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Abstract

This paper estimates trends in the transitory and permanent variance of male earnings in Italy using social security data from 1990 to 2016. Cohort-specific earnings variability is compared by the number of non-standard contracts to test the extent to which the increase in income instability is related to labour market deregulation for fixed-term contracts. Results show a relationship between the reforms that liberalised temporary contracts and increasing income instability, mainly affecting younger cohorts. In addition, younger workers exhibit an increase in the variance of permanent earnings as the number of atypical contracts increases. This is related to a decline in long-term mobility and an increase in long-term inequality. Results show that the reforms that liberalised temporary arrangements led to a short-run increase in earnings instability and a long-term increase in inequality.

JEL-Code: J31, J41

Key words: Earning instability, cohorts, labour market reforms, income mobility.

1 Introduction

Recent years have seen the accumulation of a substantial literature on trends in various measures of instability in individual earnings and household income. The identification of the distinct sources of income variation helps to ascertain whether observed annual earnings differentials can be attributed to differences that persist over time or to instability that fades out after some periods. During the 1990s in particular, many authors began to recognise the relevance of earnings instability in explaining the widening of the income distribution that occurred in the U.S. in the previous decade[1]. The evolution of permanent and transitory income trends can shape the income distribution in a persistent or temporary way. Isolating those components is crucial for determining the economic mechanisms that drive inequality among earnings profiles. This means identifying the drivers of long-term inequality, poverty risk, income mobility, and positional change.

The recent Italian experience offers the opportunity to study the evolution of earnings instability in a period of profound institutional change, during which labour market reforms 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 so-called "reforms at the margin" in shaping income inequality and job dynamics (Boeri and Garibaldi, 2007; Berton et al., 2012; Rosolia and Torrini, 2016; Franzini and Raitano, 2019). The reform process introduced a new group of non-standard contracts, the so-called "Wage and Salary Independent Contractors" (hereafter WSIC). This label indicates individuals formally acting as self-employed but usually working as substitutes for employees with fewer employment rights and more job insecurity. The use of these contracts, characterized by a lower cost of labour, has led to an increase in job turnover with consequent effects on labour market productivity (Cappellari et al., 2012). These factors have undoubtedly increased job instability, making earnings over the life-cycle more volatile.

This paper examines the effects of the institutional changes that introduced and implemented WISC on income instability. Since younger cohorts, as well as lower-skilled workers, were affected more by the reforms, they were also more likely to end up in unstable job positions (Barbieri and Scherer, 2009; Barbieri et al., 2016) and to experience larger wage differentials than older cohorts (Tomelleri, 2021). For this reason, younger cohorts should exhibit higher income instability and higher persistence of income shocks, while the instability of older cohorts should remain unaffected.

To understand whether this is the case for Italy, I make use of longitudinal administrative data from 1990 to 2016, breaking down the cohort-specific earnings structure of Italian workers into its permanent and transitory component. Secondly, I compare the different earnings instabilities within the same cohort but distinguishing by the number of non-standard job spells during their career. Finally, to better gauge the link with the labour market reforms, only the

[1] Gottschalk et al. (1994); Moffitt and Gottschalk (1995); Baker (1997); Dynarski et al. (1997); Cameron and Tracy (1998); Gottschalk and Moffitt (1999); Haider (2001); Hyslop (2001); Stevens (2001); Moffitt and Gottschalk (2002).

contractual forms introduced and regulated by the reforms at the margin have been considered; i.e. WISC.[2]

Findings show that earnings instability for younger cohorts (especially the youngest: those born in 1982) is mainly driven by the variance in the transitory component, which increases the relevance of external shocks in driving income instability. Among younger workers (the 1976 and 1979 cohorts), the high heterogeneity of the permanent component is reduced by the loading factors that capture changes in the return to skills and thus in labour market conditions. This data is consistent with part of the Italian labour market literature (Naticchioni et al., 2016; Franzini and Raitano, 2019).

Once taking account of WSIC job spells introduced by the reform 2001-2003, the transitory variability of earnings for workers who experienced at least one non-standard job increases, on average, by at least 30 per cent. Further analysis of different WSIC subgroups of workers confirms the positive relationship between atypical episodes and earnings instability. At the same time, this form of temporary employment also affects the permanent component for the youngest cohorts: 1982 and 1979. The increase in of the variance in the permanent component for those young workers with more than two WISC job spells highlights that even a small number of atypical working episodes increases the dispersion of permanent earnings. This translates into lower long-term mobility, higher income risk and more remarkable persistence of inequalities in the long run.

This work combines the study of labour market reforms with research on earnings instability, providing evidence of the effects of the former on the latter. This work is in line with work by Cappellari and Leonardi (2016) that links tenure to earnings instability by focusing on fixed-term contracts as a whole. In this framework, I extend their analysis by focusing on a specific form of temporary contracts (the WISC) and describing its evolution among different cohorts of workers. Those contracts were introduced by the reforms implemented in the 2000s and constituted the main attempt to deregulate the Italian labour market. Given the asymmetric impact this has had on younger cohorts of workers, this paper also aims to draw useful policy implications. The length of the panel makes it possible to study the effect of labour market deregulation on cohort-specific earnings variability for many years after its implementation, recognising the role of reforms in generating instability that fades after some periods or persists over time.

The paper is organised as follows: Section 2 gives some background about earnings instability, section 3 describes the dataset, while section 4 outlines the identification of the trends in transitory variances works in a panel data set. Results are presented and discussed in section 5, while section 6 concludes with directions for future research.

[2] In this paper I will use the term atypical and WSIC interchangeably.

2 Background

This section provides a brief description of the labour market reforms that occurred in Italy and a brief overview of the literature on the instability of earnings. Over the past 30 years, Italy has been 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[3]. 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 that these contracts were limited to new recruitment only. In contrast, protections for 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 these types of contracts in some particular cases, such as when skills not usually required for the standard production process were needed or for replacing 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 in various other cases[4]. Four years later, in 2001, the 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 or 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 replaced temporary work, which had already been introduced 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 law 276/2003, but entered into force in October 2003 and was implemented at different times across the regions. Despite some attempts to reduce employment protection for open-ended contracts in 2012 and 2014, they remained untouched until the Jobs Act in 2015.

The final outcome of this sequence of labour market reforms has been a two-tier labour market, divided between old, protected, stable workers and less protected, unstable, new

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

[4] For example, when production units in which, during the last 12 months, workers involved in the same occupations have been suspended or collectively dismissed.

entrants. These disparities have persisted for at least 15-18 years, as described before. The aim of this paper is to ascertain whether and how they are linked to earnings instability.

2.1 Earnings instability and Labour Market Reforms

The widening of the earnings distribution in the U.S. in the 1980s has attracted a lot of attention in the academic literature. Regarding the causes, some scholars point to increasing wage instability as a possible factor (Gottschalk et al., 1994). The main argument is that interpreting the increase of dispersion as solely reflecting the dispersion of average wages could be misleading. The general finding of this new approach identifies the permanent component of earnings as the main driver of the growing instability in the U.S. during the 1980s. This paved the ground for a part of the literature that, during the 1990s and the 2000s, consistently shed light on earnings instability in various measures and flavours: individual earnings, household income, high/lowskilled, sectors and type of contracts differentials, almost always finding increasing in instability in the U.S. over the last thirty years (Moffitt and Gottschalk (1995); Dynarski et al. (1997); Cameron and Tracy (1998); Haider (2001); Hyslop (2001); Stevens (2001); Moffitt and Gottschalk (2002); Sichel et al. (2007);Keys (2008); Jensen and Shore (2008); Shin and Solon (2010); Moffitt and Gottschalk (2011))[5].

One part of the literature analyses the effect of job instability and insecurity, linking them together with earnings volatility (Cervini-Pla´ and Ramos, 2012; Sologon and O'Donoghue, 2011, 2012). More precisely, their works take the first step towards understanding the complex relationship between earnings instability and labour market policies and institutions in Europe.

The European institutions have been long regarded as a source of labour market rigidity, but the economic reality of the 1990s pressured Europe to move towards more flexible labour markets. A series of labour market reforms have been implemented across Europe, increasing the country-heterogeneity in labour market policies and institutions (Palier, 2010). In this context, Italy seems to be a compelling case: in 1991, according to the OECD indicators of employment protection, it was the most rigid country in the OECD area.

After a massive reform process that targeted one specific segment of the labour market[6], Italy was able to reduce EPL and unemployment, at the cost of creating a two-tier labour market divided between well-protected and less-protected workers (Boeri et al., 2011). One concern regarding the reforms aimed to boost labour market flexibility in Italy, but also in Europe, is whether greater labour market flexibility is likely to increase earnings instability, and what potential labour market policies/institutions can counteract this increase (Sologon and O'Donoghue, 2011). In this direction, the Italian literature shows (Cappellari, 2004) that up until the mid-1990s, inequality trends were driven by the long-term earnings component, with a larger increase in transitory variation for younger cohorts. Moreover, younger cohorts experience a higher probability of low-paid repeated job spells. Cappellari and Leonardi (2016) use tenure as a proxy for the increased dispersion provoked by the labour marked reforms in

[5] A more detailed summary of the empirical results is provided by Doris et al. (2013a).
[6] I refer to the reforms introduced in 1995, 1997, 2001, and 2003; see previous section.

Italy, finding increasing dispersion of long-term earnings profiles with tenure while earnings instability declines.

To the best of my knowledge, the literature on earnings dispersion and labour market reforms in Italy seems to be relatively small, even taking the contributions of the authors cited here into account. This work aims to extend the literature, widening the period of analysis and developing a different strategy to understand the impact of labour market reforms in the long run. The literature is full of contributions on the short-term effects of the L.M. reforms, but only a few contributions look at the evolution of earnings variability over the life-cycle.

3 Data and descriptive statistics

The original dataset, *"LoSai"*, derives from the administrative archives of the National Social Insurance Agency and contains information on 38 million job positions held by insured workers from 1990 to 2016[6]. The sample is drawn with a ratio of about 1:10 form the universe selecting workers based on the day of birth (the first and ninth day of every month). This time window encompasses all the major labour market reforms occurred in Italy in the last 30 year, especially those aimed at deregulating fixed-term contracts (see section 2). The dataset is suitable for the analysis of life-cycle earnings since its longitudinal sample allows memakes it possible to follow many workers over their entire careers. This is crucial for distinguishing the two components of instability from the autocovariance structure of earnings.

Real yearly gross income is calculated for every male worker (y_{it}) by taking the sum of all the working episodes within a year and by deflating it using CPI at 2015 prices. The resulting logarithm is the dependent variable of a first step cohort-specific regression on year dummies, educational proxies and regional unemployment. Some authors prefer to use weekly income obtained by dividing yearly income for the number of worked weeks, but this approach reduces the transitory variance of earnings I want to analyse. In addition, to mitigate issues of endogenous female labour market participation, this analysis focuses on male earnings: selection into employment for women is very strong along the lifecycle, which induces endogenous instability.

Year dummies avoid transitory fluctuations due to macroeconomic shocks, while regional unemployment takes out the effect of evolving disparities in regional labour markets. The educational proxies help control for selection into atypical contracts. Since INPS data does not contain this information, following Rosolia and Torrini (2016), I approximate the level of education by using the entry year in the labour market[7]. I only consider observations with positive incomes and non-missing information on birth date and entry year in the labour market.

[6] It provides additional details on 1.4 million registered companies and nearly 22 million social security contributions.

[7] In fact, it is plausible to assume that workers who entered the labour market at age 21-22 have at most completed secondary education 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 the average earnings of younger cohorts. Allowing for different entry ages (18-19, 21-22, 25-26, and 28-29) accounts for different educational achievements.

Information about public employees, workers employed in the agricultural sector and self-employment is not available, but this selection is common for administrative data. I follow Cappellari and Leonardi (2016), in not modelling selection from the private sector into other states. They showed that, in Italy, workers in the private sector are quite stable: according to SHIW data[8], almost 83 per cent of male workers remain in the sector after two years, while 7.5 per cent move to the public sector, 3 per cent become self-employed, 2.5 per cent retire and the rest become unemployed[9]. Additional variability could be given by the fact that some individuals may be at the beginning of their careers or close to retirement. Therefore, the sample is restricted to workers aged 25-55 to reduce the chance that these periods of individuals' careers will inflate the estimated earnings variability. This procedure is very common in this literature (Cappellari and Leonardi, 2016; Haider, 2001).

Identifying time, cohort, and age effects requires observations of earnings at different points over the life cycle for every year in the sample (within the same cohort). This is done by widening the cohort size to obtain enough age variation within each cohort (Cappellari, 2004). The only requirement is that there should be enough age variation in each specific cohort-year cell, which is guaranteed for most of the cohorts in the dataset. The only requirement is that there should be enough age variation in each specific cohort-year cell, which is guaranteed for most of the cohorts in the dataset. I focus on workers born between 1966 and 1983 so that I can observe workers for a minimum of 10 years in the labour market[10] and ensure a proper level of age variation. Workers are divided into three-year birth cohorts, from 1966-1968 to 1981-1983, and each of them is labelled and referred to using the middle year. Following this strategy, the youngest cohort - 1982 - refers to individuals born between 1981 and 1983, while the oldest one -1967 - to individuals born between 1966 and 1968.

Tables 1 and 2 show the resulting sample size by year and cohort. Given the cohort accumulation at different points in time, even when restricting the age group between 25-55, the analysis is limited to cohort 1967- 1982 to reduce panel attrition. Furthermore, cohorts are analysed separately: in this way, attrition is lower, and convergence issues are relaxed.

The identification of atypical jobs (Wage and salary independent contractors - WSIC) within the fixed-term contracts is achieved by combining data from the INPS statements (Estratti conto). In this way, each worker can be classified according to the number of these episodes during his career. Due to the size of the categories, the first comparison is made between those who do not have atypical contracts and those with at least one WSIC job spell. A second step takes into account the differences within WISCs, obtaining three groups: up to two atypical

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

[9] For the sake of clarity, it is possible that, even if small, switching observations from the private to the public sector can be confounded with unemployment.

[10] Cohort 1985 is not identifiable because the length of the panel is not sufficient and leads to negative variances/not significant parameters. The rule of thumb is to have at least 10 points in time, as demonstrated by Doris et al. (2013b). They use Monte Carlo simulations to examine the sensitivity of parameter identification to key features such as panel length, sample size, the degree of persistence of earnings shocks and the specification of the earnings cohort, showing that long panels allow the identification of the cohort, even when persistence in transitory shocks is high. Short panels, on the other hand, are insufficient to identify the individual parameters of the cohort, even with moderate levels of persistence.

episodes, between three and four, and more than four. This threshold is arbitrary and does not always lead to consistent estimates given the small size of the subsamples, but it is informative about the evolution of these trends as the number of WISC job spells increases.

4 Estimation framework

4.1 Permanent/Temporary Earnings Decomposition

The intuition for recognizing trends in transitory variance comes from the typical error component model (ECM):

$$y_{it} = \mu_i + v_{it} \tag{1}$$

where the log of individual earnings *i* at time *t*, y_{it}, results from the sum of a time-invariant individual component μ_i and from a transitory component v_{it}. The permanent component reflects individual-specific fixed characteristics such as the level of education or unobserved ability, while the transitory component reflects temporary shocks that affect individual incomes. The latter is more related to the business cycle and expresses the year-to-year variation in the income distribution. The way in which external shocks persist – as well as their intensity - also depends on the individual position in the income distribution (see next section).

The basic assumptions of ECM are that the two components are not correlated, their expected value is equal to zero, and their variance is homoscedastic so that:

$$E(\mu_i) = E(v_{it}) = E(\mu_i v_{it}) = 0$$

$$Var(\mu_i) = \sigma_\mu^2 \qquad Var(v_i) = \sigma_v^2 \tag{2}$$

it follows:

$$V = Var(y_i) = \sigma_\mu^2 + \sigma_v^2$$

The identification comes from the fact that the transitory component should fade out after *s* periods. So, if we take the autocovariance of earnings between two sufficiently long periods (*t* > *s*) we have:

$$Cov(y_{it}, y_{is}) = \sigma_\mu^2 + Cov(v_{it}, v_{is}) \text{ with } Cov(v_{it}, v_{is}) = 0$$

and the variance of the permanent component, σ_μ^2 , fully determines the autocovariance structure. The transitory variance is obtained from the difference between the total variance and the resulting permanent variance.

$$\sigma_v^2 = Var(y_{it}) - \sigma_\mu^2$$

4.2 Model specification

In order to model earnings variability for different groups of workers within cohorts, the initial specification is extended to allow for loading factors and specifying the characterization of the two components. The inclusion of loading factors p_t and λ_t allows the two components to change over time, accentuating/attenuating individual profiles over time.

$$y_{it} = p_t\mu_i + \lambda_t v_{it} \quad \mu_i \sim iid(\overline{\mu_i}, \sigma_\mu^2) \quad v_{it} \sim iid(0, \sigma_v^2)$$
$$Cov(y_{it}, y_{is}) = \begin{cases} p_t^2\sigma_\mu^2 + \lambda_t^2\sigma_v^2, & t = s \\ p_t^2\sigma_\mu^2, & t \neq s \end{cases} \tag{3}$$

where the year-specific loading factors are normalized to one at the initial period. From an economic point of view, the permanent component of income represents relatively fixed personal characteristics, mostly related to (un)observed skills and human capital of various kinds[11]. Allowing for changes in calendar time allows for changes in returns to skills: an increase in returns to skills increases the variance of the permanent component. At the same time, λ_t allows for an increase or a reduction in the magnitude of economic shocks on earnings profiles over time.

Although the model in equation 3 makes it possible to account for time, it still overlooks several important features of earnings dynamics. Firstly, economic theory, corroborated by several studies, suggests that the permanent component is not fixed over the life cycle but evolves, typically with variances and covariances rising with age (Permanent Income Hypothesis, PIH[12]). In this framework, each worker should have an individual-specific experience–earnings profile so that rates of earnings growth vary across individuals in a systematic way (Haider, 2001). This is captured by the random growth factor ($\varsigma_i = \alpha_i + \beta_i x_{it}$) or a heterogeneous growth term which allows each individual to have a permanently higher or lower growth rate than other individuals. In this specification, the permanent component becomes:

$$y_{it} = p_t(\alpha_i + \beta_i x_{it} + u_{it}) + \lambda_t v_{it} \tag{4}$$

[11] As Ramos (2003) pointed out, permanent earnings differences may be due to the effect of time-invariant observables such as education, but also due to time-invariant unobservable factors such as ability or effort.

[12] *"The permanent income hypothesis implies that, for any cohort of people born at the same time, inequality in both consumption and income should grow with age,"* Deaton and Paxson (1994). However, the PIH does not necessarily imply that aggregate inequality should increase over time, given the fact that people do not live forever. In this hypothesis, there is no implicit assumption that overall dispersion should increase over time because inequality is higher among older cohorts and less among young people: young individuals are continually replacing older ones. In addition, the secular behaviour of aggregate inequality depends on how assets are passed from one generation to the next and on the age structure of the population, but this is beyond the scope of this paper.

$$where\ (\alpha_i,\beta_i) \sim iid[(0,0);(\sigma_\alpha^2,\sigma_\beta^2,\sigma_{\alpha\beta})]$$

The first two terms inside the parentheses in equation 4 capture the random-growth component of earnings, allowing each individual to have a different permanent life-cycle growth rate of earnings, which may be correlated with initial earnings. Indeed, individuals that share common life-cycle profiles may be subjected to shocks that permanently change the individual's place in the earnings distribution (Dickens, 2000). A positive (or negative) shock during the working life, such as a promotion (or a severe illness) could permanently affect the individual's future earnings. This is captured by u_{it} with a random walk specification, or by using unit-root model interchangeably (Baker, 1997; Ramos, 2003).

In this work, u_{it} follows a random walk specification:

$$u_{it} = u_{i,t-1} + \omega_{it} \quad \omega_{it} \sim iid(0, \sigma_\omega^2) \tag{5}$$

with $E(u_{i,t-1}\omega_{it}) = 0$.

This random walk specification reflects changes in the idiosyncratic, unpredictable component and could be associated with changes in income risk (Jäntti and Jenkins 2015). The variance at the first period (depending on the entry age in the sample) is σ_α^2 while $\omega_{it} \sim idd(0,\sigma_\omega^2)$ and represents the innovation in each period. The two approaches defining the permanent components are complementary: in the random walk specification, current earnings are sufficient statistics for future earnings, while in the random growth model, additional information to current earnings (for example, initial earnings) may be informative about the future[13].

The transitory component should, instead, represent transitory earnings shocks caused by volatility in the labour market. Serially correlated transitory differences may reflect either serially correlated independent variables or serially correlated random shocks. This component is defined as a temporary deviation from one individual's profile. The transitory error is usually serially correlated by a low-order ARMA process with the underlying transitory shock $v_{i,t-1}$ fading out at rate ρ but deviating from that smooth fade-out rate by θ in the next period.

$$v_{it} = \rho v_{i,t-1} + \epsilon_{it} + \theta\epsilon_{i,t-1} \tag{6}$$

$$with \quad \epsilon_{it} \sim (0,\sigma_\epsilon^2) \quad and \quad v_{it} \sim (0,\sigma_v^2)$$

If the primitive error term ϵ_{it} should represent the individual and time-specific transitory shock, its variance σ_ϵ can be a measure of the contemporaneous volatility of earnings. It is also true that ϵ_{it} could capture the bias coming from the measurement error. A technical issue is that serially correlated random shocks might be attributed to unobservables or to measurement error. Measurement error is a problem, especially with survey data, but also in the more stable

[13] For a detailed discussion and comparison of these two approaches, see Baker (1997) and Guvenen (2009). [16]Coming from the widely adopted approach by labour economists (MaCurdy, 1982).

administrative database, in which unemployment spells are usually not recorded. Allowing for serial autocorrelations in the error term of the transitory component helps to deal with that issue, but it makes it impossible to distinguish what comes from the contemporaneous volatility of earnings from what is due to measurement error. Even if ϵ_{it} and $\theta\epsilon_{i,t-1}$ were able also to capture any mean-reverting measurement error in the earnings data, considerable measurement error would overestimate the variance of mean-reverting earnings and the entire transitory component σ_v and, in consequence, the interpretation of the entire model. This is why the assumptions made on the sample selection strategy (section 3) should limit the issue of transition from/to unemployment spells. Under this condition, the inherent memory conserved by the ARMA process allows the transitory shocks v_{it} to build up over time in the actual distance of an individual from his profile.

A crucial aspect of lifetime inequality is that it is not a function of individual-specific parameters; it is rather a function of the variance of these parameters. Intuitively, there is no need to estimate earnings profile for each individual: all parameters in equation (4) are directly estimable as part of the autocovariance structure of earnings. The reason for why this is the case is that the autocovariance describes how earnings tend to evolve over time; by knowing the earnings distribution in various years and by knowing how earnings tend to evolve, we can back out estimates of lifetime earnings inequality. Following Doris et al. (2011) approach[16], I treat the variance at the start of the sample period, $\sigma_v{}^2{}_1$, as an additional parameter to be estimated. The GMM estimator matches sample variances and covariances to their population counterparts[14]. In the Cohort (*a*) specified by equations (4)–(6), the true variance–covariance matrix has diagonal elements:

$$\sigma_{a1}^2 = \{p_1^2(\sigma_\alpha^2 + \sigma_\beta^2 X_{a1}^2 + 2\sigma_{\alpha\beta}X_{a1} + \sigma_\omega^2 X_{a1})\} + \lambda_1^2 v_{i1}^2$$

for t=1

$$\sigma_{at}^2 = \{p_t^2(\sigma_\alpha^2 + \sigma_\beta^2 X_{at}^2 + 2\sigma_{\alpha\beta}X_{a1} + \sigma_\omega^2 X_{at})\} + \left\{\lambda_t^2\left(\rho^{(2t-2)}\sigma_{v1}^2 + K\sum_{\omega=0}^{t-2}\rho^{2\omega}\right)\right\}$$

for t >1 and the off-diagonal

elements are:

$$Cov(y_{at}, y_{a(t+s)}) = p_t p_{t+s}\left\{\sigma_\alpha^2 + \sigma_\beta^2 X_{at}X_{a(t+s)} + \sigma_{\alpha\beta}(X_{at}+X_{a(t+s)}) + \sigma_\omega^2 X_{at}\right\} + \lambda_{t+s}(\rho^s\sigma_{v1}^2 + \rho^{(s-1)}\theta\sigma_\epsilon^2)$$

t = 1 and s > 0

[14] The weighting matrix used for the estimation is the identity matrix, which is considered the most appropriate for cohorts-covariance estimation (Altonji and Segal, 1996; Clark, 1996).

$$Cov(y_{at}, y_{a(t+s)}) = p_t p_{t+s}\left\{\sigma_\alpha^2 + \sigma_\beta^2 X_{at}X_{a(t+s)} + \sigma_{\alpha\beta}(X_{at} + X_{a(t+s)}) + \sigma_\omega^2 X_{at}\right\} +$$

$$+\lambda_t\lambda_{t+s}\left\{\rho^{(2t+s-2)}\sigma_{v1}^2 + \rho^2 K\sum_{\omega=0}^{t-1}\rho^{2\omega} + \rho^{(s-1)}\theta\sigma_\epsilon^2\right\}$$

$t > 1$ and $s > 0$

where $K = \sigma^2(1+\theta^2+2\rho\theta)$, X_{at} is the average experience of individuals at time t and X_t^2 is the average value of experience-squared at time t, both for the atypical group of workers a. The parameter vector to be estimated is given by $\psi = \{\sigma_\alpha^2, \rho, \sigma_{v1}^2, \sigma_\epsilon^2, p_2...p_t, \lambda_2...\lambda_t, \sigma_\beta^2\sigma_{\alpha\beta}, \sigma_\omega^2, \theta\}$. The identification requires a normalization of the loading factors so that p_1, $\lambda 1$, q_1 and s_1 are set equal to one. Since cohorts differ by length and tenure, I analyse cohort-specific earnings profiles separately.

4.3 Testing of different model specification

In this paper, I have presented the full model specification. This section compares estimates among the full model and some relevant sub-specifications. Results are shown in table 3. For the sake of simplicity, I report and interpret the coefficients for cohort 1982 as an example. Other cohort examples can be shared on request.

Table 3 illustrates estimates for different specifications of the model outlined in equations 4–6, where the permanent component includes growth heterogeneity (column 3 and 6) or not (column 1-2, 4-5) and the transitory component is modelled as an AR(1)(column 1 and 4) or as an ARMA(1,1) (column 2, 3, 5 and 6). The coefficients refer to their sample moments; additional statistics of the cohorts are reported at the end of the table.

In order to justify the use of the full specification (column 6), I test for over-identification between the model with full specification (column 6) and the baseline model (neither RG nor RG specification, column 1) using a Hausman-type test (chi-squared distribution, extra parameters as degrees of freedom). Under the null hypothesis, there should be no difference between the two model specifications: the test result allows to reject the null hypothesis[15]. Figure 1 reports the estimated transitory and permanent component for the two model specifications. As can be seen from the figure, the cohort with the full specifications tends to better capture income shocks that affect the transitory component. Since two components are orthogonal by definition, the exclusion of one parameter could lead to an increase in the variability of another moment within the same component. For example, if we had not considered the mean-reverting coefficient θ in the transitory component, the relative loading factors would have been bigger or not significant. In other cases, σ_ϵ^2, which can be considered as a measure of variability in the labour market, would have been overestimated. By including

[15] $Chi2(22) = (b - B)'[(V_b - V_B)^{(}-1)](b - B) = 7236.81$ $Prob > chi2 = 0.0000$. It is not possible to run a test on weighting matrices since the GMM adopted in the model uses the identity matrix instead of the minimum distance estimator.

θ, we allow the external shocks to build up over time, with a consequent increase in their persistence ρ. This simple exercise helps us to deal better with all these trade-offs and justifies the use of the full model specification.

As previously described, the estimates of α and β in the first two rows capture the individual heterogeneity in the intercept and slope of the experience–earnings profile, allowing earnings growth rates to vary across individuals systematically. Thus each individual may have a different permanent life-cycle growth rate of earnings, and this growth rate may be correlated with initial earnings. It follows that σ_{α}^{2} represents the variance at the first period, depending on the individual characteristics accumulated by the cohorts of workers before entering the sample. For example, looking at the last column of table 3, estimated slope β tells us that a worker born in 1982, with an earnings growth rate one standard deviation above the mean, experiences an earnings growth about 3.87 per cent faster than the mean $\sqrt{(0.0015 * 100)}$. The negative estimate of $\alpha\beta$ indicates a trade-off between initial earnings and subsequent earnings growth, consistent with the on-the-job-training hypothesis. The transitory component is higher than the permanent, which means that earnings instability dominates the overall variability for those born in 1982 (this is not the case for cohorts born before 1967). One-to-one year variation σ_{v}^{2}seems to be persistent in this cohort: 72 per cent of the previous year variability persist to the following year(ρ).

Results

Figure 2 illustrates the predicted variances of the two components for all the cohorts using the coefficients reported in table 4. Total cohort-specific variances (bottom left panel) have been decomposed into their permanent (top left panel) and the transitory (top right panel) components[16]. This first evidence shows that earnings variability for younger cohorts is mostly driven by the transitory component, supporting the idea that this might be related to labour market deregulation. For the other cohorts, at this stage of analysis, the differences in the two components can partly be traced back to the different stages of the workers' careers[17]. Despite this, volatility trends seem to converge towards 2008 or at least to have a turning point in that year. Since year dummies in the first step cohort-specific regression (see section 4) should prevent transitory fluctuations in earnings directly generated by the business cycle, it is plausible to think that the volatility in earnings can be related to labour market dynamics. Since job turnover has increased after the reforms (as documented in chapter 2), it is plausible that the youngest cohort (1982) is more affected by job turnover and or unemployment spells. This explains why those workers exhibit the most volatile earnings among all the cohorts. In sum, the total change in the 1982 income distribution is mainly driven by substantial year-to-year variation.

[16] For greater clarity of display, the scales of the two components are different from the scales of the other two graphs.

[17] Since the two components are orthogonal and their sum constitutes the total variance, by construction, at the same level of the total variance, when the permanent component drops the transitory increases.

Cohort estimates for the two trends are shown in table 4[18]. The transitory coefficients confirm what is shown in figure 2: estimates report similar dynamics except for the 1982 cohort. The added value is the possibility to analyse the contribution of every single element: human capital depreciation due to innovations (ρ) is higher for the older cohorts and decreases as soon as we pass through younger workers. At the same time, external shocks in income dynamics (σ_{ϵ}^2) tend to increase in magnitude but become less persistent (θ). For the 1982 cohort the story is slightly different: the highest human capital depreciation sustains the high level of instability in the sample: 71.6 per cent of the transitory variance still persists after one year and it takes six years to become very small (0.13).

In terms of the permanent component, younger cohorts exhibit higher estimated variances. Cohort 1976 and 1982 are characterised by high skills heterogeneity before entering the labour market (σ_{α}^2) and by higher variability in growth rates (σ_{β}^2). For cohort 1979, the random walk captures all the variability in this component, meaning that current earnings are sufficient static for future earnings. The negative estimate of $\sigma_{\alpha\beta}$ indicates a trade-off between initial earnings and subsequent earnings growth, consistent with the on-the-job-training hypothesis for all the cohorts.

In order to assess the role of WSIC job spells as a driver of earnings instability, the same exercise has been done considering two groups of workers within each cohort: workers who have never experienced an atypical (Wage and Salary Independent Contractors) job spell and those who have had at least one. Results are shown in table 5 and graph 3. More stable workers, even including fixed-term contracts[19], show similar trends and magnitudes in the two components. Workers who experienced at least one WISC job spell, show higher transitory variance, which is, on average, at least 30 per cent higher with respect to standard workers. On the other hand, the permanent component is also affected for this group of workers. In this case, older cohorts are more affected. Earnings profiles deviate significantly for older cohorts for this group of workers, with significant implications for long-term inequality and income risk. One possible explanation is that repeated atypical spells increase the likelihood of being trapped in this type of employment with important consequences for the worker's career and earnings profile (Barbieri and Scherer, 2009). Table 5 helps to contextualise the sources of instability for the two groups of workers: trends in the transitory component for WSIC workers are driven by less persistent but more intense external shocks for younger workers. In other words, they are more exposed to income shocks.

For a more detailed picture, figures 4, 5, and 6 show the evolution of predicted permanent and transitory component for four atypical groups: zero WSIC job spells (dashdotted line), up to 2 (dotted line), between 3 and 4 (dotted line) and more than 4 (dash-dotted line). Given the low sample size of these subgroups, the results turn to be less robust than the previous ones, but this exercise helps gauge the dynamic within unstable workers. The graphical evidence confirms what is found in the general group specification: the number of WSIC job spells

[18] Loading factors are excluded for the sake of simplicity and because the predicted variances shown in the graphs depends on them.

[19] One step above the WSIC in terms of job protection and social contributions.

induces an increase in earnings instability for most of the cohort transitory. For more than two atypical episodes, the two youngest cohorts (namely cohort 1979 and 1982) are also affected in the permanent component.

The overall picture emerging from the results tells us an interesting story: earnings instability is higher for younger cohorts, but it increases as the number of WISC job spells increases. Since these non-standard contracts were those directly introduced by labour market reforms that liberalised temporary contracts, and given the estimation procedure, this effect can be seen as the result of the labour market deregulation on earnings instability. At the same time, the WISC type of employment also influences the permanent component for some older and younger cohorts. This result is concerning in policy terms and will be discussed in the last section.

5.1 Within-cohort trends differences

To test whether distances among trends within the cohorts are significantly different, I perform a standard F-test on the weighted average of the predicted variances, where the weights consist of the sample size of the two different groups. The test compares workers who did not experience any WISC job spells with those who experienced at least one:

$$F = \frac{\frac{1}{N_a}\sum_{t=1}^{T} s_a^2 n_t}{\frac{1}{N_s}\sum_{t=1}^{T} s_s^2 n_t}$$

where *s* stands for standard, *a* for atypical (WSIC) and N is the sum of the weights for each group. The null hypothesis states the equality between the weighted average of the predicted variances. The degrees of freedom are given by the number of individuals for each group. The basic assumption is that people with atypical contracts come from a normally distributed population different from the population of typical contracts.

F-test for the predicted variances of the two components

Cohort	1967	1970	1973	1976	1979	1982
Permanent	0.747	1.310	1.515	1.084	0.568	1.995**
Transitory	2.470***	2.014**	1.728*	1.851**	2.297**	1.252

The test shows that almost all the cohorts significantly differ between the two groups in their transitory component. This is reasonable since, over the life-cicle careers tend to become more stable and the variability in income should be mainly driven by transitory shocks. At the same time the variability between atypical and non-atypiacal runs through the transitory component.

What is remarkable is the statistical significance in the difference of the permanent component for the youngest cohort. Thus, while the transitory component is the main driver of earnings variability at the beginning of a career for everyone, as graph 2 shows, the 1982 cohort already exhibits a significant difference in the permanent component. This means that for WSIC workers born between 1981 and 1983, the earnings structure is more rigid in comparison to their standard colleagues.

6 Conclusion

This paper examines the source of the increasing cross-sectional and long-term variance of male earnings in Italy over the period 1990-2016 by decomposing cohort-specific covariance structures of earnings. Using social security data from the national archive INPS, this paper establishes the link between the number of non-standard job spells and earnings instability, determining the role of labour market deregulation in shaping cohort earnings profiles.

A first analysis shows that the transitory component is the main driver of increased instability for the youngest cohorts in the dataset and that the 1982 cohort has been particularly affected. This undoubtedly increases the relevance of external shocks in driving income instability and enforces the story that, on average, younger workers exhibit less stable earnings profiles. Among younger workers, the variance of the permanent component for the 1976 and 1979 cohorts is mostly determined by the loading factors, which denote the predominance of labour market conditions on individual-specific human capital in shaping earnings profiles. This finding is consistent with part of the literature on the Italian labour market (Naticchioni et al., 2016; Franzini and Raitano, 2019).

To assess the role played by the introduction of WSIC employment on income instability, I compared the permanent and the transitory component within the same cohort but distinguished by the number of atypical jobs during their career. Once taking into account the number of WSIC job spells, the transitory variability of earnings for workers who experienced at least one non-standard job increases, on average, by at least 30 per cent. There is no clear cohort pattern but, since those types of contracts were only introduced by the reform 2001-2003 reforms, this can be seen as clear evidence of the relation between earnings instability and the reforms. On the other hand, some WISC cohorts exhibit an increase in their permanent component. An F-test on the predicted variances of the two groups confirms these trends and reveals that the permanent earnings of atypical workers in the 1982 cohort are also, which indicates a deterioration of earnings for WSIC workers.

Distinguishing for more WSIC job spells groups within the cohort reinforces the relationship between atypical contracts and temporary variability for every cohort. It also reveals an increase in the permanent component for the youngest cohort (cohort 1982 who expericed more than two WISC job spells - which already emerged from the F-test on two groups for cohort 1982). This evidence highlights the fact that a considerable number of atypical spells increases the spread of permanent earnings. If we consider entrapment in the flexible segment

(Barbieri et al., 2016), a worker's prolonged exposure to WISC job spells makes his earnings variability into a permanent characteristic of his earnings profile.

In sum, the paper provides clear evidence of the effects of the WSIC contracts introduced by the labour market reforms, which liberalised temporary contracts and earnings instability. The instability increases according to the number of WSIC contracts, but there is no clear cohort pattern on the transitory component. On the other hand, young workers exhibit a worrying increase in their permanent component, which undoubtedly increases long-term inequality for those cohorts, with relevant implications on income mobility and poverty risk.

Since the literature on firm effects in individual wage dynamics is in its infancy and the use of this type of contract varies among sectors, future research could explore these dynamics, comparing contract-driven earnings instability within firms by size and sector.

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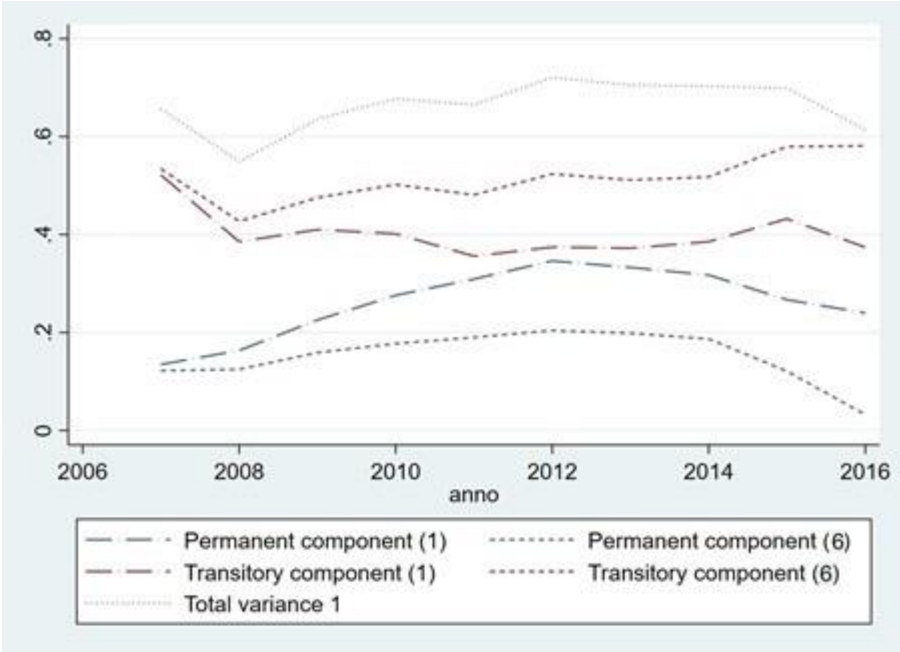
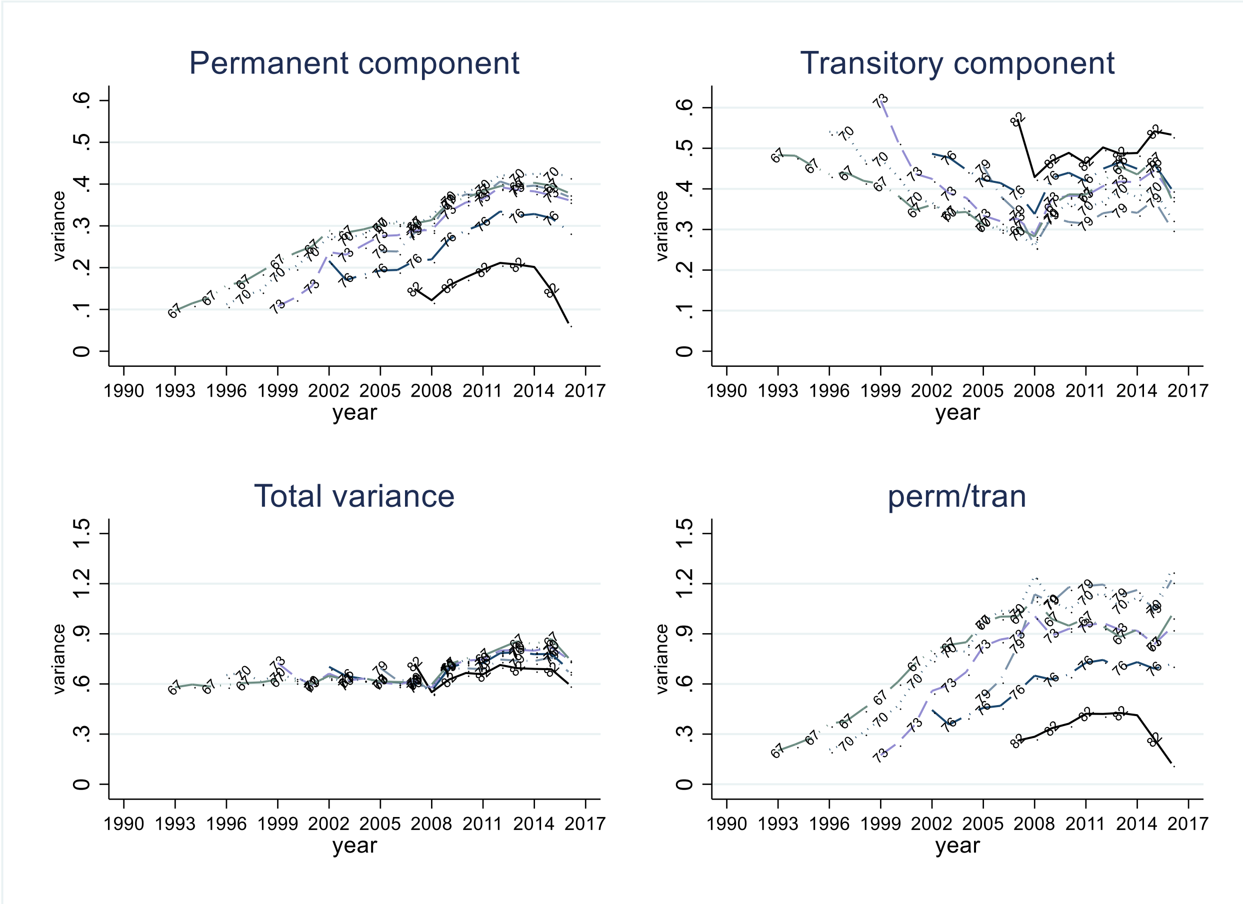
A Figures

Figure 1: Predicted variance components, simple Cohort [AR(1)] (1) ,
full Cohort [RW+RG and ARMA (1,1)] (6)



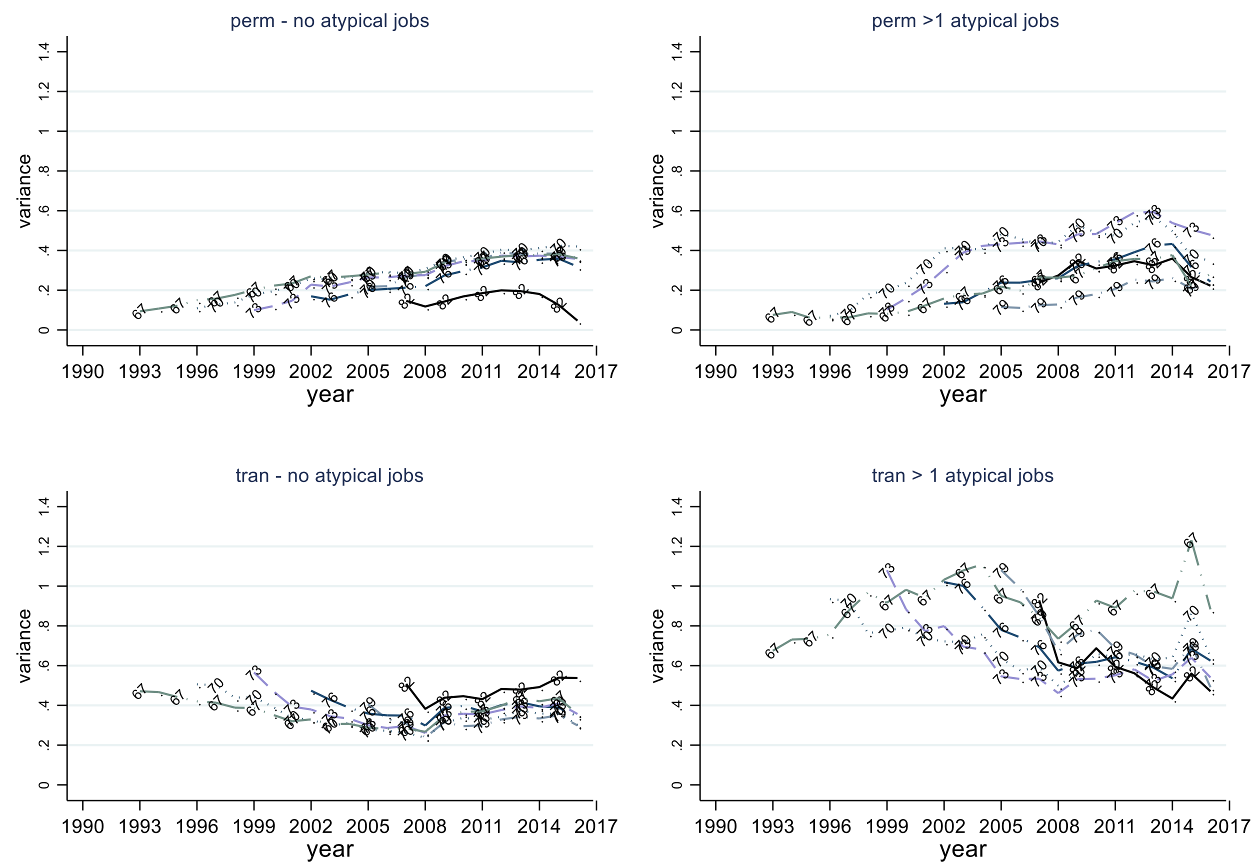
Notes: The figure presents the evolution of the permanent and the transitory component estimated for two model specifications: the full model (RG + RW - ARMA (1,1)) named model 1 and the base specification AR(1) named model 6, as presented in table 3 (column 6 and 1 respectively).

Figure 2: Predicted variances by cohorts



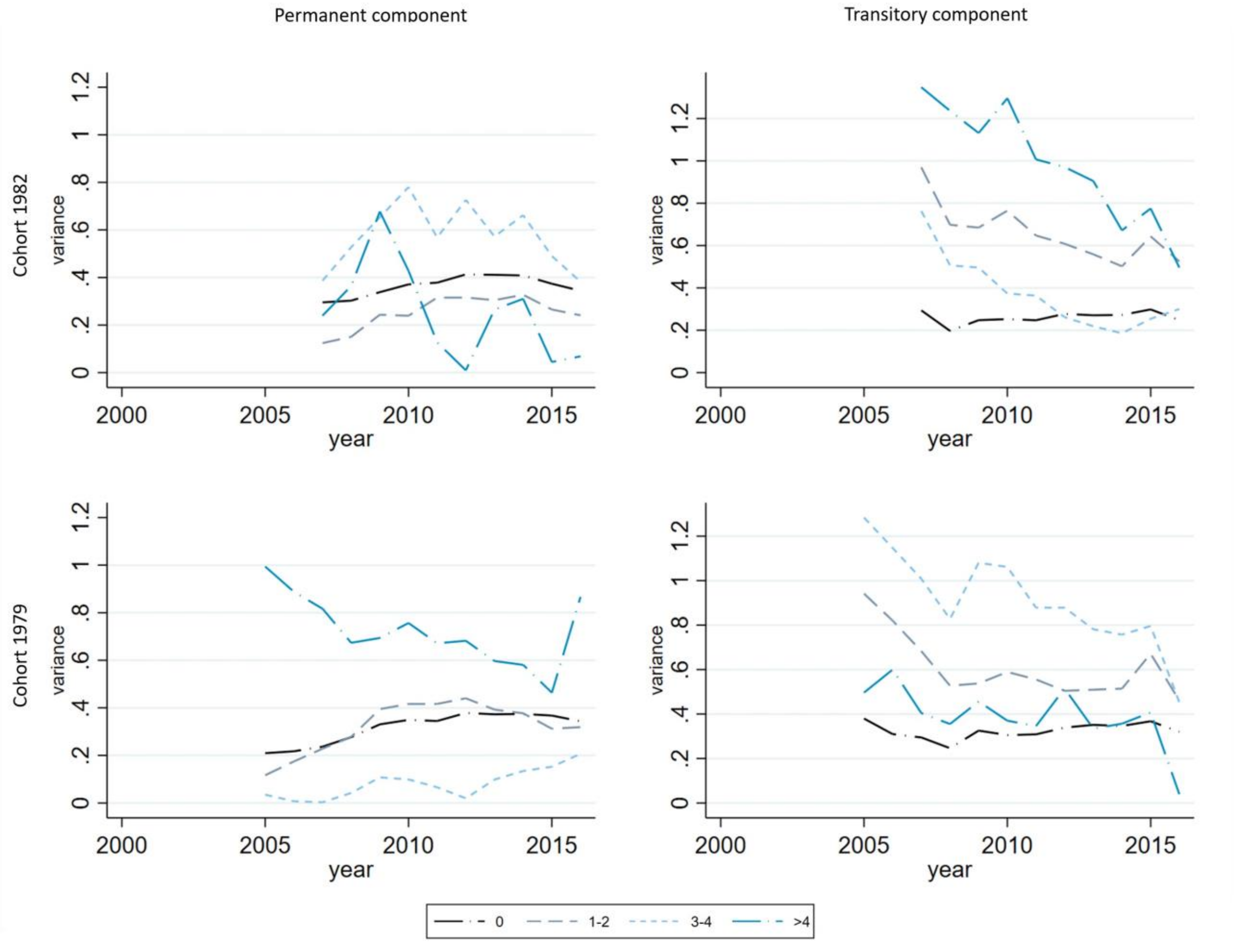
Notes: Figure 2 shows the predicted variances of the two components for all the cohorts using the coefficients reported in table 4. Total cohort-specific variances (bottom left panel) have been decomposed into their permanent (top left panel) and the transitory (top right panel) components.

Figure 3: Predicted variances by cohorts and atypical groups



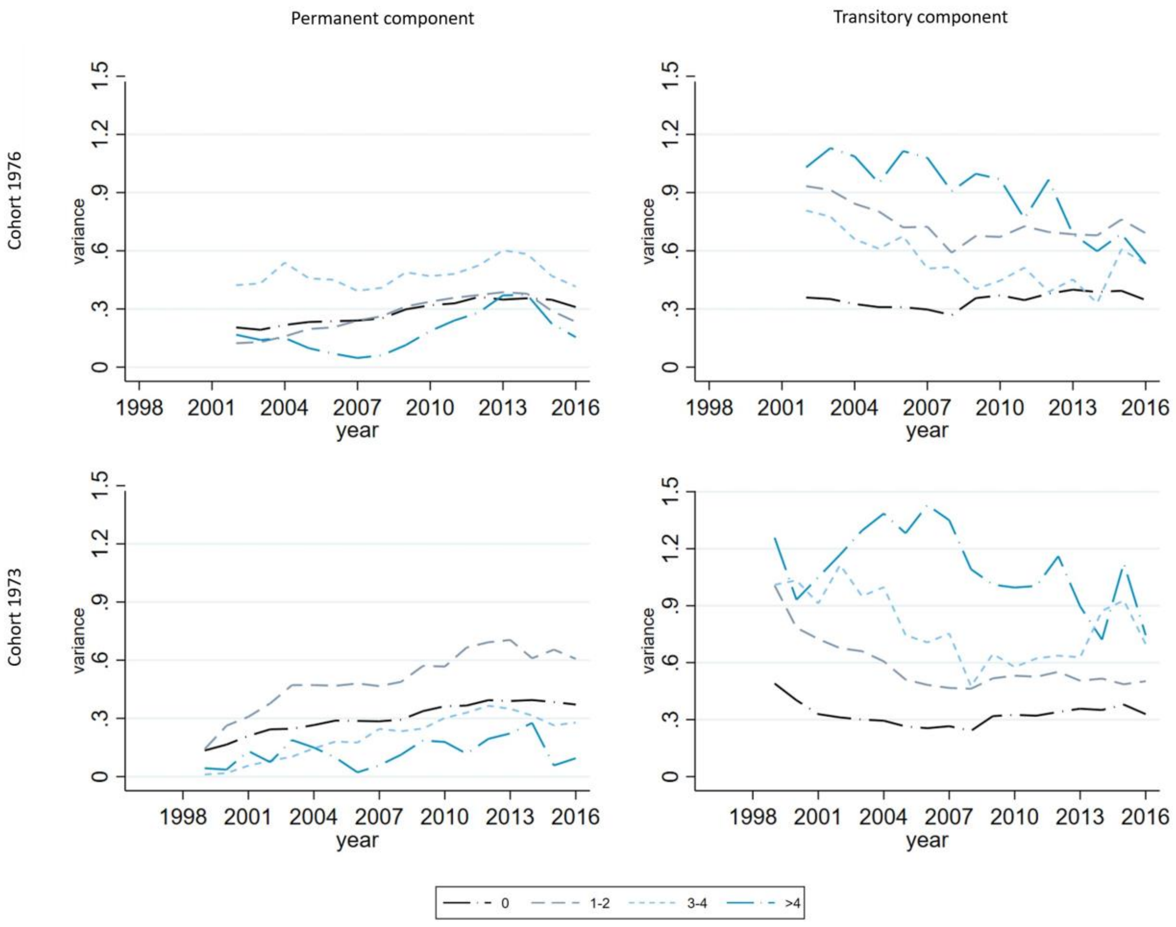
Notes: Figure 3 shows the predicted variances of the two components (top panels for the permanent, bottom panels for the transitory) for workers who have never experienced an atypical (WSIC) job spell (left-hand side) and those who have had at least one (right-hand side).

Figure 4: Predicted variances by number of WSIC job spells - 1979 and 1982 cohorts



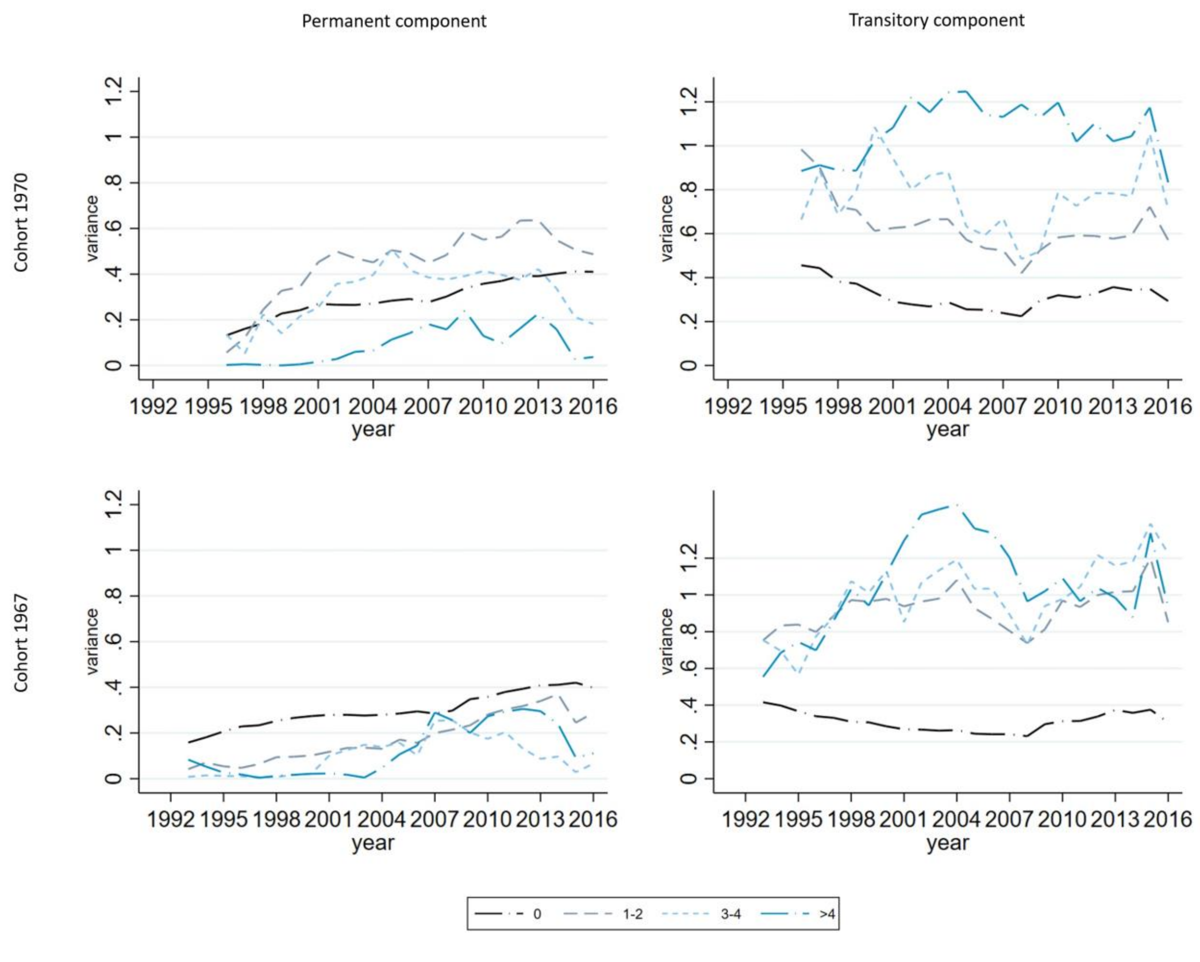
Notes: Figure 4 shows the predicted variances of the cohort 1979 and 1982 distinguishing by the four atypical groups: zero WSIC job spells (dash-dotted black line), up to 2 (dotted grey line), between 3 and 4 (dotted light blue line) and more than 4 (dash-dotted light blue line).

Figure 5: Predicted variances by number of WSIC job spells - 1973 and 1976 cohorts



Notes: Figure 4 shows the predicted variances of the cohort 1973 and 1976 distinguishing by the four atypical groups: zero WSIC job spells (dash-dotted black line), up to 2 (dotted grey line), between 3 and 4 (dotted light blue line) and more than 4 (dash-dotted light blue line)

Figure 6: Predicted variances by number of WSIC job spells - 1967 and 1967 cohorts



Notes: Figure 4 shows the predicted variances of the cohort 1967 and 1967 distinguishing by the four atypical groups: zero WSIC job spells (dash-dotted black line), up to 2 (dotted grey line), between 3 and 4 (dotted light blue line) and more than 4 (dash-dotted light blue line).

B Tables

Table 1: Real income by year and cohort

Cohorts	1967	1970	1973	1976	1979	1982
			1990			
mean	9.56	9.25				
sd	0.8	0.89				
N	37,121	9,630				
			1995			
mean	9.75	9.59	9.3			
sd	0.78	0.83	0.92			
N	43,474	34,999	25,934			
			2000			
mean	9.88	9.79	9.66	9.46	9.16	
sd	0.8	0.8	0.82	0.89	0.98	
N	50,674	48,895	43,128	32,854	15,307	
			2005			
mean	9.95	9.89	9.81	9.71	9.58	9.39
sd	0.79	0.79	0.79	0.79	0.84	0.89
N	54,402	54,734	53,846	48,088	35,464	23,139
			2010			
mean	10	9.95	9.91	9.84	9.78	9.71
sd	0.88	0.87	0.87	0.86	0.84	0.83
N	52,856	53,673	53,313	49,279	41,164	31,503
			2015			
mean	9.99	9.97	9.94	9.9	9.86	9.83
sd	0.95	0.92	0.92	0.9	0.89	0.85
N	47,239	47,963	47,814	44,219	36,712	28,675
			2016			
mean	10.04	10.02	9.98	9.96	9.92	9.89
sd	0.88	0.88	0.88	0.84	0.84	0.79
N	46,556	47,238	47,193	43,545	36,117	28,026

Notes: The table presents summary statistics for the cohorts samples used in the “LoSai” (INPS) dataset. Cohort log real income at 2015 prices, its standard deviation, and the relative number of observations are presented by years.

Table 2: Real income by cohort over the entire sample

	Standard workers			WSIC workers			Total		
Cohort	mean	sd	N	mean	sd	N	mean	sd	N
1967	9.88	0.82	61,845	9.72	1.05	7,098	9.87	0.85	68,943
1970	9.84	0.83	59,931	9.72	1.06	7,737	9.83	0.86	67,668
1973	9.79	0.84	56,859	9.68	1.06	8,416	9.78	0.87	65,275
1976	9.74	0.84	49,923	9.64	1.05	8,021	9.72	0.87	57,944
1979	9.69	0.85	39,428	9.60	1.06	6,569	9.67	0.88	45,997
1982	9.65	0.84	28,846	9.54	1.06	4,751	9.64	0.87	33,597

Notes: The table presents summary statistics for the logarithm of real income at 2015 prices variable for every cohort and by groups of workers. The two groups represent workers who have never experienced a WSIC (Wage and Salary Independent Contractors) job spell (Standard workers) and those who have had at least one (WSIC workers). The cohort label represents the median birth year of each three-years cohort.

Table 3: Estimates of earnings dynamics for cohort 1982

Permanent	no RG or RW	no RG or RW	RG	RW	RW	RG+RW
Transitory	AR(1)	ARMA (1,1)	ARMA (1,1)	AR(1)	ARMA (1,1)	ARMA (1,1)
Model	1	2	3	4	5	6
σ_{α^2}						
σ_{β^2}						
$\sigma_{\alpha\beta}$						
σ_{ω^2}				0.465***	0.100***	0.002**
				(0.073)	(0.037)	(0.001)
ρ	0.359***	0.695***	0.573***	0.070***	0.434***	0.716***
	(0.006)	(0.018)	(0.031)	(0.007)	(0.057)	(0.023)
σ_{v21}	0.572***	0.592***	0.516***	0.181***	0.396***	0.572***
	(0.013)	(0.015)	(0.031)	(0.034)	(0.043)	(0.018)
θ		-0.384***	-0.296***		-0.249***	-0.371***
		(0.014)	(0.023)		(0.042)	(0.016)
σ_{ϵ^2}	0.418***	0.490***	0.506***	0.009	0.462***	0.514***
	(0.031)	(0.019)	(0.041)	(0.008)	(0.032)	(0.021)
λ_2	0.899***	0.847***	0.814***	-3.977***	0.766***	0.842***
	(0.030)	(0.015)	(0.033)	(1.475)	(0.044)	(0.015)
λ_3	0.915***	0.882***	0.847***	5.191**	0.803***	0.868***
	(0.036)	(0.018)	(0.034)	(2.216)	(0.040)	(0.018)
λ_4	0.838***	0.894***	0.861***	5.359**	0.821***	0.881***
	(0.033)	(0.019)	(0.033)	(2.285)	(0.037)	(0.019)
λ_5	-0.511***	0.860***	0.830***	-5.027**	0.794***	0.854***
	(0.025)	(0.018)	(0.032)	(2.147)	(0.036)	(0.018)
λ_6	0.820***	0.888***	0.858***	5.490**	0.827***	0.888***
	(0.032)	(0.018)	(0.034)	(2.344)	(0.036)	(0.018)
λ_7	0.907***	0.872***		5.539**	0.812***	0.873***
	(0.035)	(0.018)	(0.034)	(2.365)	(0.035)	(0.019)
λ_8	0.949***	0.865***	0.832***	5.536**	0.808***	0.874***
	(0.037)	(0.018)	(0.034)	(2.364)	(0.036)	(0.021)
λ_9	0.994***	0.896***	0.867***	5.956**	0.857***	0.921***
	(0.039)	(0.020)	(0.035)	(2.544)	(0.037)	(0.025)
λ_{10}	0.927***	0.827***	0.800***	5.555**	0.790***	0.914***
	(0.037)	(0.020)	(0.031)	(2.369)	(0.034)	(0.036)
p_2	0.997***	1.001***	0.937***	0.673***	0.835***	0.978***
	(0.023)	(0.029)	(0.061)	(0.027)	(0.041)	(0.034)
p_3	1.211***	1.155***	0.982***	0.537***	0.800***	1.246***
	(0.028)	(0.036)	(0.148)	(0.032)	(0.067)	(0.048)
p_4	1.452***	1.248***	0.977***	0.477***	0.757***	1.504***
	(0.033)	(0.042)	(0.213)	(0.030)	(0.078)	(0.066)

p_5	1.850***	1.328***	0.954***	0.438***	0.716***	1.826***
	(0.042)	(0.046)	(0.259)	(0.029)	(0.082)	(0.083)
p_6	1.589***	1.401***	0.936***	0.405***	0.696***	2.267***
	(0.037)	(0.051)	(0.298)	(0.028)	(0.086)	(0.107)
p_7	1.410***	1.397***	0.868***	0.363***	0.649***	2.805***
	(0.034)	(0.053)	(0.313)	(0.026)	(0.084)	(0.138)
p_8	1.324***	1.404***	0.811**	0.337***	0.614***	3.690***
	(0.032)	(0.053)	(0.322)	(0.025)	(0.081)	(0.207)
p_9	1.206***	1.303***	0.709**	0.300***	0.551***	4.753***
	(0.030)	(0.050)	(0.305)	(0.022)	(0.074)	(0.396)
p_{10}	1.138***	1.248***	0.630**	0.266***	0.499***	7.272***
	(0.028)	(0.046)	(0.289)	(0.019)	(0.070)	(1.133)
N	55	55	55	55	55	55

Notes: The table reports estimates for the six model specifications outlined in equations 4-6, where the permanent component includes growth heterogeneity either captured by a random walk (RW) or a random growth (RG) specification (column 3-6) or without any specification (column 1-2), and where the transitory component is modelled as an AR(1) (column 1 and 4) or as an ARMA(1,1) (column 2, 3, 5 and 6). Time shifters are included for both two components. Total Corrected standard errors in parenthesis take into account the number of individuals used when calculating the sample moments. N represents the number of moment conditions, while the number of worker-year observations is 28,846 (see table 2). P> |*z*| *** p<0.01, ** p<0.05, * p<0.1

Table 4: Estimates of earnings dynamics for cohorts 1967-1982 (loading factors omitted)

	(2)	(3)	(4)	(5)	(6)	(7)
VARIABLES	cohort 1967	cohort 1970	cohort 1973	cohort 1976	cohort 1979	cohort 1982
$\sigma_{\alpha 2}$	0.126***	0.152***	0.074***	0.269***	0.041	0.351***
	(0.009)	(0.008)	(0.027)	(0.093)	(0.083)	(0.033)
$\sigma_{\beta 2}$	0.00003**	0.00002	0.0001	0.0087*	0.0066	0.0015***
	(0.000)	(0.000)	(0.000)	(0.005)	(0.001)	(0.000)
$\sigma_{\alpha\beta}$	-0.003***	-0.004***	-0.001	-0.036	-0.001	-0.023***
	(0.000)	(0.000)	(0.001)	(0.024)	(0.004)	(0.003)
σ_{ω}^{2}	0.001***	0.003***	0.007*	0.006	0.040***	0.002**
	(0.000)	(0.000)	(0.004)	(0.017)	(0.013)	(0.001)
ρ	0.718***	0.665***	0.595***	0.623***	0.291***	0.716***
	(0.010)	(0.011)	(0.025)	(0.023)	(0.062)	(0.023)
σ_{v21}	0.483***	0.541***	0.618***	0.487***	0.456***	0.572***
	(0.009)	(0.010)	(0.012)	(0.045)	(0.017)	(0.018)
θ	-0.495***	-0.468***	-0.383***	-0.362***	-0.140***	-0.371***
	(0.007)	(0.009)	(0.014)	(0.011)	(0.046)	(0.016)
$\sigma_{\epsilon 2}$	0.367***	0.405***	0.490***	0.491***	0.314***	0.514***
	(0.010)	(0.011)	(0.018)	(0.017)	(0.041)	(0.021)
N	300	231	171	120	78	55

Notes: Loading factors are omitted and the corrected standard errors take into account the number of individuals used when calculating the sample moments. N earnings moments over the period 1990–2016 are cohort-specific. σ_{α}^{2} represent the earnings capacity at the beginning of the working life, σ_{β}^{2} the variability in growth rates and $\sigma_{\alpha\beta}$ the trade-off between initial earnings and subsequent earnings growth. σ_{ω}^{2} is the random walk. The transitory error is serially correlated by a low-order ARMA process. $\sigma_{v}{}^{2}{}_{1}$ represents the variability of the transitory shock fading out at rate ρ but deviating from that smooth fade-out rate by θ in the next period. σ_{ϵ}^{2} represents the variance of the primitive error term ϵ_{it}. P> |*z*| *** p<0.01, ** p<0.05, * p<0.1

Table 5: Estimates of earnings dynamics for cohorts of standard and WSIC workers

	(2)	(3)	(4)	(5)	(6)	(7)
VARIABLES	cohort 1967	cohort 1970	cohort 1973	cohort 1976	cohort 1979	cohort 1982
			Standard workers			
$\sigma_{\alpha 2}$	0.123***	0.146***	0.072***	0.269***	0.049	0.351***
	(0.010)	(0.007)	(0.026)	(0.011)	(0.074)	(0.033)
$\sigma_{\beta 2}$	0.00004***	0.00001	-0.00001	0.00004***	-0.0009	0.0015***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)
$\sigma_{\alpha\beta}$	-0.003***	-0.004***	-0.001	-0.011***	0.001	-0.023***
	(0.000)	(0.000)	(0.001)	(0.001)	(0.004)	(0.003)
σ^2_ω	0.001***	0.003***	0.006*	0.002***	0.033***	0.003***
	(0.000)	(0.000)	(0.003)	(0.001)	(0.011)	(0.001)
ρ	0.720***	0.653***	0.588***	0.663***	0.289***	0.704***
	(0.010)	(0.012)	(0.025)	(0.015)	(0.065)	(0.023)
σ_{v21}	0.471***	0.506***	0.566***	0.474***	0.406***	0.508***
	(0.010)	(0.010)	(0.011)	(0.010)	(0.015)	(0.017)
θ	-0.492***	-0.461***	-0.383***	-0.424***	-0.138***	-0.358***
	(0.007)	(0.010)	(0.014)	(0.011)	(0.048)	(0.016)
$\sigma_{\epsilon 2}$	0.360***	0.371***	0.442***	0.416***	0.272***	0.439***
	(0.010)	(0.011)	(0.017)	(0.011)	(0.040)	(0.020)
N*	300	231	171	120	78	55
			WSIC workers			
$\sigma_{\alpha 2}$	0.293**	0.114***	0.159***	0.215***	0.558**	0.716
	(0.140)	(0.039)	(0.041)	(0.054)	(0.263)	(0.748)
$\sigma_{\beta 2}$	0.0019*	0.00013**	0.00016**	0.00038***	0.0085*	0.0208
	(0.001)	(0.000)	(0.000)	(0.000)	(0.005)	(0.031)
$\sigma_{\alpha\beta}$	-0.011	-0.004***	-0.007***	-0.010***	-0.039	-0.095
	(0.007)	(0.001)	(0.002)	(0.003)	(0.026)	(0.137)
$\sigma_{\omega 2}$	0.027**	-0.000	0.002*	0.001	0.062**	-0.039
	(0.012)	(0.000)	(0.001)	(0.001)	(0.028)	(0.080)
ρ	0.817***	0.770***	0.664***	0.750***	0.639***	0.645***
	(0.018)	(0.026)	(0.037)	(0.029)	(0.050)	(0.083)

σ_{v21}	0.675***	0.935***	1.080***	1.020***	1.081***	0.929***
	(0.047)	(0.047)	(0.048)	(0.048)	(0.071)	(0.104)
θ	-0.488***	-0.535***	-0.455***	-0.477***	-0.303***	-0.327***
	(0.017)	(0.022)	(0.029)	(0.023)	(0.030)	(0.066)
$\sigma_{\epsilon 2}$	0.598***	0.707***	0.770***	0.816***	0.910***	2.821***
	(0.042)	(0.051)	(0.059)	(0.053)	(0.077)	(1.040)
N*	300	231	171	120	78	55

Notes: Loading factors are omitted and the corrected standard errors take into account the number of individuals used when calculating the sample moments. N earnings moments over the period 1990–2016 are cohort-specific. σ_α^2 represent the earnings capacity at the beginning of the working life, σ_β^2 the variability in growth rates and $\sigma_{\alpha\beta}$ the trade-off between initial earnings and subsequent earnings growth. σ_ω^2 is the random walk. The transitory error is serially correlated by a low-order ARMA process. $\sigma_v{}^2{}_1$ represents the variability of the transitory shock fading out at rate ρ but deviating from that smooth fade-out rate by θ in the next period. σ_ϵ^2 represents the variance of the primitive error term ϵ_{it}. P> |z| *** p<0.01, ** p<0.05, * p<0.1