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The role of skills and tasks in changing employment trends and income inequality in Chile

Gabriela Zapata-Román*

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Abstract: Using decomposition methods, we analyse the role of the changing nature of work in explaining changes in employment, wage inequality, and job polarization in Chile from 1992 to 2017. Changes in occupational structure confirm a displacement of workers from low-skill occupations towards jobs demanding non-routine higher skills (professionals and technicians), and to jobs demanding routine manual and cognitive tasks (services and sales). Changes in occupational earnings have had an equalizing effect, with more substantial gains in favour of lower-skill occupations and also at the top of the skill premium. Inequality reductions since the 2000s are explained by a fall in earnings in the top percentiles of the distribution, which have been reallocated most noticeably around the median (2000–06) and the bottom 30 per cent (2006–17). Changes in the returns to education and the relocation of workers towards less-routine occupations have contributed to the inequality reduction.

Key words: wage inequality, job polarization, skills, tasks, decomposition methods, Chile

JEL classification: J23, J24, J31, J6, O33

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Note: The Technical Appendix is available [here](https://www.wider.unu.edu/publication/role-skills-and-tasks-changing-employment-trends-and-income-inequality-chile) (<https://www.wider.unu.edu/publication/role-skills-and-tasks-changing-employment-trends-and-income-inequality-chile>).

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1 Introduction

A key issue in development economics has been to understand the effects of technological changes in the labour market, in terms of their impact on both wage inequality and job creation and destruction. The literature of the late 1990s suggested that technological change was skill-biased and would favour high-skill workers and replace routine tasks. Skill-biased technological change (SBTC) increases the marginal productivity of skilled labour in relation to unskilled labour, and consequently its demand and salary premium, which leads to an increase in wage inequality (Berman et al. 1998).

More recent literature has built on Autor et al.'s (2003) hypothesis, which argues that technological change has two effects on labour markets: first, it replaces workers in performing routine cognitive and manual tasks that can be achieved by following explicit rules (which can be automated); second, it complements workers in the performance of non-routine problem solving and complex communications. Therefore, technological change will lead to a lower demand not necessarily for all low-skilled workers, only for those involved in routine tasks that can now be replaced with the use of technology. At the same time, this can lead to a greater demand for workers whose tasks are complementary to computerization, such as people who work in occupations where non-routine cognitive skills are required (Acemoglu and Restrepo 2017), which are generally measured at the occupational level (Firpo et al. 2011).

The relative share of cognitive and manual routine jobs has declined over time in the US and other developed economies (Autor et al. 2003; Goos et al. 2014; Jensen and Kletzer 2010; Michaels et al. 2013), contributing to wage polarization and therefore higher levels of inequality. While this is true for advanced economies, there is evidence suggesting that developing countries and emerging economies are not following the same trends. Surveys in China and some Central and Eastern European countries show that the proportion of people employed in routine-intensive occupations has increased in recent decades (Du and Park 2017; Hardy et al. 2018).

Inequality trends also behave differently in developing countries. While most of the developed world has experienced rising inequality since the 2000s, most countries in Latin America have followed the opposite pattern. Messina and Silva (2019) argue that the absence of skill-biased technological change and little evidence of job polarization in Latin America have facilitated the decline of wage inequality in the region. They found that wages expanded rapidly in low-paying occupations relative to high-paying occupations, while technological advances that complement skill-intensive occupations predict the opposite.

Building on these important bodies of literature, this paper investigates the trends in earnings inequality in Chile from the early 1990s to 2017, exploring how the nature of work and the structural composition of employment have changed over time, and which factors have contributed to these changes. First, it documents the main changes in inequality in Chile, the institutional factors that might have had an impact over these trends, and the evolution of the skill supply and premium. Using household survey data, it analyses changes in real earnings over time and across skill groups and occupations. In this vein, it examines the role of tasks in explaining the variability of earnings, testing for job polarization. Finally, it decomposes changes in earnings inequality to understand whether these changes are due to variations in the characteristics of occupations (i.e. gender, age, years of schooling, and the different skills or routine task intensity contents of occupations) or to changes in rewards depending on these characteristics. The empirical analysis builds on the Chilean household income surveys for 1992, 2000, 2006, and 2017 (Encuesta de Caracterización Económica Nacional; CASEN) matched with the skill content of job indicators at the occupational level (ISCO-88) obtained from two different sources: the US estimation of tasks derived from the

US Occupation Information Network survey (O*NET 2003); and the country-specific values of standard task measures at the ISCO-88 two-digit level estimated for Chile by Lewandowski et al. (2020), using information on the task content of occupations from PIAAC data, collected by the OECD (2014/15).

Taking advantage of the trajectory that income inequality has followed in Chile, we divide the analysis into three sub-periods: 1992–2000, 2000–06, and 2006–17. The first part of our analysis shows that the share of the top earnings decile has been falling since 2000. In the period 2000–06, wages grew faster around the median of the distribution, with pro-poor growth only after 2006. The period 2006–17 describes strong growth for the bottom 30 per cent of the wage distribution and below-average growth for the top 30 per cent. Therefore, the decrease in total inequality in 2000–06 is explained by a fall in the top decile of income distributed, more noticeably, around the median, while the fall in total inequality in 2006–17 is related to a redistribution from the richest 30 per cent to the poorest 30 per cent.

Sectorial changes in the occupational structure confirm a displacement of workers from low-skill occupations such as skilled agricultural, craft and trade, and elementary occupations, towards jobs demanding non-routine higher skills, including professionals and technicians. There is also a significant increase in the share of service and sales workers, who tend to perform routine manual and cognitive tasks. Changes in occupational earnings have had a positive equalizing effect, with more substantial gains in favour of lower-skill occupations such as skilled agricultural workers, craft and related trade workers, plant and machine operators, and elementary occupations. The equalizing effect is also noticeable at the top of the skill premium, with earnings of managers and professionals becoming closer. Despite these positive changes to inequality, we still observe substantial differences between the rewards of low- and high-skill occupations.

We do not find statistically significant evidence of employment or earnings polarization. The polarization phenomenon predicts an increase in the relative demand for well-paid skilled jobs (which consist of non-routine cognitive tasks), and low-paid low-skill jobs (linked to non-routine manual tasks), diminishing the relative demand in the middle of the distribution, which commonly executes routine manual and cognitive tasks. We find a significant opposite pattern (inverted U-shaped growth) in (log) earnings in 2000–06. This suggests that real earnings grew more in the middle of the distribution. We find that the routine task intensity (RTI) explains an important part of the variability of earnings, and to a lesser extent, the variability of employment. There is a positive and significant relationship between changes in mean log wage and both RTI measures (O*Net and country-specific) in 2000–06 and 2006–17, suggesting that earnings tend to increase more in more routine occupations, which is not observed in employment in 2006–17.

The first part of the decomposition analysis (Shapley decomposition) shows that the dispersion of earnings is large both between and within occupations, although with a strong decline in inequality between occupations from the 2000s. This is driven mostly by changes in average earnings, not in shares, despite all the structural changes in employment experienced in Chile, such as increasing average years of education, displacement of workers from low-skill occupations towards jobs demanding non-routine higher skills, reduction of informal jobs, and increasing female participation. Average earnings across occupations have become less unequal over time, and the strong monotonic correlation with RTI has been reducing.

The recentred influence function (RIF) decomposition shows that both the composition and the structure effect are important in explaining the changes in inequality in Chile, and the latter is more relevant from 2000. In the decomposition of changes in the Gini coefficient, we observe an inequality-enhancing effect of the returns to education and an inequality-reducing effect of the returns to tasks in the 2006–17 period (structure effect). The composition effect is mainly driven by changes in education (increasing schooling levels) and routinization (movements towards high-

skill or less-routine occupations), and informality. When analysing the changes in the variability of earnings by percentiles, we also observe the preponderant role of routinization and education. The total effect of RTIs is positive throughout the entire earnings distribution and accounts for the majority of the changes in the variability of earnings. Education is the second most relevant covariate in explaining changes in inequality in the overall period. Since the composition and returns effects have opposite signs, the total effect of education is inequality-reducing in the bottom part of the distribution and inequality-enhancing in the upper part.

The remainder of the paper is structured as follows: the next section describes the data and the conceptual framework of occupational tasks and labour market outcomes, job polarization, and inequality decompositions. The third section describes the general trends in inequality, minimum wage, unemployment, and informality in Chile in the period 1992–2017, analysing structural changes in education in terms of its returns over time. In this section we also review the trend in inequality in real earnings and occupations over time. The fourth section examines the role of tasks and skills in changing earnings inequality over time and provides evidence to discard the hypothesis of occupational and earnings polarization. The final empirical section analyses the role of occupational changes in shaping the evolution of inequality by performing two inequality decompositions, i.e. the Shapley decomposition and the RIF regression decomposition.

2 Data and methodology

This study draws on the Chilean household survey CAsEN in four waves: 1992, 2000, 2006, and 2017. This is a cross-sectional household survey that uses a multi-stage stratified sampling design, representative at the national and regional levels. The 1992 wave is the first using the ISCO-88 classification of jobs at the three-digit level, and from subsequent waves ISCO-88 at the four-digit level is used. The CAsEN survey holds a wealth of information on the demographics and income sources of all household members aged 14 and above. This analysis focuses on a subsample of the working-age population, this being individuals aged between 15 and 64 years active in the labour market as employees, employers, or self-employed. Hence, unpaid family workers are excluded from the sample.

The income concept used is labour earnings from the main occupation. This includes earnings from dependent and independent work (cash and in kind), net of direct taxes and social security contributions, while also incorporating income from self-production. We chose this income concept since the occupational data are associated with the main occupation. The survey provides net monthly earnings in Chilean pesos for each year, which have been transformed into weekly earnings. These have been corrected to observe real earnings at November 2017 prices in purchasing power parity (PPP) to ensure comparability over time and across countries.

Traditionally, income concepts from the survey were adjusted to match the national accounts. This practice was removed in 2015, correcting previous waves to allow comparability. Initially they were adjusted back to the 2006 wave, but recently all databases since 1990 have been updated. This study uses the complementary income bases published in March 2020 by the Ministry of Social Development, adjusted to the new methodology, which allows comparability of the income concepts for the entire period of analysis, in our case 1992–2017.

We divide the analysis into three subperiods—1992–2000, 2000–06, and 2006–17—as well as looking at overall change from 1992 to 2017. The selection of these particular years is based on the trajectory that income inequality has followed in Chile. Between 1992 and 2000 the net Gini coefficient rose slightly. From 2000 it began on a downward trajectory, with the largest drop between 2000 and 2006. The last period, longer than the previous one, saw a milder drop in

inequality, since it remained almost constant until 2012, then it fell and rose slightly between 2015 and 2017.

In order to analyse the distributional changes and task composition, this paper uses a task-based approach, comparing the results obtained by two different methods of imputing RTI to occupations, as in Gradín and Schotte (2020). The first method is the standard method used in the literature that matches country survey data at the ISCO-88 three-digit level to the US estimation of tasks derived from O*NET. The second uses country-specific values of standard task measures at the ISCO-88 two-digit level estimated for Chile by Lewandowski et al. (2020). They construct country-specific task measures for 46 countries, using information on the task content of occupations from PIAAC data in the case of Chile, collected in 2014/15 by the OECD.

2.1 Occupational tasks and labour market outcomes

To identify the effect of technological change on occupations, the model developed by Autor et al. (2003) (here after called the ALM model) shifts attention from skills (usually measured by years of schooling) to the task contents of work. The ALM model predicts two outcomes depending on the type of task that workers perform. First, there will be a progressive substitution of workers performing routine tasks that are simple to codify, which can be easily replicated by machines. Second, the ALM model predicts complementarity between technology and abstract tasks. Abstract tasks, which require complex analytical thinking, flexibility, creativity, and communication skills, are not only difficult to replace by machines, but they can also be complementary to computer technologies.

Goos and Manning (2007) used the ALM model to understand the impact of technology on job polarization. This phenomenon occurs when the relative demand for well-paid skilled jobs and low-paid low-skilled jobs increases, diminishing the relative demand in the middle of the distribution. While skilled jobs are characterized by the performance of non-routine cognitive tasks, low-skilled jobs consist mostly of non-routine manual tasks. Middle-skill jobs, on the other hand, commonly involve executing routine manual and cognitive tasks. Routine tasks that can be displaced by technology include jobs such as manual crafting and bookkeeping, which require precision and, hence, were never the lowest-paid occupations in the labour market. Non-routine tasks that are complementary to technology include skilled professional and managerial jobs that tend to be in the upper part of the wage distribution. Non-routine manual tasks that make up many of the less-skilled jobs, such as cleaning, are not greatly affected by technology. However, the impact of technology in other parts of the economy is likely to lead to a rise in employment in these less-skilled jobs.

Country-specific measures of the task content of jobs have only recently become available for some developing countries (Lewandowski et al. 2019). For that reason, most studies have relied on standardized indices of different types of job tasks derived from the US Occupation Information Network survey (O*NET), as in Acemoglu and Autor (2011). They associated the task measures with common occupational categories: non-routine cognitive analytical (managerial, professional, and technical occupations), routine cognitive (clerical, administrative, and sales occupations), routine manual (production and operative occupations), and non-routine manual (service occupations). The use of O*NET task data essentially relies on the assumption that the task content of occupations is identical across countries. This assumption might be problematic particularly for less developed countries, considering that large differences in labour productivity, technology adoption, and skills still persist. As shown by Lewandowski et al. (2019), the task content of occupations differs across countries, with workers in countries with higher technology use, higher skills, and broader participation in global value chains tending to perform less-routine tasks than their counterparts in countries with lower technology use, lower skills, and narrow specialization in global value chains.

Following Autor and Dorn (2009; 2013) and Goos et al. (2014), Lewandowski et al. (2020) construct country-specific task measures for 46 countries including Chile, using information on the task content of occupations from the STEP, CULS, and PIAAC surveys (PIAAC in the case of Chile).

They define a measure of relative RTI as:

$$RTI = \ln(r_{cognitive}) - \ln\left(\frac{nr_{analytical} + nr_{personal}}{2}\right) \quad (1)$$

where $r_{cognitive}$, $nr_{analytical}$, and $nr_{personal}$ are routine cognitive, non-routine cognitive analytical, and non-routine cognitive personal task levels, respectively. Their definition omits manual tasks, since the survey data do not distinguish between routine and non-routine manual tasks and the available manual task measure is not entirely comparable across countries. Nevertheless, the survey-based RTI measure successfully captures the routine nature of work, even for manual jobs.

2.2 Test for job polarization

To identify the presence of job polarization, we closely follow Goos and Manning (2007) and Sebastian (2018), who test the significance of the parameters of the following quadratic model:

$$\Delta \log E_{j,t} = \alpha_0 + \alpha_1 \log(y_{j,t-1}) + \alpha_2 \log(y_{j,t-1})^2 \quad (2)$$

where $\Delta \log E_j$ is the change in the (log) employment share of occupation j between survey wave $t - 1$ and t , $\log(y_{j,t-1})$ is the logarithm of the mean labour earnings in occupation j in survey wave $t - 1$, and $\log(y_{j,t-1})^2$ is the square of initial (log) mean labour earnings.

The same model is also estimated using (log) change in earnings as the dependent variable (Sebastian 2018):

$$\Delta \log(y_{j,t}) = \beta_0 + \beta_1 \log(y_{j,t-1}) + \beta_2 \log(y_{j,t-1})^2 \quad (3)$$

Both equations are estimated by weighting each occupation by its initial employment share to avoid results being biased by compositional changes in small occupation groups. A polarization U-shaped pattern implies that the first coefficient is significantly negative, with a positive quadratic coefficient.

Following Sebastian (2018), in the next step we estimate a quadratic regression, at the three-digit occupational level, of the log change in employment share on the initial level of routine intensity. We aim to explain the variance of employment and earnings using our measures of the RTI of jobs. Where RTI_j measures the (time-invariant) RTI of occupation j :

$$\Delta \log E_{j,t} = \delta_0 + \delta_1 RTI_j + \delta_2 (RTI_j)^2 \quad (4)$$

$$\Delta \log(y_{j,t}) = \varphi_0 + \varphi_1 RTI_j + \varphi_2 (RTI_j)^2 \quad (5)$$

A negative relationship between the two variables would be expected, indicating that higher RTI leads to larger declines in employment and earnings.

2.3 Shapley decomposition

Initially applied to game theory, the Shapley value (Shapley 1953, in Roth 1989) provides a framework to decompose total inequality by factor components (Shorrocks 1982) or by subgroups of variables (Shorrocks 2013). Intuitively, the decomposition, also known as the Shapley-Shorrocks decomposition, allows us to estimate the partial shares of the contribution of income inequality to changes in within-occupations inequality and between-occupations inequality.

As the Gini index is not additively decomposable, to perform the Shapley decomposition we estimate the marginal contribution of the within- and between-occupations components of the overall inequality following Duclos and Araar (2006). To compute the marginal contribution of each of these factors, first we eliminate within-occupations inequality by replacing each observation's earnings, y , with the average earnings of the occupation the person belongs to, y_b , calculating between-occupations inequality. Second, we eliminate between-occupations inequality by rescaling each worker's earnings so that all occupations have the same average earnings, y_w .

More formally, we want to express total inequality I as:

$$I = I_{between} + I_{within} \quad (6)$$

To compute the contribution of between-occupations inequality, we calculate the change in inequality observed when the mean incomes of the occupations are equalized. Hence, the Shapley contribution to between-occupations inequality is given by:

$$I_{between} = \frac{1}{2}[I(y_b) + I - I(y_w)] \quad (7)$$

Similarly, the Shapley contribution of within-occupations inequality is given by:

$$I_{within} = \frac{1}{2}[I(y_w) + I - I(y_b)] \quad (8)$$

Therefore, changes in the Gini index can be decomposed into the contribution of each component.

We repeat the analysis with counterfactual distributions in which either the occupational shares or the occupational earnings are kept constant, to check whether the trend is explained by changes in the distributions of employment or changes in earnings.

2.4 Concentration index

We use the concentration index derived from the concentration curve that is commonly used to analyse inequalities in health (Wagstaff et al. 1991) to investigate the relevance of the task composition of occupations in explaining trends in inequality between occupations. The concentration curve shows the share of the population that receives a proportion of the earnings when we order the population from highest to lowest RTI content of jobs, instead of by earnings as in the Lorenz curve. If RTI is equally distributed across occupations, the concentration curve will coincide with the diagonal; if high-routine jobs are concentrated among the worst-paid occupations, the concentration curve lies below the diagonal. The further the curve lies below the diagonal, the higher the degree of inequality related to the routine-task contents of jobs.

The concentration index denoted by C is defined as twice the area between the concentration curve and the diagonal. The concentration index is positive when the concentration curve lies below the diagonal and negative when it lies above the diagonal. Thus, the lowest value that C can take is -1 , when all routine tasks are done by the most disadvantaged person (so that C is shaped as follows: \lceil).

The maximum value the index can take is +1, when all routine tasks are concentrated in the hands of the richest person (so that C is shaped as follows: \downarrow). C corresponds to the Gini index when RTI is perfectly correlated to average earnings. Therefore, the closer the value of the concentration index is to the Gini index, the higher the correlation between RTI and earnings.

2.5 RIF regression decomposition

Developed by Firpo et al. (2011, 2018), recentred influence function (RIF) regression is an extension of the Oaxaca-Blinder (OB) decomposition (Blinder 1973; Oaxaca 1973). The OB procedure provides a way of decomposing differences in mean earnings into a composition effect (changes due to varying worker characteristics) and a structure effect (changes in the return to those characteristics). It also allows us to further divide these two components into the contribution of each covariate. The main advantage of using the RIF regression method in an OB-type decomposition is that it provides a linear approximation of highly non-linear functionals, such as the quantiles or the Gini coefficient (Firpo et al. 2018).

The RIF method is a two-stage procedure that can be used to perform OB-type decompositions on any distributional measure, not only the mean. The first stage consists of decomposing the distributional statistic of interest (i.e. interquartile ranges and the Gini coefficient) into an earnings structure and a composition component using a reweighting approach, where the weights are either parametrically or non-parametrically estimated. In a second stage, the wage structure and composition effects are further divided into the contribution of each covariate, as in the usual OB decomposition (Firpo et al. 2018).

Closely following Firpo et al. (2011), we focus on differences in the wage distributions, Δ_o^v , for two time periods, 1 and 0:

$$\Delta_o^v = v(F_{Y_1|T=1}) - v(F_{Y_0|T=0}) \quad (9)$$

where $v(F_{Y_0|T=0})$ is the wage distribution in time period 0, and $v(F_{Y_1|T=1})$ is the wage distribution in time period 1. Adding and subtracting the term $v(F_{Y_0|T=1})$, we obtain:

$$\Delta_o^v = \underbrace{v(F_{Y_1|T=1}) - v(F_{Y_0|T=1})}_{\Delta_S^v} + \underbrace{v(F_{Y_0|T=1}) - v(F_{Y_0|T=0})}_{\Delta_X^v} \quad (10)$$

where Δ_S^v is the wage structure effect, Δ_X^v is the composition effect, and $v(F_{Y_0|T=1})$ is the counterfactual distribution that would have prevailed if workers observed in the end period ($T = 1$) had been paid under the wage structure of period 0.

The composition effect Δ_X^v consists of changing the distribution of X (characteristics) from its value at $T = 0$ to its value at $T = 1$, holding the wage structure constant. The wage structure effect Δ_S^v measures changes in the return to those characteristics, holding the distributions of X constant.

Following DiNardo et al. (1996), Firpo et al. (2011) estimate the counterfactual distribution $v(F_{Y_0|T=1})$ by reweighting the period 0 data to have the same distribution of covariates as in period 1. Details of the estimation procedure can be found in Firpo et al. (2011; 2018), Fortin et al. (2011), and the Methodological Appendix of Gradín and Schotte (2020).

3 Inequality and employment trends

3.1 Country context and inequality trends

Chile has frequently been described as a successful case of rapid economic growth, sound economic management, macroeconomic stability, export orientation, and bold structural reforms, such as trade and foreign investment liberalization. Most of these pro-market reforms were implemented during the military dictatorship in the 1980s. They also included a bundle of social reforms in the areas of education, health, and pensions that aimed to increase the private sector role in the provision of these services.

Market-oriented reforms boosted the economy strongly during the 1990s, allowing average growth rates of more than 7 per cent between 1991 and 1998 (Figure A1 in the Appendix). The return to democracy was a period of rising private investment and job creation that helped to reverse the rises in unemployment and depression of real wages of the dictatorship period in the 1980s (Contreras and French-Davis 2012). The rapid growth moved Chile from having the third-lowest GDP per capita in South America, US\$4,511, in 1990 to taking the lead in the region from 2010, reaching \$25,155 in 2019 (Figure A2 in the Appendix).

High growth had a positive effect, facilitating the reduction of poverty from almost 40 per cent in 1990 to 20.2 per cent in 2000 (Contreras 2003). After 2000 the poverty rate reduced further, reaching 8.7 per cent in 2017 (MDS and PNUD 2020).¹ This was accompanied by increased social spending and the creation of a social protection system, which has played a key role in overcoming extreme poverty and improving the quality of life of the most deprived in the last few decades.

Despite the good economic results and poverty reduction, other social indicators have not had such a satisfactory evolution. Chile exhibits persistent inequality of income and wealth, with high asset concentration among powerful economic elites. The Gini coefficient for both monetary incomes (adjusting for transfers) and net wealth places Chile as the most unequal country in the OECD, and it ranks 28th among the countries with the highest inequality in the world, preceded only by other countries in Latin America and Sub-Saharan Africa (OECD 2020; World Bank 2020c).

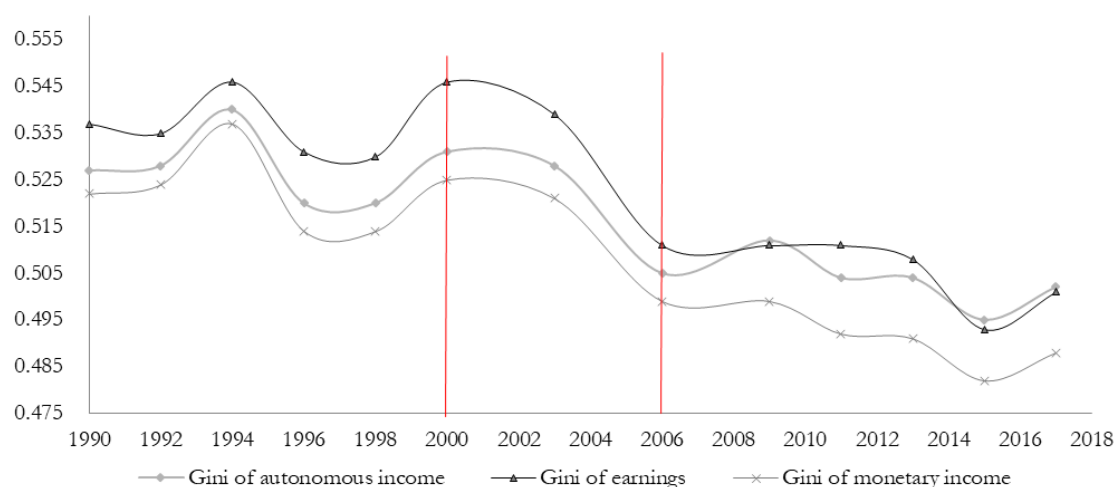
An important cause of the inequality in Chile is the large income gap between the elite and the rest of the population. In 2017, the richest 1 per cent captured 27.8 per cent of national income; at the same time, the income share of the wealthiest 10 per cent was 60.2 per cent (survey and tax data; WID 2020). Additionally, the wealthiest 10 per cent's share of autonomous income was 30.8 times higher than the share of the poorest decile (survey data only). Considering job earnings, this ratio increases to 39.1 (MDS and PNUD 2020). When considering monetary household income, this gap is reduced due to transfers and state subsidies, which have increased since the 1990s. However, analysing the redistributive power of these social policies, we observe that this is rather limited and much lower than that of other OECD countries. Before taxes and transfers, income inequality in Chile is similar to that of countries such as Belgium and Austria and even lower than that of Finland, France, and Ireland (OECD 2020). The big difference is the redistributive capacity of the state, which in Chile is minimal, leaving the country the most unequal of all the OECD members.

¹ This poverty line is calculated using the 'historical methodology' applied by the Economic Commission for Latin America and the Caribbean, ECLAC (MDS and PNUD 2020), which estimates the poverty threshold from the basic food basket (BFB) based on the IV Family Budget Survey 1987–88 (EPF). This value is updated over time according to the variation in the price of each of the elements in the BFB. As a welfare indicator, it uses total per capita household income corrected for non-response and adjusted to match the national accounts.

Social reforms implemented since the 1980s were promoted as a way to improve efficiency and increase individual choice. However, the segmentation in health, education, and social security benefits has fostered profound inequalities in access to quality services which, combined, enhance inequalities in other areas of life. For example, limited access to quality education for the poorest translates into unequal opportunities in the labour market, which also influences participation in the health system and limits contributions to the pension scheme. Unequal access to opportunities, a greater demand for quality public services, and the high level of indebtedness of Chilean families has formed great social tensions for more than a decade, which erupted in the outbreak of social unrest of October 2019. This social unrest has been positively led towards a process of constitutional change that began at the end of October 2020, when a public vote approved changing the constitution implemented during the dictatorship. The new constitution is seen as a step towards a new social contract in Chile.

Although inequality in Chile is high, it has been declining slightly since the turn of the century, as shown in Figure 1. While most of the developed world experienced rising inequality in the 2000s, Chile and many countries in Latin America followed the opposite pattern. In Chile the Gini coefficient of earnings fell from 0.546 in 2000 to 0.501 in 2017, with the largest drop of 0.035 points between 2000 and 2006. The literature mentions as the main causes of this inequality drop the reduction in the wage gap between the highest- and lowest-skilled workers due to faster growth of real wages at the bottom of the wage distribution than at the top, improvements in the minimum wage, a lower skill premium, and better-targeted cash transfers to the poor, combined with a positive economic environment and the commodity price boom (Messina and Silva 2019; PNUD 2017; Torche 2014).

Figure 1: Gini of households' earnings, Chile, 1990–2017



Note: the income series used in this graph have recently been adjusted by the Ministerio de Desarrollo Social (MDS) to the new methodology, to allow the comparison of inequality measures since the 1990s.

Source: author's illustration based on data from MDS and PNUD (2020).

3.2 Labour market institutional factors that affect inequality

The Chilean labour market is characterized by low wages. In 2018, 57 per cent of those employed did not earn enough to lift an average family out of poverty.² In the case of female heads of households, this percentage was 64 per cent. Additionally, 51 per cent of private sector workers

² This is based on the monthly income poverty line for an average household of four people, which in November 2018 was 430,763 Chilean pesos, equivalent to US\$621.

with full-time jobs, were in the same situation, revealing high levels of precariousness in the job market (Kremerman and Durán 2019).

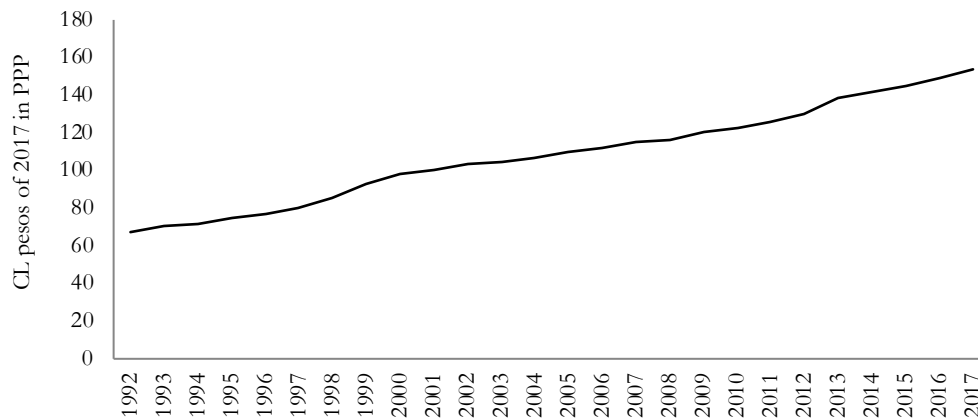
In addition to low incomes, the precariousness of the Chilean labour market has various other origins, including excessive dependence on self-employment and short-term contracts. The share of temporary contracts, although it has decreased since 2012, is the second-highest among OECD countries (27 per cent). The level of informality, or the proportion of wage earners and self-employed workers not making contributions to the pension system, is also one of the highest in the OECD, standing at 32 per cent of employment in 2015, held back only by cyclical conditions (OECD 2018). Informality particularly affects lower-skilled workers, young people, immigrants, indigenous people, and women. Between 2017 and 2019, women had informality rates almost three percentage points higher than those of men (INE 2017). Temporary and informal workers generally face lower wages and frequent periods of unemployment and inactivity. Given that Chile has a private pension system based mainly on individual savings, high levels of informality puts pressure on the pension scheme. This is why the pension law established voluntary contributions for self-employed workers in 2014; these have been compulsory only since 2018 (SII 2020).

Chilean labour market regulations may seem rigid *de facto*, but in practice it is quite easy for companies to hire and fire workers. The type of employment contract—permanent or temporary—is a fundamental distinguishing characteristic that creates a segmented or dual market, where temporary contracts are generally associated with flexibility and permanent contracts with rigidity (Ruiz-Tagle and Schnbruch 2015). In 2014, 51 per cent of workers in the formal sector had contracts of less than three years, mainly in the services sector—the sector with the highest level of job creation in the last two decades. In addition, a third of workers had short-term fixed contracts, used largely in construction and agriculture (Dirección del Trabajo 2014); the OECD average for these types of contracts is 12 per cent (OECD 2016). While in more developed countries a short-term contract can be the path to a permanent job, in Chile 40.9 per cent of these contracts are renewed as short-term after their expiration, and only 36.8 per cent lead to permanent jobs (Dirección del Trabajo 2014, cited in PNUD 2017). Another factor that affects job stability is outsourcing; this is a common practice in Chile that in 2014 affected 17 per cent of the workforce (Dirección del Trabajo 2014).

These practices limit the real labour rights of employees, preventing their access to severance pay, the possibility of creating effective unions, and access to benefits such as nurseries. Other aspects of labour market flexibility include low unionization rates, limited strike rights (replacement of striking workers is allowed), decentralized and fragmented bargaining power, and highly flexible lay-off laws for workers on permanent contracts (OECD 2018).

The short duration of contracts and high job turnover also limits the coverage and benefits of unemployment insurance—which is financed with contributions from the employee and the employer. Only 50 per cent of those whose contracts end in a year have enough contributions in their accounts to access unemployment insurance. In 2015, 50 per cent of workers with a fixed-term contract had gaps in their contributions of more than three months, which prevents them from accessing the public unemployment fund (Fondo de Cesantía Solidario) (Schnbruch et al. 2019). All of this ‘flexibility’ in the Chilean labour market transfers the risks from the employer (and the state) to the employee, leaving workers more vulnerable to possible external shocks and increasing inequality as there are no adequate safety nets for them (World Bank 2017).

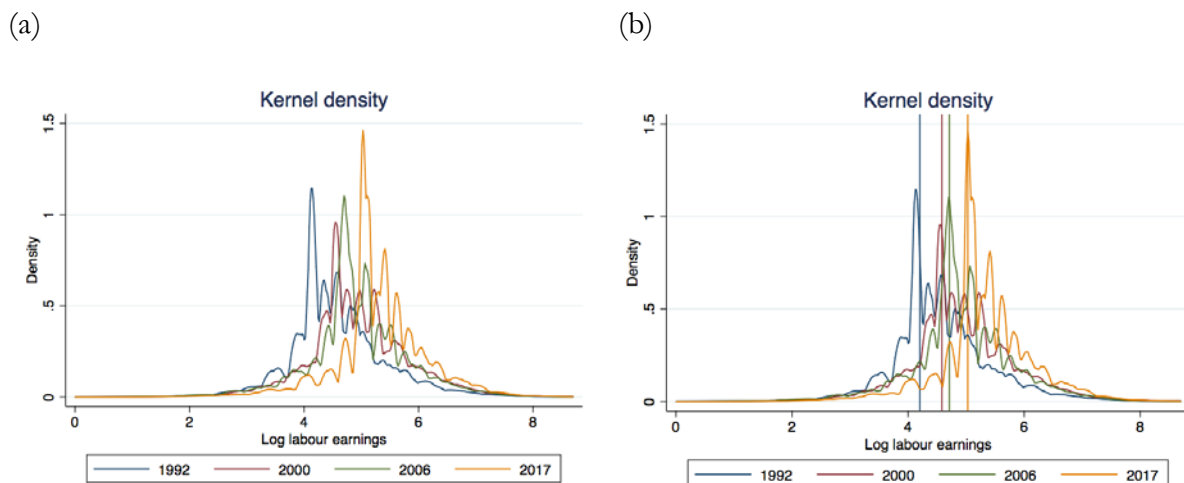
Figure 2: Weekly minimum wage, Chile



Note: the Chilean Congress adjusts nominal minimum wage annually; in all tables and figures in this paper, monthly values in Chilean pesos for each year have been converted into weekly values in 2017 pesos and then adjusted by purchasing power parity.

Source: author's illustration based on annual changes to the minimum wage law published by Congreso de Chile.

Figure 3: Kernel density functions



Source: authors' elaboration based on CASEN (1992, 2000, 2006, 2017).

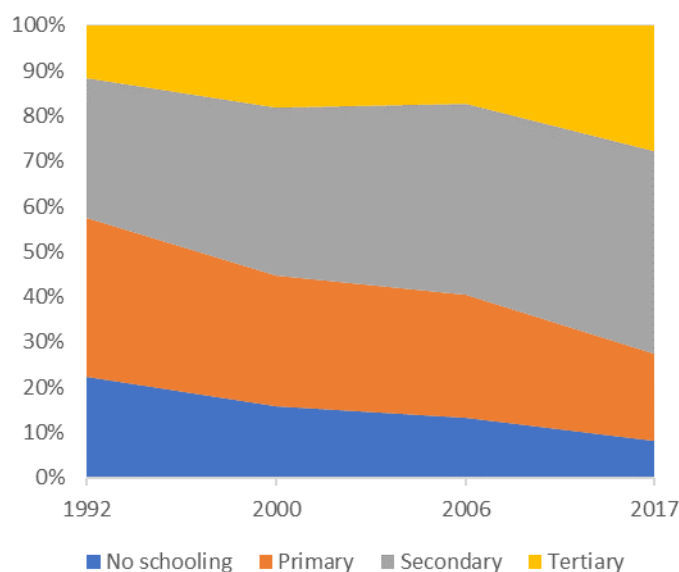
Sustained increases in the minimum wage have been mentioned as a preponderant factor in the reduction of inequality. The real minimum wage increased at an average annual rate of 4 per cent during the 1990s, reducing to an average of 3 per cent annually during the 2000s (Figure 2). Kernel densities (Figure 3, graph b) show the effect of the minimum wage on the earnings distribution. Vertical lines indicate the minimum wages of each year, which coincide with the jumps in the density function. We observe increases in the minimum wage as movements of the vertical lines to the right, and a flattening of the density functions below the minimum wage over time. The percentage of the population with earnings below the minimum wage first increases from 35 to 37 per cent between 1992 and 2000, which coincides with the largest jump in the minimum wage (Figure 2). From 2000, the population below the minimum wage dropped to 33 per cent in 2006 and to 31 per cent in 2017.

3.3 Skill supply and premium

Education impacts earnings through diverse channels. It affects labour participation at different stages of the life cycle, as well as the amounts of time worked, and the frequency and duration of unemployment and part-time employment, among other factors (INE 2017). Chile, like the rest of Latin America, has been characterized by high returns to secondary and tertiary education (notably higher education in the case of Chile). This high school premium has been the result of educational policies that focused on increasing the coverage of tertiary education before expanding secondary schooling:³ a very different strategy compared with Asian countries, which prioritized eliminating the bottom tail of the educational distribution by universalizing secondary education (Morley 2001). The result is a heavily polarized distribution of educational attainment, which gives a historically significant premium to those with secondary and post-secondary education (Torche 2014).

Average years of education have risen rapidly, from 12.9 in 1990 to 16.5 in 2018, due to a large structural expansion that increased school coverage since the 1980s and access to higher education since the 1990s (UNDP 2019). Figure 4 displays the level of educational attainment of the adult population aged between 15 and 64 at the time of observation. We differentiate between four completed levels of education: no formal education, completed primary, completed secondary, and completed tertiary. Although a significant share of the population still has low levels of education (8 per cent in 2017), the expansion at all levels has been pronounced.

Figure 4: Distribution of workers by level of education



Source: author's illustration based on CASEN (1992, 2000, 2006, 2017).

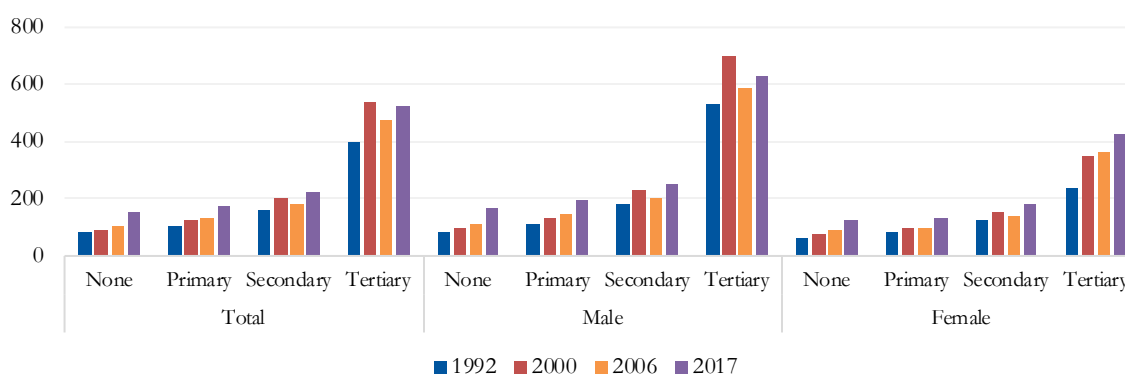
The increase in schooling has been reflected in real wages, which have grown at all educational levels. Figure 5 displays average weekly earnings (primary occupation) across different schooling levels. This is a cross-section of the population at one point in time rather than an analysis of individual lifetime earnings; it tells us how much workers earn according to the level of education they have attained (Table A1 in the Appendix).

³ Secondary education in Chile has been compulsory since 2003 (Law No. 19,876) and the expansion of university education began with the educational reform of 1981, increasing more strongly since 1990 with the return to democracy in the country (Gaentsch and Zapata-Román 2020).

We observe that returns to tertiary education in Chile are very high: earnings of higher education graduates by far exceed those of all other levels. These differences are accentuated by gender differences. The salary of men with a higher education degree in 1992 was 6.2 times higher than that of their peers without formal education, while that of women at the same level was only 3.6 times higher (Table A2 in the Appendix). We notice that polarization of educational returns has decreased since 2000: the earnings ratio between people holding a university degree and those having no formal education (or primary incomplete) has moved from 4.9 in 1992 to 5.8 in 2000, decreasing to 4.5 and 3.5 in 2006 and 2017 respectively.

Returns to education have grown differently for different groups in the periods analysed. From 1992 to 2000, we observe higher school premium growth as the educational level increases (Figure A2 in the Appendix): the average annual growth rate of the salaries of workers with no formal education was 1.9 per cent, while that of people with primary, secondary, and tertiary education was 2.1, 2.7, and 3.9 per cent respectively. In the period 2000 to 2006, we observe the opposite pattern: the wages that grew the most were those of less-qualified workers, at an average annual rate of 2.2 per cent, while the salary increase for workers with primary education was 1.2 per cent per year, and a negative annual growth rate of -1.9 and -2.0 is observed for the groups with secondary and tertiary education. A similar development is observed from 2013 to 2017: smaller premiums as the educational level increases, but not negative growth for the most skilled workers.

Figure 5: Mean weekly real earnings by level of education



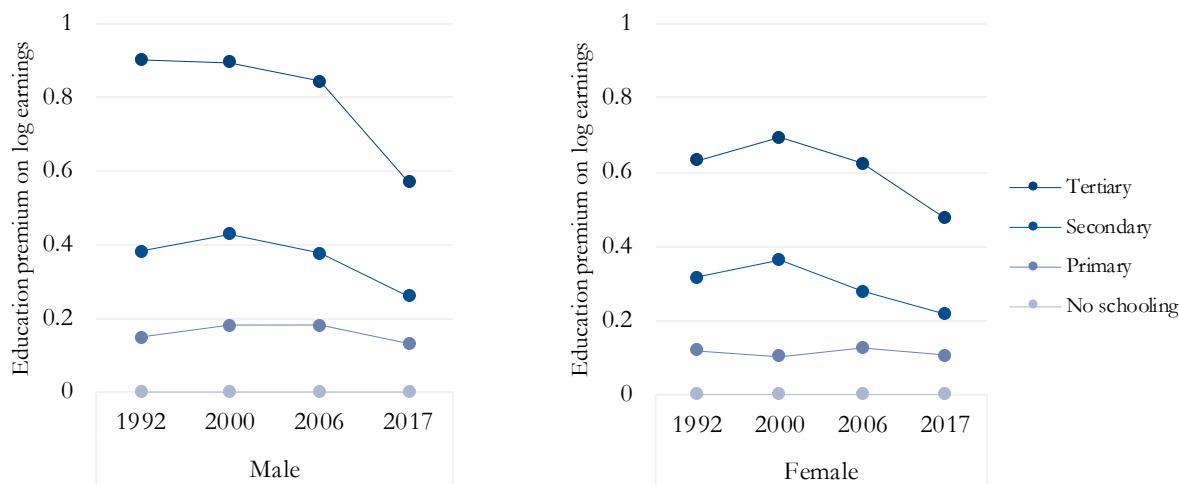
Source: author's illustration based on CASEN (1992, 2000, 2006, 2017).

When controlling for age, macro region of residence, having a formal job, and occupations at two-digit level for both men and women, we confirm sizeable gender differences (Figure 6): returns to education are always lower for women. We observe that average school premiums increased for men from 1992 to 2000, at every level of education, except for the most skilled workers, for whom the premium remains almost unchanged in the period. For women, returns to secondary and tertiary education increase in the period, but they decrease slightly for those with primary education. Between 2000 and 2006, educational premiums decrease slightly, except for women with primary education. After 2006, there is a more pronounced reduction in the returns to education in general for both men and women, but it is more so for those holding a higher education degree. Even though returns to tertiary education decreased, particularly for men, they are still very high compared with those for lower levels of education.⁴

⁴ The large skill premium of higher education in Chile is mainly driven by university graduates who come from a background of having highly educated parents. As suggested by the theory of inequality of opportunity, parental

Undoubtedly, these falls in the returns to education have contributed strongly to the reduction of inequality in Chile. However, this analysis does not allow us to establish whether or not changes in returns to education are the main source of wage inequality in Chile, as mentioned in the literature (PNUD 2017; Torche 2014). We expect to complement this analysis and provide further insights into the relevance of educational premiums to inequality movements in the decomposition section.

Figure 6: Changes in the education premium on log labour earnings



Note: log weekly earnings are regressed in each year separately by gender, dummy variables for three education levels (tertiary, secondary, primary, with no schooling as the base category), two age groups (ages 15–24 and 45–64, with 25–44 as the base category), three regional dummies (north, centre, and capital, with south as the base category), occupations at the ISCO-88 two-digit level, and a dummy variable for formality in the job market. The figure shows the coefficient estimates on the educational categories, which directly measure the returns to attaining a higher level of education in terms of (log) weekly earnings across survey waves, separately by gender.

Source: author's illustration based on CASEN (1992, 2000, 2006, 2017).

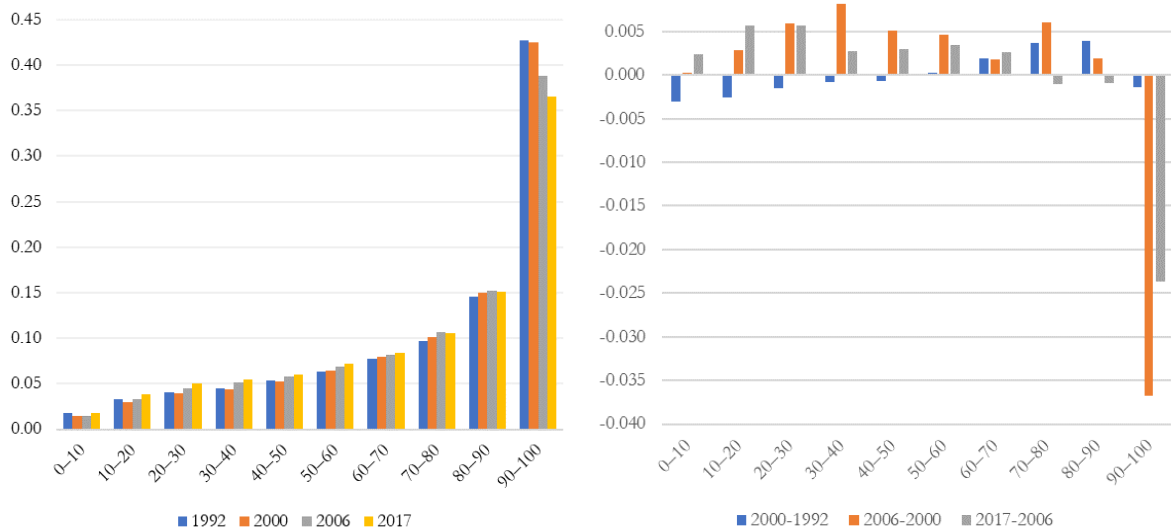
4 Earnings inequality

4.1 Trend in inequality in real earnings over time

As mentioned in the previous section, a significant source of inequality in Chile is high income shares at the top of the distribution. Analysing the data from the income survey CASEN, in 2017 the wealthier decile appropriated 36.5 per cent of total earnings, while the most deprived decile only got 1.7 per cent, as shown in Figure 7. In other words, the richest decile had 21 times the earnings of the poorest decile in 2017. Although the share of the bottom decile did not increase significantly between 2000 and 2006, that of the wealthiest decile decreased by 3.7 percentage points. Between 2006 and 2017, the top share fell a further 2.5 percentage points. It is interesting to notice that the major gains in both periods after the 2000s were below the median of the distribution.

education often intersects with other forms of advantage such as financial and social capital, which help graduates with more-advantaged family backgrounds to secure better-paid jobs (Gaentzsch and Zapata-Román 2020).

Figure 7: Decile shares and variations (weekly log real earnings)



Source: author's illustration based on CASEN (1992, 2000, 2006, 2017).

Summary inequality indices and inter-quantile ratios in Table 1, as well as the growth incidence curves (GIC) in Figure 8, complement the preceding analysis. Table 1 shows, on the left-hand side, the evolution of three inequality indices for the whole earnings distribution. We observe the rise previously described in the period 1992–2000, and subsequent falls after 2000. Inter-quantile ratios on the right-hand side of the table show differences at three points of the distribution. The gap between the 90th and the 10th percentile shows the income level of individuals in the top 10 per cent of the income distribution relative to those of individuals in the bottom 10 per cent. The 90–10 ratio confirms a gain for the wealthiest decile relative to the poorest in the first period (1992–2000), followed by relative losses for the top decile in subsequent periods. The 90–50 ratio shows the gap between the 90th percentile and the median, which also increases in the first period and shrinks thereafter. The 50–10 ratio illustrates the gap between the median and the 10th percentile, which, interestingly, increased until 2006 and only slightly declined after 2006—suggesting larger gains for the middle of the distribution between 2000 and 2006 and pro-poor growth only after 2006.

Table 1: Summary inequality indices and Inter-quantile ratios

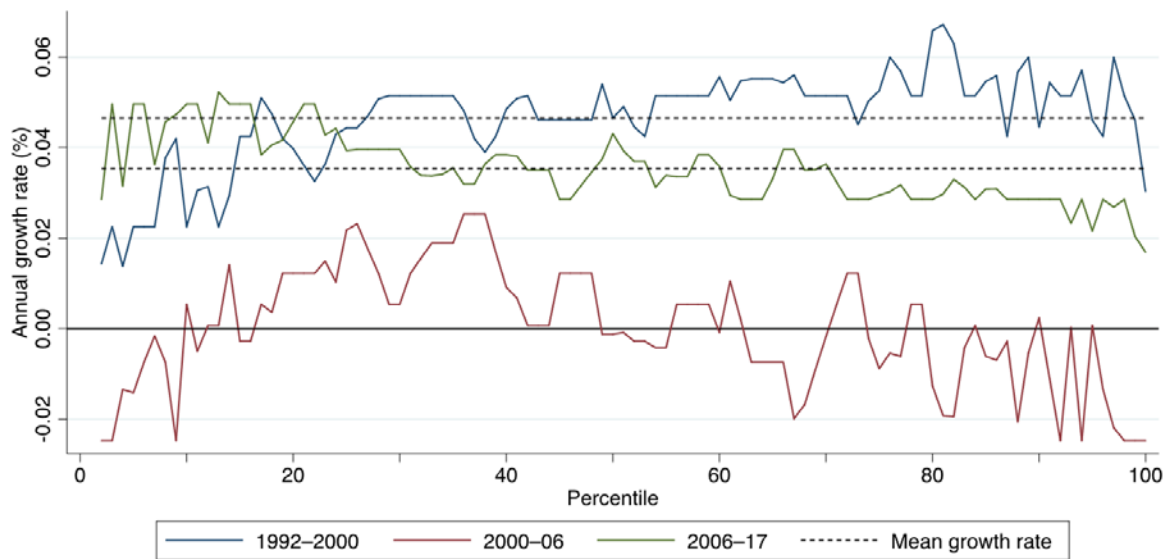
Summary indices	Inter-quantile ratios					Inter-quantile ratios			
	1992	2000	2006	2017		1992	2000	2006	2017
Var (log earn)	0.718	0.806	0.761	0.658	ln(q90)–ln(q10)	1.974	2.157	2.120	1.897
Gini (log earn)	0.099	0.098	0.094	0.081	ln(q90)–ln(q50)	1.186	1.226	1.165	1.050
Gini (earn)	0.504	0.514	0.475	0.443	ln(q50)–ln(q10)	0.789	0.931	0.956	0.847

Source: author's construction based on CASEN (1992, 2000, 2006, 2017).

The GIC (Figure 8) indicates the growth rate in income between two points in time at each percentile of the distribution. Between 1992 and 2000 (blue line), real earnings grew along the whole distribution. However, we observe some redistribution from those below the median (growth rates mainly below the average marked by the top dotted line) to those above the median (growth rates mainly above the average). In the second period, 2000–06 (red line), we observe negative growth—also below the median—for the top quintile (from the 80th percentile), as well as for the bottom decile, and positive and above-average growth mainly from the 20th percentile to the median. This is very different from the growth pattern of the last period (2006–17), for

which we observe strong growth for the bottom 30 per cent and below-average growth for the top 30 per cent. This last trend at the extremes of the distribution would have been inequality-reducing.

Figure 8: Growth incidence curves



Source: author's illustration based on CASEN (1992, 2000, 2006, 2017).

4.2 Structural changes in employment

Structural transformations in the Chilean productive structure in the last 50 years have had a strong impact on the country's employment structure in the present. We observe a reduction in the shares of agriculture and the manufacturing sector, along with the growth of the services and financial sectors, as well as the mining sector. Services tend to be labour-intensive but not technology-intensive; and mining is technology-intensive but requires few workers, most of whom are highly qualified (Solimano and Zapata-Román 2019). Table 2 shows the large decline in the share of agricultural employment, which in 1992 accounted for almost 16 per cent of total jobs but in 2017 had declined to 9 per cent. A similar development was experienced by the manufacturing sector, which in 1992 had almost 18 per cent of the workforce, falling to less than 10 per cent in 2017. The services sector absorbed the decrease in employment in agriculture, mining, and manufacturing, becoming the largest sector by employment, with 70 per cent of the total workforce and 86 per cent of female workers, in 2017.

Real wages grew between 1992 and 2000 in all sectors for men and women, except for women employed in industries that comprised electricity, gas, water supply, and construction—and this represented only 1.3 per cent of the female workforce (Table 3). We observe the opposite development in 2000–06, with real earnings decreasing on average, particularly in mining, which had had the largest rise in the previous period. In the last period (2006–17), we observe positive and similar growth rates between sectors. Summarizing, we find that the first period of growing inequality is associated with an increase in wages in all economic sectors. The second period (the shortest), with the most substantial decrease in inequality, is associated with a reduction in real wages, particularly in the better-paid industries. Finally, the most recent period was one of decreasing inequality but in which wages grew more homogeneously in all sectors.

Table 2: Distribution of workers by industry and gender

	All				Male				Female			
	1992	2000	2006	2017	1992	2000	2006	2017	1992	2000	2006	2017
Agriculture (A+B)	15.77	12.73	12.39	8.99	20.48	17.12	15.91	11.65	6.28	5.29	6.88	5.66
Mining (C)	2.21	1.60	1.75	1.85	3.14	2.40	2.71	2.99	0.35	0.25	0.26	0.41
Manufacturing (D)	17.09	14.11	13.82	9.38	17.82	15.99	15.84	11.84	15.62	10.92	10.65	6.31
Other industries (E+F)	9.79	9.18	10.08	9.86	14.07	13.83	15.61	16.42	1.15	1.31	1.43	1.64
Services (G-Q)	55.13	62.37	61.95	69.92	44.50	50.65	49.93	57.10	76.59	82.23	80.78	85.97

Source: author's construction based on CASEN (1992, 2000, 2006, 2017).

Table 3: Average weekly earnings by sectors and gender

Sector	Male							Female						
	Mean weekly earnings				Annual growth rate			Mean weekly earnings				Annual growth rate		
	1992	2000	2006	2017	1992–2000	2000–06	2006–17	1992	2000	2006	2017	1992–2000	2000–06	2006–17
Agriculture (A+B)	94	145	136	197	5.57	–1.06	3.43	80	101	114	157	2.96	2.04	2.95
Mining (C)	252	457	368	475	7.72	–3.55	2.35	211	576	400	466	13.38	–5.90	1.40
Manufacturing (D)	174	269	226	288	5.60	–2.86	2.23	115	164	143	206	4.54	–2.26	3.37
Other industries (E+F)	178	203	206	287	1.66	0.24	3.06	271	228	267	343	–2.14	2.67	2.30
Services (G–Q)	188	282	260	360	5.20	–1.34	3.00	120	181	181	256	5.27	0.00	3.20

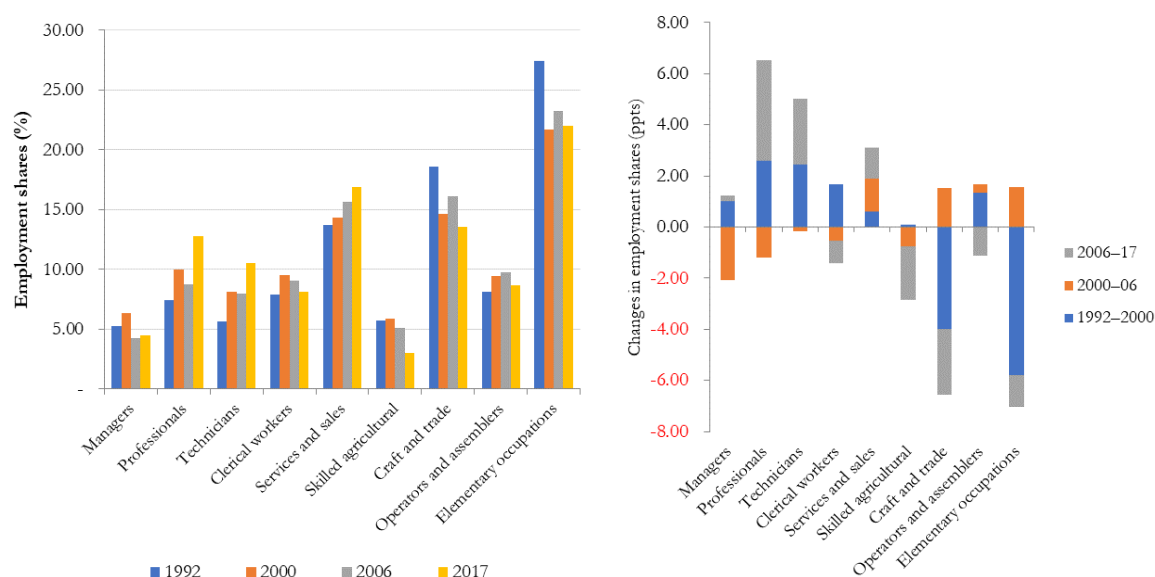
Source: author's construction based on CASEN (1992, 2000, 2006, 2017).

4.3 Trend in occupations

In 1992, 60 per cent of the workforce in Chile was concentrated in elementary occupations, craft and trade work, and sales (Figure 9). The share of workers in other intermediate occupations was around 7–8 per cent, while the share in occupations associated with higher skill levels (managers and professionals) varied between 5 and 7 per cent. In the period 1992–2000, only the participation in elementary and trade occupations decreased, by six and four percentage points respectively. The main growths were registered in both professional and technician occupations, where the share increased by 2.5 percentage points, coinciding with the expansion of higher education. A low level of growth was observed in the share of sales workers and almost no growth in the share of skilled agriculture. The period 2000–06 registers a fall in the share of managers, clerical workers, and skilled agriculture. Only the share of medium- and other low-skill occupations increased. In 2006–17, the share of high-skill occupations (managers, professionals, and technicians) and sales increased, and the share of lower-skill occupations decreased.

These sectorial changes in the occupational structure imply a displacement of workers from low-skill occupations such as skilled agricultural, craft and trade, and elementary occupations,⁵ towards jobs demanding non-routine higher skills, including professionals and technicians. There is also a significant increase in the share of services and sales workers, who tend to perform routine manual and cognitive tasks. Additionally, there is a net drop in the share of managers, which is redistributed among other professionals (at the same skill level).

Figure 9: Employment shares and changes by occupation



Note: ppts = percentage points.

Source: author's illustration based on CASEN (1992, 2000, 2006, 2017).

When examining earnings across occupations (Figure 10), we observe large differences in returns in favour of high-skill occupations. The earnings ratio between people in managerial positions and those in elementary occupations was 7 in 1992, while the ratio between professionals and elementary occupations was 5. Earnings concentration at the top was so marked in 1992 that those employed as technicians and as clerks, who on average have a similar level of education to managers (Figure A5 in the Appendix), had an income equivalent to half and one-third of that of managers

⁵ These occupations are those with the lowest average years of education; see Figure A5 in the Appendix.

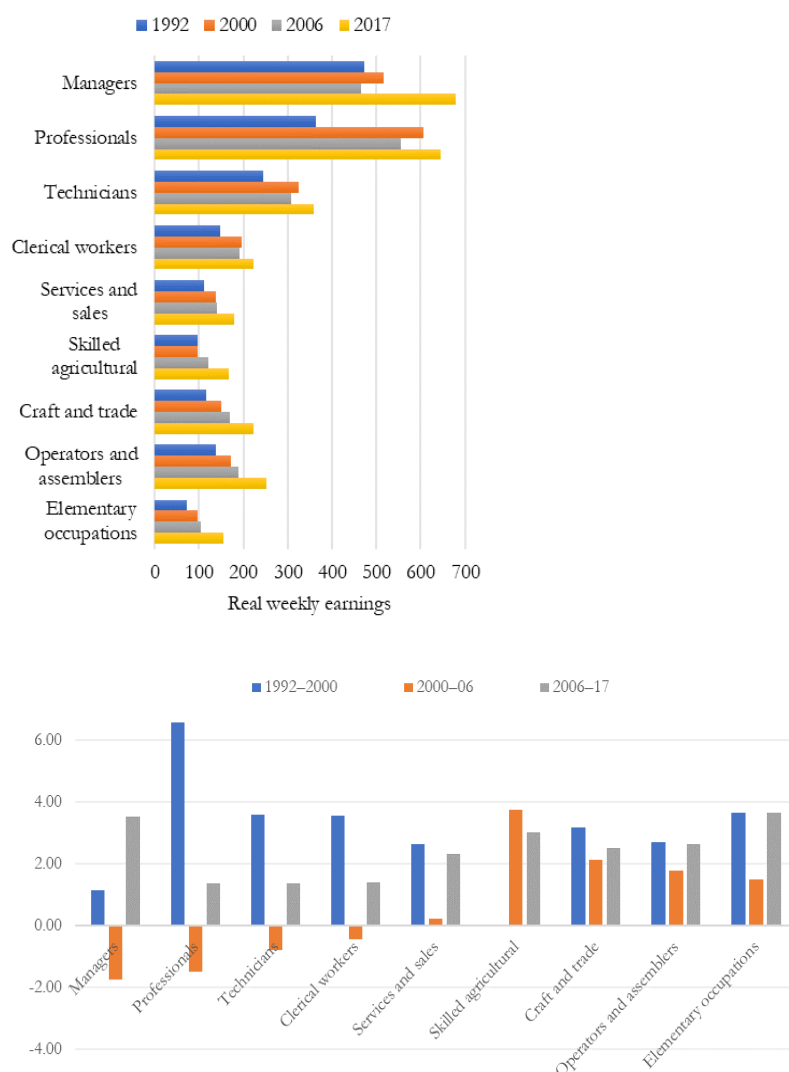
respectively. This suggests that other factors besides education might play a more decisive role in determining the earnings of this well-rewarded occupation.

Earnings gaps have been gradually shortening over the years, since the earnings of most occupations have grown faster than those of managers. The quickest adjustment was for professionals, whose income grew at an average rate of 6.58 per cent between 1992 and 2000 (Figure 10, right-hand side), with the sole exception of skilled agricultural jobs, for which incomes did not change in the period. Other occupations' annual earnings grew on average by 1.14 per cent between 2000 and 2006 and 3.66 per cent between 2006 and 2017.

In the period 2000–06, the average growth rates of income were higher for the lowest-paid occupations. The most significant increase in earnings was for skilled agricultural workers, followed by craft and related trade workers, plant and machine operators, and elementary occupations, whose annual average wages improved by around 3 per cent annually. The income growth for those employed in elementary occupations, craft and trade workers, and operators continued in the period 2013–17, at an average annual rate of around 3.6, 2.5, and 2.6 per cent respectively. In this period, managers' earnings also increased, at a rate of 3.5 per cent per year. The income of professionals, technicians, and clerks also slightly increased, by 1.4 per cent annually on average.

Changes in occupational earnings have had a positive equalizing effect, with more substantial gains in favour of lower-skill occupations such as skilled agricultural workers, craft and related trade workers, plant and machine operators, and elementary occupations. We also observe an equalizing effect at the top of the skill premium, with the earnings of managers and professionals becoming closer. Despite these positive changes on inequality, we still observe substantial differences between the rewards of low- and high-skill occupations.

Figure 10: Real weekly earnings and average annual growth rate by occupational groups



Source: author's illustration based on CASEN (1992, 2000, 2006, 2017).

5 The role of tasks and skills in changing earnings inequality over time

5.1 The RTI of jobs

Up until now, we have implicitly associated skill levels with ISCO-88 one-digit occupations and educational attainment. In this section we incorporate a formal task-based approach to explore job polarization and changes in earnings inequality in Chile. We compare the results obtained by two different methods of imputing RTI to occupations classified using the ISCO-88 two-digit level: the O*NET standard values and the country- and occupation-specific values of standard task measures predicted for Chile by Lewandowski et al. (2020), using PIAAC data (OECD 2014/15).

Country-specific RTI measures are, in general, lower than O*NET measures. This is more noticeable particularly for occupations at the extremes of the distribution (elementary occupations and professionals and managers). For sales, at the centre of the skill distribution, a higher routine content is predicted using country-specific RTI measures, as shown in Table 4.

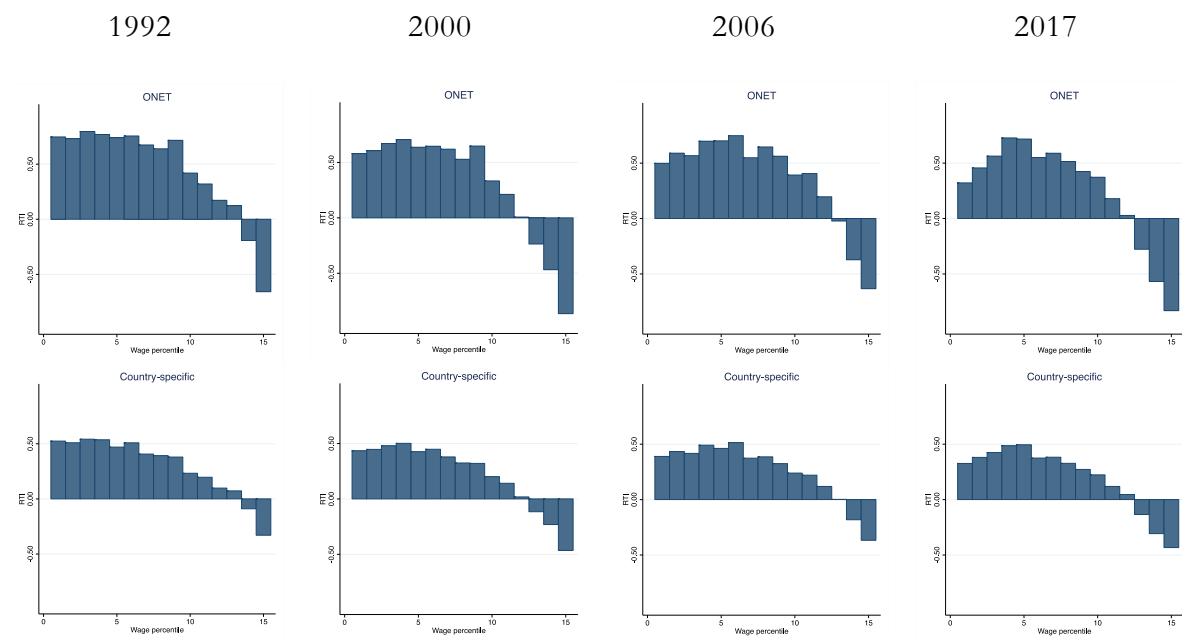
Table 4: O*NET and country-specific RTI, average by year

	O*NET	Country RTI	O*NET	Country RTI	O*NET	Country RTI	O*NET	Country RTI
Managers	-1.20	-0.43	-1.19	-0.42	-1.21	-0.42	-1.20	-0.42
Professionals	-1.23	-0.66	-1.20	-0.65	-1.17	-0.66	-1.15	-0.64
Technicians	-0.47	-0.28	-0.45	-0.28	-0.46	-0.25	-0.44	-0.23
Clerks	0.13	0.05	0.16	0.07	0.14	0.10	0.16	0.15
Service and sales	-0.15	0.30	-0.21	0.29	-0.21	0.29	-0.21	0.28
Skilled agricultural	0.51	0.51	0.46	0.51	0.44	0.51	0.39	0.51
Craft and trade	1.18	0.39	1.17	0.37	1.16	0.37	1.16	0.36
Operators and assemblers	1.13	0.62	1.17	0.62	1.15	0.61	1.13	0.66
Elementary occupations	1.13	0.71	1.15	0.70	1.09	0.70	1.15	0.69
Total	0.46	0.30	0.31	0.23	0.36	0.27	0.25	0.21

Source: author's construction based on CASEN (1992, 2000, 2006, 2017).

Figure 11 displays RTI by earnings percentile and shows a strong monotonic relationship between RTI and earnings percentiles using both the O*NET and the country-specific measures in 1992 and 2000, which flattens at the bottom in subsequent years and increases slightly before the middle of the distribution in 2006 and more markedly in 2017. An inverted U shape, with the routine-task-intensive occupations dominating close to the middle of the earnings distribution, is only clearer in 2017 with both measures, although it is more compressed with country-specific RTI. Overall, average RTI has declined over the whole period of 1992 to 2017, whether measured using O*NET or the country-specific measures, despite an increase in 2006 (see more details of RTI at ISCO-88 two-digit level in Table A3 in the Appendix). As the RTI values are estimated at ISCO-88 two-digit level and do not change over time, this average decline in the RTI of jobs is driven by a restructuring of the labour force away from more-routine and towards less-routine occupations. Interestingly, we observe this 'reshuffling' at the bottom and at the top of the distribution, while the average RTI of workers in middle-income occupations has remained relatively unchanged, leading to an increasingly hump-shaped pattern (visibly especially for O*NET).

Figure 11: RTI by earnings percentile

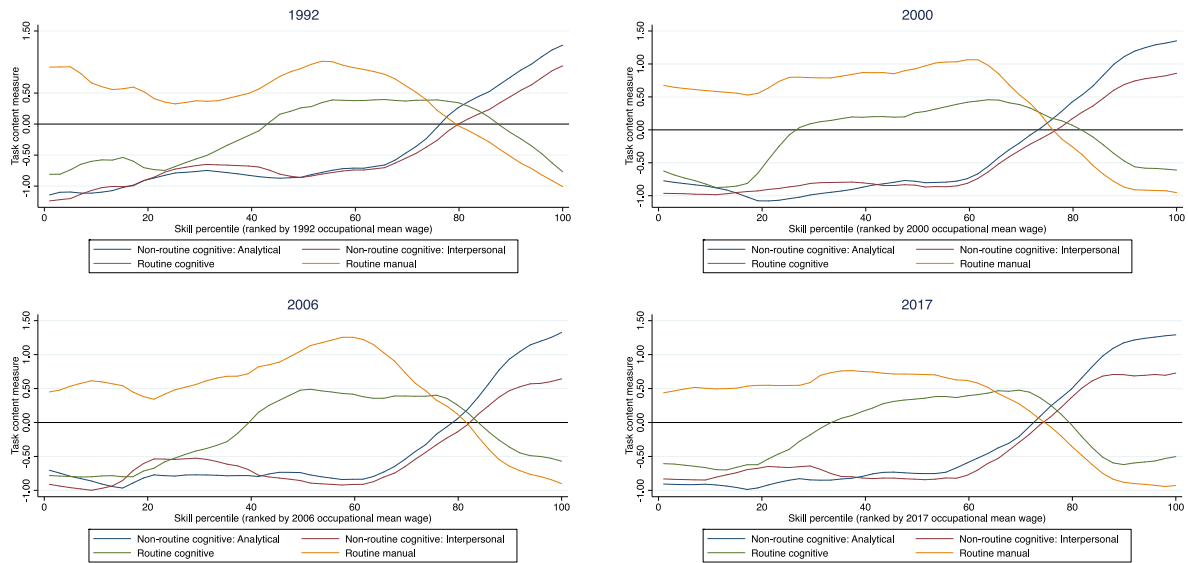


Source: author's illustration based on CASEN (1992, 2000, 2013, 2017).

Table 4 and Figure 11 use a single measure of the routine contents of tasks. Using O*NET estimates for different types of task—non-routine cognitive analytical, routine cognitive, non-routine cognitive interpersonal, and routine manual—we construct Figure 12, by grouping ISCO-88 three-digit occupations into skill percentiles at these four task levels. The skill percentiles are measured as the employment-weighted percentile rank of the occupation's mean log wage in each survey wave. For instance, the graph labelled 1992 uses the employment-weighted percentile rank of the occupation's mean log wage in 1992, and so on. The lines show the content of each type of task in the corresponding income percentile. In the first period, we observe that the routine manual content of tasks decreases until the 20th percentile and then increases until just below the 60th percentile, decreasing steadily thereafter as income increases. The opposite occurs with non-routine cognitive analytical, routine cognitive, and non-routine cognitive interpersonal levels. The downward trajectory before the 20th percentile of routine manual tasks smooths over time. In 2006, we observe an increase in these types of tasks near the 60th percentile of the earnings distribution, which then flattens almost completely in 2017. Routine cognitive tasks are only positive around the 40th percentile (except in 2000, when the line is above the 20th percentile) and remain constant between the 60th and the 80th percentile of income.

The literature suggests that in developed countries, non-routine cognitive tasks are mainly found at the top of the income distribution, while non-routine manual tasks are at the bottom. Occupations at the middle of the distribution commonly execute routine manual and cognitive tasks (Autor 2019; Goos and Manning 2007). In Figure 12, we find a concentration of non-routine cognitive tasks at the top of the income distribution. We observe that the routine manual component is high up to the 80th percentile of the distribution, and highest between the median and the 60th percentile of the distribution. The routine cognitive component that would be replaced by technology is present from the 40th percentile (or the 30th in more recent years) to the 80th percentiles. Therefore, the distribution of task content of jobs in Chile seems quite similar to that of more developed countries, but with a higher proportion of routine manual tasks throughout the income distribution.

Figure 12: Local polynomial regression of task content per earnings percentile (years 1992, 2000, 2006, and 2017)



Source: author's illustration based on CASEN (1992, 2000, 2006, 2017).

5.2 Job polarization

Simple test for job polarization

The polarization phenomenon predicts an increase in the relative demand for well-paid skilled jobs (consisting of non-routine cognitive tasks), and low-paid low-skill jobs (linked to non-routine manual tasks), diminishing the relative demand in the middle of the distribution, where routine manual and cognitive tasks are commonly executed. Therefore, jobs that would be displaced by technology include routine tasks that require precision, such as manual craft and bookkeeping jobs. Jobs that are complementary to technology, such as skilled professional and managerial jobs, consist of non-routine tasks. Other non-routine manual jobs, such as cleaning, which are not directly affected by technology, might rise due to the effects of technology in other parts of the economy (Autor 2019; Goos and Manning 2007).

To test for job polarization, we regress the log change in employment share, and the change in log mean earnings between survey waves, on initial log mean weekly earnings (and its square), testing the significance of the parameters following Goos and Manning (2007) and Sebastian (2018) as explained in Section 2. Both equations are estimated by weighting each occupation—at three-digit level—by its initial employment share to avoid the results being biased by compositional changes in small occupation groups.

A U-shaped pattern of polarization implies that the first coefficient is significantly negative, with a positive quadratic coefficient, indicating that employment and/or earnings decline in middle-income occupations while increasing at the extremes of the income distribution (See Figure A6 in the Appendix for visual inspection of the correlation). We find this pattern in the second and third periods for changes in employment shares, and in the first period for changes in log mean earnings, although none of these findings are statistically significant. The opposite pattern (inverted U-shaped growth) is found, and is significant, for changes in log mean earnings in 2000–06, suggesting that real earnings grew more in the middle of the distribution, as we detected in the growth incidence curves in Figure 8 (see Table 5).

Table 5: Regressions for job and earnings polarization

Variables	Log change in employment share			Change in (log) mean wage		
	1992–2000	2000–06	2006–17	1992–2000	2000–06	2006–17
(log) mean weekly earnings (initial period)	0.983 (1.125)	–0.459 (0.727)	–0.076 (1.266)	–0.197 (0.568)	0.629** (0.272)	–0.015 (0.362)
Sq. (log) mean weekly earnings (initial period)	–0.066 (0.109)	0.031 (0.069)	0.032 (0.120)	0.020 (0.056)	–0.069*** (0.025)	–0.009 (0.034)
Constant	–3.175 (2.861)	1.466 (1.891)	–0.478 (3.306)	0.740 (1.438)	–1.353* (0.726)	0.601 (0.966)
Observations	114	113	113	114	113	113
R-squared	0.225	0.069	0.127	0.002	0.236	0.245
Adjusted R-squared	0.211	0.052	0.111	–0.016	0.222	0.231
F test	0.000	0.027	0.001	0.921	0.000	0.000

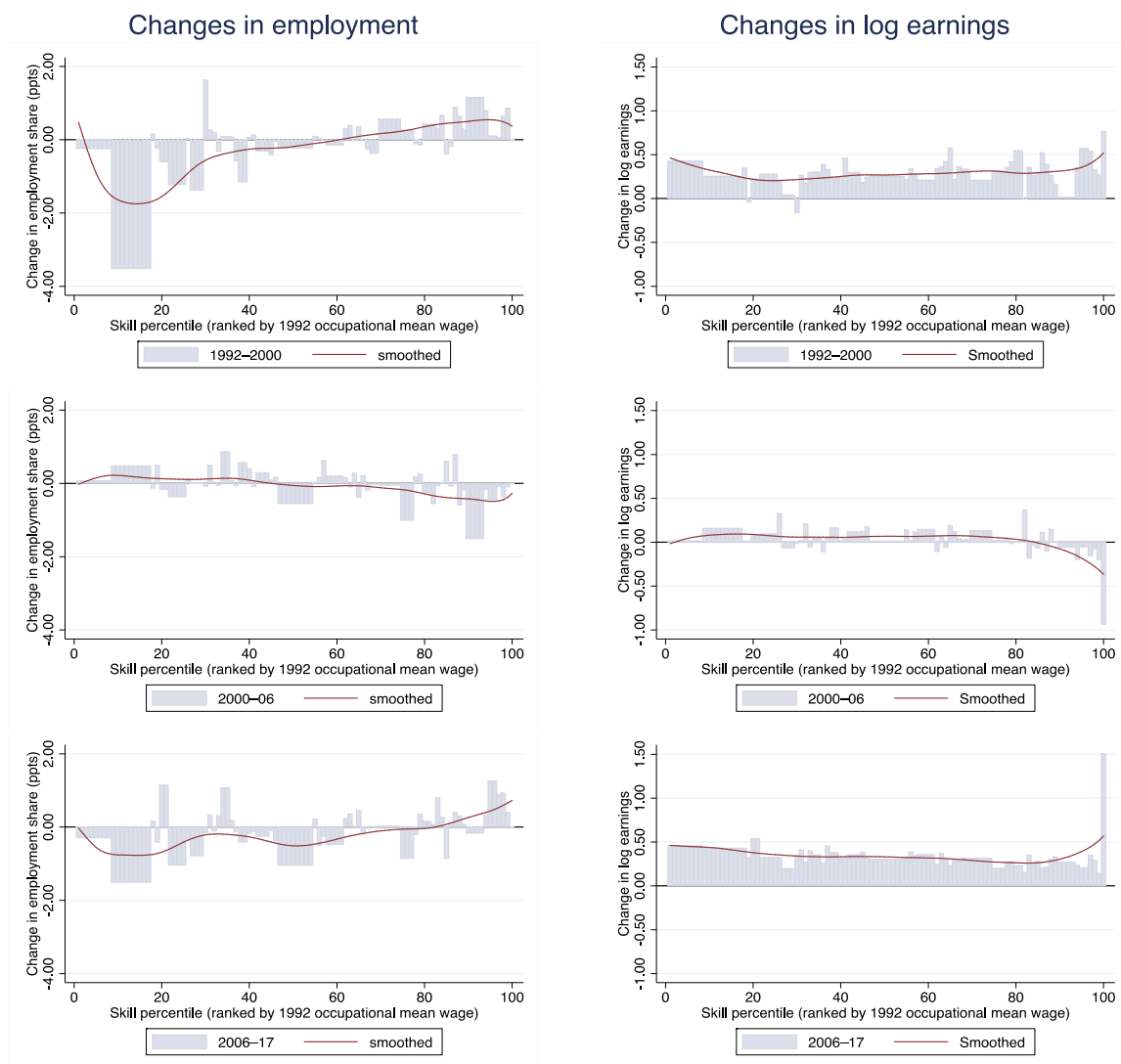
Note: robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1.

Source: author's construction based on CASEN (1992, 2000, 2006, 2017).

We can observe these trends also in Figure 13, which plots log changes in employment shares and changes in mean log earnings against occupations at ISCO-88 three-digit level ranked by earnings skill percentile. In the first period we notice a sharp drop in the employment shares of the percentiles below the median of the distribution, and a subtle U shape in earnings, since the rise in income is polarized slightly towards the ends of the distribution, with a lowered centre.

The second period (2000–06) shows a small displacement of employment away from high-paid occupations towards middle- and low-income occupations, with even smaller gains in earnings for low- and middle-income occupations and bigger losses at the top (subtle inverted U shape). The final period (2006–17) describes a displacement of employment at the bottom and the median of the skill distribution towards the best-rewarded occupations, and higher gains in earnings before the median and at the top of the skill distribution.

Figure 13: Smoothed changes in employment shares and real weekly wages, by skill percentile



Note: this figure is constructed by grouping ISCO-88 three-digit occupations into skill percentiles. These are measured as the employment-weighted percentile rank of the occupation's mean log wage in the 1992 survey. To avoid bias due to small occupation groups dominating results, each job is weighted by its total employment (Autor and Dorn 2013; Sebastian 2018). Therefore, large occupation groups such as sales, services, and elementary occupations comprise a relatively large percentile range. The figure plots the skill percentile rank against log changes in employment shares and changes in mean log earnings, showing the smoothed changes in red.

Source: author's illustration based on CASEN (1992, 2000, 2006, 2017).

Regression of changes in employment and earnings on the level of routine intensity

Now we test for job polarization by estimating a quadratic regression in which we try to explain the variance of employment and earnings using our measures of the RTI of jobs. Tables 6 and 7 present the results of the ordinary least squares (OLS) quadratic regressions of changes in employment share and log mean earnings for the periods 1992–2000, 2000–06, and 2006–17, along with the initial level of routine intensity of each occupation, at the three-digit occupational level (the initial year is 1992). A negative relationship would be expected between the two variables, indicating that higher RTI leads to larger declines in employment and earnings.

Comparing the results of the OLS regressions with both RTI measures, we obtain the expected negative and significant relationship in employment shares in the periods 1992–2000 and 2006–17

for both O*NET and country-specific RTI (this is also observed in Figure A7 in the Appendix, top left-hand side). The estimated coefficients are considerably higher using the country-specific RTI, indicating that a higher level of employment displacement is expected as the routine content of tasks increases. In earnings, we find the negative correlation in 1992–2000 although it is not significant, and a positive and significant relationship between changes in mean log wage and both RTI measures in 2000–06 and 2006–17, suggesting that earnings tend to increase more in more-routine occupations, which is not observed in employment in 2006–17. Overall, the routine content of tasks explains an important part of the variability of earnings, and to a lesser extent the variability of employment (higher R-squared in earnings regressions). Therefore, in this period of declining earnings inequality (pro-poor growth) the degree of routinization of occupations seem to play a significant role.

Table 6: OLS regression of changes in employment share and in log mean wage, at the initial level of routine intensity, using O*NET RTI

Variables	Log change in employment share			Change in (log) mean wage		
	1992–2000	2000–06	2006–17	1992–2000	2000–06	2006–17
O*NET RTI	–0.153*** (0.039)	0.093*** (0.031)	–0.131*** (0.036)	–0.023 (0.039)	0.049*** (0.017)	0.045*** (0.011)
Sq. O*NET RTI	0.012 (0.021)	–0.044** (0.019)	0.043* (0.024)	0.017 (0.015)	–0.022** (0.010)	0.008 (0.007)
Constant	–0.014 (0.055)	–0.022 (0.039)	–0.065 (0.049)	0.259*** (0.024)	0.043** (0.017)	0.290*** (0.016)
Observations	114	113	113	114	113	113
R-squared	0.156	0.089	0.106	0.032	0.142	0.218
Adjusted R-squared	0.140	0.072	0.090	0.015	0.127	0.204
F test	0.000	0.011	0.002	0.520	0.014	0.000

Note: robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1.

Source: author's illustration based on CASEN (1992, 2000, 2006, 2017).

Table 7: OLS regression of changes in employment share and in log mean wage, at the initial level of routine intensity, using country-specific RTI

	Log change in employment share			Change in (log) mean wage		
	1992–2000	2000–06	2006–17	1992–2000	2000–06	2006–17
Variables						
Country-specific RTI	–0.311*** (0.073)	0.197*** (0.067)	–0.227*** (0.067)	–0.064 (0.062)	0.093*** (0.034)	0.105*** (0.021)
Sq.country-specific RTI	0.026 (0.096)	–0.154* (0.092)	0.156 (0.101)	0.115* (0.059)	–0.045 (0.051)	0.036 (0.033)
Constant	0.016 (0.044)	–0.038 (0.045)	–0.056 (0.052)	0.250*** (0.031)	0.027 (0.018)	0.276*** (0.014)
Observations	114	113	113	114	113	113
R-squared	0.168	0.095	0.084	0.065	0.124	0.289
Adjusted R-squared	0.153	0.079	0.067	0.048	0.108	0.277
F test	0.000	0.016	0.004	0.148	0.029	0.000

Note: robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1.

Source: author's illustration based on CASEN (1992, 2000, 2006, 2017).

6 The role of occupational changes in shaping the evolution of inequality

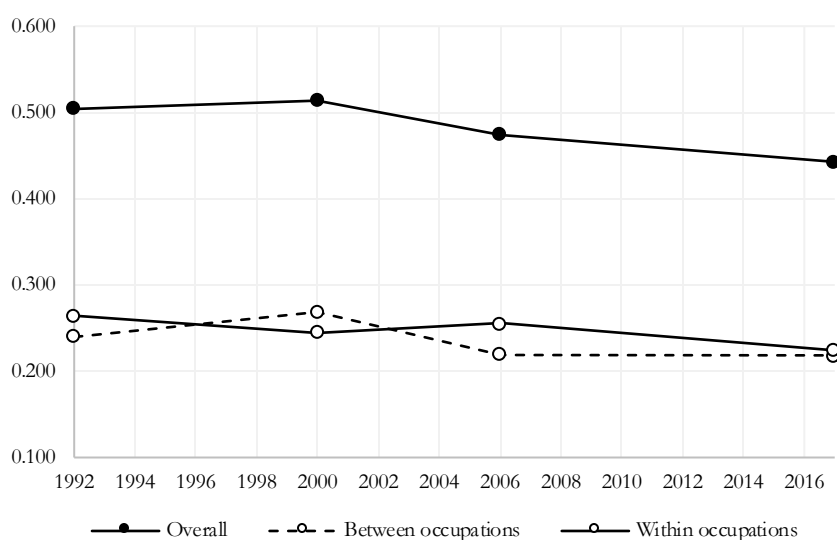
As we identified in the last section, occupations seem to play a key role in explaining changes in earnings inequality in Chile. In this section, we use two decomposition methods to investigate this issue further. We decompose total inequality to understand whether its changes are due to variations in the characteristics of occupations (i.e. average years of schooling, different skills, or RTI contents) or to changes in the reward of occupations. Then, we examine the role played by the RTI of occupations in shaping inequality.

6.1 Shapley decomposition

The Shapley decomposition allows us to disaggregate total inequality, measured using the Gini index, into inequality between and within occupations. As shown in Table 8, in all periods both components are very similar. Despite the similarity in these components, we observe a dominance of inequality within occupations in 1992, 2006, and 2017. This indicates that inequality variations are mostly associated with changes in factors not related to the occupations' characteristics, such as differences in skills, or elements that affect worker's productivity in performing similar jobs. Higher within-occupation earnings dispersion might also be reinforced by other unknown elements that favour workers unequally, such as family and contact networks or financial and social capital, which are very common elements in the Chilean labour market.

Table 8: Shapley decomposition of Gini index into inequality between and within occupations

	Actual			
Gini	1992	2000	2006	2017
Overall	0.504	0.514	0.475	0.443
Shapley decomposition				
Between occupations	0.240	0.269	0.219	0.218
Share %	48%	52%	46%	49%
Within occupations	0.264	0.245	0.256	0.224
Share %	52%	48%	54%	51%



Source: author's construction based on CASEN (1992, 2000, 2006, 2017).

We decompose the non-monotonic trajectory of inequality between occupations into variations in mean earnings (holding occupation shares constant) and changes in occupational shares (holding mean earnings constant). When holding occupation shares constant, changes in inequality will be associated with changes in the remuneration of skills, tasks, or other job characteristics (return effect). When holding mean earnings constant, shifts in inequality will be associated with movements of workers to jobs with different skill or RTI contents (composition effect). Table 9 presents the results of the decomposition. Inequality between occupations increased from 1992 to 2000 and decreased sharply thereafter. In all years, we observe that holding the occupational shares constant results in a reduction in between-occupations inequality whereas holding the mean earnings constant has an inequality-enhancing effect. Therefore, the strong decline in inequality between occupations from the 2000s is driven by changes in average earnings, not in shares—despite all the structural changes in employment discussed earlier, such as increasing average years of education, displacement of workers from low-skill occupations towards jobs demanding non-routine higher skills, reduction of informal jobs, and increasing female participation.

Table 9 also presents the results of the concentration index. This index provides a measure of how low (high) average remuneration by occupation is correlated with a high (low) degree of job routinization. The concentration index is equivalent to the Gini index when RTI is perfectly correlated to average earnings. Hence, the ratio between both indexes is a measure of the association between RTI and average earnings. In Chile the concentration index is very high, and it is higher using country-specific RTIs instead of O*NET measures. In the first period, the

association between RTI and average earnings intensifies, as the concentration index rises with both RTI measures. It declines considerably in the second period (2000–06), and it keeps falling according to country-specific RTI (slightly rising with the O*NET measures). In sum, average earnings across occupations have become less unequal over time, and the strong monotonic correlation with RTI has been reducing, shown by a lower concentration index, especially if shares are kept constant.

Table 9: Gini between occupations and concentration index

	Actual				Shares constant				Means constant			
	1992	2000	2006	2017	1992	2000	2006	2017	1992	2000	2006	2017
Gini between occupations	0.345	0.379	0.319	0.311	0.345	0.358	0.314	0.278	0.345	0.365	0.352	0.374
Concentration index												
RTI (country-specific)	0.302	0.337	0.278	0.262	0.302	0.323	0.275	0.236	0.302	0.315	0.307	0.322
% ratio	87%	89%	87%	84%	87%	90%	88%	85%	87%	86%	87%	86%
RTI (O*NET)	0.272	0.307	0.245	0.250	0.272	0.285	0.240	0.210	0.272	0.293	0.278	0.302
% ratio	79%	81%	77%	80%	79%	80%	77%	76%	79%	80%	79%	81%

Source: author's construction based on CASEN (1992, 2000, 2006, 2017).

6.2 RIF regression decomposition

In the final section, we use the RIF regression approach to decompose inequality differences into a composition effect (changes due to varying worker characteristics e.g. age, gender, schooling, formality, and occupations) and a structure effect (changes in the return to those characteristics). It also allows us to further divide these two components into the contribution of each covariate.

Table 10 presents the results of the RIF decomposition of the Gini coefficient. The bottom part of the table shows the contribution of each covariate to each effect. The covariates used in the RIF regressions are age (in three categories, 15–24, 45–65, and 25–44 omitted), sex (male omitted), education (seven categories of complete education, with primary complete omitted), informality (having a formal job omitted), and RTI (continuous variable), plus all of their interactions.

Table 10: RIF regression decomposition

	Country-specific RTI				O*NET RTI			
Distribution	1992–2000	2000–06	2006–17	1992–2017	1992–2000	2000–06	2006–17	1992–2017
Final Gini	0.5172	0.4766	0.4435	0.4435	0.5172	0.4766	0.4435	0.4435
Initial Gini	0.5058	0.5172	0.4766	0.5058	0.5058	0.5172	0.4767	0.5058
Total change	0.0113	–0.0406	–0.0331	–0.0623	0.0113	–0.0406	–0.0332	–0.0623
	(0.0103)	(0.0100)	(0.0050)	(0.0054)	(0.0103)	(0.0100)	(0.0050)	(0.0054)
Reweighting								
Composition	0.0294	–0.0163	0.0121	0.0255	0.0292	–0.0177	0.0127	0.0225
	(0.0023)	(0.0033)	(0.0017)	(0.0027)	(0.0023)	(0.0030)	(0.0016)	(0.0027)
Earnings structure	–0.0181	–0.0243	–0.0451	–0.0878	–0.0179	–0.0229	–0.0458	–0.0848
	(0.0103)	(0.0081)	(0.0048)	(0.0051)	(0.0102)	(0.0086)	(0.0047)	(0.0051)
RIF								

Composition	0.0388	-0.0117	0.0290	0.0703	0.0391	-0.0119	0.0305	0.0702
	(0.0028)	(0.0034)	(0.0022)	(0.0046)	(0.0026)	(0.0025)	(0.0021)	(0.0045)
Specification error	-0.0093	-0.0046	-0.0169	-0.0448	-0.0099	-0.0058	-0.0179	-0.0477
	(0.0022)	(0.0019)	(0.0013)	(0.0031)	(0.0021)	(0.0018)	(0.0014)	(0.0031)
Earnings structure	-0.0179	-0.0236	-0.0448	-0.0861	-0.0175	-0.0226	-0.0454	-0.0847
	(0.0102)	(0.0081)	(0.0048)	(0.0050)	(0.0102)	(0.0086)	(0.0047)	(0.0051)
Reweighting error	-0.0003	-0.0007	-0.0004	-0.0017	-0.0004	-0.0003	-0.0004	-0.0001
	(0.0001)	(0.0002)	(0.0001)	(0.0005)	(0.0001)	(0.0002)	(0.0001)	(0.0004)
RIF composition								
age	0.0027	0.0032	0.0037	0.0110	0.0027	0.0030	0.0038	0.0107
	(0.0005)	(0.0011)	(0.0005)	(0.0015)	(0.0005)	(0.0011)	(0.0006)	(0.0015)
sex	-0.0030	-0.0017	-0.0015	-0.0080	-0.0037	-0.0023	-0.0027	-0.0106
	(0.0004)	(0.0004)	(0.0003)	(0.0010)	(0.0005)	(0.0006)	(0.0004)	(0.0010)
education	0.0221	-0.0030	0.0221	0.0575	0.0229	-0.0036	0.0260	0.0603
	(0.0023)	(0.0014)	(0.0020)	(0.0048)	(0.0022)	(0.0017)	(0.0020)	(0.0045)
informality	0.0065	-0.0033	-0.0059	-0.0043	0.0061	-0.0033	-0.0059	-0.0044
	(0.0008)	(0.0006)	(0.0006)	(0.0006)	(0.0007)	(0.0005)	(0.0005)	(0.0006)
rti	0.0105	-0.0069	0.0106	0.0141	0.0112	-0.0057	0.0094	0.0142
	(0.0014)	(0.0018)	(0.0013)	(0.0014)	(0.0012)	(0.0007)	(0.0009)	(0.0013)
explained	0.0388	-0.0117	0.0290	0.0703	0.0391	-0.0119	0.0305	0.0702
	(0.0028)	(0.0034)	(0.0022)	(0.0046)	(0.0026)	(0.0025)	(0.0021)	(0.0045)
RIF earnings structure								
age	-0.0004	0.0023	0.0074	0.0129	-0.0019	0.0048	0.0070	0.0091
	(0.0085)	(0.0080)	(0.0053)	(0.0064)	(0.0084)	(0.0083)	(0.0055)	(0.0065)
sex	-0.0039	0.0173	0.0030	0.0168	-0.0066	0.0172	0.0007	0.0101
	(0.0049)	(0.0051)	(0.0036)	(0.0050)	(0.0054)	(0.0061)	(0.0042)	(0.0052)
education	0.0000	0.0024	0.0314	0.0361	0.0058	0.0066	0.0251	0.0344
	(0.0065)	(0.0071)	(0.0066)	(0.0077)	(0.0058)	(0.0063)	(0.0063)	(0.0072)
informality	-0.0133	0.0051	0.0047	-0.0013	-0.0111	0.0054	0.0033	-0.0009
	(0.0059)	(0.0034)	(0.0023)	(0.0035)	(0.0057)	(0.0032)	(0.0024)	(0.0033)
rti	0.0140	0.0026	-0.0181	-0.0116	-0.0045	-0.0040	0.0141	0.0005
	(0.0141)	(0.0121)	(0.0062)	(0.0067)	(0.0048)	(0.0039)	(0.0039)	(0.0039)
intercept	-0.0142	-0.0533	-0.0732	-0.1389	0.0007	-0.0526	-0.0956	-0.1379
	(0.0158)	(0.0145)	(0.0115)	(0.0149)	(0.0200)	(0.0207)	(0.0112)	(0.0120)

Note: bootstrapped standard errors are in parentheses (100 replications); estimates in grey p>0.1.

Source: author's calculation based on data from Income Survey CASEN 1992, 2000, 2006, and 2017.

In the first period (1992–2000), we observe that the variation in total inequality is not statistically significant. However, the small increase in inequality is the result of two forces working in the

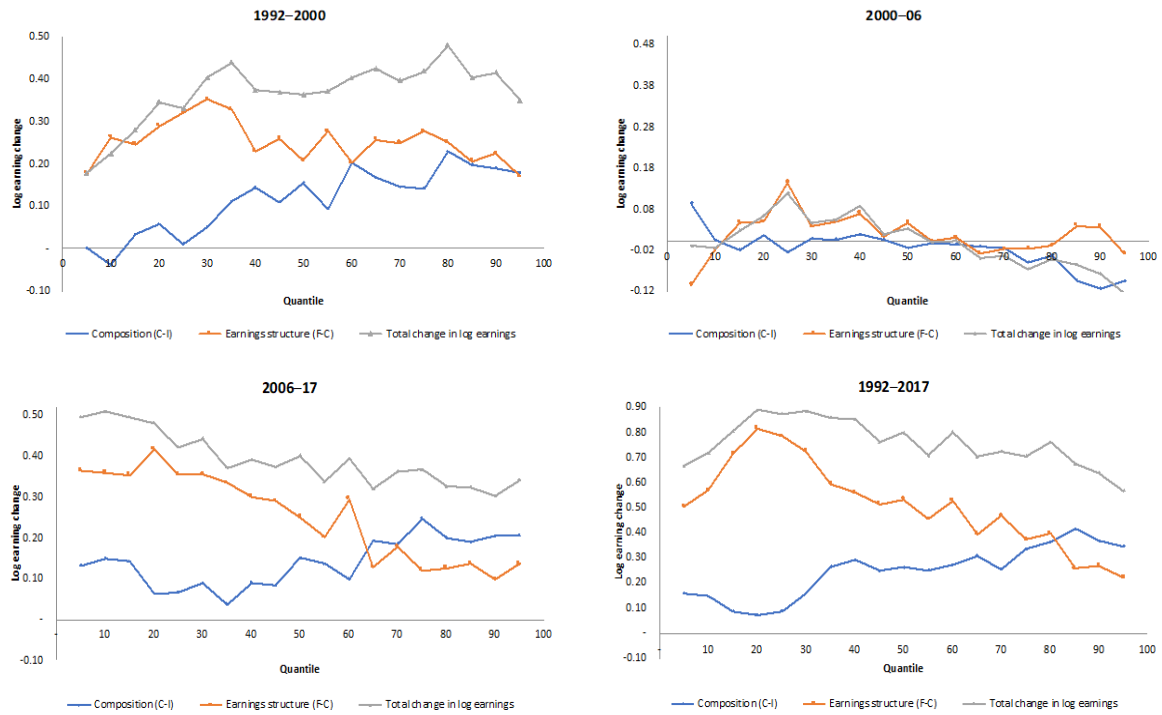
opposite direction: an inequality-enhancing composition effect (positive sign), and an inequality-reducing structure effect (negative sign). The composition effect is mainly driven by changes in education (increasing schooling levels), routinization (movements towards less-routine occupations), and informality (increase from 28.34 per cent in 1992 to 32.65 per cent in 2000).⁶ We cannot distinguish the associated characteristics behind the equalizing effect in the wage structure, since most of it is in the constant. In the following periods, we observe falls in inequality mainly driven by changes in the wage structure. In 2000–06, the return effect explains 60 per cent of the inequality reduction, with a composition effect also contributing to this inequality reduction (negative sign). Most of the structure effect is again in the constant. Unlike in the previous period, education, routinization, and informality contribute to the reduction in inequality in the composition effect. In the second period, there is a larger expansion of secondary education (Table A1 in the Appendix), average RTI decreases—indicating a displacement of workers towards less-routine occupations—and there is a reduction in informality. In the third period (2006–17), the earnings structure or return effect is more relevant in explaining the fall in earnings inequality, compensating even for the inequality-enhancing role played by the composition effect (the composition effect is positive, while inequality is dropping). In this period, there is an important contribution to the changes associated with the average income per occupation as a function of its RTI. In contrast, there are other effects in the opposite direction (equalizing) associated with the returns to education and, to a lesser extent, informality.

One of the features of the RIF regression decomposition is that it allows us to observe changes in inequality at different points of the earnings distribution, unlike the previous case in which we use the Gini index to summarize distributional changes in the whole earnings distribution. Figure 14 shows the RIF decomposition of changes in (log) quantiles over time. The grey line shows changes in the variability of (log) wages at each percentile of the earnings distribution (composition and structure effects added). We observe that changes in the earnings structure mostly drive the larger increase in earnings at the bottom and middle of the distribution. The composition effect tends to be more relevant at the top and only surpasses the return effect in 2006–17 after the 70th percentile. In the whole period (1992–2017), the curve describing overall wage changes approximates to an inverted U shape, showing increasing inequality around the middle of the distribution (in this case below the mean) and decreasing inequality at the extremes of the wage distribution.

Regarding the disaggregation of the composition effect (Figure 15), we notice that education accounts for most of the inequality rise. Increasing schooling is inequality-enhancing at every percentile, but particularly for the upper part of the distribution. The composition effect linked to RTI is also positive, indicating that the movement of workers towards less-routine tasks has contributed to a rise in inequality. The exception is in 2000–06, when average RTI increases and its effect reduces inequality.

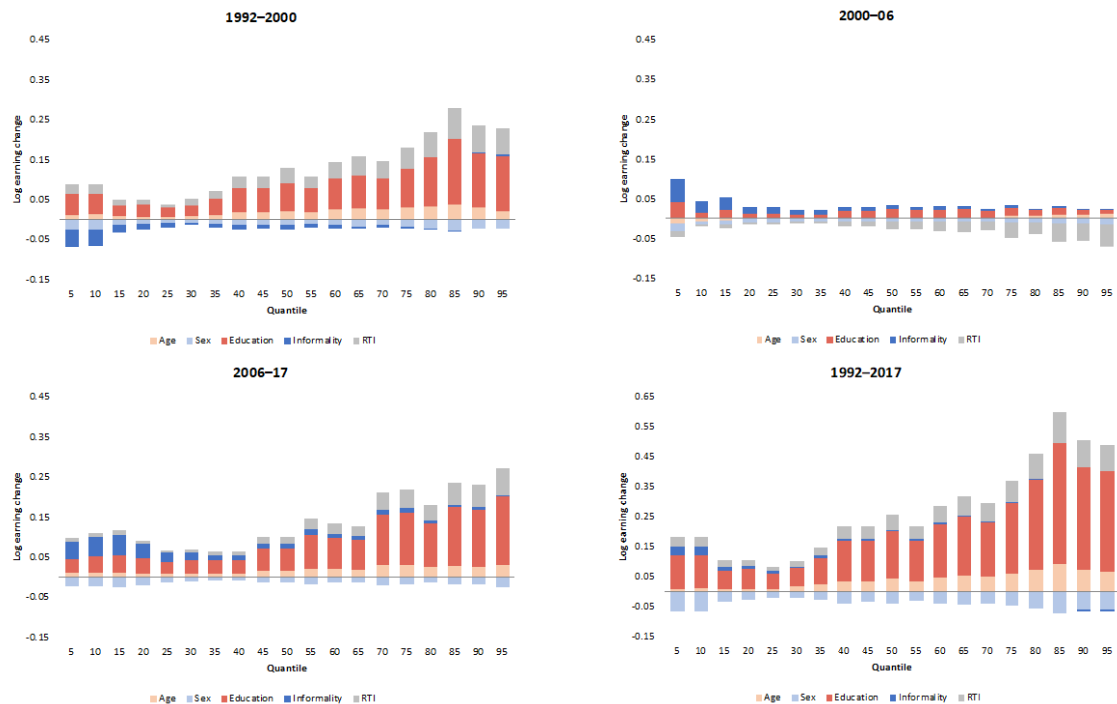
⁶ These figures were calculated using the CASEN survey for the respective year, and they refer to the main occupation.

Figure 14: RIF regression decomposition (country-specific) by earning quantiles



Source: author's illustration based on CASEN (1992, 2000, 2006, 2017)

Figure 15: Detailed RIF decomposition—composition effect by earning quantiles

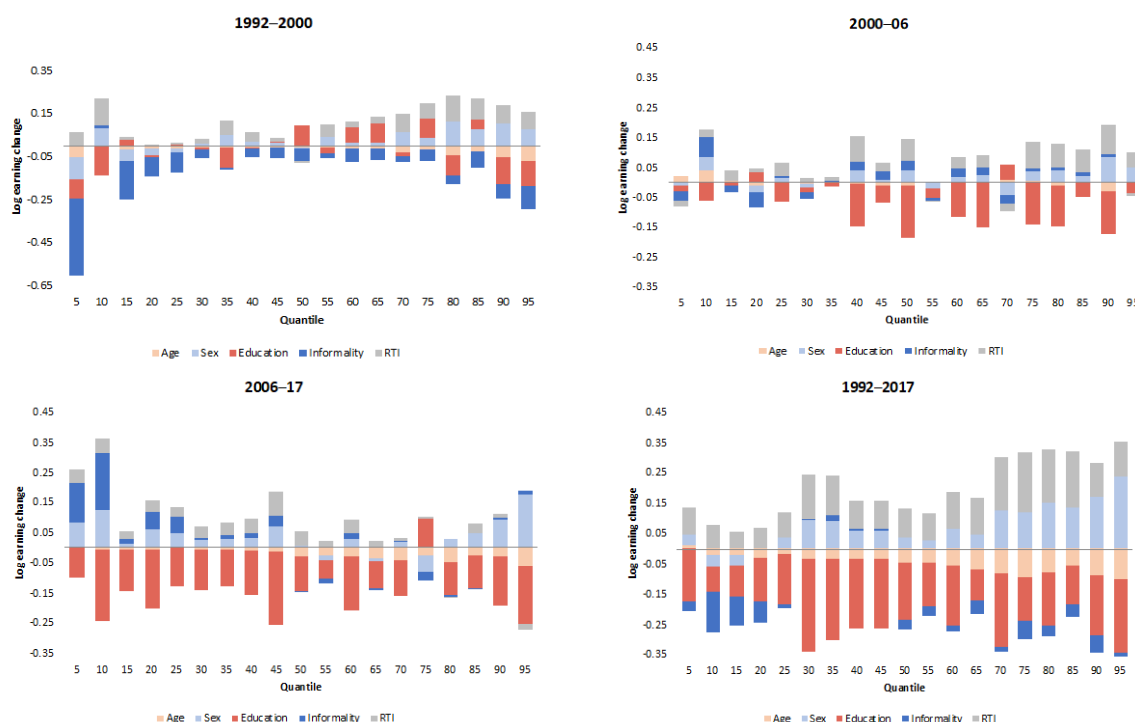


Source: author's illustration based on CASEN (1992, 2000, 2006, 2017).

From the covariates, education dominates the earnings structure effect, as shown in Figure 16. With very few exceptions, returns to education have an inequality-diminishing effect in all periods, mainly above the median in 2000–06 and below the median in 2006–17. Informality has an inverted U-shaped pattern in the first period (1992–00), contributing to decreasing inequality mostly at the

extremes of the wage distribution. In the following periods, informality slightly increases earnings dispersion around the median in 2000–06, and below the median in 2006–17. Changes in the returns to routine versus non-routine tasks have an inequality-enhancing effect in every period and throughout the entire distribution. In the first period, the positive effect is more noticeable at the bottom and upper tails of the distribution. In the second period, the effect is larger for the top of the distribution. In the third period the effect is smaller, and it is concentrated before the median of the distribution. To sum up, in the whole period (1992–2017) we observe an inequality-enhancing effect of changes in returns to RTI and the opposite effect of returns to education—the first with a slight ‘pro-rich’ bias and the second with a slight ‘pro-poor’ bias, as the effect is more negative above the 30th percentile. However, when analysing changes in the earnings structure by percentiles, we observe that most of the effect is found in the constant, as in the Gini decomposition (see Figure A8 and Tables A4, A5, and A6 in the Appendix).

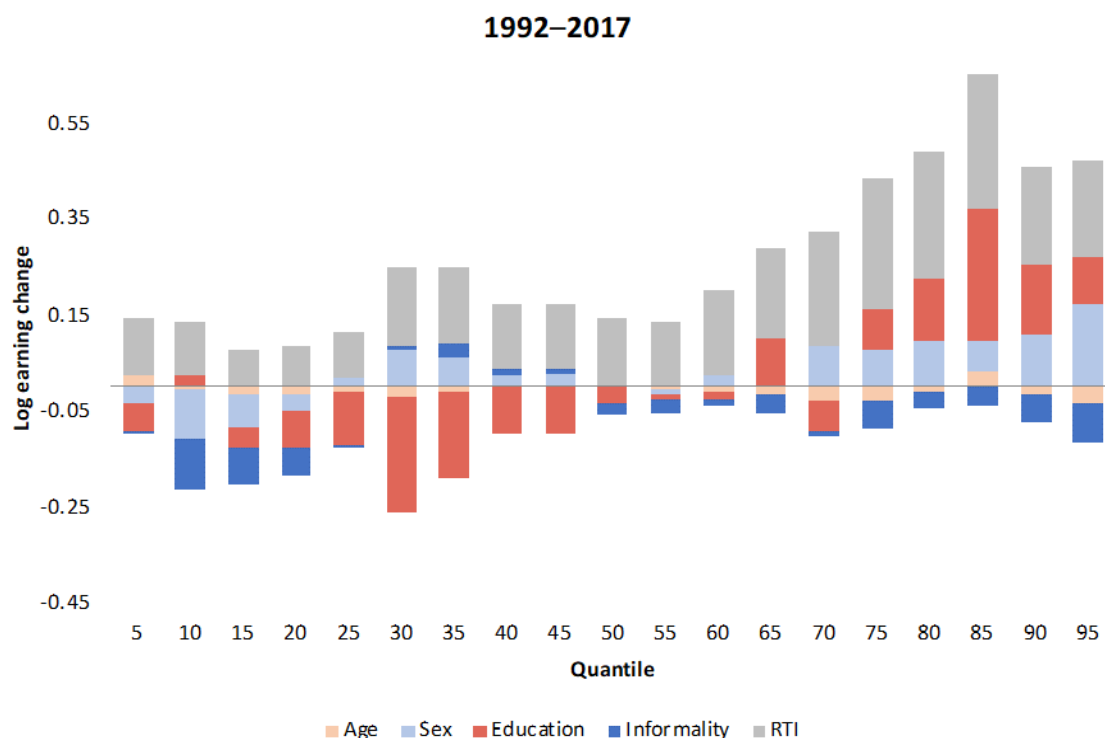
Figure 16: Detailed RIF decomposition—earnings structure effect by earnings quantiles



Source: author's illustration based on CASEN (1992, 2000, 2006, 2017).

Finally, the total effect of each covariate (wage structure plus composition effect) is reported in Figure 17. The total effect of RTI accounts for most of the changes in the variability of earnings. This shows that the net movement of workers towards less-routine tasks has contributed to rising earnings variability. Education is the second most-relevant covariate in explaining changes in inequality in the overall period. Since the composition and return effects have opposite signs, the total effect of education is to reduce inequality in the bottom part of the distribution and to increase inequality in the upper part of the distribution.

Figure 17: Detailed total effect by earning quantiles—composition plus earnings structure effects



Source: author's illustration based on CASEN (1992, 2000, 2006, 2017).

7 Conclusions

Using household data from the income survey CASEN, this paper analyses the trends in earnings inequality in Chile from 1992 to 2017, and the role of tasks and skills in shaping inequality movements. The estimations show that inequality has dropped in Chile since the 2000s, explained by a fall in earnings in the top percentiles of the distribution which has been reallocated most noticeably around the median (2000–06) and the bottom 30 per cent of the distribution (2006–17). The results highlight the role of education and a decrease in the routinization of tasks in explaining changes in earnings inequality.

We observe an average reduction of the RTI of jobs over time. Given that the RTI values are constant, this average decline in routinization is driven by a restructuring of the labour force away from more-routine towards less-routine occupations, with the decrease mainly manifesting in the lower part of the earnings distribution. The results of the RIF decomposition by percentiles show a strong inequality-enhancing effect of the movement of workers towards less-routine tasks, as well as a disqualifying effect on the returns to RTI. Nevertheless, when we look at inequality changes using the Gini coefficient, the effect of RTI is weaker, combining a positive composition effect with a negative wage structure effect. The robust effect of RTI in explaining changes in inequality at different percentiles is in line with the polarization analysis of Section 5.2. We find that the routine content of tasks explains an important part of changes in the variability of earnings, and to a lesser extent the variability of employment. However, the strong monotonic correlation of earnings with RTI has been reducing over time, as shown by the Shapley decomposition. The Shapley decomposition also shows that average earnings across occupations have become less unequal over time, contributing to the overall decline in inequality.

It has been argued that changes in returns to education are the main driver of wage inequality dynamics in Chile (PNUD 2017; Torche 2014). In line with the literature, our results confirm a reduction in the returns to education, particularly higher education (Section 3.3). The inequality decomposition by percentiles shows that changes in the composition of education, such as the expansion of secondary and higher education, have contributed to increasing earnings dispersion throughout the distribution, with a strong bias towards the upper percentiles. As an opposite force, changes in the returns to education have contributed to reducing earnings variability, especially below the median of the distribution. Still, the net effect of education on changes in inequality between 1992 and 2017 is different depending on the income percentile. It is negative until the 60th percentile and positive after that, with a peak at the 85th percentile. Therefore, the equalizing role of education is particularly important for the lower part of the income distribution, and declining returns to education alone would not be enough to offset the disequalizing effect of educational expansion at the top of the distribution.

Changes in the occupational structure confirm a displacement of workers from low-skill occupations towards jobs demanding non-routine higher skills. Changes in occupational earnings have had a positive equalizing effect, with more substantial gains in favour of lower-skill occupations and at the top of the skill premium, with earnings of managers and professionals becoming closer. Despite these positive changes in inequality, we still observe substantial differences between the rewards of low- and high-skill occupations which cannot be explained by the educational premium. As discussed by Messina and Silva (2019), there are several factors related to the drop in earnings inequality which changes in education cannot account for, such as changes in the labour supply due to the experience premium and compression of wages across workers with similar skills.

Another factor that is slightly significant in inequality changes is the reduction of informality. Establishing the link between formalization and inequality is not trivial, since the direction of causality is unclear (Messina and Silva 2019). Job market reforms helped to increase formal work in Chile during the 2000s. The RIF decomposition shows that changes in the distribution of wages associated with this process contributed slightly to reducing inequality. This is mainly through changes in the composition of employment, since changes in formal–informal wage gaps are not significant for the whole distribution, although they are in percentile analysis.

It is important to acknowledge that the decomposition of changes in inequality due to changes in structure and composition is primarily an analytical exercise, since these are not fully separable effects. A clear example is that changes in the returns to education (structure effect) may be due to a change in the population's overall level of education (composition), which in turn adjusts the educational premium.

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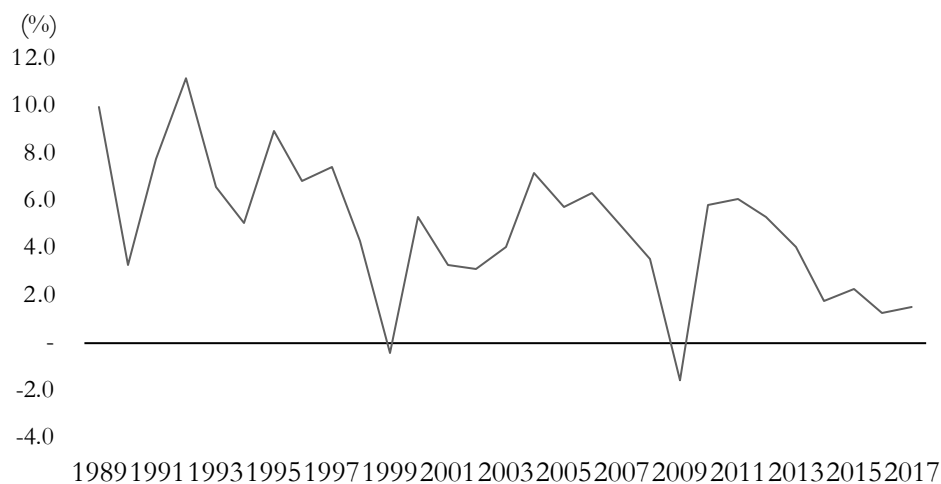
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Appendix

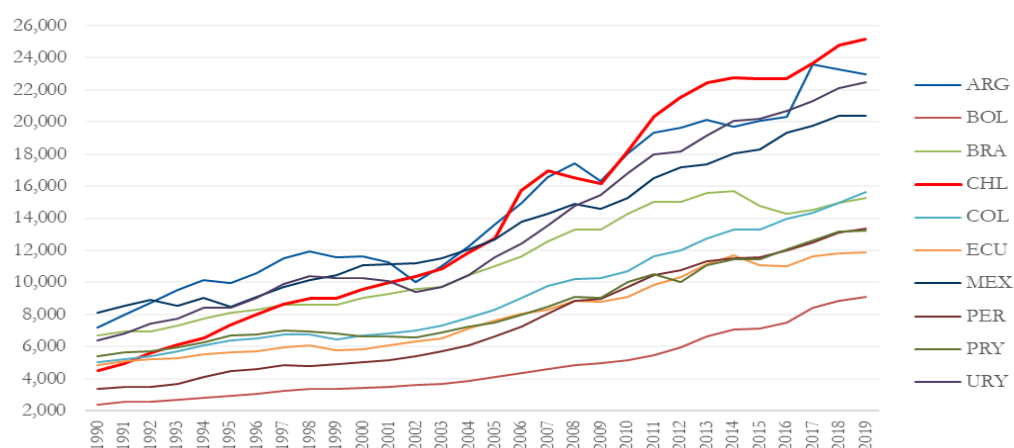
Figure A1: Annual GDP growth



Note: annual percentage growth rate of GDP at market prices based on constant local currency.

Source: authors' illustration based on World Bank (2020a).

Figure A2: GDP per capita, PPP (current international \$), South America and Mexico



Note: country codes are ARG (Argentina), BOL (Bolivia), BRA (Brazil), CHL (Chile), COL (Colombia), ECU (Ecuador), MEX (Mexico), PER (Peru), PRY (Paraguay), URY (Uruguay).

Source: author's illustration based on World Bank (2020b).

Table A1: Distribution of workers by level of education completed

	Total				Male				Female			
	1992	2000	2006	2017	1992	2000	2006	2017	1992	2000	2006	2017
No schooling	22.24	15.71	13.24	8.01	24.38	17.94	14.68	8.83	17.93	11.93	10.98	6.99
Primary	35.28	28.91	27.18	19.37	37.20	30.56	29.31	21.79	31.42	26.11	23.85	16.33
Secondary	30.89	37.34	42.23	44.82	28.89	36.10	41.18	45.21	34.93	39.43	43.86	44.34
Tertiary	11.58	18.04	17.36	27.79	9.54	15.40	14.83	24.17	15.72	22.53	21.31	32.35

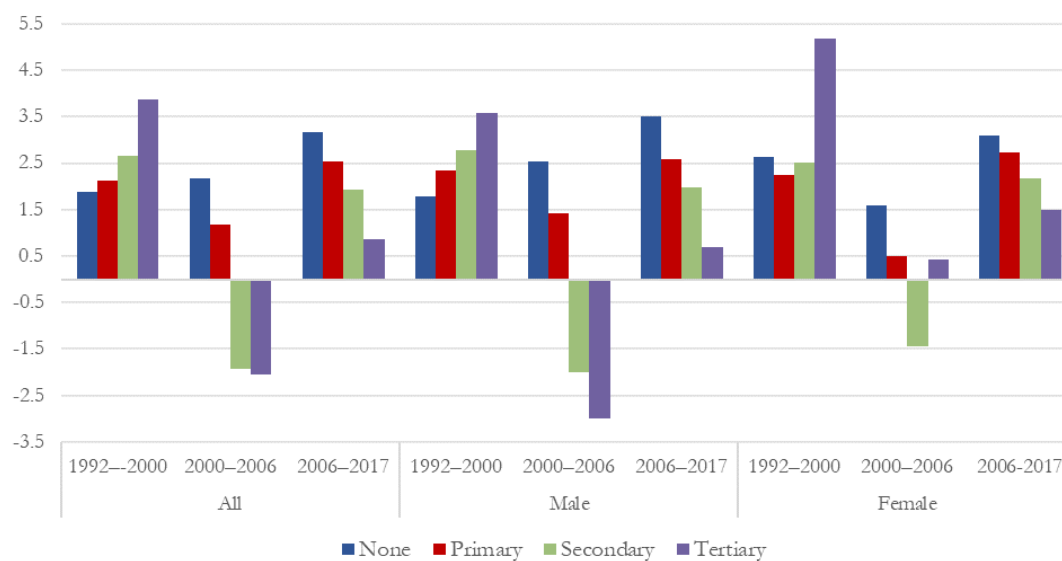
Source: author's construction based on CASEN (1992, 2000, 2006, 2017).

Table A2: Average weekly earnings (main occupation) and earnings ratios

	Total				Male				Female			
	None	Primary	Secondary	Tertiary	None	Primary	Secondary	Tertiary	None	Primary	Secondary	Tertiary
1992	81	104	163	399	86	113	184	531	65	82	128	235
2000	94	123	201	541	99	136	229	703	80	98	156	352
2006	107	132	179	478	115	148	203	586	88	101	143	361
2017	151	174	221	525	168	196	252	632	123	136	181	425
Earning ratios												
1992	1.0	1.3	2.0	4.9	1.0	1.3	2.1	6.2	1.0	1.3	2.0	3.6
2000	1.0	1.3	2.1	5.8	1.0	1.4	2.3	7.1	1.0	1.2	2.0	4.4
2006	1.0	1.2	1.7	4.5	1.0	1.3	1.8	5.1	1.0	1.1	1.6	4.1
2017	1.0	1.2	1.5	3.5	1.0	1.2	1.5	3.8	1.0	1.1	1.5	3.5

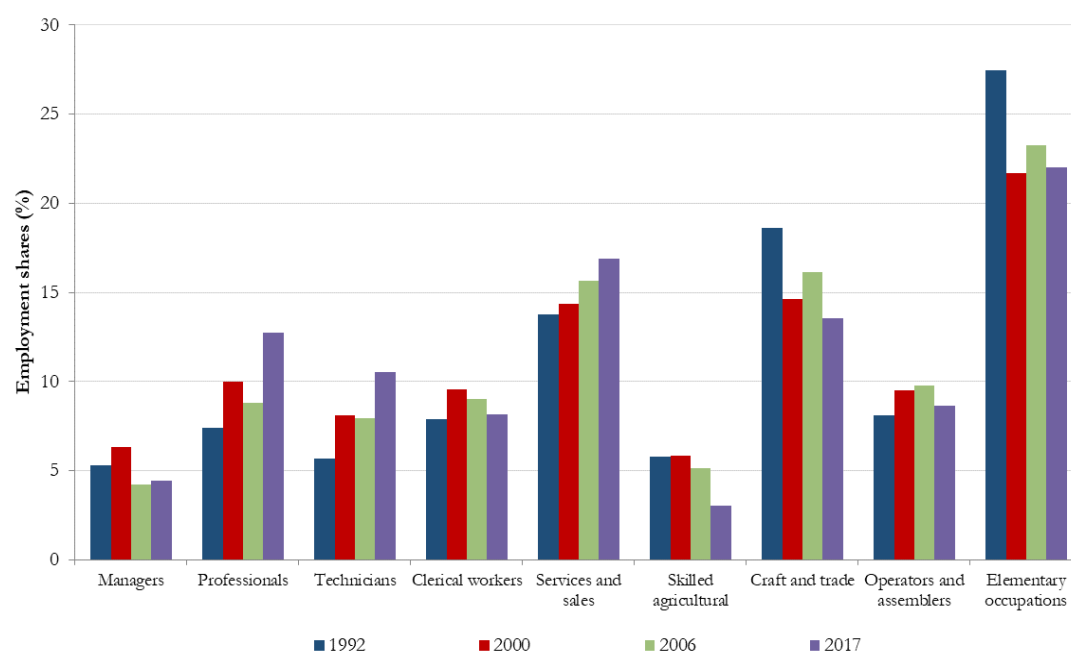
Source: author's construction based on CASEN (1992, 2000, 2006, 2017).

Figure A3: Average growth rate in mean weekly earnings by level of education completed



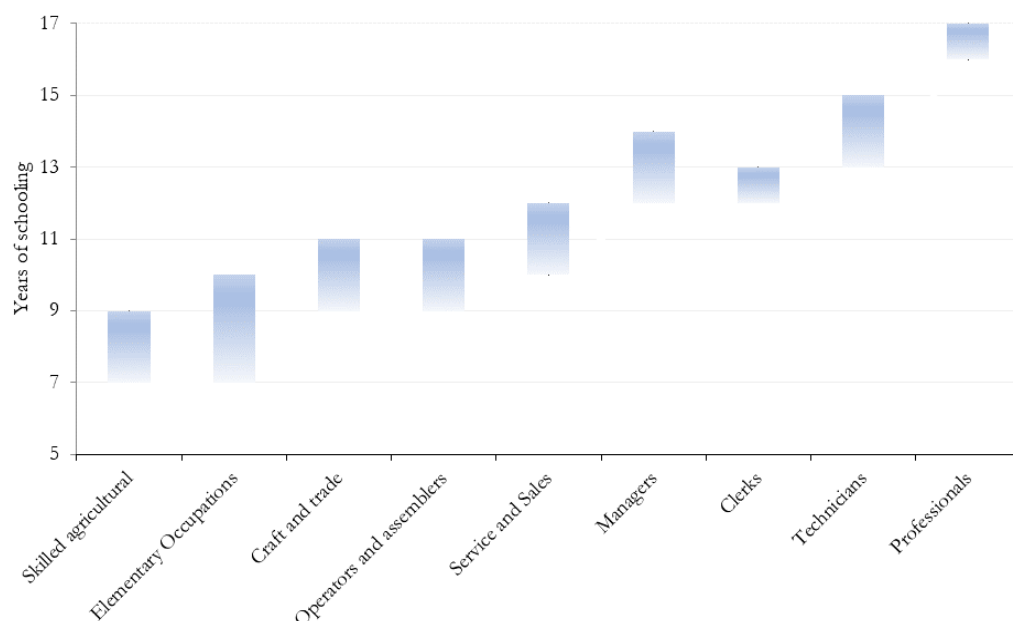
Source: author's illustration based on CASEN (1992, 2000, 2006, 2017).

Figure A4: Employment shares by occupational groups



Source: author's illustration based on CASEN (1992, 2000, 2006, 2017).

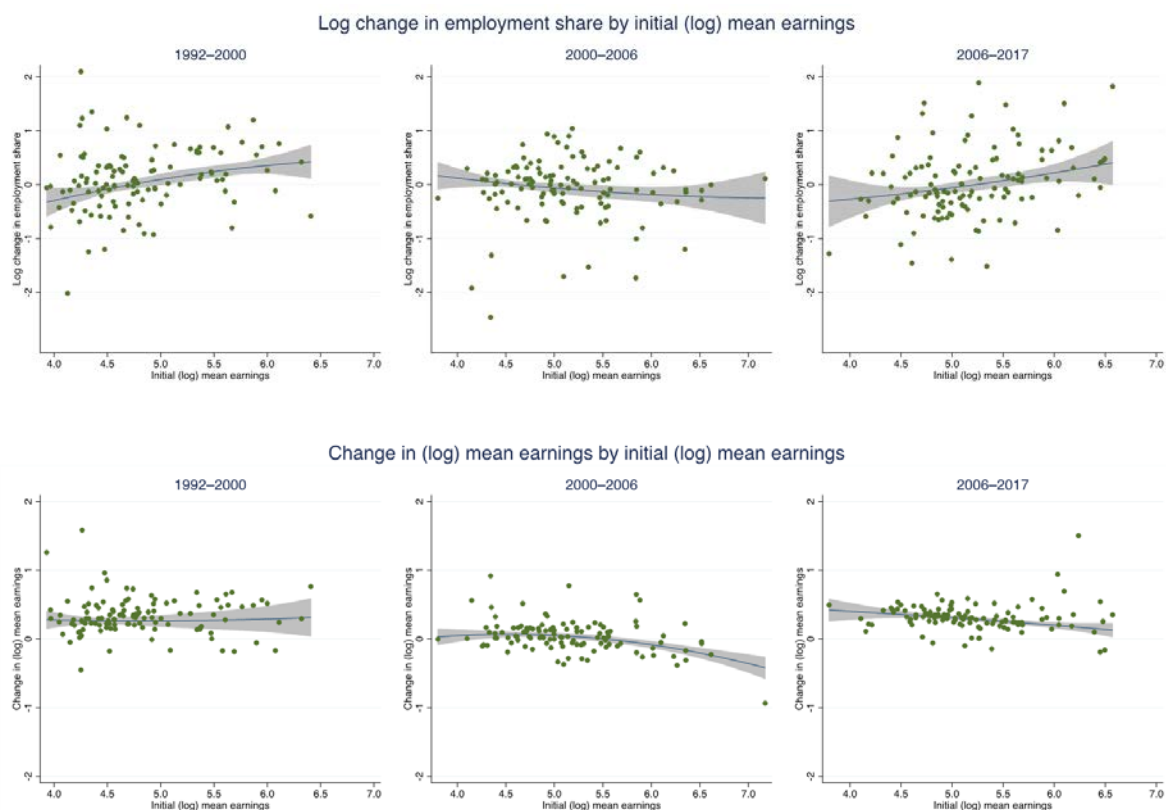
Figure A5: Distribution of workers by occupation and years of schooling



Note: the marked area shows average years of schooling in each occupation in all waves.

Source: author's illustration based on CASEN (1992, 2000, 2006, 2017).

Figure A6: Correlation between initial (log) earnings and changes in average employment and earnings by occupation



Note: scatter plots with fitted quadratic prediction and 95 per cent confidence interval. Occupations are at ISCO-88 three-digit level.

Source: author's illustration based on CASEN (1992, 2000, 2006, 2017).

Table A3: O*NET and country-specific RTI—average RTI by year (ISCO-88 two-digit level)

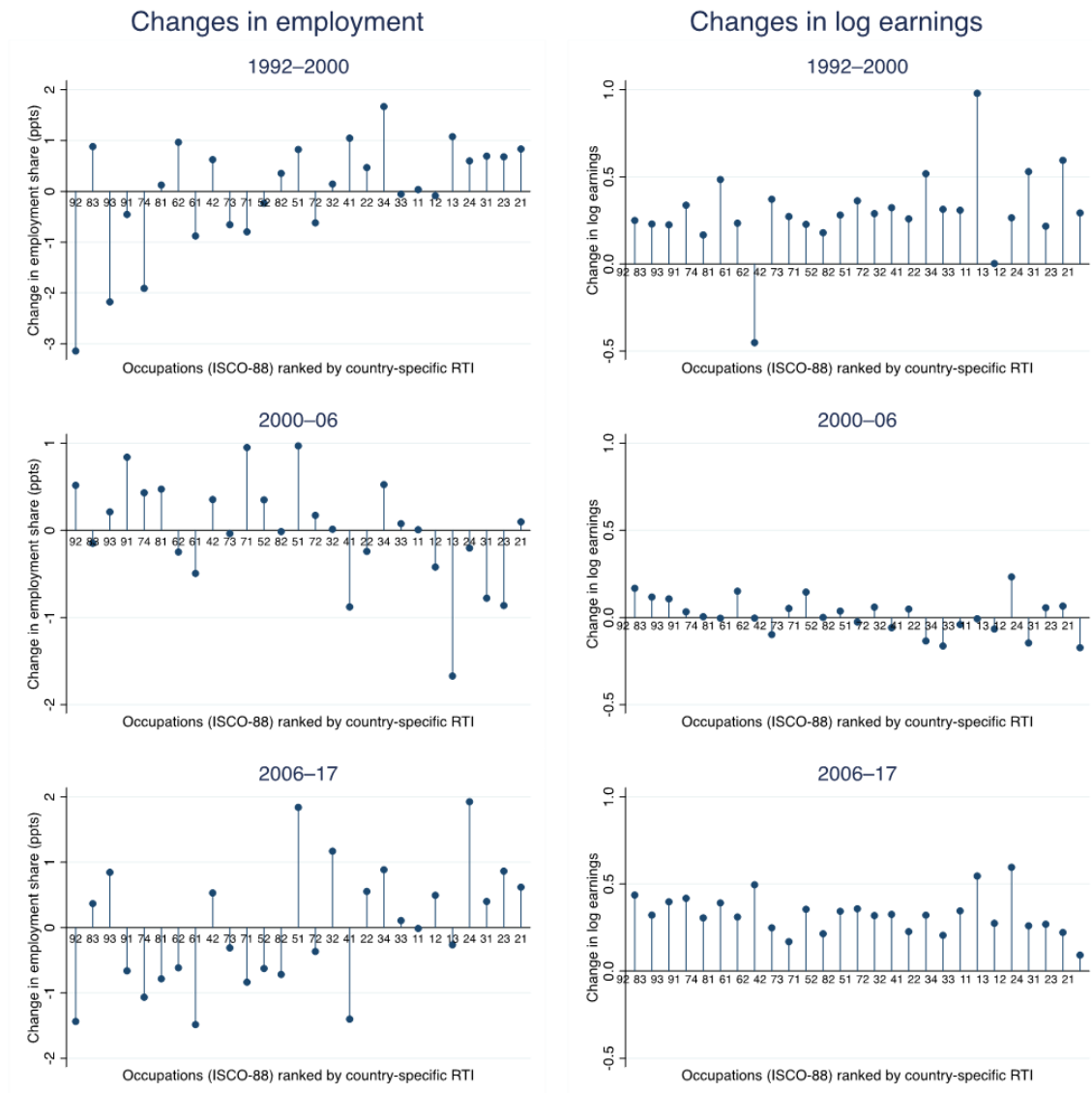
	1992		2000		2006		2017	
ISCO-88 (two-digit)	O*NET	Country RTI	O*NET	Country RTI	O*NET	Country RTI	O*NET	Country RTI
Legislators and senior officials	-1.992	-0.346	-1.987	-0.346	-1.983	-0.346	-1.989	-0.346
Corporate managers	-1.243	-0.426	-1.195	-0.426	-1.360	-0.426	-1.198	-0.426
Managers of small enterprises	-1.179	-0.426	-1.179	-0.426	-1.179	-0.426	-1.179	-0.426
Physical, mathematical, and engineering	-0.800	-0.876	-0.799	-0.876	-0.801	-0.876	-0.804	-0.876
Life science and health professionals	-0.756	-0.061	-0.773	-0.061	-0.777	-0.061	-0.773	-0.061
Teaching professionals	-1.613	-0.758	-1.619	-0.758	-1.613	-0.758	-1.622	-0.758
Other professionals	-1.113	-0.576	-1.120	-0.576	-1.138	-0.576	-1.090	-0.576
Physical and engineering science associate professionals	-0.134	-0.595	-0.167	-0.595	-0.193	-0.595	-0.156	-0.595
Life science, and health associate professionals	-0.286	0.038	-0.224	0.038	-0.292	0.038	-0.322	0.038
Teaching associate professionals	-1.019	-0.287	-1.008	-0.287	-0.999	-0.287	-0.991	-0.287
Other associate professionals	-0.586	-0.196	-0.572	-0.196	-0.495	-0.196	-0.503	-0.196
Office clerks	0.139	-0.051	0.181	-0.051	0.156	-0.051	0.207	-0.051
Customer services clerk	0.070	0.486	0.074	0.486	0.080	0.486	0.082	0.486
Personal and protective services workers	-0.117	0.230	-0.139	0.230	-0.096	0.230	-0.061	0.230
Models, salespersons, and demonstrators	-0.176	0.340	-0.258	0.340	-0.295	0.340	-0.371	0.340
Skilled agricultural and fishery workers	0.505	0.512	0.443	0.512	0.421	0.512	0.372	0.512
Subsistence agricultural and fishery workers	0.561	0.512	0.561	0.512	0.561	0.512	0.561	0.512
Extraction and building trades workers	1.185	0.409	1.167	0.409	1.139	0.409	1.156	0.409
Metal, machinery, and related trades workers	1.047	0.120	1.067	0.120	1.076	0.120	1.063	0.120
Precision, handicraft, printing, and related trades workers	1.097	0.476	1.086	0.476	1.041	0.476	0.967	0.476
Other craft and related trades workers	1.333	0.590	1.334	0.590	1.323	0.590	1.347	0.590
Stationary plant and related operators	1.208	0.530	1.148	0.530	1.101	0.530	0.951	0.530
Machine operators and assemblers	1.691	0.243	1.744	0.243	1.718	0.243	1.795	0.243
Drivers and mobile plant operators	0.907	0.774	0.949	0.774	0.942	0.774	0.979	0.774
Sales and services elementary occupations	1.192	0.652	1.222	0.652	1.148	0.652	1.194	0.652
Agricultural, fishery, and related labour	0.557	0.821	0.557	0.821	0.557	0.821	0.557	0.821
Labourers in mining, construction,	1.938	0.668	1.944	0.668	1.854	0.668	1.726	0.668

manufacturing, and
transport

Total	0.458	0.305	0.311	0.228	0.365	0.268	0.252	0.209
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Source: author's construction based on CASEN (1992, 2000, 2006, 2017).

Figure A7: Changes in employment share and real weekly wages by country-specific RTI



Note: this figure plots changes in employment shares and (log) mean earnings against occupations at ISCO-88 two-digit level, presented in ascending order of their country-specific RTI (horizontal axis). Therefore, we observe occupations with a higher RTI close to the vertex, such as 92: agricultural, fishery, and 83: drivers, at the beginning of the distribution and occupations with low RTI at the end of the distribution, such as 23: teaching professional, and 21: physical, mathematical, and engineering science professionals.

Source: author's illustration based on CASEN (1992, 2000, 2006, 2017.)

Table A4: RIF regression decomposition by quantiles, 1992–2000

Quantiles	q=5	q=10	q=15	q=20	q=25	q=30	q=35	q=40	q=45	q=50	q=55	q=60	q=65	q=70	q=75	q=80	q=85	q=90	q=95
Final Gini	3.561	3.997	4.254	4.409	4.487	4.590	4.651	4.676	4.810	4.863	5.005	5.059	5.218	5.328	5.451	5.631	5.830	6.135	6.561
Initial Gini	3.383	3.774	3.975	4.064	4.157	4.187	4.212	4.302	4.441	4.500	4.635	4.655	4.793	4.933	5.033	5.152	5.426	5.721	6.212
Total change	0.178	0.223	0.279	0.345	0.330	0.403	0.439	0.374	0.369	0.363	0.370	0.403	0.425	0.396	0.418	0.479	0.403	0.414	0.349
Reweighting																			
Composition	0.002	-0.039	0.033	0.057	0.010	0.051	0.111	0.145	0.110	0.155	0.093	0.202	0.167	0.146	0.141	0.229	0.197	0.191	0.179
Earning structure	0.176	0.262	0.246	0.289	0.320	0.352	0.328	0.229	0.259	0.208	0.277	0.202	0.257	0.249	0.276	0.250	0.206	0.224	0.170
RIF																			
Composition	0.019	0.023	0.017	0.024	0.021	0.037	0.054	0.083	0.085	0.105	0.089	0.121	0.137	0.128	0.159	0.196	0.254	0.212	0.206
Specification error	-0.017	-0.062	0.016	0.033	-0.011	0.014	0.058	0.062	0.024	0.050	0.004	0.080	0.030	0.019	-0.018	0.032	-0.057	-0.022	-0.027
Earnings structure	0.176	0.262	0.246	0.289	0.320	0.352	0.328	0.229	0.260	0.209	0.278	0.203	0.258	0.250	0.278	0.252	0.208	0.225	0.171
Reweighting error	0.000	0.000	0.000	0.000	0.000	0.000	-0.001	-0.001	-0.001	-0.001	-0.001	-0.001	-0.001	-0.001	-0.001	-0.002	-0.002	-0.002	-0.002
RIF composition																			
age	0.011	0.012	0.007	0.007	0.005	0.008	0.012	0.018	0.018	0.022	0.019	0.024	0.027	0.025	0.030	0.033	0.040	0.029	0.023
sex	-0.025	-0.024	-0.013	-0.010	-0.007	-0.008	-0.010	-0.014	-0.013	-0.015	-0.012	-0.015	-0.016	-0.015	-0.018	-0.021	-0.028	-0.023	-0.023
education	0.053	0.051	0.029	0.031	0.024	0.029	0.041	0.060	0.059	0.069	0.058	0.077	0.085	0.078	0.097	0.124	0.165	0.139	0.135
informality	-0.046	-0.043	-0.021	-0.016	-0.011	-0.008	-0.009	-0.012	-0.010	-0.010	-0.008	-0.008	-0.006	-0.005	-0.004	-0.003	0.000	0.002	0.006
rti	0.024	0.026	0.016	0.013	0.010	0.015	0.021	0.032	0.032	0.038	0.032	0.043	0.048	0.044	0.054	0.064	0.078	0.065	0.064
explained	0.019	0.023	0.017	0.024	0.021	0.037	0.054	0.083	0.085	0.105	0.089	0.121	0.137	0.128	0.159	0.196	0.254	0.212	0.206
RIF earnings structure																			
age	-0.054	-0.004	-0.020	-0.013	-0.014	-0.006	-0.005	-0.009	-0.008	-0.009	-0.010	-0.015	-0.013	-0.030	-0.019	-0.040	-0.025	-0.052	-0.069
sex	-0.103	0.083	-0.049	-0.029	-0.019	0.009	0.051	0.024	0.015	-0.005	0.046	0.016	0.013	0.065	0.041	0.113	0.079	0.105	0.076
education	-0.089	-0.135	0.026	-0.009	0.004	-0.014	-0.099	-0.002	0.006	0.094	-0.024	0.073	0.095	-0.015	0.090	-0.096	0.044	-0.123	-0.120
informality	-0.353	0.013	-0.182	-0.093	-0.094	-0.036	-0.005	-0.043	-0.050	-0.059	-0.026	-0.061	-0.048	-0.033	-0.052	-0.044	-0.078	-0.071	-0.109
rti	0.069	0.122	0.015	0.005	0.013	0.021	0.067	0.045	0.017	-0.009	0.054	0.024	0.029	0.088	0.067	0.121	0.097	0.084	0.079
intercept	0.706	0.183	0.456	0.427	0.431	0.379	0.318	0.214	0.281	0.195	0.238	0.166	0.183	0.175	0.150	0.198	0.091	0.282	0.315

Note: estimates in grey p>0.1.

Source: author's construction based on CASEN (1992, 2000, 2006, 2017).

Table A5: RIF regression decomposition by quantiles, 2000–06

Quantiles	q=5	q=10	q=15	q=20	q=25	q=30	q=35	q=40	q=45	q=50	q=55	q=60	q=65	q=70	q=75	q=80	q=85	q=90	q=95
Final Gini	3.550	3.982	4.282	4.472	4.606	4.635	4.705	4.762	4.828	4.894	5.003	5.062	5.177	5.295	5.385	5.588	5.775	6.058	6.436
Initial Gini	3.561	3.997	4.254	4.409	4.487	4.590	4.651	4.676	4.810	4.863	5.005	5.059	5.218	5.328	5.451	5.631	5.830	6.135	6.561
Total change	-0.010	-0.015	0.027	0.063	0.119	0.046	0.054	0.087	0.018	0.031	-0.002	0.003	-0.041	-0.034	-0.066	-0.043	-0.055	-0.078	-0.125
Reweighting																			
Composition	0.094	0.005	-0.019	0.015	-0.025	0.008	0.006	0.018	0.005	-0.015	-0.002	-0.006	-0.012	-0.015	-0.049	-0.033	-0.094	-0.113	-0.096
Earning structure	-0.105	-0.019	0.047	0.048	0.144	0.038	0.048	0.068	0.013	0.047	0.001	0.009	-0.029	-0.018	-0.017	-0.010	0.039	0.035	-0.029
RIF																			
Composition	0.054	0.024	0.030	0.016	0.014	0.009	0.009	0.012	0.010	0.010	0.004	0.002	-0.001	-0.004	-0.015	-0.016	-0.026	-0.030	-0.048
Specification Error	0.040	-0.019	-0.050	-0.001	-0.039	-0.001	-0.004	0.007	-0.005	-0.026	-0.007	-0.008	-0.010	-0.011	-0.035	-0.017	-0.068	-0.083	-0.049
Earnings structure	-0.106	-0.021	0.045	0.047	0.143	0.037	0.048	0.068	0.013	0.047	0.001	0.009	-0.028	-0.018	-0.015	-0.008	0.041	0.038	-0.026
Reweighting error	0.001	0.002	0.001	0.001	0.001	0.000	0.000	0.000	0.000	-0.000	-0.000	-0.000	-0.001	-0.001	-0.002	-0.002	-0.002	-0.003	-0.003
RIF composition																			
age	-0.013	-0.005	-0.005	-0.002	-0.002	-0.001	-0.001	0.000	0.000	0.001	0.001	0.001	0.002	0.002	0.007	0.006	0.010	0.011	0.013
sex	-0.019	-0.009	-0.011	-0.007	-0.006	-0.004	-0.004	-0.006	-0.006	-0.007	-0.007	-0.007	-0.007	-0.006	-0.009	-0.008	-0.011	-0.012	-0.015
education	0.040	0.017	0.022	0.013	0.014	0.011	0.011	0.018	0.019	0.024	0.020	0.021	0.021	0.016	0.020	0.014	0.016	0.011	0.007
informality	0.059	0.027	0.033	0.018	0.015	0.010	0.010	0.012	0.011	0.012	0.009	0.010	0.009	0.006	0.008	0.005	0.006	0.003	0.002
rti	-0.014	-0.007	-0.009	-0.006	-0.008	-0.007	-0.007	-0.013	-0.014	-0.019	-0.019	-0.024	-0.026	-0.023	-0.040	-0.033	-0.047	-0.044	-0.055
explained	0.054	0.024	0.030	0.016	0.014	0.009	0.009	0.012	0.010	0.010	0.004	0.002	-0.001	-0.004	-0.015	-0.016	-0.026	-0.030	-0.048
RIF earnings structure																			
age	0.023	0.041	0.005	-0.008	0.003	-0.004	-0.002	-0.004	-0.007	-0.007	-0.000	0.003	0.002	0.009	0.007	-0.008	-0.001	-0.029	-0.000
sex	-0.011	0.042	-0.001	-0.024	0.012	-0.012	-0.000	0.041	0.010	0.040	-0.019	0.014	0.024	-0.041	0.031	0.043	0.023	0.084	0.048
education	-0.019	-0.061	-0.009	0.035	-0.063	-0.016	-0.009	-0.142	-0.060	-0.176	-0.034	-0.115	-0.149	0.053	-0.142	-0.137	-0.047	-0.144	-0.037
informality	-0.031	0.066	-0.024	-0.053	0.007	-0.023	0.005	0.029	0.027	0.034	-0.008	0.029	0.024	-0.029	0.009	0.007	0.009	0.012	-0.009
rti	-0.018	0.027	0.037	0.012	0.045	0.014	0.013	0.084	0.029	0.073	-0.002	0.039	0.042	-0.026	0.089	0.079	0.079	0.098	0.051
intercept	-0.050	-0.137	0.038	0.086	0.141	0.079	0.041	0.061	0.014	0.084	0.064	0.038	0.029	0.016	-0.009	0.007	-0.023	0.018	-0.079

Note: estimates in grey p>0.1.

Source: author's construction based on CASEN (1992, 2000, 2006, 2017).

Table A6: RIF regression decomposition by quantiles, 2006–17

Quantiles	q=5	q=10	q=15	q=20	q=25	q=30	q=35	q=40	q=45	q=50	q=55	q=60	q=65	q=70	q=75	q=80	q=85	q=90	q=95
Final Gini	4.044	4.489	4.775	4.951	5.027	5.069	5.069	5.152	5.200	5.295	5.340	5.454	5.495	5.656	5.738	5.911	6.098	6.358	6.777
Initial Gini	3.549	3.981	4.280	4.471	4.606	4.627	4.698	4.762	4.827	4.894	5.003	5.061	5.176	5.294	5.372	5.586	5.774	6.057	6.436
Total change	0.495	0.509	0.495	0.480	0.422	0.442	0.371	0.390	0.373	0.401	0.337	0.393	0.319	0.362	0.366	0.325	0.324	0.301	0.341
Reweighting																			
Composition	0.131	0.149	0.142	0.063	0.066	0.088	0.037	0.090	0.083	0.151	0.136	0.098	0.191	0.184	0.247	0.200	0.189	0.203	0.206
Earning structure	0.364	0.359	0.354	0.417	0.355	0.354	0.334	0.300	0.290	0.250	0.201	0.294	0.127	0.178	0.120	0.125	0.136	0.098	0.135
RIF																			
Composition	0.075	0.085	0.091	0.072	0.054	0.056	0.053	0.053	0.086	0.086	0.129	0.118	0.113	0.192	0.199	0.164	0.219	0.211	0.245
Specification Error	0.056	0.064	0.051	-0.009	0.012	0.032	-0.016	0.037	-0.003	0.065	0.007	-0.020	0.079	-0.008	0.047	0.036	-0.031	-0.008	-0.039
Earnings structure	0.364	0.359	0.354	0.417	0.356	0.355	0.334	0.301	0.291	0.252	0.202	0.296	0.129	0.179	0.121	0.127	0.138	0.100	0.139
Reweighting error	0.000	0.000	-0.000	-0.000	-0.000	-0.000	-0.001	-0.001	-0.001	-0.002	-0.001	-0.002	-0.002	-0.002	-0.002	-0.002	-0.002	-0.003	-0.003
RIF composition																			
age	0.009	0.009	0.010	0.009	0.007	0.008	0.008	0.008	0.015	0.015	0.022	0.020	0.019	0.030	0.030	0.024	0.028	0.026	0.031
sex	-0.023	-0.024	-0.026	-0.019	-0.013	-0.012	-0.010	-0.010	-0.014	-0.014	-0.018	-0.015	-0.014	-0.020	-0.019	-0.015	-0.018	-0.019	-0.027
education	0.033	0.042	0.046	0.039	0.031	0.033	0.033	0.033	0.055	0.055	0.084	0.078	0.074	0.126	0.131	0.109	0.146	0.144	0.170
informality	0.047	0.049	0.050	0.035	0.022	0.019	0.013	0.013	0.012	0.012	0.014	0.010	0.009	0.013	0.011	0.008	0.007	0.005	0.004
rti	0.008	0.009	0.011	0.009	0.008	0.009	0.009	0.009	0.017	0.017	0.027	0.026	0.025	0.043	0.046	0.039	0.057	0.055	0.067
explained	0.075	0.085	0.091	0.072	0.054	0.056	0.053	0.053	0.086	0.086	0.129	0.118	0.113	0.192	0.199	0.164	0.219	0.211	0.245
RIF earnings structure																			
age	-0.002	-0.002	-0.004	-0.004	0.000	-0.005	-0.005	-0.007	-0.013	-0.026	-0.022	-0.029	-0.035	-0.040	-0.025	-0.045	-0.022	-0.029	-0.060
sex	0.085	0.128	0.015	0.060	0.051	0.027	0.030	0.034	0.072	0.009	-0.015	0.030	-0.009	0.021	-0.052	0.032	0.052	0.093	0.177
education	-0.096	-0.236	-0.138	-0.197	-0.128	-0.133	-0.121	-0.148	-0.242	-0.119	-0.063	-0.178	-0.089	-0.120	0.097	-0.109	-0.111	-0.160	-0.194
informality	0.130	0.185	0.015	0.059	0.053	0.007	0.012	0.015	0.037	-0.005	-0.016	0.019	-0.008	0.001	-0.033	-0.008	-0.002	0.009	0.013
rti	0.045	0.052	0.023	0.038	0.030	0.039	0.042	0.047	0.078	0.044	0.024	0.042	0.022	0.014	0.009	-0.000	0.029	0.011	-0.016
intercept	0.202	0.234	0.443	0.462	0.349	0.420	0.377	0.359	0.359	0.348	0.295	0.411	0.247	0.304	0.126	0.258	0.193	0.177	0.219

Note: estimates in grey p>0.1.

Source: author's construction based on CASEN (1992, 2000, 2006, 2017).

Figure A8: Detailed RIF decomposition—earnings structure effect (including constant) by earning quantiles



Source: author's illustration based on CASEN (1992, 2000, 2006, 2017).