overline{\boldsymbol{X}}'_{2013})(\boldsymbol{\beta}_{2013}^{U} - \boldsymbol{\beta}_{2013}^{L}) + \overline{\boldsymbol{X}}'_{2017}[(\boldsymbol{\beta}_{2017}^{U} - \boldsymbol{\beta}_{2013}^{U}) - (\boldsymbol{\beta}_{2017}^{L} - \boldsymbol{\beta}_{2013}^{L})]$$

Thus, the first and second terms on the right-hand side of equation (5) represent the contribution of the difference in the composition and wage structure effects between the upper and lower quantiles to the evolution of wage inequality, respectively. Note that we choose *U* as the 90[th] quantile and *L* as the 50[th] and 10[th] quantiles, respectively. This is because income inequality is fundamentally derived from the large inequality between the richest 10 percent and the rest in Chile, while the country's inequality among the rest is relatively small (Núñez & Gutiérrez, 2004).

3. Data and descriptive statistics

The data used for the analysis are sourced from Socio-economic Characterization Survey (*Encuesta de Caracterización Socioeconómica Nacional*, CASEN) for 2013 and 2017.[4] CASEN is a nationally representative household survey conducted every two or three years by the Ministry of Social Development and Family of Chile. The survey provides detailed information on demographic characteristics, education, health, housing, employment, and various sources of income. We define wages as monetary earnings from principal occupation, deflated by the national consumer price index (December 2008 = 1).[5] We limit the sample to male workers who are employed full-time (more than 35 hours per week) and are aged between 15 and 64 years, excluding self-employed workers and military personnel. Since the survey provides expansion weights, we use them for all estimations in this study.

The surveys have reported the educational institution from which individuals obtained their final degree for those who attended higher education since CASEN 2013.[6] However, the category of college degree has been incorporated into the category of professional degree since CASEN 2011. Therefore, the available degree types for our

[4] 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).

[5] 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).

[6] Although CASEN 2017 reports more disaggregated classification of the institution from which an individual obtained the degree, we aggregated some categories such that the results corresponded with the categories in CASEN 2013.

analysis are technical, professional, and post-graduate degrees, while the available institution types are CFTs, IPs, new private universities, and traditional universities. We note that, while universities can offer all those three degrees, IPs can offer technical and professional degrees, and CFTs can offer only technical degrees. We set a separate category for those who did not complete the given program and thus did not obtain the degree, irrespective of the type of institution that they attended. To minimize missing observations, we also set a category for those who do not know the types of institution that they attended or did not respond. The resulting degree-institution type combinations are listed in Table 1.

Table 1 presents the descriptive statistics of the selected variables. We find that 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 90^{th} and 10^{th} quantiles and the 90^{th} and 50^{th} quantiles decreased from 1.56 to 1.41 and 1.06 to 1.00, respectively. We find that the share of workers with higher education increased from 25.7% to 31.7% in this period. Although we find this increase across all types of higher education degrees and institutions, it is especially evident in workers with professional degrees.

4. Estimation results

Table 2 reports the estimation results of mean and unconditional quantile regressions for 2013 and 2017, respectively. The returns to higher education (relative to secondary education) are revealed to be heterogeneous across different types of higher education degrees and institutions. Expectedly, returns to professional degrees are substantially higher than to technical degrees, after controlling for the parents' educational achievements, supporting the findings of studies that analyzed previous periods in Chile (e.g., González-Velosa et al., 2015; Murakami & Nomura, 2020; Puentes, 2000; Rodríguez et al., 2016; Urzúa, 2017). Interestingly, the omission of parents' educational achievements indeed results in a moderate overestimation of the returns to higher education across all types of degrees and institutions in both years, which is consistent with the findings of Contreras et al. (1999) and Rodríguez et al. (2016). Thus, the result strongly supports the inclusion of these variables in our decomposition analysis. We also find that the institution from which the worker obtained the degree is indeed an important source of within-degree heterogeneity in the returns to degrees in Chile, supporting the finding of González-Velosa et al. (2015). The types of institutions especially matter in the case of professional degrees: the returns obtained from traditional universities are substantially higher than those from private universities and the gap further widened from 2013 to 2017, expectedly. 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.

Since we find that returns to higher education degrees exhibit some important changes (e.g., a clear decreasing trend in the returns to professional degrees) and these changes are substantially heterogeneous across different quantiles, we analyze the impact on the observed reduction in wage inequality. Table 3 reports the estimation results of the decomposition of wage change from 2013 to 2017 at selected quantiles into the composition and wage structure effects of each explanatory variable. Table 4 reports the contribution of the difference in the composition and wage structure effects between the selected quantiles to the evolution of wage inequality.

In line with the compositional changes toward more workers with higher education across all types of degrees and institutions, as shown in Table 1, the composition effects are positive and larger at the 90th quantile, thereby exerting an unequalizing effect on the wage distribution. In contrast, wage structure effects are substantially heterogeneous across degrees and educational institutions. Importantly, the aggregate wage structure effect of professional degrees is negative and larger in magnitude at the 90th quantile. In particular, the wage structure effect of professional degrees from new private universities has a prominent role in the observed reduction in wage inequality, accounting for 12.6% and 26.7% of the observed decrease in differences between the 90th and 10th quantiles and the 90th and 50th quantiles, respectively (see Table 4). The decrease in returns to professional degrees from traditional universities has a similar effect but is smaller in magnitude. The decrease in returns to technical degrees from new private universities, which is larger in magnitude at the 90th quantile, also contributed to the observed reduction in wage inequality. However, the returns to technical degrees from CFTs are stable and even increase at the 90th quantile. The returns to post-graduate degrees exhibit the same trend, thereby having an unequalizing effect on wage distribution. The finding may indicate that technical degrees can be an alternative to professional degrees, especially for those who cannot enroll in traditional universities due to low test scores, given that new private universities require longer enrollment periods and higher annual tuition costs. In summary, we find that the significant decline in the values of professional degrees, especially from new private universities, contributed to the observed reduction in wage inequality, thereby supporting the “degraded tertiary” hypothesis.

To confirm the predictions of the “degraded tertiary” hypothesis, we test the robustness of the results of our decomposition analysis across different age groups (see Table 5). If the “degraded tertiary” hypothesis is correct, the returns among younger graduates should decrease; meanwhile, the returns among older workers should decrease if the alternative "skill-obsolescence" hypothesis is correct (Messina & Silva, 2018). We find that the degraded values of both professional and technical degrees from private universities are more evident among younger workers (aged between 15 and 30 years), and thus contribute to the reduction in wage inequality in larger magnitude, thereby strongly supporting the "degraded tertiary" hypothesis. In contrast, interestingly, the values of professional degrees did not decrease among older workers (aged between 51 and 64 years).[7] On the contrary, the returns to the professional degrees from both traditional and private universities increased and the effects are larger at the 90th quantile, thereby contradicting the "skill-obsolescence" hypothesis. A sharp decrease in experience premiums at the 90th quantile is the fundamental reason for the observed reduction in wage inequality among older workers.

5. Concluding remarks

After an increase in both returns to higher education and wage inequality in the 1990s, LACs have experienced a significant reduction in both since the early 2000s. The recent decrease in returns to higher education degrees is likely to be associated with the deterioration of quality, as predicted by the "degraded tertiary" and "skill obsolescence" hypotheses (Campos-Vázquez et al., 2016; Messina & Silva, 2018). In this context, Chile presents a particularly interesting case study because it has experienced prominent expansion and diversification of higher education.

Thus, this study analyzed the impact of changes in returns to degrees on the

[7] Note that most of the workers in this age group (i.e., born between 1949 and 1966) enrolled in higher education before the higher education reform in 1980. Thus, they obtained their technical degrees or professional degrees from new private universities after obtaining some work experience. Since such degrees are more likely to be associated with their professions and to increase their wages, an increase in returns to degrees even from new private universities is plausible.

evolution of wage inequality in Chile from 2013 to 2017, using the latest available data from nationally representative household surveys. We found that the returns to professional degrees decreased substantially during this period, while the returns to technical and post-graduate degrees were mostly stable. Moreover, the type of institution from which the worker obtained the degree, which is closely related to the quality of education, was indeed an important source of within-degree heterogeneity. We also found that the omission of parental education levels, which can be a proxy for both an individual's unobserved inherent ability and family background, results in a moderate overestimation of the returns to degrees. Thus, we included them in our wage equation. As a result of the recently developed method proposed by Firpo et al. (2009) using unconditional quantile regression, we found that a significant decrease in returns to professional degrees from new private universities played a prominent role in the reduction in wage inequality. Moreover, since the effect was especially evident among younger graduates, the finding strongly supported the "degraded tertiary" hypothesis, which argues that the returns to degrees from new private universities degraded due to the lower quality of their programs and/or students who enrolled in them.

The findings indicate that universities, especially new private 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, since only students of traditional universities are eligible for the university credit solidarity fund (*Fondo Solidario de Crédito Universitario*, FSCU), students of new private universities must instead 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 not only have low benefits in terms of income and job status, but also have to repay their student loans under disadvantaged conditions. Although, some issues have been addressed, such a situation may underlie the growing dissatisfaction with higher education systems, which can be at least one of the causes for the recent widespread protests.[8] Therefore, new improved policies to ensure the quality of education imparted at the new private universities may be required.

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References

Ashenfelter, O., and D.J. Zimmerman. (1997). "Estimates of the returns to schooling from sibling data: Fathers, sons, and brothers", *Review of Economics and Statistics*, Vol. 79 (1); 1-9.

Blinder, A.S. (1973). "Wage discrimination: Reduced form and structural estimates", *Journal of Human Resources*, Vol. 8 (4); 436-455.

Brunner, J.J. (1993). "Chile's higher education: Between market and state", *Higher Education*, Vol. 25 (1); 35-43.

[8] For example, a higher interest rate (almost 6 per year) of CAE was one important reason for massive student protests from 2011 to 2012 (Solís, 2017). Although the annual interest rate was reduced to 2% in 2012, which is same as that of FSCU, the CAE loan granted have been still suffering from high debt burden, mainly due to their longer enrolment periods and adjustability based on inflation rates (Tusso Chomali, 2021).

Camacho, A., J. Messina, and J. P. Uribe. (2016). "The expansion of higher education in Colombia: Bad students or bad programs?", *Discussion Paper*, No. IDP-DP-452, Inter-American Development Bank.

Campos-Vázquez, R.M., L.F. López-Calva, and N. Lustig. (2016). "Declining wages for college-educated workers in Mexico: Are younger or older cohorts hurt the most?", *World Bank Policy Research Working Paper*, No. 7546, World Bank.

Chumacero, R. A., D. Gómez, and R. D. Paredes (2011). "I would walk 500 miles (if it paid): Vouchers and school choice in Chile", *Economics of Education Review*, Vol. 30 (5); 1103-1114.

Coady, D., and A. Dizioli. (2018). "Income inequality and education revisited: persistence, endogeneity and heterogeneity", *Applied Economics*, Vol. 50 (25); 2747-2761.

Contreras, D., D. Bravo, and P. Medrano. (1999). "Measurement error, unobservables and skill bias in estimating the return to education in Chile", *Documento de Trabajo*, Departamento de Economía, Universidad de Chile.

Contreras, D., E. Melo, and S. Ojeda. (2005). "¿ Estimando el retorno a la educación o a los no observables?: Evidencia de datos de panel", *Estudios de Economía*, Vol. 32 (2); 187-199.

Cox, C. (1996). "Higher education policies in Chile in the 90s", *Higher Education Policy*, Vol. 9 (1); 29-43.

Espinoza, Ó., and L.E. González. (2013). "Accreditation in higher education in Chile: results and consequences", *Quality Assurance in Education*, Vol. 21 (1); 20-38.

Fernández, M., and J. Messina. (2018). "Skill premium, labor supply, and changes in the structure of wages in Latin America", *Journal of Development Economics*, Vol. 135; 555-573.

Firpo, S., N.M. Fortin, and T. Lemieux. (2009). “Unconditional quantile regressions”, *Econometrica*, Vol. 77 (3); 953-973.

Fortin, N., T. Lemieux, and S. Firpo. (2011). “Decomposition methods in Economics”. In: Ashenfelter, O., and Card, D. (Eds.). *Handbook of Labor Economics*, Vol. 4, Part A, Elsevier, Amsterdam; 1-102.

Gasparini, L., S. Galiani, G. Cruces, and P. Acosta. (2011). “Educational upgrading and returns to skills in Latin America: evidence from a supply-demand framework, 1990-2010”, *IZA Discussion Papers*, No. 6244, Institute of Labor Economics (IZA).

Gómez, D., R. A. Chumacero, and R. D. Paredes. (2012). “School choice and information”, *Estudios de Economía*, Vol. 39 (2); 143-157.

Gong, B. (2019). “Like father like son? Revisiting the role of parental education in estimating returns to education in China”, *Review of Development Economics*, Vol. 23 (1); 275-292.

González-Velosa, C., G. Rucci, M. Sarzosa, and S. Urzúa. (2015). “Returns to higher education in Chile and Colombia”, *IDB Working Paper Series*, No. 587, Inter-American Development Bank.

Hofflinger, A., D. Gelber, and S. Tellez Cañas. (2020). “School choice and parents’ preferences for school attributes in Chile”, *Economics of Education Review*, Vol. 74, Article 101946.

Knight, J.B., and R.H. Sabot. (1983). “Educational expansion and the Kuznets effect”, *American Economic Review*, Vol. 73 (5); 1132-1136.

Messina, J., and J. Silva. (2018). *Wage Inequality in Latin America: Understanding the Past to Prepare for the Future.* World Bank, Washington, DC, Montoya, A.M., C. Noton, and A. Solis. (2017). “Returns to Higher Education: Vocational Education vs College”, *Documentos de Trabajo*, No. 334, Centro de Economía Aplicada (CEA), Universidad de Chile.

Murakami, Y., and T. Nomura. (2020). “Expanding higher education and wage inequality in Chile”, *Journal of Economic Studies*, Vol. 47 (4); 877-889.

Núñez, J., and R. Gutiérrez. (2004). “Class discrimination and meritocracy in the labor market: evidence from Chile”, *Estudios de Economía*, Vol. 31 (2); 113-132.

Oaxaca, R. (1973). “Male-female wage differentials in urban labor markets”, *International Economic Review*, Vol. 14 (3); 693-709.

Organization for Economic Co-operation and Development (OECD). (2017) *Education in Chile, Reviews of National Policies for Education*, OECD Publishing, Paris.

Parro, F., and L. Reyes. (2017). “The rise and fall of income inequality in Chile”, *Latin American Economic Review*, Vol. 26 (3); 1-31.

Puentes, E. (2000). *Relación entre salarios y tipo de educación, evidencia para hombres en Chile 1990-1998*. Ministerio de Planificación y Cooperación (Mideplan), Santiago.

Rodríguez-Castelán, C., L.F. López-Calva, N. Lustig, and D. Valderrama. (2016). “Understanding the dynamics of labor income inequality in Latin America”, *Policy Research Working Paper*, No. 7795, World Bank.

Rodríguez, J., S. Urzúa, and L. Reyes. (2016). “Heterogeneous economic returns to postsecondary degrees: Evidence from Chile”, *Journal of Human Resources*, Vol. 51 (2); 416-460.

Sámano-Robles, C. (2018). “The impact of education on income inequality in Latin America between 2000 and 2010”. In: Bishop, J.A., and Rodríguez, J.G. (Eds.).

Inequality, Taxation and Intergenerational Transmission, Emerald Publishing, Bingley; 109-148.

Seneviratne, P. (2019). “Explaining changes in Sri Lanka’s wage distribution, 1992-2014: a quantile regression analysis”, *Oxford Development Studies*, Vol. 47 (2); 238-256.

Solís, A. (2017), “Credit Access and College Enrollment”, *Journal of Political Economy*, Vol. 125 (2); 562-622.

Tusso Chomali, P. (2021). “La gran mochila financiera del CAE no es culpa del CAE”, *El Mostrador*, March 20. https://www.elmostrador.cl/noticias/opinion/2021/03/20/la-gran-mochila-financiera-del-cae-no-es-culpa-del-cae/ (acceced on March 24, 2021).

Urzúa, S. (2017). “The economic impact of higher education”. In: Ferreyra, M.M., Avitabile, C., Álvarez, J.B., Paz, F.H., and Urzúa, S. (Eds.), *At a Crossroads: Higher Education in Latin America and the Caribbean*, World Bank, Washington, DC; 115-148.

Yang, J., and M. Gao. (2018). “The impact of education expansion on wage inequality”, *Applied Economics*, Vol. 50 (12); 1309-1323.

Table 1. Descriptive statistics of the variables

	2013	2017
Observations	32,081	31,270
Log hourly wage		
Mean	7.485	7.559
Q10	6.879	7.012
Q50	7.379	7.430
Q90	8.444	8.426
Primary education or less	0.207	0.176
Secondary education graduate	0.535	0.507
Higher education graduate	0.257	0.317
Technical degree	0.087	0.107
CFT	0.020	0.021
IP	0.042	0.050
New private university	0.003	0.005
Traditional university	0.001	0.005
Does not know/Did not respond	0.002	0.005
Incomplete	0.018	0.021
Professional degree	0.153	0.210
IP	0.011	0.019
New private university	0.040	0.047
Traditional university	0.066	0.082
Does not know/Did not respond	0.006	0.004
Incomplete	0.030	0.034
Post-graduate degree	0.017	0.023
New private university	0.004	0.005
Traditional university	0.011	0.015
Does not know/Did not respond	0.001	0.001
Incomplete	0.002	0.002
Experience	22.67	22.77
Father's educational achievement		
Primary education or less	0.275	0.201
Secondary education graduate	0.156	0.125
Higher education graduate	0.055	0.055
Technical degree	0.013	0.012
Professional degree	0.040	0.041
Post-graduate degree	0.002	0.002
Does not know/Did not respond	0.515	0.618
Mother's educational achievement		
Primary education or less	0.326	0.245
Secondary education graduate	0.170	0.144
Higher education graduate	0.040	0.047
Technical degree	0.011	0.011
Professional degree	0.027	0.034
Post-graduate degree	0.002	0.001
Does not know/Did not respond	0.464	0.564

Note: Q10, Q50, and Q90 represent the 10^{th}, 50^{th}, and 90^{th} unconditional quantiles, respectively.

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

Table 2. Estimation results of mean and unconditional quantile regressions (2013 and 2017)

	2013					2017				
Explanatory variables	Mean	Mean	Q10	Q50	Q90	Mean	Mean	Q10	Q50	Q90
Primary	-0.196***	-0.186***	-0.128***	-0.199***	-0.089**	-0.167***	-0.157***	-0.083***	-0.198***	-0.099***
	(0.008)	(0.008)	(0.015)	(0.017)	(0.035)	(0.008)	(0.008)	(0.010)	(0.013)	(0.019)
Technical degree										
CFT	0.328***	0.297***	0.091***	0.371***	0.290***	0.322***	0.302***	0.062***	0.355***	0.301***
	(0.020)	(0.019)	(0.018)	(0.028)	(0.107)	(0.019)	(0.018)	(0.013)	(0.029)	(0.082)
IP	0.402***	0.371***	0.119***	0.374***	0.301***	0.315***	0.293***	0.051***	0.313***	0.332***
	(0.014)	(0.014)	(0.014)	(0.035)	(0.085)	(0.012)	(0.012)	(0.010)	(0.022)	(0.055)
New private university	0.504***	0.472***	0.040	0.382***	1.836***	0.233***	0.192***	0.009	0.148*	0.389**
	(0.049)	(0.049)	(0.042)	(0.056)	(0.649)	(0.038)	(0.038)	(0.054)	(0.076)	(0.184)
Traditional university	0.464***	0.446***	0.095*	0.477***	0.667*	0.585***	0.539***	0.072***	0.476***	1.235***
	(0.077)	(0.077)	(0.055)	(0.069)	(0.392)	(0.036)	(0.036)	(0.023)	(0.040)	(0.261)
Does not know/Did not respond	0.345***	0.324***	0.056	0.347***	0.590**	0.230***	0.221***	0.083***	0.233***	0.026
	(0.056)	(0.055)	(0.044)	(0.060)	(0.288)	(0.037)	(0.037)	(0.015)	(0.060)	(0.120)
Incomplete	0.073***	0.051**	-0.093	0.114**	-0.039	0.181***	0.167***	0.020	0.195***	0.247***
	(0.020)	(0.020)	(0.076)	(0.055)	(0.072)	(0.018)	(0.018)	(0.021)	(0.032)	(0.074)
Professional degree										
IP	0.707***	0.667***	0.131***	0.522***	1.265***	0.605***	0.569***	0.068***	0.476***	1.347***
	(0.026)	(0.026)	(0.018)	(0.032)	(0.235)	(0.019)	(0.019)	(0.014)	(0.027)	(0.151)
New private university	0.920***	0.841***	0.108***	0.524***	2.117***	0.714***	0.666***	0.052**	0.457***	1.661***
	(0.015)	(0.015)	(0.015)	(0.021)	(0.151)	(0.013)	(0.013)	(0.021)	(0.031)	(0.122)
Traditional university	1.102***	1.016***	0.117***	0.534***	2.887***	1.056***	0.999***	0.087***	0.564***	2.744***
	(0.012)	(0.012)	(0.013)	(0.017)	(0.116)	(0.010)	(0.011)	(0.007)	(0.015)	(0.092)

	2013					2017				
Explanatory variables	Mean	Mean	Q10	Q50	Q90	Mean	Mean	Q10	Q50	Q90
Does not know/Did not respond	0.805***	0.760***	0.126***	0.516***	1.769***	0.786***	0.752***	0.107***	0.490***	1.836***
	(0.034)	(0.034)	(0.015)	(0.037)	(0.291)	(0.041)	(0.041)	(0.011)	(0.042)	(0.246)
Incomplete	0.454***	0.408***	0.083***	0.364***	0.710***	0.316***	0.293***	0.052***	0.266***	0.597***
	(0.016)	(0.016)	(0.015)	(0.027)	(0.205)	(0.015)	(0.015)	(0.014)	(0.029)	(0.095)
Post-graduate degree										
New private university	1.312***	1.182***	-0.074	0.416***	3.374***	1.430***	1.316***	0.064***	0.549***	4.009***
	(0.045)	(0.045)	(0.107)	(0.082)	(0.419)	(0.036)	(0.036)	(0.015)	(0.027)	(0.361)
Traditional university	1.462***	1.331***	0.101***	0.507***	4.231***	1.499***	1.401***	0.079***	0.570***	4.370***
	(0.027)	(0.027)	(0.014)	(0.029)	(0.210)	(0.022)	(0.023)	(0.010)	(0.021)	(0.169)
Does not know/Did not respond	1.595***	1.413***	0.073**	0.533***	4.215***	0.960***	0.909***	0.091***	0.521***	1.936**
	(0.074)	(0.074)	(0.037)	(0.052)	(0.388)	(0.086)	(0.085)	(0.024)	(0.123)	(0.871)
Incomplete	1.230***	1.106***	0.105***	0.573***	2.761***	1.118***	1.056***	0.097***	0.561***	2.980***
	(0.065)	(0.065)	(0.035)	(0.048)	(0.895)	(0.060)	(0.060)	(0.012)	(0.049)	(0.523)
Father’s educational achievement										
Primary education or less		-0.081***	0.013	-0.091***	-0.188*		-0.088***	-0.007	-0.049**	-0.247***
		(0.011)	(0.015)	(0.024)	(0.097)		(0.011)	(0.010)	(0.021)	(0.064)
Technical degree		0.018	-0.118	-0.093*	0.335		0.038	0.022	0.023	0.017
		(0.025)	(0.083)	(0.051)	(0.206)		(0.026)	(0.014)	(0.029)	(0.227)
Professional degree		0.182***	-0.006	-0.037	0.875***		0.096***	0.017	0.004	0.326**
		(0.018)	(0.018)	(0.031)	(0.202)		(0.017)	(0.011)	(0.031)	(0.147)
Post-graduate degree		0.229***	-0.084	-0.062	0.813		0.285***	0.025	0.097**	1.108***
		(0.068)	(0.081)	(0.056)	(0.598)		(0.069)	(0.022)	(0.047)	(0.386)

	2013					2017				
Explanatory variables	Mean	Mean	Q10	Q50	Q90	Mean	Mean	Q10	Q50	Q90
Does not know/Did not respond		-0.075***	0.012	-0.063**	-0.186**		-0.074***	0.001	-0.038	-0.252***
		(0.012)	(0.017)	(0.031)	(0.087)		(0.012)	(0.012)	(0.031)	(0.062)
Mother's educational achievement										
Primary education or less		-0.054***	-0.008	-0.006	-0.097		-0.046***	0.002	-0.006	-0.167***
		(0.010)	(0.014)	(0.024)	(0.082)		(0.011)	(0.010)	(0.024)	(0.059)
Technical degree		-0.080***	0.006	-0.002	0.172		0.106***	-0.023	0.010	0.603***
		(0.028)	(0.040)	(0.048)	(0.292)		(0.027)	(0.021)	(0.034)	(0.221)
Professional degree		0.031	-0.004	-0.068*	0.272		0.058***	-0.024	-0.020	0.259*
		(0.020)	(0.022)	(0.039)	(0.221)		(0.018)	(0.015)	(0.033)	(0.143)
Post-graduate degree		0.269***	0.033	0.020	1.464**		-0.154*	-0.022	-0.185***	-0.123
		(0.070)	(0.038)	(0.050)	(0.649)		(0.083)	(0.055)	(0.069)	(0.410)
Does not know/Did not respond		-0.074***	-0.057***	-0.044	-0.063		-0.085***	-0.020	-0.057	-0.222***
		(0.012)	(0.018)	(0.032)	(0.070)		(0.013)	(0.014)	(0.036)	(0.060)
Experience	0.015***	0.015***	0.005***	0.013***	0.022***	0.020***	0.020***	0.006***	0.017***	0.035***
	(0.001)	(0.001)	(0.002)	(0.002)	(0.005)	(0.001)	(0.001)	(0.001)	(0.001)	(0.003)
Experience-squared	-0.000***	-0.000***	-0.000**	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Constant	6.951***	7.089***	6.728***	7.035***	7.868***	7.012***	7.170***	6.909***	7.038***	7.959***
	(0.014)	(0.016)	(0.031)	(0.028)	(0.074)	(0.013)	(0.018)	(0.025)	(0.031)	(0.076)
Observations	32,081	32,081	32,081	32,081	32,081	31,270	31,270	31,270	31,270	31,270
R-squared	0.505	0.516	0.073	0.306	0.432	0.500	0.509	0.059	0.277	0.400

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

Demographic dummies, industry dummies, and region dummies are also included.

Table 3. Decomposition of wage changes at selected quantiles into composition and wage structure effects of each explanatory variable (2013 to 2017)

	Composition effect				Wage structure effect			
Explanatory variables	Mean	Q10	Q50	Q90	Mean	Q10	Q50	Q90
Primary	0.0058***	0.0040***	0.0062***	0.0028***	0.0051**	0.0080***	0.0002	-0.0018
	(0.0006)	(0.0005)	(0.0007)	(0.0008)	(0.0020)	(0.0019)	(0.0024)	(0.0061)
Technical degree	0.0069***	0.0014***	0.0072***	0.0098***	-0.0027*	-0.0017	-0.0033*	0.0014
	(0.0009)	(0.0005)	(0.0009)	(0.0016)	(0.0015)	(0.0015)	(0.0017)	(0.0045)
CFT	0.0002	0.0001	0.0003	0.0002	0.0001	-0.0006	-0.0003	0.0002
	(0.0003)	(0.0001)	(0.0004)	(0.0003)	(0.0006)	(0.0005)	(0.0006)	(0.0017)
IP	0.0031***	0.0010***	0.0031***	0.0025***	-0.0039***	-0.0034***	-0.0031***	0.0016
	(0.0006)	(0.0002)	(0.0006)	(0.0006)	(0.0009)	(0.0009)	(0.0011)	(0.0028)
New private university	0.0008***	0.0001	0.0006***	0.0029***	-0.0013***	-0.0001	-0.0011***	-0.0068***
	(0.0002)	(0.0001)	(0.0002)	(0.0009)	(0.0003)	(0.0003)	(0.0003)	(0.0010)
Traditional university	0.0018***	0.0004	0.0019***	0.0027***	0.0005	-0.0001	-0.0000	0.0030**
	(0.0004)	(0.0003)	(0.0004)	(0.0009)	(0.0004)	(0.0005)	(0.0005)	(0.0013)
Does not know/Did not respond	0.0009***	0.0001	0.0009***	0.0016***	-0.0005	0.0001	-0.0006	-0.0028***
	(0.0002)	(0.0002)	(0.0002)	(0.0005)	(0.0003)	(0.0003)	(0.0004)	(0.0010)
Incomplete	0.0002*	-0.0003**	0.0004**	-0.0001	0.0025***	0.0024***	0.0017**	0.0061***
	(0.0001)	(0.0001)	(0.0001)	(0.0002)	(0.0006)	(0.0006)	(0.0007)	(0.0018)
Professional degree	0.0277***	0.0038***	0.0169***	0.0704***	-0.0155***	-0.0075***	-0.0051*	-0.0352***
	(0.0026)	(0.0005)	(0.0016)	(0.0069)	(0.0023)	(0.0022)	(0.0026)	(0.0068)
IP	0.0054***	0.0011***	0.0042***	0.0102***	-0.0019***	-0.0012*	-0.0009	0.0016
	(0.0007)	(0.0003)	(0.0006)	(0.0014)	(0.0006)	(0.0006)	(0.0007)	(0.0018)
New private university	0.0060***	0.0008***	0.0037***	0.0151***	-0.0083***	-0.0026***	-0.0032***	-0.0215***
	(0.0014)	(0.0002)	(0.0009)	(0.0034)	(0.0010)	(0.0009)	(0.0011)	(0.0029)
Traditional university	0.0162***	0.0019***	0.0085***	0.0461***	-0.0014	-0.0025*	0.0024	-0.0117***

	(0.0021)	(0.0003)	(0.0011)	(0.0060)	(0.0013)	(0.0013)	(0.0016)	(0.0040)
Does not know/Did not respond	-0.0019***	-0.0003***	-0.0013***	-0.0043***	-0.0000	-0.0001	-0.0001	0.0003
	(0.0004)	(0.0001)	(0.0003)	(0.0010)	(0.0002)	(0.0002)	(0.0003)	(0.0006)
Incomplete	0.0019***	0.0004***	0.0017***	0.0034***	-0.0039***	-0.0011	-0.0034***	-0.0038*
	(0.0006)	(0.0001)	(0.0005)	(0.0010)	(0.0008)	(0.0007)	(0.0009)	(0.0022)
Post-graduate degree	0.0072***	0.0003	0.0027***	0.0220***	0.0012*	0.0004	0.0016**	0.0038*
	(0.0014)	(0.0002)	(0.0006)	(0.0044)	(0.0007)	(0.0007)	(0.0008)	(0.0021)
New Private university	0.0021***	-0.0001	0.0007***	0.0060***	0.0007**	0.0007**	0.0007**	0.0034***
	(0.0006)	(0.0001)	(0.0002)	(0.0018)	(0.0003)	(0.0003)	(0.0004)	(0.0010)
Traditional university	0.0054***	0.0004***	0.0021***	0.0173***	0.0010*	-0.0003	0.0009	0.0021
	(0.0012)	(0.0002)	(0.0005)	(0.0038)	(0.0005)	(0.0005)	(0.0006)	(0.0016)
Does not know/Did not respond	-0.0006	-0.0000	-0.0002	-0.0017	-0.0005***	0.0000	-0.0000	-0.0021***
	(0.0004)	(0.0000)	(0.0001)	(0.0011)	(0.0001)	(0.0001)	(0.0001)	(0.0005)
Incomplete	0.0002	0.0000	0.0001	0.0005	-0.0001	-0.0000	-0.0000	0.0004
	(0.0004)	(0.0000)	(0.0002)	(0.0009)	(0.0002)	(0.0002)	(0.0002)	(0.0005)
Father's educational achievement	-0.0016	0.0004	0.0002	-0.0046	-0.0037	-0.0085	0.0271*	-0.0784**
	(0.0011)	(0.0011)	(0.0012)	(0.0035)	(0.0129)	(0.0124)	(0.0150)	(0.0388)
Mother's educational achievement	-0.0030***	-0.0051***	-0.0044***	0.0027	-0.0019	0.0221*	-0.0054	-0.1039***
	(0.0011)	(0.0011)	(0.0012)	(0.0031)	(0.0126)	(0.0120)	(0.0146)	(0.0378)
Experience	0.0016	0.0005	0.0014	0.0024	0.1170***	0.0228	0.0802***	0.2870***
	(0.0016)	(0.0005)	(0.0014)	(0.0024)	(0.0253)	(0.0244)	(0.0294)	(0.0759)
Experience-squared	-0.0030**	-0.0011**	-0.0029**	-0.0041**	-0.0634***	-0.0174	-0.0328*	-0.1478***
	(0.0013)	(0.0005)	(0.0013)	(0.0019)	(0.0153)	(0.0147)	(0.0177)	(0.0457)
Demographic dummies	-0.0053***	-0.0021***	-0.0056***	-0.0061***	-0.0291***	-0.0161***	-0.0129*	-0.0670***
	(0.0006)	(0.0004)	(0.0006)	(0.0012)	(0.0065)	(0.0061)	(0.0076)	(0.0198)
Industry dummies	-0.0035***	-0.0007	-0.0032***	-0.0011	-0.0529***	-0.0640***	-0.0280*	-0.0788**
	(0.0011)	(0.0009)	(0.0012)	(0.0025)	(0.0129)	(0.0125)	(0.0150)	(0.0388)
Region dummies	-0.0009	-0.0007	-0.0011	-0.0003	0.0076	0.0130***	0.0095*	0.0179

	(0.0006)	(0.0005)	(0.0007)	(0.0009)	(0.0048)	(0.0046)	(0.0055)	(0.0143)
Constant					0.0808***	0.1803***	0.0027	0.0916
					(0.0238)	(0.0227)	(0.0277)	(0.0717)
Total	0.0317***	0.0007	0.0174***	0.0938***	0.0424***	0.1315***	0.0338***	-0.1113***
	(0.0041)	(0.0016)	(0.0031)	(0.0102)	(0.0039)	(0.0038)	(0.0045)	(0.0117)
Observations	63,351	63,351	63,351	63,351	63,351	63,351	63,351	63,351

Note: Numbers in parentheses represent standard errors. ***, **, and * indicate significance at the 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

	All workers (15-64)			
	Q90-Q10		Q90-Q50	
2013	1.564		1.065	
2017	1.414		0.996	
Overall difference	-0.150		-0.069	
Total composition effect	0.093	-62.28%	0.076	-111.4%
Primary education or less	-0.001	0.806%	-0.003	4.963%
Technical degree	0.008	-5.638%	0.003	-3.717%
CFT	0.000	-0.106%	0.000	0.094%
IP	0.002	-1.016%	-0.001	0.895%
New private university	0.003	-1.927%	0.002	-3.398%
Traditional university	0.002	-1.523%	0.001	-1.103%
Does not know/Did not respond	0.001	-0.947%	0.001	-0.937%
Incomplete	0.000	-0.120%	-0.001	0.731%
Professional degree	0.067	-44.52%	0.053	-77.84%
IP	0.009	-6.092%	0.006	-8.693%
New private university	0.014	-9.577%	0.011	-16.54%
Traditional university	0.044	-29.54%	0.038	-54.68%
Does not know/Did not respond	-0.004	2.679%	-0.003	4.451%
Incomplete	0.003	-1.982%	0.002	-2.383%
Post-graduate degree	0.022	-14.56%	0.019	-28.18%
New private university	0.006	-4.073%	0.005	-7.613%
Traditional university	0.017	-11.27%	0.015	-22.14%
Does not know/Did not respond	-0.002	1.085%	-0.001	2.101%
Incomplete	0.000	-0.299%	0.000	-0.537%
Father’s educational achievement	-0.005	3.384%	-0.005	7.049%
Mother’s educational achievement	0.008	-5.172%	0.007	-10.28%
Experience	0.002	-1.266%	0.001	-1.408%
Experience-squared	-0.003	2.027%	-0.001	1.693%
Demographic dummies	-0.004	2.665%	0.000	0.665%
Industry dummies	0.000	0.273%	0.002	-3.045%
Region dummies	0.000	-0.283%	0.001	-1.273%
Total wage structure effect	-0.243	162.3%	-0.145	211.4%
Primary education or less	-0.010	6.571%	-0.002	2.845%
Technical degree	0.003	-2.057%	0.005	-6.842%
CFT	0.001	-0.557%	0.001	-0.826%
IP	0.005	-3.344%	0.005	-6.796%
New private university	-0.007	4.421%	-0.006	8.252%
Traditional university	0.003	-2.065%	0.003	-4.324%
Does not know/Did not respond	-0.003	1.966%	-0.002	3.256%
Incomplete	0.004	-2.478%	0.004	-6.403%

Professional degree	-0.028	18.54%	-0.030	43.87%
IP	0.003	-1.839%	0.002	-3.556%
New private university	-0.019	12.60%	-0.018	26.66%
Traditional university	-0.009	6.152%	-0.014	20.59%
Does not know/Did not respond	0.000	-0.234%	0.000	-0.550%
Incomplete	-0.003	1.860%	0.000	0.719%
Post-graduate degree	0.003	-2.249%	0.002	-3.171%
Private university	0.003	-1.805%	0.003	-3.970%
Traditional university	0.002	-1.590%	0.001	-1.647%
Does not know/Did not respond	-0.002	1.432%	-0.002	3.079%
Incomplete	0.000	-0.286%	0.000	-0.633%
Father's educational achievement	-0.070	46.77%	-0.106	153.8%
Mother's educational achievement	-0.126	84.18%	-0.098	143.4%
Experience	0.264	-176.5%	0.207	-301.0%
Experience-squared	-0.130	87.18%	-0.115	167.5%
Demographic dummies	-0.051	34.03%	-0.054	78.68%
Industry dummies	-0.015	9.905%	-0.051	74.05%
Region dummies	0.005	-3.321%	0.008	-12.31%
Constant	-0.089	59.29%	0.089	-129.4%

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 the wage inequality among different age groups

	Younger workers (age 15-30)				Older workers (age 51-64)			
	Q90-Q10		Q90-Q50		Q90-Q10		Q90-Q50	
2013	1.272		0.900		1.651		1.182	
2017	1.095		0.748		1.497		1.075	
Overall difference	-0.177		-0.153		-0.154		-0.107	
Total composition effect	0.120	-68.00%	0.103	-67.68%	-0.023	14.74%	-0.026	24.72%
Primary education or less	-0.002	0.981%	-0.002	1.346%	0.001	-0.587%	-0.004	4.183%
Technical degree	0.031	-17.60%	0.024	-15.89%	0.002	-1.118%	-0.006	5.703%
CFT	0.000	-0.221%	0.000	0.026%	0.000	-0.033%	0.000	-0.032%
IP	0.006	-3.370%	0.003	-2.155%	0.004	-2.629%	0.001	-0.929%
New private university	0.013	-7.309%	0.012	-7.625%	-0.005	3.172%	-0.005	4.332%
Traditional university	0.007	-4.007%	0.006	-3.974%	0.002	-1.427%	0.000	0.415%
Does not know/Did not respond	0.004	-2.239%	0.003	-1.824%	0.000	0.158%	-0.001	0.853%
Incomplete	0.001	-0.452%	0.001	-0.336%	0.001	-0.358%	-0.001	1.064%
Professional degree	0.075	-42.38%	0.059	-38.90%	0.003	-1.794%	0.003	-3.216%
IP	0.013	-7.121%	0.009	-5.629%	0.002	-1.571%	0.002	-1.801%
New private university	0.032	-18.16%	0.027	-17.45%	-0.010	6.389%	-0.008	7.760%
Traditional university	0.032	-18.05%	0.027	-17.82%	0.018	-11.51%	0.015	-14.33%
Does not know/Did not respond	-0.003	1.447%	-0.001	0.840%	-0.002	1.545%	-0.002	1.689%
Incomplete	0.001	-0.489%	-0.002	1.163%	-0.005	3.350%	-0.004	3.463%
Post-graduate degree	0.006	-3.485%	0.006	-3.754%	-0.008	5.153%	-0.007	7.004%
New private university	0.007	-3.792%	0.006	-4.023%	0.006	-3.618%	0.005	-4.541%
Traditional university	0.000	0.221%	0.000	0.223%	0.002	-0.984%	0.001	-1.305%
Does not know/Did not respond	-0.001	0.826%	-0.001	0.864%	-0.017	10.96%	-0.015	14.41%
Incomplete	0.001	-0.741%	0.001	-0.818%	0.002	-1.204%	0.002	-1.565%

Father's educational achievement	-0.010	5.564%	0.000	0.268%	0.004	-2.362%	-0.001	1.331%
Mother's educational achievement	0.003	-1.633%	0.000	-0.121%	0.000	0.029%	0.002	-1.413%
Experience	0.006	-3.108%	0.002	-1.222%	0.015	-9.654%	0.007	-6.924%
Experience-squared	-0.004	2.101%	-0.001	0.919%	-0.019	12.39%	-0.011	10.02%
Demographic dummies	0.000	-0.150%	0.000	-0.276%	0.000	0.034%	0.002	-1.829%
Industry dummies	0.007	-4.080%	0.007	-4.846%	-0.017	10.90%	-0.010	9.461%
Region dummies	0.007	-4.214%	0.008	-5.211%	-0.003	1.743%	0.000	0.396%
Total wage structure effect	-0.298	168.0%	-0.256	167.7%	-0.131	85.26%	-0.080	75.28%
Primary education or less	0.000	0.142%	0.006	-4.009%	0.001	-0.658%	-0.009	8.519%
Technical degree	-0.037	21.00%	-0.039	25.36%	0.017	-10.94%	0.020	-18.96%
CFT	0.003	-1.720%	0.002	-1.074%	-0.005	3.356%	-0.005	4.707%
IP	0.000	-0.037%	-0.004	2.605%	0.007	-4.284%	0.007	-6.165%
New private university	-0.019	11.01%	-0.018	11.99%	-0.008	5.109%	-0.008	7.311%
Traditional university	-0.006	3.479%	-0.006	4.053%	0.014	-9.392%	0.015	-14.00%
Does not know/Does not respond	-0.007	4.035%	-0.006	4.110%	0.002	-0.996%	0.002	-1.498%
Incomplete	-0.007	4.235%	-0.006	3.680%	0.007	-4.734%	0.010	-9.308%
Professional degree	-0.015	8.482%	-0.011	7.009%	0.021	-13.42%	0.018	-16.56%
IP	0.008	-4.409%	0.007	-4.627%	0.000	-0.277%	-0.001	0.779%
New private university	-0.040	22.74%	-0.035	22.81%	0.005	-3.236%	0.005	-4.892%
Traditional university	0.010	-5.476%	0.007	-4.539%	0.011	-7.336%	0.010	-9.635%
Does not know /Did not respond	0.003	-1.822%	0.004	-2.391%	0.002	-1.571%	0.002	-2.261%
Incomplete	0.005	-2.553%	0.006	-4.240%	0.002	-0.995%	0.001	-0.549%
Post-graduate degree	-0.005	3.096%	-0.005	3.240%	0.005	-3.512%	0.005	-4.300%
Private university	-0.001	0.362%	-0.001	0.459%	0.003	-1.716%	0.003	-2.351%
Traditional university	-0.002	1.116%	-0.001	0.899%	0.004	-2.447%	0.003	-2.942%
Does not know/Did not respond	0.000	-0.068%	0.000	-0.040%	-0.001	0.843%	-0.001	1.220%
Incomplete	-0.003	1.686%	-0.003	1.923%	0.000	-0.192%	0.000	-0.227%
Father's educational achievement	-0.173	97.51%	-0.304	199.3%	0.098	-63.66%	0.101	-94.16%

Mother's educational achievement	-0.028	15.80%	-0.006	4.042%	-0.064	41.71%	-0.128	119.7%
Experience	0.055	-31.14%	-0.022	14.12%	-1.581	1028%	-2.124	1988%
Experience-squared	0.000	0.277%	0.000	0.245%	0.674	-438.0%	0.889	-832.6%
Demographic dummies	-0.040	22.55%	-0.037	24.12%	-0.010	6.573%	-0.031	29.39%
Industry dummies	0.050	-28.08%	0.126	-82.69%	-0.063	41.03%	-0.061	57.09%
Region dummies	0.072	-40.82%	0.100	-65.15%	-0.150	97.29%	-0.136	127.3%
Constant	-0.176	99.19%	-0.064	42.10%	0.921	-599.0%	1.376	-1288%

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