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Fakultät für Wirtschaftswissenschaften
Facoltà di Economia
Faculty of Economics and Management

BEMPS –
Bozen Economics & Management
Paper Series

NO 71/ 2020

The Role of Temporary Jobs in Explaining Increasing Inequality for Recent Cohorts in Italy

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June 30, 2020

Abstract

Using tax-based longitudinal microdata from 1985 to 2016, I document how the widening income distribution in Italy is driven by younger cohorts. Entry wages started to decrease around the mid-1990s, at the same time returns to experience of new entrants in the labour market declined. Falling wage growth is linked to the institutional changes that occurred in the Italian labour market in the decade across the 2000s. I examine the impact of Italian labour market reforms on cohort-specific wage inequality by looking at the relationship between the number of temporary job spells and individual earnings. Results confirm that young and high-skilled new entrants show higher wage differential in comparison to older workers and that the increase in temporary jobs is a crucial factor in explaining the cohort wage gap.

Key words: income inequality, cohort analysis, labour market institutions
Jel classification: J31, J41

1 Introduction

Income inequality has increased dramatically over the last three decades in most OECD countries, becoming a major international policy concern (Sarfati, 2018). During the same period, there has been a rising share of non-standard contracts, growing careers fragmentation, high levels of unemployment, and increasing difficulties for young people to enter the labour market and find a stable job position. Most previous research has examined inequality from a cross-sectional perspective which fails to distinguish between changes for workers already in the workforce versus differences over time for new cohorts of workers. Despite the wide range of evidence for labour market flexibility and age-period effects on income dynamics, there is less evidence on the generational pattern in the relationship between income, non-standard contracts and cohorts.

The recent Italian experience offers an opportunity to study the evolution of earnings inequality in a period of increasing labour market flexibility, where key institutional changes have mainly affected cohorts of new entrants. Since the early 1990s, the literature on the Italian labour market highlights the central role played by the reform at the margin in shaping income inequality and job dynamics (Boeri and Garibaldi, 2007; Berton et al., 2012; Cappellari et al., 2012; Rosolia and Torrini, 2016; Franzini and Raitano, 2019). This term refers to the reforms that introduced flexibility in many European labour markets, reducing regulation on fixed-term contracts while leaving employment protection for open-ended contracts untouched.

In this paper, I compare income profiles of subsequent cohorts of workers, assessing the magnitude and the evolution of the income gap between old workers and young new entrants. By identifying the link between the number of non-standard job spells and wage cohort differentials, I establish the role played by the reforms at the margin in shaping cohort inequality. The definition of non-standard contracts in the literature is wide, but among the variety of atypical form of employment, the focus of this work is on the "Wage and Salary Independent Contractors"(WSIC[1]). They are workers formally acting as self-employed, but usually, and most of the time, working as employees. WSIC types of contracts were the ones introduced by the reforms at the margin.

The analysis has been conducted using labour income data from the administrative archives managed by the Italian National Social Security Institute (INPS). Taking advantage of this long panel dataset, I focus on cohorts born between 1959 and 1991 that have been employed in the private sector from 1985 to 2016. I start by giving descriptive evidence about the evolution of the income distribution and the relative cohort dynamics in earnings profiles. Earnings-experience profiles of Italian workers over the period are estimated for eight birth cohorts, from cohort 1959-1963 to cohort 1988-1991. The identification of cohort, experience and (cyclical) time

[1]For simplicity, I will use atypical terms and WSIC interchangeably. Although not formally appropriate, this term facilitates reading.

effects follows the conventional literature (e.g., Deaton and Paxson (1994); Attanasio (1993)), whereas a conditional quantile regression is used to understand the magnitude of the cohort income gap along with the income distribution. The use of weekly and daily income controls for differences in the intensive margins for different cohorts. A proxy of net income captures the redistributive power of the taxation system with the following caveat: even if the proxy does not take into account all the tax deduction at the household level, it indeed frames the lower bound of the disposable income. Finally, I examine heterogeneity in wages and inequality for workers with different numbers of non-standard job spells. This identification allows for examining the role played by the reforms at the margin in shaping cohort inequality.

During the period under analysis, 1985-2016, inequality has slightly increased in Italy along with the presence of an unusual dynamic: while average compensations broadly stagnated throughout the 90s, entry wages have fallen. Moreover, falling entry wages have not been followed by faster, or at least similar, subsequent wage growth, and have thus led to an increasing wage gap among younger cohorts. On the one hand, instability of initial wage growth could be related to the business cycle, with weaker dynamics for those entering during a recession. On the other hand, business cycle alone cannot entirely explain the slowdown experienced by all new entrants after the mid-90s. I argue that increasing fragmentation of work experiences for new entrants is the key explanatory factor that links labour market reforms and the income gap among subsequent cohorts of workers. Further, increasing instability at the beginning of one's career is a direct outcome of institutional changes that led to the extensive use of non-standard contracts. Results show that from 1985 to 2016, new entrants exhibit income differentials between 4 and 5 per cent higher in comparison to the previous cohort, in terms of gross annual income. The difference over the life-cycle becomes even bigger if the first ten years in the labour market are taken into account. The income gap has substantially increased for those workers born after 1980; these are precisely the cohorts that entered during the reform period. The quantile regression suggests that the cohort income gap affected to a greater degree the upper tail of the distribution in which high-skilled workers are usually represented. The number of atypical contracts over a career increases the differentials, and it is indicative of the role played by the reforms in shaping the income distribution among the cohorts.

This is the first study to document persistent earnings losses for a large number of representative cohorts of male workers. The resulting panel length allows for controlling whether persistent losses arise even from temporary adverse labour market conditions. Starting from the cornerstone research conducted by Card and Lemieux (2001), this paper contributes to the literature on cohort patterns and inequality trends (e.g., Smeeding and Sullivan (1998); Gosling et al. (2000); Beaudry and Green (2000); Fitzenberger et al. (2002); Osberg (2003); Chetty et al. (2017); Sarfati (2018)). This steam of the literature has generated empirical evidence from various countries demonstrating that, in terms of income, younger generations are falling behind compared to the older ones. In addition, this study assesses the role of labour market institutions based on the underlying observed earnings losses among young cohorts.

As its point of departure, this study directs attention to the number of WSIC spells to consider how reforms shaped income profiles among subsequent cohorts of workers. My results add evidence to the Italian stream of the literature on the effect of labour market reforms on wages (Naticchioni et al., 2008; Berton et al., 2012; Cappellari et al., 2012; Naticchioni et al., 2016; Rosolia and Torrini, 2016; Franzini and Raitano, 2019). Finally, my findings have implications that go beyond deepening the characterisation of wage patterns per se, since changes in (mean) returns to education, captured by changes in the life-cycle profiles for (mean) incomes, may impact consumption, saving, capital accumulation and growth.

The paper is organised as follows: Section 2 reviews labour market outcomes and changes that occurred in the Italian labour market institutions. Section 3 describes the dataset, while section 4 gives some descriptive statistics to provide evidence in favour of the research questions and outlines the models used. Results are presented and discussed in section 5, while section 6 concludes with direction for future research.

2 Background

This section provides a brief description of the labour market reforms that occurred in Italy and a brief overview of temporary employment in the literature. Over the past 30 years, Italy is the OECD country that has done the most to reduce hiring and firing costs for non-standard contracts. This increase in labour flexibility resulted from the implementation of new forms of fixed-term contracts in 1997, 2001 and 2003[2]. New agreements allowed for a decrease in the total cost of labour by reducing employment protection, hiring and firing constraints, and by decreasing the amount of social pension contributions. The peculiarity of these reforms is the limited applicability of such contracts for new recruitments only. In contrast, the protections for the existing employment relationships, mostly standard contracts, remained unaffected. For this reason, the economic literature uses the label of reforms at the margin. Various laws enacted the crucial steps in the reform process from 1997 to 2003, and a brief description is offered hereafter.

The Treu package in 1997 was the first tangible initial step, introducing two forms of WSIC: the coordinated and continuous collaboration - co.co.co. (*collaborazione coordinata e continuativa*) and the temporary agency work (*lavoro interinale*). Firms were allowed to hire workers with this types of contracts in some particular cases, such as when skills not usually required for the standard production process were needed or for substituting temporarily absent workers (with the exceptions of workers on strike). The law prevented firms from using those contracts for low-skilled job positions, dangerous jobs, and other cases[3]. Four years later, in 2001, the

[2] Law No. 196 of 1997; L.D. Legislative Decree No. 368 of 2001 and Law No. 30 of 2003.

[3] For example when production units in which, during the last 12 months, workers involved in the same

use of temporary contracts was eased while maintaining existing employment protections for workers with permanent contracts. More specifically, this reform allowed for direct-hire with fixed-term contracts for any firm, production-related, technical, organisational or substitution reason.

The cornerstone of WSIC contracts was the 2003 Biagi Law, which significantly reduced restrictions applied to temporary agency work contracts and to part-time work. Among the set of new rules, it substituted temporary work, which had already been instituted by the "Pacchetto Treu", with an even more flexible form of employment: the so-called "*somministrazione di lavoro* (*istituto giuridico*)" a type of temporary employment. Moreover, it provided for new forms of atypical contracts: wage and salary independent contractors (WSIC, which labels the entire category of this type of employment) which can be considered a new form of pseudo-self-employment and job on-call contracts (*contratto a chiamata*). Its implementation occurred through the law 276/2003, but entered into force in October 2003 and was implemented with different time-regional differences. Despite some attempts to reduce employment protection also for open-ended contrasts in 2012 and 2014, those contracts have been remained untouched until the Jobs Act in 2015.

The final outcome was a two-tier labour market divided between old protected, stable workers and less protected, unstable new entrants. As we have seen, these disparities have remained for at least 15-18 years. The aim of this paper is to link them to cohort inequality.

2.1 Labour Market Outcomes

The spread of fixed-term contracts has fueled scientific and institutional debate around the implications of such contracts for productivity, wages and, more generally, the competitiveness of the economic system in the medium and long-term periods. To these debates, economic literature does not provide a clear answer. On the question of competitiveness, economists agree that one of the aims of the reforms at the margins was to allow companies the ability to operate more efficiently under the pressures of economic uncertainty that were associated with the introduction of new technologies and competition on a global scale. The possibility of adjusting employment according to fluctuations in the demand of goods and services with lower hiring and firing costs made this contract more appealing for firms (Bentolila and Saint-Paul, 1992; Nunziata and Staffolani, 2007) with positive effects on competitiveness and productivity (Vidal and Tigges, 2009; Hagen, 2003). Under these terms, hiring on fixed-term contracts offered the possibility of more optimal screening processes in workers' selection, with positive effects on labour productivity (Wang and Weiss, 1998; Konings et al., 2016). Since fixed-term contracts increase workers' commitment to transitioning to a permanent contract, companies are able to select a more productive labour force (Gerfin et al. 2005, Addison e

occupations have been suspended or collectively dismissed.

Surfield 2009, Boockmann e Hagen 2008, Gash 2008, McGinnity et al. 2005, Mertens e McGinnity 2004, Amuedo-Dorantes 2000). At the same time, the existence of constraints on the termination of employment contracts can limit the phenomena of “moral hazard” and “adverse selection” that are inherent in decisions to invest in specific training and, therefore, stimulate the competitiveness of enterprises (Belot et al., 2007; Ricci and Waldmann, 2015).

A different stream of the literature shows how fixed-term contracts can weaken the incentives of companies and workers to invest in on-the-job (vocational) training with negative effects on labour productivity (Arulampalam et al., 2004; Booth et al., 2002; Zwick, 2006) and size-sector-specific differences (Dosi et al., 2018). For some sector, investment in training is difficult to account because of the intangible and unverifiable nature of the knowledge and skills accumulated by the worker through his career. The high turnover produced by the reforms at the margin may lead to under-investment in human capital on the job, lowering productivity and increasing wage compression. At the same time, workers’ propensity to invest in specific skills decreases when there is the perception of non-durable employment; additionally, workers tend to invest in general skills when they perceive a high risk of job loss (Wasmer, 2006).

Concerning the empirical evidence, Cappellari and Leonardi (2016) have used Italian data at the company level for the period 2004-2007 to point out the unintended effects of flexibility at the margin: by negatively affecting job reallocation and favouring the use of external collaborators (Wage and salary independent contractors), the reform has hampered the optimal allocation of resources and consequently reduced the level of productivity. On the same side, Boeri and Garibaldi (2007) show a negative effect of the share of fixed-term contracts on labour productivity growth for a sample of manufacturing enterprises. Another report on these pernicious effects comes from Lucidi and Kleinknecht (2010) who show that a high share of workers on fixed-term contracts can negatively affect labour productivity growth.

Less controversial in the literature is the link between fixed-term employment and wages. At the microeconomic level, various studies find evidence of a pay gap between individuals employed with fixed-term contracts with respect to those employed on a temporary basis (Brown and Sessions 2003, Comi e Grasseni 2012, De la Rica 2004). Furthermore, Amuedo-Dorantes and Serrano-Padial (2007) point out that workers with short-term employment contracts should receive higher wages in order to compensate for the disadvantage resulting from a condition of uncertainty inherent in the fixed-term contract. Most of the empirical evidence shows fixed-term workers are worse off in terms of wages (Stancanelli 2002, Kahn 2016, da Silva et al. 2015, Comi e Grasseni 2012, Brown and Session 2003, Picchio 2008, Bosio 2014). Looking at the wage differential between fixed-term and permanent contracts along with the distribution of average company wages, Comi and Grasseni (2012) compare workers with the same characteristics, showing that temporary workers would receive higher wages if they worked on permanent contracts. This negative wage gap for workers employed on fixed-term contracts can thus be partly explained by arguments related to labour productivity explained above.

If the link between fixed-term employment and wages is clear, there is no evidence on the contribution of this type of contracts on the cohort income gap. This paper aims to shed some light on this aspect by analysing the introduction of a specific set of non-contracts (WSIC), on income differential among cohorts of workers.

3 Data

Analysis of earnings trends across cohorts requires the use of long panel datasets. The sample LoSai comes from the administrative archives managed by the Italian National Social Security Institute (INPS). It records gross earnings and the relative number of working weeks and days for each working episode, in each year, within the period 1985-2016. This time window encompasses all the major labour market reforms that occurred in Italy in the last 30 years, especially those aimed at deregulating fixed-term contracts (see section 2). It also includes socio-demographic characteristics, social security contributions and, for a restricted period, data on employers and unemployment benefits. I calculate yearly gross income for every male worker (y_{it}) using two strategies: retaining the highest-paid episode within the year and by taking the sum of all the working episodes. This total/partial gross income has been deflated using CPI at 2015 prices. The resulting logarithm denotes the dependent variable. Potential disposable income[4] is obtained by subtracting the amount of taxes to pay from the total gross income. In order to account for unemployment spells and career fragmentation, I obtain weekly and daily income by dividing yearly income by the number of worked weeks/days. Wages can be seen as a measure of marginal productivity in a competitive labour market, since worked weeks/days also reflect institutional constrains. Thus, total earnings is a good welfare measure even if it incorporates endogenous decisions.

The analysis is restricted to male workers to mitigate issues of endogenous female labour market participation[5]. Administrative archives record only the information needed for administrative purposes: individuals' education, which is, of course, a crucial determinant of earnings, is not recorded. Following Rosolia and Torrini (2007, 2016), I overcome this issue by approximating educational achievements with the (observed) entry age in the labour market. In fact, it is plausible to assume that workers who entered the labour market at age 21-22 have at most completed secondary education[6] and that workers entered at age 25-26 presumably obtained a college degree. This strategy seems to be consistent with the empirical evidence provided by OECD (2019). It is also true that the significant changes in educational achievements recorded over the past 40 years, could have boosted average earnings of younger cohorts. Allowing for

[4]Potential because it is not known the real amount of taxes to pay due to possible tax deduction: i.e., health care costs, expenses for secondary and tertiary education, interest on mortgage loans etc.

[5]According to OECD data, in 2016 female labour force participation in Italy was about 55 per cent.

[6]Most likely they do not hold a university degree.

different entry ages (18-19, 21-22,25-26, 28-29), accounts for different education achievements. The resulting sample consists of male workers between 18 and 64 years who have worked for at least one full week (also in terms of part-time equivalent) in a year. Observations are grouped into eight five-year birth cohorts from 1959 to 1991. Following this strategy, the youngest cohort refers to individuals born between 1988 and 1991, while the oldest cohort refers to individuals born between 1959 and 1963. This provides sufficient age variation in each cohort-specific year for disentangling age-cohort-period linearity, which is discussed in the next section. The resulting sample consists of 4,480,870 worker-year-income observations for the eight cohorts observed in the dataset. Table 1, panel A, reports the dependent variable, the log of the yearly real gross total income, by cohorts and by entry ages as a proxy for education. The cohort lengths depend on different levels of experience acquired in the labour market and influence the size of the cohort. To overcome this problem, I also focus on the initial years of workers' career (i.e., with less than 11 years of experience in the LM), as reported in panel B of table 1.

Social security records offer a comprehensive picture of the career of all individuals working in Italy. However, information about public employees, workers employed in the agricultural sector, and self-employment is not available. This selection is common for administrative data, which typically include the private sector only. I follow Cappellari and Leonardi (2016) in choosing to not model selection from the private sector into this type of jobs: they show that, in Italy, workers are very stable in the private sector (according to SHIW data[7], almost 83 per cent of male workers remain in the sector after two years, whether 7.5 per cent moves to the public sector, 3 per cent becomes self-employed, 2.5 per cent goes into retirement while the rest become unemployed). Moreover, to control for regional local labour market dynamics, the yearly regional unemployment rate (ISTAT) has been included as a control variable.

The atypical job spell (wage and salary independent contractors - WSIC) has been determined using the pension accounts ("Estratti conto" - INPS statements) since the archives do not distinguish among all the atypical forms of fixed-term contracts. The identification comes from the fact that WSICs have to pay contributions into a different pension account. Distinguishing the number of atypical jobs within the fixed-term contracts is necessary in order to build an indicator of these episodes throughout one worker's career. I divide workers into four categories: no atypical contracts, up to two atypical episodes, between three and four, and more than four. This threshold is arbitrary, but it is based on the distribution of atypical contracts over cohorts. On the other hand, the low number of episodes with respect to all careers could drive up the estimates. The main difference stands between those who have never ended up in a WSIC job position and those who experienced at least one in their career. The other specifications are shown in the appendix.

[7] Survey on Household Income and Wealth - Bank of Italy

4 Empirical Strategy and Descriptive Evidence

This section provides descriptive evidence and illustrates the strategy adopted for identifying the wage gap among cohorts. The first part depicts the changes in the wage distribution over time and across the age dimension from different perspectives. The second part describes the models used to link the wage gap among cohorts to the labour market reforms. As explained in the previous section, the unit of analysis are employees who had at least one job spell during the period 1985-2016.

Figure 1 reports the mean, the median, the tenth and ninetieth percentile of the real yearly income for male workers. For ease of comparison, gross incomes at 2010 prices are indexed to an average of 100 in 1985 for all four series. The solid lines on the x-axis represent the years of the reforms at the margin, whereas the dotted lines indicate the reforms that also affected open-ended contracts. The mean wage series tells a well-known story: average real income increases relatively steadily from 1985 through about 1992 (approximately 15 per cent), declines slightly from 1993 up to the early 2000s and remains stable until 2016 (about 10 per cent over the 1985 level). The slowdown in growth occurred after the economic crisis lasted four years until 2012. After 1992, the median and the top 10th percentile trends follow the average income even if they do so with different magnitudes, showing no real growth for the upper part of the income distribution. That matches the evolution of the Italian GDP in the period 1985-2016. The wage indexation mechanism operating in Italy up to 1992 helped to compress the wage distribution and somehow protect the lower percentiles. From the mid-90s, the bottom 10 per cent fluctuates around the median moving back to its 1985 in 2008. The dramatic loss that occurred after 2007 sees a partial catch up only in 2015. This looks peculiar in the sense that we should have expected decreasing inequality within the lower part of the income distribution: during a recession, low-skilled workers are usually excluded from the labour force. As suggested by Maré and Hyslop (2008), the composition of the labour force along the business cycle plays a crucial role in explaining earnings patterns. The turnover effect and the lower entry wages generated by the new non-standard contracts could have reduced real wages at the bottom part of the income distribution. Figure 2 supports this argument, highlighting the similar trends between the bottom 10 per cent and average entry wages. Despite this, the loss in entry wages over the entire period is about 20 per cent. If we distinguish by entry wages among different education proxies, figure 3,it is evident that the low-skilled workers drive the downward trend (-25 per cent from 1985), while the high-skilled lead the catching up trend.

To see how this has evolved across cohorts of workers, figure 4 and 5 give preliminary evidence about the four different educational proxies as described in section 3. They present average earnings profiles for different cohorts of workers[8]. The general shape seems to be

[8]In this case, I maintained one cohort distance between the fours showed in the graphs in order to better distinguish earnings patterns.

similar to what is commonly reported in the literature: earnings profiles are slightly concave with rapid initial earnings growth and a consequent slowdown in the last part of working life. What is surprising is the downward shift for younger workers, especially high-skilled. In general, the slope of the curve for new entrants is less steep for all the educational groups, with the exception of the less skilled ("at maximum secondary degree students", 18-19). This might be related to a decrease in the skill premium for high-skilled workers, but also related to slower career progression (turnover effect) produced by the new non-standard contracts. Figure 6 incorporates entry wages and earnings profiles for the two central educational proxies: the red line represents the average entry wages for high and low-skilled workers, while the blue one the wage profile for each cohort analysed in this study (8 five-years cohorts from 1959 to 1988). Entry conditions in the labour market have deteriorated since the early 1990s[9] especially for low-skilled, whereas both high and low skilled workers experienced less steep earnings profiles. This descriptive evidence enforces the idea of an increasing wage gap between young and old cohorts, as suggested by (Rosolia and Torrini, 2016). Moreover, the less steep profiles for new entrants reduces the possibility of catching up with the negative trend in entry wages, figure 3.

This preliminary analysis highlights a deterioration in the lower part of the income distribution. People in the early years of their career along with low-skilled workers are more likely to find themselves in this part of the distribution. Even considering that the pre-crisis level was reached only by the HS new entrants, age-earnings profiles have been, in general, deteriorating among all young cohorts. If the age-earnings curve is less steep and the entry wage declines even among the same educational group, it is reasonable to think about the existence of a cohort income gap between old workers and young new entrants.

The descriptive evidence provided so far has certain limitations for several reasons. First, it does not account for business cycle effects on the patterns characterizing different cohorts at different points in their life-cycle (i.e., years of experience) in the labour market. Secondly, it does not control for changes in the labour force composition over time, e.g. change in individual characteristics such as an increase in the average educational attainment within cohorts. To overcome this issue and identify the cohort wage gap, I make use of a mincer equation and a quantile regression with an Age-Period-Cohort specification. The magnitude of the cohort gap is estimated using both gross and net income. This is the case when the redistributive power of the taxation mechanism reshapes inequality and cohort differentials. I finally control for the number of atypical (Wage and salary independent contractors) episodes by running the model for different groups of workers. The grouping follows the number of atypical job spells experienced by workers during their career. The next section describes the model used to estimate the cohort income gap and the effect of WSIC job spells on it.

[9] as documented in figure 3

4.1 The model

The identification of the wage gap among cohorts relies on the mincer earnings function estimated through an OLS along with the inclusion of the relevant control variables discussed in section 3. This regression has been estimated on thousands of datasets for a large number of countries and time periods, which clearly makes it one of the most widely used models in empirical economics[10].

An important issue to take into account while comparing outcomes of subsequent cohorts at the same point of their life-cycle is the underlying two-dimensional aspect: temporal and cyclical. The risk is to capture several confounding factors related to the development of wages over lifetime. Age (life cycle) effects, time (business cycles) effects, cohort (year of birth) effects are all likely to be important but, unfortunately, without additional information and/or structure, it is not possible to identify them separately(Attanasio, 1993). The linear relation among them makes it impossible to know whether the differences between two individuals observed at the same age are due to time or cohort effects and there is no way of disentangling them[11]. The easiest way to overcome this issue is to constrain the year effects, so they sum up to zero and are orthogonal to a linear trend, as done by Deaton and Paxson (1994). This is equivalent to assuming that all the linear trends among these three dimensions can be interpreted as a combination of age and cohort effects. This identification assumption is useful for estimating both a common age profile and how it varies across cohorts. Although this restriction is quite strong, it can be justified in several ways (Attanasio, 1993). For instance, since age, time and cohort dummies are perfectly collinear[12] (Deaton and Paxson, 1994; Attanasio, 1993) it is sufficient to impose as identification assumptions, that time effects (i) sum up to zero, and (ii) are orthogonal to a linear trend. Without any further specification, these assumptions assign all observed wage growth to the changing demographics (cohort age) structure, which over time modifies the relative weights of the common age profile, and to the change in the permanent component of the average income of each subsequent cohort. An additional way to enforce this approach is to increase age variation extending the width within the cohorts (as described in section 3).

[10]At this point, it is useful to underline that it has always been a significant gap between the theory underlying the human capital earnings function and the data used to estimate it. From a theoretical point of view, the age-earnings profile concerns the evolution of the earnings of a given individual or cohort of individuals over the life cycle (Lemieux, 2006). By contrast, empirical age-earnings are typically based on a cross-section of individuals at different points in their life cycle. Mincer was well aware of this problem in his early work (Mincer, 1958), and conjectured that the cross-sectional age-earnings profiles were probably understating life-cycle earnings growth since, in those days, there was substantial secular growth in average earnings, concluding that earnings profiles were a reasonable approximation of the life cycle profiles.

[11]Similarly, the difference between two individuals observed at the same time could be due to age or cohort effect (*ibidem*).

[12]year = age + birth year

Following this strategy, I set year dummies allowing the different earnings profile to vary according to the business cycle with respect to a reference year, which is 1985. The cohort variable is a categorical variable which allows for differences in cohort earnings profile. The difference among local labour markets is captured by the regional unemployment rate (contained in X) while the proxy for educational attainment is captured by the entry age, as discussed in the data session. Experience refers to potential experience. In order to estimate the mean earnings dynamics, the baseline model is as follows:

$$w_{i,c,t} = \alpha + \beta_0 Cohort_c + \beta_1 Educ_{i,c} + \beta_2 Exp_{i,c,t} + \beta_3 Exp^2_{i,c,t} + X'_{i,t}\beta_4 + \epsilon_{i,c,t} \tag{1}$$

where $w_{i,c,t}$ stands for the dependent variables, individual annual (log) earnings (where i is the individual, c the birth cohort and t the year). Individual income has been estimated in different configurations: yearly/weekly/daily both for gross and net income. In the case of multiple job spells during the year, total income represents their sum. In the appendix, the comparison between total income and the highest-paid episode (table 5) shows no significant differences: as experience grows, careers tend to become more stable. For this reason, and for the sake of simplicity, I consider total income as dependent variables, thereby taking into account the weekly/daily variation. By using the total yearly income, it is possible to identify the cohort gap more exhaustively, also considering career fragmentation across individuals. The logarithm of weekly and daily wages helps to gauge career fragmentation and unemployment spells during the year within individual careers. Most of the time, the daily spells are missing because the worker has a full-time job or a standard contract so that it is easy to compute the number of the worked days. Where it is not possible to reconstruct the number, the observation has been treated as missing. The use of net income gives a further robustness check: this measure is obtained by subtracting from the yearly gross income the total amount of progressive taxes to be paid. Even though this raw approximation tends to underestimate the actual disposable income[13], it identifies the lower bound between the actual disposable income and the real gross income. Estimated mean earnings along the working life can deviate from the standard profile according to the cohort coefficient β_0, while education and potential experience are cohort-specific.

A quantile regression determines the extent to which several covariates are related to workers at various points of the income distribution. As reported by Gibson et al. (2007) the advantages of this approach discussed by Zhang (2003) are the following: (1) the cohort gap can be generated at any point of the distribution, not just a single measure of the overall mean cohort gap; (2) the method is semi-parametric so that no distributional assumptions on the dependent variable are needed; (3) the estimator is less sensitive to outliers; and (4) tests of the statistical significance of the gaps can easily be conducted. In general, the q^{th} quantile regression fits the

[13]This is the case since tax deduction depends on household income.

dependent variable as a linear function of some explanatory variables through the q^{th} quantile of the dependent variable. The coefficients are the same as the previous model, but estimated at different quantiles of the income distribution:

$$w^q_{i,c,t} = \alpha + \beta^q_0 Cohort_c + \beta^q_1 Educ_{i,c} + \beta^q_2 Exp_{i,c,t} + \beta^q_3 Exp^2_{i,c,t} + X'_{i,t}\beta^q_4 + \epsilon^q_{i,c,t} \tag{2}$$

The estimate of β^q_0 represents the income gap between the c cohort and the reference cohort 1959/1963 at the specific q^{th} quantile of the income distributions. For the sake of simplicity, I considered the 10th, 25th, 50th, 75th and 90th percentiles of the total gross/net income.

The last regression links the cohort gap with the labour market reforms at the margins grouping workers according to the number of atypical (Wage and salary independent contractors) job spells experienced during their career. This strategy allows me to better understand how the structure of the cohort differential changes between standard workers and those who have had at least one atypical spell. By counting the number of these episodes during the time I am observing the worker, I obtain four categories: no atypical contracts in the observed career, one episode, between three and four, and more than four. This threshold is arbitrary, but it is based on the distribution of atypical contracts. On the other hand, the low number of episodes with respect to all careers could bias the estimates. This is why table 10 reports in column two and three the difference between those who have never ended up in an "WSIC" job position and those who got at least one in their career. At the same time, columns three to four explore income differential by the number of "WSIC" episodes.

5 Results

Table 2 below sets out the regression results for the log of yearly (column 1,2), weekly (column 2,3) and daily income (column 5,6) for the entire period of analysis (1985-2016). Each time specification is presented for both gross and net income[14]. The central variable in this model is the birth cohort, which is a categorical variable that groups years of birth into eight equal-sized classes. The reference category is workers born between 1959 and 1963. The wage gap follows the same structure for every income variable mentioned above: the gap increases steadily for all the cohort, but it becomes more significant for those born after the 1980s.

[14]The outcome variable used is the total income, but since one worker could have more than one job spell during the year, also the highest pay episode has been considered. As seen in table 5 in the appendix, the outcome looks very similar. The use of the highest pay episode it is very common in the literature as the link with individual characteristics is straightforward. Since the individual characteristics I am controlling for are not necessarily linked to one specific job spell, I prefer to use total income: it is more informative about the wages earned by a worker during the year, not considering the number of jobs he had. At the same time, total weekly income is a good proxy to control for unemployment spells during the year.

In comparison to the 1959-1963 born workers, cohort 1980-1983 and cohort 1984-1987 experienced an average reduction of between 15 and 18 per cent over the experience earnings profile of yearly gross income (column 1). Higher differentials for younger cohorts are also shown by the other income specifications (column 3-6), but with different magnitudes. The use of net income mitigates the effect for these cohorts, but the story remains the same: workers born after the 80s suffer from higher income differentials. Only the effect on net weekly income turns out to be less pronounced for the two youngest cohorts, but presumably, this income measure overestimates the tax correction for the older cohorts. Even controlling for the labour market experience, cohort differentials could be driven by confounding factors due to the different lengths in the career patterns. Table 7 in the appendix shows the same exercise but only considers the first ten years of experience. Cohort differentials, in this case, become even higher for all the cohorts, but with similar progressive patterns. This exercise provides evidence in favour of increasing income inequality for those born after 1980 and underscores the fact that the wage gap is more intense in the early years of a worker's career.

A quantile regression determines the extent to which the cohort income gap is related to workers at various points of the income distribution. Results coming from the quantile regression model for the 10th, 25th, 50th (median), 75th and 90th percentiles for both gross and net income are shown in table 3. These coefficients tell us something significant: the difference between those born before and after 1980 persists below the median of the income distribution. In the upper tail, the wage differential among subsequent cohorts of workers is more progressive, showing that only the baby boomers were better off. The same story looks similar for net income: the income gap is more progressive among cohorts in the upper part of the distribution while below the median, it is possible to identify the same split around 1980.

The empirical evidence suggests that new entrants have suffered from higher wage differentials with respect to older incumbents, which means lower wages for the youngest cohorts. Among them, the high skilled workers experience the highest income gaps. These findings are consistent with Naticchioni et al. (2016), in which the best of the youth, i.e., the young cohorts of high-skilled workers, have experienced a significant wage deterioration in comparison to the older ones. Raitano and Fana (2019) argue that post-2001 reform graduates experience worse economic conditions compared to the previous cohort.

By looking at heterogeneity in inequality by the number of atypical job spells, I extend these findings to the generational income impact of the reforms. I run the first model presented above for two different groups of workers: those who have never experienced an atypical spell and those who have had at least one. Then I explore cohort differential by the number of WSIC job spell. Column two and three in table 4 show that, having experienced at least one atypical episode, income differentials increase, on average, by more than one half. This is the case if we keep considering the difference between people born before and after 1980. Column four to six distinguish by the number of WSIC job spells: as the number of this type of atypical episode increases, the cohort differentials increase[15]. These results show that the extensive use of Wage and salary independent contractors in the Italian labour market have widened the cohort income gap, but it is not the only factor explaining this mechanism. It is also true that other types of non-standard contracts existed before the reforms at the margins, and have only been strengthened during that period. Nevertheless, since WSIC were only introduced by those reforms, this work gives a clear idea of the additional effect of a change in the institutional setting on the income cohort gap.

6 Conclusion

In this paper, I compared income profiles of subsequent cohorts of workers, assessing the magnitude and the evolution of the income gap between old workers and young new entrants. By identifying the link between the number of non-standard job spells and wage cohort differentials, I established the role played by the reforms at the margin in shaping cohort inequality. Among the wide range of non-standard contracts, the focus of this work has been on the "Wage and Salary Independent Contractors", workers formally acting as self-employed, but usually, and most of the time, working as employees. The use of WSIC contracts provided a direct link to the reforms at the margin. A long panel dataset (1985 -2016) managed by the Italian National Social Security Institute (INPS) allowed me to decompose wage profiles into cohort, age and (cyclical) time effects, showing that the income gap between old workers and young new entrants has increased substantially during the period of analysis. The wage differentials turned to be more pronounced for individuals born after the 80s, for all the income specification adopted in this study.

In terms of real gross income, cohort 1980/1983 and cohort 1984/1987 show an average loss between 15 and 18 per cent over the experience earnings profile. Weekly and daily income differentials are lower in the magnitude (around 9 per cent) but follow the same pattern. The same story is true for the net income specifications. In this framework, the first ten years of labour market experience results crucial for the development of the cohort gap. The quantile regression highlighted how income differentials are higher for young cohorts in the upper tail of the income distribution. If high income is a proxy for high-skilled workers, then according to the Italian literature (Naticchioni et al., 2016; Raitano and Fana, 2019), the most skilled workers suffer from higher cohort wage differentials. By looking at heterogeneity in inequality by the number of atypical job spells, I extended these findings to the generational income impact of the reforms: having experienced at least one atypical episode increases income differentials, on average, by more than one half for people born before and after 1980. OLS estimates were

[15]The low number of cases for the more unstable workers makes their coefficients not significant. All the coefficients are shown in table 10 in the appendix.

obtained for workers who have never experienced an atypical spell, for those who have had at least one and, among them, for different groups according to the number of WSIC job spells. General findings confirm what hypothesized before: as the number of WSIC job spells increases, the cohort differentials widen.

In conclusion, the collected descriptive evidence and the empirical model are supportive of a structural deterioration of earnings opportunities for new cohorts of entrants in the labour market, especially high skilled. This result can probably be traced back to the combined effects of changes in the institutional arrangements that mainly affected the entry wage (i.e., younger cohorts) and to a slowdown in the Italian economy, which occurred before the global financial crisis and weakened the conditions of those who were overwhelmed by the economic contraction thereafter. All these effects produced an asymmetric impact on younger cohorts of entrants and older cohorts of incumbents. Importantly, this asymmetry occurred also within younger cohorts of entrants, exhibiting lower return to education for the high skilled, supporting the thesis that firms took advantage of the lower cost of labour due to the reform at the margin to invest in other assets different from human capital.

These findings on the cohort income gap as well as the limitations of the data set, raise additional questions that could direct future research. For example, firm sector and firm size could have played an important role. Small firms are less prone to invest in human capital and may have increased the turnover contributing to the career fragmentation. Thus, it would be interesting to see how firms reacted to the institutional incentives provided by the reforms and how this increased turnover, income inequality and instability.

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A Figures

Figure 1: Indexed real yearly wages by percentile and mean, 1985-2016

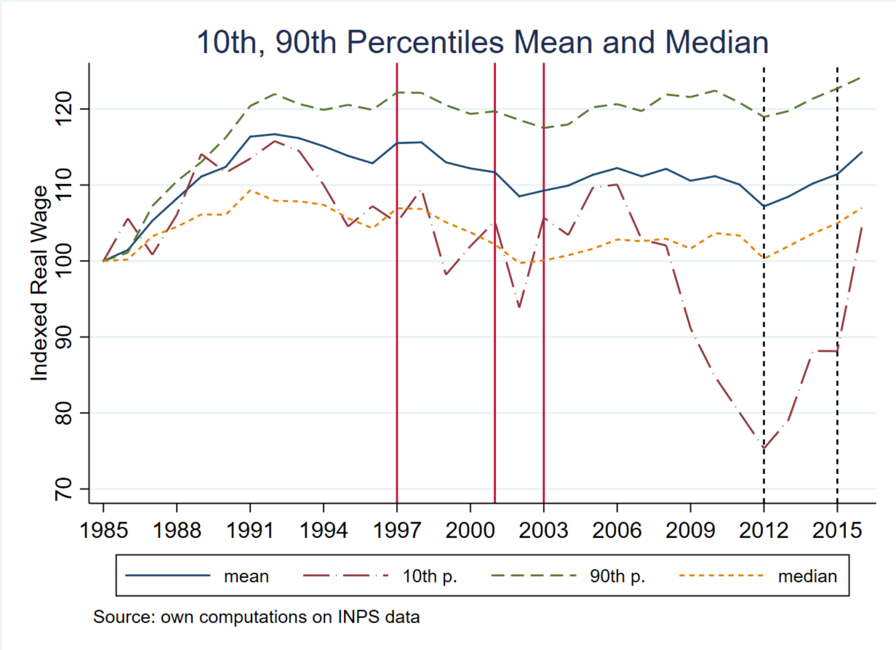


Figure 2: Indexed real yearly wages by entry wage, 10th percentile and mean, 1985-2016

Figure 3: Indexed real entry wages by entry year as a proxy for education, 1985-2016

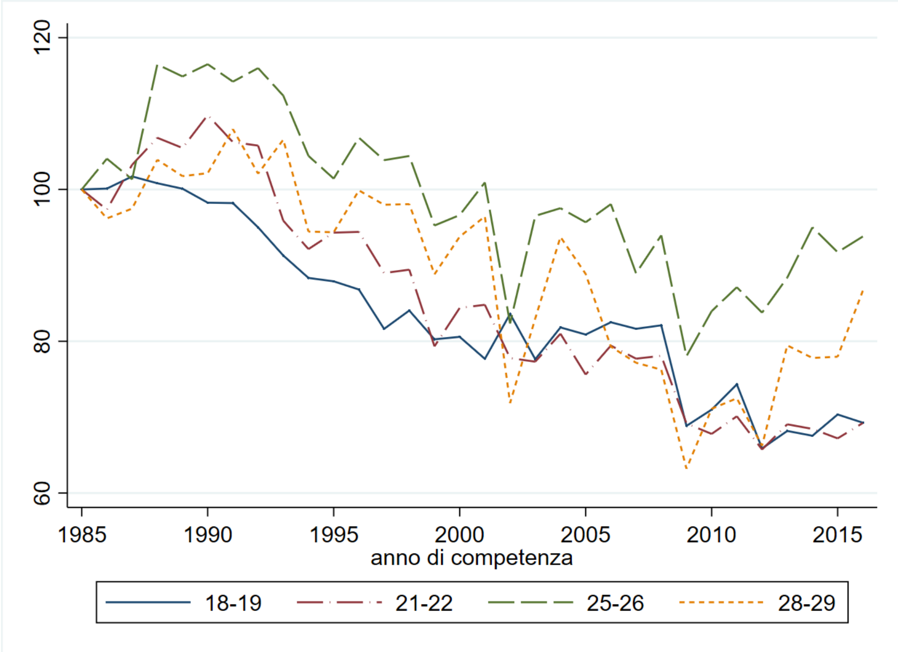
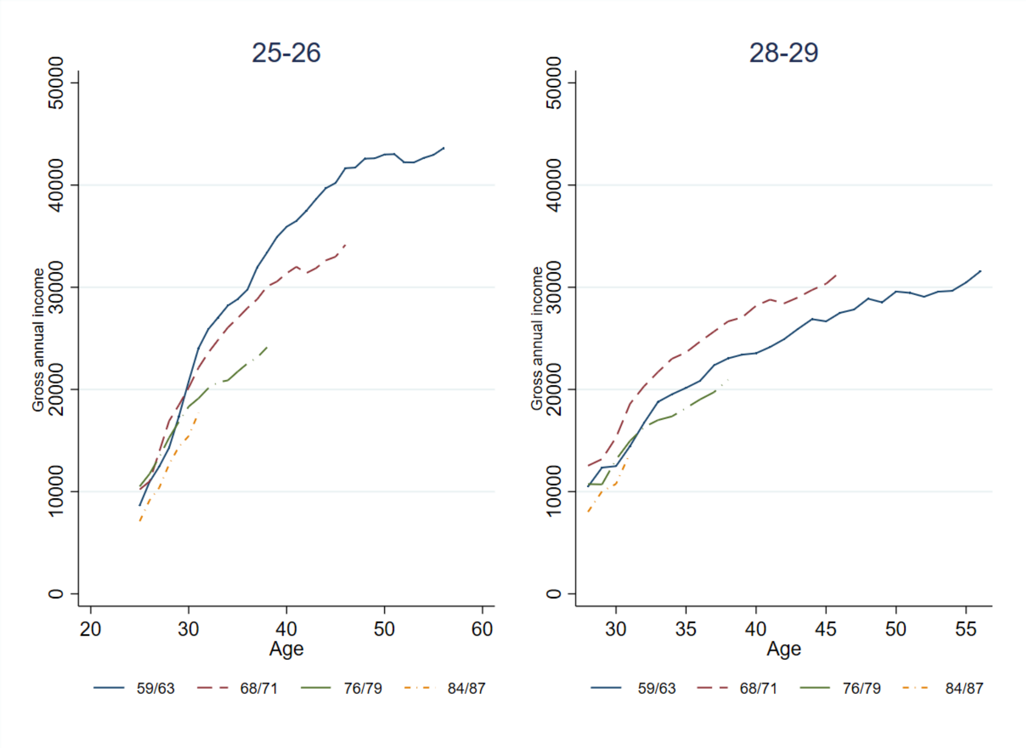


Figure 4: Age-Earnings profiles by entry age (proxy for educational achievements)

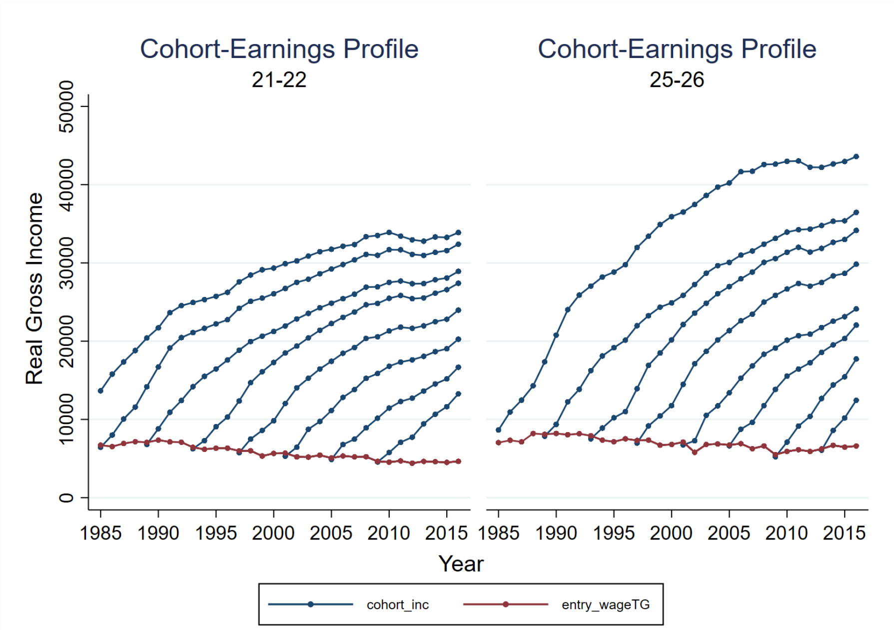
Notes: Each line represents the age-earnings profile for each cohort. Labels 18-19 and 21-22 represent the entry age as a proxy for educational achievements.

Figure 5: Age-Earnings profiles by entry age (proxy for educational achievements)



Notes: Each line represents the age-earnings profile for each cohort. Labels 25-26 and 28-29 represent the entry age as a proxy for educational achievements.

Figure 6: Entry wages and career profiles



B Tables

Table 1: Log of real income by birth cohorts and education

Birth cohort	**Mean**	**Std. dev.**	**N**	**Entry age** (proxy for education)			
				18-19	**21-22**	**25-26**	**28-29**
Panel A: full sample selection							
1959/1963	9.88	0.93	809,842	9.92	9.92	9.85	9.63
1964/1967	9.77	0.97	744,739	9.78	9.83	9.69	9.63
1968/1971	9.68	1.00	788,636	9.67	9.72	9.68	9.66
1972/1975	9.59	1.03	655,152	9.56	9.68	9.62	9.45
1976/1979	9.48	1.06	577,717	9.52	9.53	9.41	9.27
1980/1983	9.28	1.14	434,062	9.34	9.29	9.27	8.87
1984/1987	9.11	1.18	290,178	9.18	9.04	8.96	8.79
1988/1991	8.85	1.25	180,544	8.89	8.76	8.75	8.37
Panel B: first 10 years of experience							
1959/1963	9.58	0.99	227,593	9.59	9.64	9.62	9.45
1964/1967	9.47	1.03	294,675	9.40	9.53	9.49	9.48
1968/1971	9.40	1.06	363,757	9.25	9.43	9.52	9.56
1972/1975	9.38	1.07	370,502	9.18	9.45	9.52	9.39
1976/1979	9.32	1.08	386,736	9.24	9.38	9.36	9.26
1980/1983	9.17	1.15	343,301	9.16	9.21	9.27	8.87
1984/1987	9.06	1.18	266,642	9.12	9.03	8.96	8.79
1988/1991	8.85	1.25	180,544	8.89	8.76	8.75	8.37

The table presents summary statistics for the cohorts samples used in the LoSai (INPS) dataset. The full sample selection consists of all male workers in the administrative archives who (i) were employed in the private sector for at least one year in the period 1985-2016, (ii) were born between 1959 and 1991, and (iii) have had positive incomes. We report summary statistics of the logarithm of gross real income, the number of observations and its mean by different entry ages used as a proxy for education. See section 3 for further details on variables and sample definitions. Panel A shows statistics for the entire sample selection, whether panel B considers only the first ten years of experience in the labour market.

Table 2: OLS estimates of cohort differentials on the logarithm of real total income

	Yearly		Weekly		Daily	
VARIABLES	Gross	Net	Gross	Net	Gross	Net
Birth cohorts						
1964/1967	-0.050***	-0.048***	-0.031***	-0.037***	-0.022***	-0.021***
	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)
1968/1971	-0.082***	-0.080***	-0.051***	-0.059***	-0.038***	-0.036***
	(0.003)	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)
1972/1975	-0.085***	-0.083***	-0.062***	-0.072***	-0.045***	-0.044***
	(0.005)	(0.004)	(0.002)	(0.002)	(0.002)	(0.002)
1976/1979	-0.092***	-0.090***	-0.074***	-0.085***	-0.059***	-0.057***
	(0.006)	(0.006)	(0.003)	(0.003)	(0.003)	(0.003)
1980/1983	-0.151***	-0.142***	-0.091***	-0.092***	-0.082***	-0.073***
	(0.008)	(0.007)	(0.004)	(0.004)	(0.004)	(0.004)
1984/1987	-0.180***	-0.156***	-0.099***	-0.078***	-0.093***	-0.069***
	(0.009)	(0.008)	(0.005)	(0.004)	(0.005)	(0.004)
1988/1991	-0.272***	-0.233***	-0.115***	-0.053***	-0.111***	-0.072***
	(0.011)	(0.010)	(0.005)	(0.005)	(0.005)	(0.005)
Observations	4,437,729	4,437,729	4,437,729	4,437,729	4,437,729	4,437,729
Year dummies	YES	YES	YES	YES	YES	YES
Adj. R^2	0.191	0.187	0.131	0.0957	0.109	0.0756

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

This table reports OLS estimates (Model 1) of the cohort income gap between a specific birth cohort and the reference cohort 1959/1963. Each column reports estimates from a regression on three different real income specifications: yearly, weekly and daily. All these income specifications have been estimated for both gross and net income. Educational achievements (low, medium and high education) are proxied by the entry year in the labour market, as explained in section 3. Education and the other control variables (regional unemployment, experience and experience squared) are reported in the table 6 in the appendix.

Table 3: Quantile regression estimates of cohort differentials the logarithm of real total income

VARIABLES	10th	25th	50th	75th	90th
Model 1: Cohort differentials of real gross income					
1964/1967	0.003	-0.024***	-0.048***	-0.074***	-0.076***
	(0.014)	(0.005)	(0.003)	(0.003)	(0.003)
1968/1971	-0.023	-0.050***	-0.076***	-0.132***	-0.130***
	(0.021)	(0.008)	(0.005)	(0.004)	(0.005)
1972/1975	-0.025	-0.036***	-0.067***	-0.161***	-0.182***
	(0.030)	(0.012)	(0.007)	(0.006)	(0.007)
1976/1979	-0.022	-0.034**	-0.076***	-0.179***	-0.206***
	(0.038)	(0.016)	(0.009)	(0.008)	(0.009)
1980/1983	-0.161***	-0.135***	-0.122***	-0.209***	-0.227***
	(0.047)	(0.020)	(0.011)	(0.009)	(0.011)
1984/1987	-0.199***	-0.228***	-0.169***	-0.230***	-0.249***
	(0.057)	(0.024)	(0.013)	(0.011)	(0.013)
1988/1991	-0.303***	-0.387***	-0.288***	-0.269***	-0.265***
	(0.066)	(0.028)	(0.016)	(0.013)	(0.015)
Model 2: Cohort differentials of real net income					
1964/1967	-0.015	-0.029***	-0.042***	-0.066***	-0.067***
	(0.012)	(0.005)	(0.003)	(0.003)	(0.003)
1968/1971	-0.033*	-0.061***	-0.066***	-0.115***	-0.113***
	(0.019)	(0.008)	(0.004)	(0.004)	(0.004)
1972/1975	-0.018	-0.053***	-0.060***	-0.140***	-0.156***
	(0.027)	(0.011)	(0.006)	(0.005)	(0.006)
1976/1979	0.009	-0.050***	-0.074***	-0.157***	-0.175***
	(0.034)	(0.015)	(0.008)	(0.007)	(0.008)
1980/1983	-0.098**	-0.116***	-0.122***	-0.188***	-0.196***
	(0.043)	(0.018)	(0.010)	(0.008)	(0.010)
1984/1987	-0.125**	-0.159***	-0.167***	-0.212***	-0.217***
	(0.051)	(0.022)	(0.012)	(0.010)	(0.012)
1988/1991	-0.232***	-0.279***	-0.250***	-0.251***	-0.231***
	(0.060)	(0.026)	(0.014)	(0.012)	(0.013)
Observations	1,108,764	1,108,764	1,108,764	1,108,764	1,108,764
Year dummies	YES	YES	YES	YES	YES

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

This table follows the same logic as the tables before in terms of cohort comparison. It reports estimates of the cohort income gap along the conditional quantiles of the income distribution (Model 2). Each column reports estimates from the 10th, 25th, 50th, 75th and 90th percentiles for both total gross and net income. Due to computational issues, only 25% of the sample has been used.

Table 4: OLS estimates on gross and net income by WSIC job spells

VARIABLES	No atypical	At least one atypical episode	Within Atypical (number of episodes) 1	2-4	more than 4
Model 1: Cohort differentials of real gross income					
1964/1967	-0.046***	-0.091***	-0.080***	-0.112***	-0.059
	(0.002)	(0.006)	(0.007)	(0.013)	(0.165)
1968/1971	-0.079***	-0.119***	-0.103***	-0.150***	-0.022
	(0.004)	(0.010)	(0.011)	(0.020)	(0.287)
1972/1975	-0.076***	-0.136***	-0.119***	-0.174***	0.199
	(0.005)	(0.013)	(0.015)	(0.028)	(0.398)
1976/1979	-0.085***	-0.130***	-0.122***	-0.145***	0.397
	(0.006)	(0.017)	(0.019)	(0.036)	(0.528)
1980/1983	-0.149***	-0.171***	-0.176***	-0.151***	0.107
	(0.008)	(0.021)	(0.024)	(0.044)	(0.674)
1984/1987	-0.171***	-0.255***	-0.250***	-0.284***	0.059
	(0.010)	(0.025)	(0.029)	(0.053)	(0.763)
1988/1991	-0.260***	-0.435***	-0.441***	-0.448***	0.554
	(0.011)	(0.030)	(0.034)	(0.062)	(0.891)
Model 2: Cohort differentials of real net income					
1964/1967	-0.045***	-0.085***	-0.076***	-0.105***	-0.033
	(0.002)	(0.006)	(0.007)	(0.012)	(0.145)
1968/1971	-0.077***	-0.113***	-0.098***	-0.141***	-0.007
	(0.003)	(0.009)	(0.010)	(0.018)	(0.244)
1972/1975	-0.075***	-0.130***	-0.115***	-0.164***	0.199
	(0.005)	(0.012)	(0.014)	(0.026)	(0.337)
1976/1979	-0.084***	-0.125***	-0.118***	-0.138***	0.332
	(0.006)	(0.016)	(0.018)	(0.033)	(0.454)
1980/1983	-0.139***	-0.160***	-0.164***	-0.143***	0.0489
	(0.007)	(0.020)	(0.022)	(0.041)	(0.576)
1984/1987	-0.148***	-0.224***	-0.219***	-0.250***	-0.0136
	(0.009)	(0.023)	(0.026)	(0.049)	(0.647)
1988/1991	-0.222***	-0.379***	-0.385***	-0.389***	0.543
	(0.010)	(0.027)	(0.031)	(0.058)	(0.760)
Observations	3,710,721	727,008	545,362	180,090	1,556
Year dummies	YES	YES	YES	YES	YES
Adj. R^2 model 1	0.204	0.155	0.154	0.162	0.228
Adj. R^2 model 2	0.199	0.152	0.156	0.158	0.221

Robust standard errors in parentheses: *** p<0.01, ** p<0.05, * p<0.1

This table reports OLS estimates of the cohort income gap between two groups of workers according to the number WSIC job spells experienced during their career: no atypical contracts (2) and at least one (3). A further set of regression exploit the difference within atypical episodes: up to two (4), between three and four (5) and more than four (6).

C Appendix

Table 5: OLS estimates on the highest paid episode (HPE) and the total income (TI)

	Yearly Gross Income			
VARIABLES	HPE	HPE	TI	TI
Proxy for education				
low education	0.133***	0.134***	0.127***	0.128***
	(0.002)	(0.002)	(0.001)	(0.001)
medium education	0.186***	0.187***	0.179***	0.180***
	(0.003)	(0.003)	(0.003)	(0.003)
high education	0.120***	0.121***	0.113***	0.113***
	(0.004)	(0.004)	(0.004)	(0.004)
experience	0.120***	0.120***	0.117***	0.117***
	(0.000)	(0.000)	(0.000)	(0.000)
experience^2	-0.003***	-0.003***	-0.003***	-0.003***
	(0.000)	(0.000)	(0.000)	(0.000)
Reg. Unemp. Rate	-0.040***	-0.085***	-0.040***	-0.086***
	(0.000)	(0.004)	(0.000)	(0.004)
Birth cohorts				
1964/1967	-0.048***	-0.049***	-0.050***	-0.050***
	(0.002)	(0.002)	(0.002)	(0.002)
1968/1971	-0.080***	-0.081***	-0.082***	-0.083***
	(0.003)	(0.003)	(0.003)	(0.003)
1972/1975	-0.084***	-0.084***	-0.085***	-0.085***
	(0.005)	(0.005)	(0.005)	(0.005)
1976/1979	-0.095***	-0.096***	-0.092***	-0.093***
	(0.006)	(0.006)	(0.006)	(0.006)
1980/1983	-0.161***	-0.162***	-0.151***	-0.151***
	(0.008)	(0.008)	(0.008)	(0.008)
1984/1987	-0.200***	-0.201***	-0.180***	-0.181***
	(0.009)	(0.009)	(0.009)	(0.009)
1988/1991	-0.300***	-0.301***	-0.272***	-0.273***
	(0.011)	(0.011)	(0.011)	(0.011)
Constant	8.879***	9.179***	8.941***	9.247***
	(0.006)	(0.026)	(0.006)	(0.026)
Observations	4,437,729	4,437,729	4,437,729	4,437,729
R-squared	0.198	0.199	0.191	0.192
Year dummies	YES	YES	YES	YES
Year*reg_unemp	NO	YES	NO	YES
Adjusted R-squared	0.198	0.199	0.191	0.192

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 6: OLS estimates of cohort differentials on the logarithm of real total income

	Yearly		Weekly		Daily	
VARIABLES	Gross	Net	Gross	Net	Gross	Net
Proxy for education						
low education	0.127***	0.117***	0.068***	0.062***	0.052***	0.042***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
medium education	0.179***	0.165***	0.114***	0.104***	0.092***	0.078***
	(0.003)	(0.003)	(0.001)	(0.001)	(0.001)	(0.001)
high education	0.113***	0.106***	0.072***	0.071***	0.052***	0.045***
	(0.004)	(0.004)	(0.002)	(0.002)	(0.002)	(0.002)
experience	0.117***	0.108***	0.037***	0.029***	0.034***	0.026***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
experience^2	-0.003***	-0.002***	-0.001***	-0.001***	-0.001***	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Reg. Unemp. Rate	-0.040***	-0.037***	-0.019***	-0.015***	-0.015***	-0.011***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Birth cohorts						
1964/1967	-0.050***	-0.048***	-0.031***	-0.037***	-0.022***	-0.021***
	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)
1968/1971	-0.082***	-0.080***	-0.051***	-0.059***	-0.038***	-0.036***
	(0.003)	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)
1972/1975	-0.085***	-0.083***	-0.062***	-0.072***	-0.045***	-0.044***
	(0.005)	(0.004)	(0.002)	(0.002)	(0.002)	(0.002)
1976/1979	-0.092***	-0.090***	-0.074***	-0.085***	-0.059***	-0.057***
	(0.006)	(0.006)	(0.003)	(0.003)	(0.003)	(0.003)
1980/1983	-0.151***	-0.142***	-0.091***	-0.092***	-0.082***	-0.073***
	(0.008)	(0.007)	(0.004)	(0.004)	(0.004)	(0.004)
1984/1987	-0.180***	-0.156***	-0.099***	-0.078***	-0.093***	-0.069***
	(0.009)	(0.008)	(0.005)	(0.004)	(0.005)	(0.004)
1988/1991	-0.272***	-0.233***	-0.115***	-0.053***	-0.111***	-0.072***
	(0.011)	(0.010)	(0.005)	(0.005)	(0.005)	(0.005)
Constant	8.941***	8.733***	5.849***	5.604***	4.185***	3.977***
	(0.006)	(0.006)	(0.003)	(0.002)	(0.003)	(0.003)
Observations	4,437,729	4,437,729	4,437,729	4,437,729	4,437,729	4,437,729
Year dummies	YES	YES	YES	YES	YES	YES
Adj. R^2	0.191	0.187	0.131	0.0957	0.109	0.0756

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Educational achievements (low, medium and high education) are proxied by the entry year in the labour market, as explained in section 3. I obtained 4 levels based on the entry age in the LM: 18-19 (basic education), 21-22 (low education), 25-26 (medium education), 28-29 (high education).

Table 7: OLS estimates on total income and up to 10 years experience in the LM

	Yearly		Weekly		Daily	
VARIABLES	Gross	Net	Gross	Net	Gross	Net
Proxy for education						
low education	0.179***	0.167***	0.079***	0.073***	0.055***	0.043***
	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)
medium education	0.269***	0.248***	0.143***	0.127***	0.115***	0.095***
	(0.004)	(0.004)	(0.002)	(0.002)	(0.002)	(0.002)
high education	0.200***	0.185***	0.103***	0.095***	0.075***	0.060***
	(0.006)	(0.005)	(0.003)	(0.003)	(0.003)	(0.003)
experience	0.324***	0.302***	0.083***	0.050***	0.071***	0.048***
	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)
experience^2	-0.020***	-0.019***	-0.005***	-0.002***	-0.004***	-0.002***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Reg. Unemp. Rate	-0.034***	-0.031***	-0.014***	-0.011***	-0.009***	-0.007***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Birth cohorts						
1964/1967	-0.021***	-0.026***	-0.024***	-0.040***	-0.015***	-0.020***
	(0.004)	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)
1968/1971	-0.083***	-0.086***	-0.057***	-0.076***	-0.045***	-0.048***
	(0.005)	(0.005)	(0.003)	(0.002)	(0.002)	(0.002)
1972/1975	-0.135***	-0.137***	-0.086***	-0.112***	-0.068***	-0.071***
	(0.007)	(0.007)	(0.003)	(0.003)	(0.003)	(0.003)
1976/1979	-0.173***	-0.176***	-0.109***	-0.140***	-0.091***	-0.094***
	(0.009)	(0.008)	(0.004)	(0.004)	(0.004)	(0.004)
1980/1983	-0.233***	-0.230***	-0.129***	-0.153***	-0.115***	-0.112***
	(0.011)	(0.010)	(0.005)	(0.005)	(0.005)	(0.005)
1984/1987	-0.224***	-0.210***	-0.130***	-0.135***	-0.112***	-0.098***
	(0.013)	(0.012)	(0.006)	(0.006)	(0.006)	(0.006)
1988/1991	-0.268***	-0.242***	-0.137***	-0.105***	-0.116***	-0.089***
	(0.015)	(0.014)	(0.007)	(0.007)	(0.007)	(0.007)
Constant	8.499***	8.323***	5.733***	5.536***	4.080***	3.904***
	(0.007)	(0.006)	(0.003)	(0.003)	(0.003)	(0.003)
Observations	2,405,510	2,405,510	2,405,510	2,405,510	2,405,510	2,405,510
Year dummies	YES	YES	YES	YES	YES	YES
Adjusted R-squared	0.191	0.188	0.104	0.0690	0.0794	0.0525

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Educational achievements (low, medium and high education) are proxied by the entry year in the labour market, as explained in section 3. I obtained 4 levels based on the entry age in the LM: 18-19 (basic education), 21-22 (low education) ,25-26 (medium education), 28-29 (high education).

Table 8: Quantile regression estimates on real gross income

VARIABLES	10th	25th	50th	75th	90th
Proxy for education					
low education	0.145***	0.117***	0.108***	0.109***	0.114***
	(0.009)	(0.004)	(0.002)	(0.002)	(0.002)
medium education	0.058***	0.070***	0.105***	0.199***	0.323***
	(0.018)	(0.008)	(0.004)	(0.004)	(0.004)
high education	-0.033	-0.013	0.025***	0.123***	0.294***
	(0.025)	(0.011)	(0.006)	(0.005)	(0.006)
experience	0.189***	0.153***	0.088***	0.067***	0.070***
	(0.003)	(0.001)	(0.001)	(0.000)	(0.001)
experience^2	-0.004***	-0.004***	-0.002***	-0.001***	-0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Reg. Unemp. Rate	-0.075***	-0.055***	-0.035***	-0.027***	-0.023***
	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)
Birth cohorts					
1964/1967	0.003	-0.024***	-0.048***	-0.074***	-0.076***
	(0.014)	(0.005)	(0.003)	(0.003)	(0.003)
1968/1971	-0.023	-0.050***	-0.076***	-0.132***	-0.130***
	(0.021)	(0.008)	(0.005)	(0.004)	(0.005)
1972/1975	-0.025	-0.036***	-0.067***	-0.161***	-0.182***
	(0.030)	(0.012)	(0.007)	(0.006)	(0.007)
1976/1979	-0.022	-0.034**	-0.076***	-0.179***	-0.206***
	(0.038)	(0.016)	(0.009)	(0.008)	(0.009)
1980/1983	-0.161***	-0.135***	-0.122***	-0.209***	-0.227***
	(0.047)	(0.020)	(0.011)	(0.009)	(0.011)
1984/1987	-0.199***	-0.228***	-0.169***	-0.230***	-0.249***
	(0.057)	(0.024)	(0.013)	(0.011)	(0.013)
1988/1991	-0.303***	-0.387***	-0.288***	-0.269***	-0.265***
	(0.066)	(0.028)	(0.016)	(0.013)	(0.015)
Constant	7.546***	8.431***	9.359***	9.780***	9.948***
	(0.039)	(0.017)	(0.013)	(0.006)	(0.007)
Observations	1,108,764	1,108,764	1,108,764	1,108,764	1,108,764
Year dummies	YES	YES	YES	YES	YES

Robust standard errors in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

This table follows the same logic as the tables before in terms of cohort comparison. It reports estimates of the cohort income gap along the conditional quantiles of the income distribution. Each column reports estimates from the 10th, 25th, 50th, 75th and 90th percentiles of the total gross/net income. Due to computational issues, only the 25% of the sample has been used.

Table 9: Quantile regression estimates on net net income

VARIABLES	10th	25th	50th	75th	90th
Proxy for education					
low education	0.130***	0.107***	0.099***	0.099***	0.103***
	(0.008)	(0.004)	(0.002)	(0.002)	(0.002)
medium education	0.066***	0.066***	0.095***	0.181***	0.291***
	(0.016)	(0.007)	(0.004)	(0.003)	(0.004)
high education	-0.005	-0.008	0.019***	0.112***	0.266***
	(0.022)	(0.010)	(0.005)	(0.005)	(0.005)
experience	0.183***	0.137***	0.081***	0.062***	0.063***
	(0.002)	(0.001)	(0.001)	(0.000)	(0.001)
experience^2	-0.004***	-0.003***	-0.002***	-0.001***	-0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Reg. Unemp. Rate	-0.066***	-0.050***	-0.032***	-0.025***	-0.021***
	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)
Birth cohorts					
1964/1967	-0.015	-0.029***	-0.042***	-0.066***	-0.067***
	(0.012)	(0.005)	(0.003)	(0.003)	(0.003)
1968/1971	-0.033*	-0.061***	-0.066***	-0.115***	-0.113***
	(0.019)	(0.008)	(0.004)	(0.004)	(0.004)
1972/1975	-0.018	-0.053***	-0.060***	-0.140***	-0.156***
	(0.027)	(0.011)	(0.006)	(0.005)	(0.006)
1976/1979	0.009	-0.050***	-0.074***	-0.157***	-0.175***
	(0.034)	(0.015)	(0.008)	(0.007)	(0.008)
1980/1983	-0.098**	-0.116***	-0.122***	-0.188***	-0.196***
	(0.043)	(0.018)	(0.010)	(0.008)	(0.010)
1984/1987	-0.125**	-0.159***	-0.167***	-0.212***	-0.217***
	(0.051)	(0.022)	(0.012)	(0.010)	(0.012)
1988/1991	-0.232***	-0.279***	-0.250***	-0.251***	-0.231***
	(0.060)	(0.026)	(0.014)	(0.012)	(0.013)
Constant	7.298***	8.237***	9.162***	9.559***	9.717***
	(0.034)	(0.021)	(0.014)	(0.006)	(0.006)
Observations	1,108,864	1,108,864	1,108,864	1,108,864	1,108,864
Year dummies	YES	YES	YES	YES	YES

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

This table follows the same logic as the tables before in terms of cohort comparison. It reports estimates of the cohort income gap along the conditional quantiles of the income distribution. Each column reports estimates from the 10th, 25th, 50th, 75th and 90th percentiles of the total gross/net income. Due to computational issues, only the 25% of the sample has been used.

Table 10: OLS estimates on yearly gross income for atypical contracts 4 levels

	Yearly Gross Income			
VARIABLES	No atypical	1	2-4	more than 4
Proxy for education				
low education	0.124***	0.151***	0.177***	0.178*
	(0.002)	(0.005)	(0.009)	(0.098)
medium education	0.139***	0.340***	0.434***	0.705***
	(0.003)	(0.009)	(0.016)	(0.220)
high education	0.060***	0.326***	0.439***	0.963***
	(0.004)	(0.013)	(0.023)	(0.299)
experience	0.114***	0.128***	0.144***	0.212***
	(0.000)	(0.001)	(0.002)	(0.034)
experience^2	-0.002***	-0.003***	-0.003***	-0.004***
	(0.000)	(0.000)	(0.000)	(0.001)
Reg. Unemp. Rate	-0.042***	-0.035***	-0.033***	0.001
	(0.000)	(0.000)	(0.001)	(0.009)
Birth cohorts				
1964/1967	-0.046***	-0.080***	-0.112***	-0.059
	(0.002)	(0.007)	(0.013)	(0.165)
1968/1971	-0.079***	-0.103***	-0.150***	-0.022
	(0.004)	(0.011)	(0.020)	(0.287)
1972/1975	-0.076***	-0.119***	-0.174***	0.199
	(0.005)	(0.015)	(0.028)	(0.398)
1976/1979	-0.085***	-0.122***	-0.145***	0.397
	(0.006)	(0.019)	(0.036)	(0.528)
1980/1983	-0.149***	-0.176***	-0.151***	0.107
	(0.008)	(0.024)	(0.044)	(0.674)
1984/1987	-0.171***	-0.250***	-0.284***	0.059
	(0.010)	(0.029)	(0.053)	(0.763)
1988/1991	-0.260***	-0.441***	-0.448***	0.554
	(0.011)	(0.034)	(0.062)	(0.891)
Constant	8.957***	8.873***	8.938***	8.684***
	(0.007)	(0.020)	(0.030)	(0.318)
Observations	3,710,721	545,362	180,090	1,463
Year dummies	YES	YES	YES	YES
Adjusted R-squared	0.204	0.154	0.162	0.230

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

This table reports OLS estimates of cohort income gap for different groups of workers according to the number WSIC job spells experienced during their career: no atypical contracts (2) and at least one (3), between three and four (4) and more than four (5).