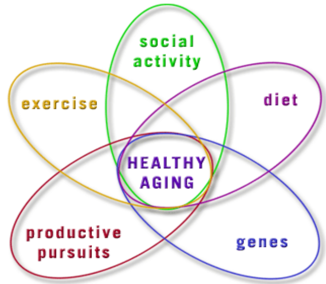


HALM

HEALTHY AGEING AND THE LABOUR MARKET

HALM Working Paper

Characterizing Income Shocks over the Life-cycle

Koray Aktaş
Lorenzo Cappellari

Working Paper n. 1-2017

UNIVERSITÀ
CATTOLICA
del Sacro Cuore

Characterizing Income Shocks over the Life-cycle

Koray Aktaş
Università Cattolica del Sacro Cuore
Lorenzo Cappellari
Università Cattolica del Sacro Cuore, IZA

Working Paper n. 1-2017

HALM Project
Dipartimento di Economia e Finanza
Università Cattolica del Sacro Cuore
Largo Gemelli 1 - 20123 Milano – Italy
tel: +39.02.7234.2976 - fax: +39.02.7234.2781
e-mail: dip.economiaefinanza@unicatt.it

The HALM Working Paper Series is intended to circulate research results of the Università Cattolica del Sacro Cuore D3.2. strategic project on the “Socio-economic implications of active ageing and the effects on health” by team members of the project. (more details at http://progetti.unicatt.it/progetti-ateneo-halmhome).

Characterizing Income Shocks over the Life-cycle

Koray Aktaş[a] and Lorenzo Cappellari[a,b]

[a] *Department of Economics and Finance, Università Cattolica, Milan*
[b] *IZA, Bonn*

February 7, 2017

Abstract

In this paper, using a large-scale administrative data from the archives of Italian Social Security Administration, we decompose income inequality into its permanent and transitory components over the life-cycles of Italian male workers. We adopt a novel semi-parametric specification that minimises assumptions about life-cycle earnings dynamics. We show that there is a substantial increase in inequality after age 50. Both permanent and transitory components contribute to the increase; however, we find a distinctive acceleration driven by the rise in the income instability. We show that only about half of this increased instability is coming from movements in and out of employment, the rest being the outcome of earnings fluctuations.

Keywords: Income inequality, instability, permanent and transitory variance, variance component model, older workers.

JEL codes: J21, J31

Correspondence: Aktas: Email: koray.aktas@unicatt.it; Cappellari: Email: lorenzo.cappellari@unicatt.it

Acknowledgments: We gratefully thank the "HALM- Healthy Ageing and the Labour Market" D3.2 Strategic Grant at Università Cattolica for financial support.

1 Introduction

Increasing income inequality has been a topic of emerging concern since the late 1970s in Western economies and is still considered as one of the biggest economic challenges for nations. A substantial amount of studies have documented the changes in the income distributions for Western countries–mostly for US and UK. Thanks to the availability of large-scale panel datasets, applied economists have been paying attention to the dynamic structure of individuals income and examining the sources of rising income inequality. These studies in the literature are based on the Friedman (1957)'s permanent income hypothesis and decompose the income inequality into permanent and transitory components by using variance-component models. Many of these studies mainly focus on the trends in income inequality over the *years* and demonstrate whether these trends are driven by the changes in dispersion of permanent or transitory incomes.

The present paper provides an up-to-date evidence for Italy with a specific focus on the characterization of income shocks over the individuals' *life-cycles* using an administrative panel from the archives of Italian Social Security Administration (INPS). We aim to shed some light on the recent debates on the struggles older workers have been facing in the Italian labor market by estimating income instability with a semi-parametric econometric model that releases the restrictions that are used in the existing literature on the specification of transitory shocks. In theory, transitory shocks have no impact on individuals welfare since these shocks are assumed to be perfectly insurable. However, an important point needs to be addressed concerning the possible effects of an increase in the transitory fluctuations on individuals welfare. As discussed by Haider (2001) and Baker and Solon (2003), growth in transitory inequality can still force individuals, especially the liquidity-constrained ones, to reduce their consumption and hence affect their welfare even though their long-term incomes are not affected. Furthermore, when individuals are hit by transitory shocks at late stage in their life-cycles, they may not have enough time to smooth the effect of these shocks out given that some transitory shocks are quite persistent, or even if they do, this "smoothing" period can be costly for them (e.g. one could decide to postpone, or anticipate, his retirement decision in such period, which would be a considerable welfare loss). Therefore, characterizing income shocks accurately over the life-cycle is important to understand which type of shocks workers are exposed to at which stage of their working life.

According to the permanent income hypothesis, there are two components to account for the growth in income inequality: permanent (long-term) and transitory (short-term) components. Permanent inequality can be increased by the changes in the demand for skilled labor or by the skill biased technological developments (Moffitt and Gottschalk (1995)). Basically, given ability as a persistent characteristic of individuals, it is plausible to expect the changes in labor market conditions relevant for skills to have an impact on the lifetime incomes of individuals. Rising transitory inequality, on the other hand, is an outcome of increasing labor market fluctuations, decrease in the power of unions, increase in international trade, and it affects the incomes of individuals only in the short-run. Although the initial argument of Friedman (1957) claimed that transitory shocks are just white noise and do not have any effect on neither consumption nor welfare of individuals, evidence shows that transitory shocks are rather serially-correlated –a low order autoregressive process such as ARMA (1,1)– and that they may play as important role as the long-term component does in terms of explaining the increase in earnings inequality (Lillard and Willis (1978); Lillard and Weiss (1979); Moffitt and Gottschalk (1995)). Nevertheless, the core argument on transitory shocks as being of secondary importance remains the same since these shocks are easier to be smoothed than the permanent ones.

There is a vast amount of studies on the characterization of income process and inequality. As mentioned above, the empirical strategies in this literature are motivated by Friedman's permanent income hypothesis. Early studies worked on individuals' permanent and transitory incomes by fitting those two into parametric models (see Lillard and Willis (1978); Lillard and Weiss (1979); Hause (1980); MaCurdy (1982); Abowd and Card (1989)). Since the seminal work of Moffitt and Gottschalk (1995), economists have been particularly focusing on the components of inequality, permanent-transitory, using variance-component models. A big body of this literature provided evidence on the trends in permanent and transitory inequality over time for different countries: Moffitt and Gottschalk (1995), Haider (2001), Meghir and Pistaferri (2004), Moffitt and Gottschalk (2012), DeBacker et al. (2013) for the US; Dickens (2000), Kalwij and Alessie (2007) for the UK; Baker and Solon (2003) on Canada; Cappellari (2004), Cappellari and Leonardi (2016) for Italy; Bingley et al. (2013) on Denmark; and Sologon and Van Kerm (2014) on Luxembourg. Although some of the studies mentioned above have also provided, to some extent, evidence on income inequality that individuals experience over their life-cycles, the econometric specifications used in those studies impose parametric restrictions, especially, on the characterization of transitory shocks. In this paper, we relax those restrictions and provide an unrestricted life-cycle profile of transitory shocks.

On the other hand, Cunha and Heckman (2016) take a further discussion on the current literature of earnings inequality and its components. They discuss the extent to which transitory components are predictable by the agents–i.e. transitory components might be predicted perfectly or partially, or might not be predicted at all by the agents. They shift their focus to the predictable and unpredictable components of earnings variance, and find that both components have increased in the US, while a big proportion of increase in inequality for less skilled workers is driven by the increase in uncertainty–unpredictable component.

As mentioned previously, income inequality is also linked to consumption inequality, thereby, to the macroeconomic literature. Individuals respond differently to permanent and transitory shocks and adjust their consumptions and savings in order to smooth out the effects of these shocks. There are several studies that explore the link between earnings and consumption inequality. Blundell et al. (2008) provide evidence on the latter and their results suggest that a significant amount of consumption smoothing appears to respond to transitory income shocks while much less to permanent shocks. Krueger et al. (2010) investigate different types of inequalities such as income, consumption and wealth for nine countries–US, Canada, UK, Germany, Italy, Spain, Sweden, Russia and Mexico. Their findings show that the increase in the disposable income inequality over the life-cycle is greater than the increase in the consumption inequality for those countries. The latter result can be explained by the presence of insurable shocks. If the rise in income inequality is driven by the insurable transitory shocks or by the partially insurable permanent shocks, consumption inequality will stay at a lower level than the income inequality. Liquidity constrains, on the other hand, would reduce the gap between income and consumption inequality. Huggett et al. (2011), show that the initial condition of individuals, age 23, is the main derivative of the differences in lifetime earnings and lifetime wealth rather than the shocks that individuals are hit by during their life-cycle. However, the latter result is obtained by a model that does not take into account the transitory shocks and they conclude that it will take a further research to develop a richer model that captures all kind of shocks.

In this article, we develop a rich econometric model to decompose annual income inequality into permanent and transitory components for Italian male workers and quantify the income risks they are facing over their labor market life-cycles. Italy has undergone some significant labor market reforms in last two decades, yet there is no evidence on the income dynamics of Italian labor market regarding the years after early 2000s. A recent study of Cappellari and Leonardi (2016) explore the trends in inequality and the effects of tenure on earnings instability in Italy for the years of 1986-2003. They report that one year of tenure reduces instability about 11%, moreover, workers holding temporary contracts have from 50% to 100% higher instability than the workers on permanent contracts. We use an updated version of their data spanning the years of 1985 to 2012 and estimate the patterns of income shocks (permanent-transitory) over life-cycle[1]. We observe a substantial amount of increase in the variance of annual log-incomes from ages of 50 to 60 while the variance follows a flat pattern in the early ages. Our results indicate that that increase after age 50 is driven by the increases in the variances of both transitory and permanent components, however, the accelerating pattern in that increase is consistent with the pattern that transitory variance follows. The latter result is robust as it holds for both different econometric specifications and sample selections.

[1]Results for inequality trends over the years can be found in Appendix.

Basten et al. (2014) provide evidence on a significant severance payment effect on unemployment durations (reduction in re-employment after 12 months) of workers at age 50 in Norway. Their findings suggest that sensitivity in unemployment durations for cash-on-hand is most likely caused by the existence of liquidity constraints. Considering the fact that Norway has one of the richest and most equitable wealth distributions in the world (Basten et al. (2014)), older workers in Italy might be facing, even stronger, liquidity constraints as well. In which case, unlike the common perception on the effects of transitory shocks in the existing literature, workers over age 50 can experience severe welfare losses due to the significant increase in income instability.

On the other hand, our findings are in line with the arisen concerns for older workers in Italy. According to The National Institute for Statistics of Italy (ISTAT), unemployment rate of individuals over age 55 has increased from 2.4% in 2007 to 5.5% in 2012. Moreover, in accordance with the INPS, the poverty and unemployment have proportionally increased in the space of six years (from 2008 to 2014) within age group of 55-65 years[2]. Accordingly, a policy proposal has been made by INPS to the Italian government concerning the workers in that age group. The proposed legislation was to establish a minimum income amounting to €500 per month for households with at least one 55-year-old (or older) member. Although the concerns regarding older workers have been acknowledged by the government, the proposal has been rejected as it was found inapplicable due to its costs.

Another contribution of this paper is to set up a more flexible variance-component model to estimate the covariance structure of incomes than

[2]http://www.corriere.it/economia/15_novembre_05/inps-reddito-minimo-garantito-500-55-anni-su-d08dfbda-83bf-11e5-8754-dc886b8dbd7a.shtml

the rest of the literature. In our featured econometric model, permanent income shocks specified as random walk process while allowing its variance to vary at age level (Dickens (2000); Sologon and Van Kerm (2014)), and transitory shocks specified as ARMA (1,1) process with an age-specific variance. More specifically, we do not impose any parametric restriction on the specification of the variance of transitory component. As a result, our model accurately estimates the income instability over the life-cycle. To the best of our knowledge we are the first in existing literature to establish such flexible structure in characterizing transitory shocks by allowing age-level heterogeneity in its variance[3]. Additionally, our model takes into account the fluctuations in incomes generated by the workers' labor market entries and exits. Manovskii et al. (2015) show that estimating income dynamics without taking into account these fluctuations produces higher estimates for the variance of transitory (permanent) shocks if the estimation based on the levels (differences) in earnings. Our results are in line with the latter evidence and suggest that it is essential to disentangle the effects of repetitive in-and-out movements of workers in the labor market on estimated variance of transitory shocks in order to capture a genuine lifetime income instability.

The rest of the paper is organized as follows: we provide information on our data and present descriptive statistics in Section 2. In Section 3 and Section 4, we construct our econometric model and explain the estimation method, respectively. Section 5 contains our empirical results, we summarize and conclude the main findings in Section 6.

[3]Previous studies have characterized transitory shocks as low order autoregressive process (mostly as ARMA (1,1) or AR (1)) as well but either with a constant variance or with a variance that is allowed to vary as a linear or quartic function in age (for the latter see Baker and Solon (2003); Moffitt and Gottschalk (2012); Sologon and Van Kerm (2014)).

2 Data and Descriptive Statistics

2.1 Data

The data used in this study come from the archives of Italian Social Security Administration (INPS) covering the years from 1985 to 2012. The data draw randomly social security records from a one out of ninety samples of employees who were born on the 10th of March, June, September and December of each year.

Our data only contain information on private sector workers. The reason behind this is the INPS aims to assess retirement benefits for the private sector employees. As a result, we lose the track on individuals who leave private sector for such reasons as self-employment, flowing into public and agricultural sectors. This is one of the common restrictions of using administrative data. Another restriction that we have is the limited information on individuals' observable characteristics. In our case, the data provide information on annual earnings, year of birth, gender, type of contract (permanent, temporary), occupation and working weeks of employees.

2.2 Sample Selection

Our main target group is white and blue-collar male workers holding full-time contracts in the private sector. We also set an age restriction and focus on only the individuals between the ages of 25 and 60. These individuals are more likely to complete their educational studies and are too young to flow into retirement since the retirement age for males is 65 in Italy. This restriction is a recurrent one in this literature, especially considering the fact that many of the administrative data do not hold information on education levels of individuals. Therefore, excluding younger workers allows us to have consistent results that are not affected by the educational choices of those who proceed with their graduate studies. In the light of previous studies (such as Haider (2001); Baker and Solon (2003)), we identify 45 birth-cohort groups for the individuals who have positive incomes and matched with the restrictions stated above while allowing each birth-cohort to be observed at least ten years of period in the data. Since our focus is on the life-cycles of individuals and we observe the same ages in different years in the data, it is crucial for our analysis to take into account cohort and time effects so that we will be able to estimate income inequality over the life-cycle more accurately.

The oldest cohort in our working sample is 1934 (51 years old in 1985) and the youngest one is 1978 (34 years old in 2012)[4]. Cohorts from 1952 to 1960 are fully observed in between the years 1985-2012. The last restriction we set is to keep only the individuals who are observed in the data at least 5 consecutive years. Two reasons to have such a restriction. First, to have a consistent working sample that consists of individuals who continuously participate in the labor market (Baker and Solon (2003); Cappellari and Leonardi (2016)). Second, it makes easier to distinguish transitory and permanent shocks from one another (Blundell et al. (2015)). Although transitory shocks have effects on the workers mostly in the first year they hit and they fade as the individual ages, some of these shocks can be more persistent and behave like a permanent shock. Therefore, having individuals who are continuously observed in our working sample allows us to separate permanent and transitory shocks.

[4] As stated above, we want to observe each birth-cohort at least 10 years. Therefore, given 1985 is the first year in our data and 60 is the oldest age; 1985-60=1925, 1925+9=1934 is the oldest cohort in our working sample. The last year in our data is 2012 and the youngest age is 25; 2012-25=1987, 1987-9=1978 is the youngest cohort in our working sample.

Table 1: **Sample size by birth-cohort**

Cohort	Person	Person-Year	Age range	Year range
1934	8,384	67,828	51-60	1985-1994
1935	9,110	79,612	50-60	1985-1995
1936	9,050	82,616	49-60	1985-1996
1937	9,920	94,821	48-60	1985-1997
1938	11,276	112,254	47-60	1985-1998
1939	12,055	124,273	46-60	1985-1999
1940	12,287	132,426	45-60	1985-2000
1941	11,406	129,183	44-60	1985-2001
1942	11,647	139,604	43-60	1985-2002
1943	11,790	146,848	42-60	1985-2003
1944	12,374	162,128	41-60	1985-2004
1945	12,288	170,702	40-60	1985-2005
1946	15,974	233,698	39-60	1985-2006
1947	16,718	258,121	38-60	1985-2007
1948	17,115	279,215	37-60	1985-2008
1949	16,362	277,259	36-60	1985-2009
1950	16,456	289,700	35-60	1985-2010
1951	15,742	291,431	34-60	1985-2011
1952	15,825	300,954	33-60	1985-2012
1953	16,017	307,616	32-59	1985-2012
1954	16,728	321,352	31-58	1985-2012
1955	17,052	329,529	30-57	1985-2012
1956	17,546	334,255	29-56	1985-2012
1957	18,219	345,724	28-55	1985-2012
1958	18,417	347,552	27-54	1985-2012
1959	19,296	364,986	26-53	1985-2012
1960	20,164	374,522	25-52	1985-2012
1961	20,577	370,310	25-51	1986-2012
1962	21,517	374,148	25-50	1987-2012
1963	22,111	371,517	25-49	1988-2012
1964	23,806	386,080	25-48	1989-2012
1965	24,130	377,334	25-47	1990-2012
1966	23,509	354,361	25-46	1991-2012
1967	22,939	332,317	25-45	1992-2012
1968	23,211	321,279	25-44	1993-2012
1969	22,595	298,483	25-43	1994-2012
1970	22,392	284,108	25-42	1995-2012
1971	22,150	269,439	25-41	1996-2012
1972	21,374	248,719	25-40	1997-2012
1973	20,752	232,719	25-39	1998-2012
1974	20,732	219,296	25-38	1999-2012
1975	19,341	193,852	25-36	2000-2012
1976	18,346	173,759	25-35	2001-2012
1977	16,604	146,434	25-34	2002-2012
1978	15,337	125,113	25-33	2003-2012
Total	770,641	11,177,477		

2.3 Descriptive Statistics

In the end, our working sample is an unbalanced panel that consists of 770,641 individuals with 11,177,477 person-year observations spanning the years 1985-2012. Table 1 contains the summary statistics of the structure of our working sample for each cohort. As can be seen in Table 1, older cohorts are smaller in sample size than the younger ones. Nevertheless, our data is a very large administrative panel set, thereby, even our smallest sample, cohort 1934, consists of 8,384 individuals and yet, is still bigger than the biggest sample size of many other studies in this literature (i.e. the biggest sample of Baker and Solon (2003) contains 3,049 individuals as a sum of two birth-cohorts 1960-61).

Figure 1: **The variance of log labor incomes over the life-cycle.**

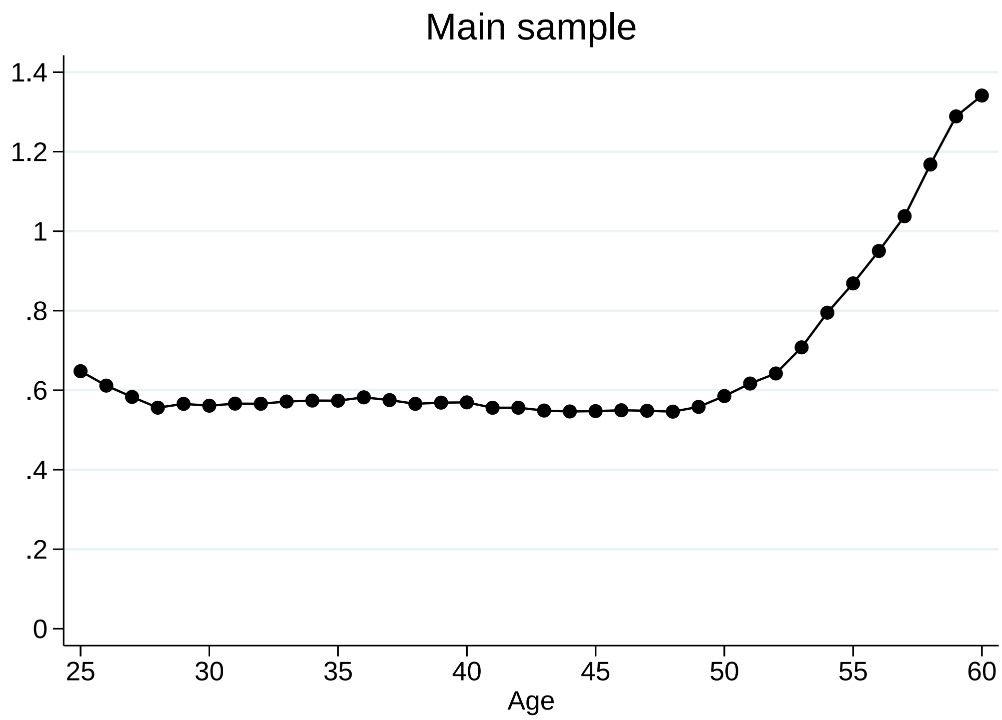
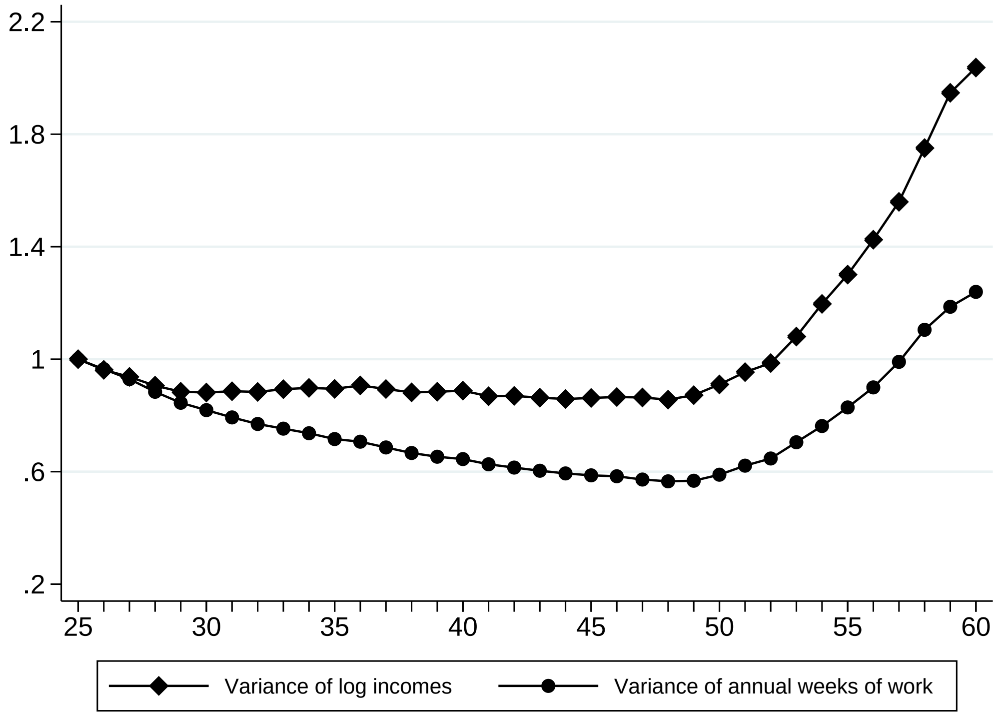


Figure 1 highlights the variance of log labor incomes over the life-cycle of individuals in our working sample. The variance of our initial age, 25, is 0.66

and follows a downward trend until age 29. This can be explained by the fact that during the early stages of the life-cycle individuals tend to change their jobs more frequently than the later stages. For example, one can accept a low-pay job offer just to enter the labor market and then when he finds a better offer he will move to his new job. According to the findings of Celik et al. (2012), job-to-job mobility increases earnings volatility. At age 29 the variance is 0.59 and stays rather stable until age 49 at around 0.58. An increase in the variance of log incomes starts with the age 50 and it strictly and significantly increases until the end of life-cycle and reaches 1.36 at age 60. The substantial increase in the variance after age 50 shows, in a descriptive way, how much the Italian labor market is volatile for elder workers. However, the increase displayed in Figure 1 is very heterogeneous. Meaning that, it involves time and cohort effects along with the sum of increases in the variances of permanent and transitory components. Our aim is to provide an insight on the determinants of such an upward trend during the late stage of life-cycle by estimating the inequality with a flexible model. The model and the results shall be discussed later in this paper.

Figure 2 displays the variances of both log labor incomes and annual weeks of work through the life-cycle. In order to be able to compare the patterns, variances are normalized to 1 at age 25. The variance of annual weeks of work follows a U-shaped pattern over the life-cycle and it is on the increase after age 50 as the variance of log incomes. It can be clearly seen in Figure 2 that the increase in the variance of annual working weeks plays an important role on the increase in the variance of incomes. The increase in the volatility of working weeks is an outcome of increases in job instability in the labor markets (Cameron and Tracy (1998)). One important question on this increase in the annual weeks of work is that whether or not workers reduce their working weeks

Figure 2: **The variance of log labor incomes and the variance of annual weeks of work over the life-cycle**



Both lines are normalized to 1 at age 25.

voluntarily. In theory, individuals anticipate their labor market life-cycle once they enter the market and flow into retirement at the age they anticipated in the first place (Meghir and Pistaferri (2011)). Therefore, if the reduction in the amount of weeks of work is happening voluntarily, it should increase the permanent inequality. On the other hand, as stated above, older workers in Italy have been suffering from high level of a job instability, which is linked to the transitory shocks, so when the latter is the case an increase in the variance of transitory component should be observed for older workers.

3 Econometric Model

In this section we specify a rich econometric model in order to decompose the labor income inequality into its components (permanent-transitory) over the life-cycle by exploiting our large-scale administrative data. Having a parametric model is necessary to detail the structure of earnings inequality, which is something not possible to do by analyzing only the descriptive statistics. Our main goal is to show that the increase in the variance of incomes to what extent caused by the changes in the permanent, long-term, inequality and to what extent caused by the changes in the transitory, short-run, inequality. To answer this question we develop a flexible model of incomes dynamics that accounts for the life-cycle effects in permanent incomes and the serially correlated transitory shocks while controlling for the unobserved heterogeneity within birth-cohorts and time-periods.

Additionally, we estimate the labor market fluctuations generated by the in-and-out labor market movements of workers along with the permanent and transitory components of earnings inequality. This fluctuations are going to be referred as "rare shocks" in the rest of this paper. Especially at the early and late stages of the life-cycle the variance of incomes inflated by these rare shocks. One possible way to overcome this issue is to drop first and last observations of individuals (Baker and Solon (2003)). Another way is to include these shocks into the estimation procedure (Manovskii et al. (2015)). Our preferred model involves the latter, however, we shall also present the results from a model that comprises the former.

We first de-mean log-incomes from its time- and cohort-specific means by running cohort-specific regressions on time dummies, then we denote these log-deviations (residuals) with y_{it}:

$$y_{it} = \mu_{it} + \upsilon_{it};\;\; E(\mu_{it}\upsilon_{it}) = 0;\;\; i = 1, ..., N;\;\; t = t_c, ...T_c, \tag{1}$$

where i stands for the individuals, t denotes time periods, $c = c(i)$ is for the birth-cohort of individual i and y_{it} is the individual log-income deviations from cohort- and period-specific means consist of the sum of permanent (μ) and transitory (υ) components which are specified as random walk (RW) and autoregressive moving average (ARMA(1,1)) processes, respectively. μ_{it} and υ_{it} are orthogonal to each other by assumption.

So the simplest variance-component model would be the following:

$$Var(y_{it}) = \sigma^2_\mu + \sigma^2_\upsilon, \tag{2}$$

where σ^2_μ and σ^2_υ are the variances in permanent and transitory components, respectively. However, Equation 2 has several weaknesses given the actual structure of earnings dynamics (Baker and Solon (2003)). For instance, it does not capture the changes in income inequality over time and birth-cohorts. Therefore, we include time-specific factor loadings into our model (Moffitt and Gottschalk (1995); Haider (2001); Baker and Solon (2003)) and our model becomes

$$\begin{aligned} y_{it} &= p_t\mu_{it} + \pi_t\upsilon_{it}, & (3)\\ Var(y_{it}) &= p_t^2\sigma^2_\mu + \pi_t^2\sigma^2_\upsilon, & (4) \end{aligned}$$

where p_t and π_t are the year-specific factor loadings on the permanent and transitory components, respectively, and both are normalized to 1 in year 1985.

The roles of p_t and π_t are explained explicitly in Baker and Solon (2003). As a summary, an increase in p_t does not change the order of individuals in the income distribution but does increase the gap between their income and this increased-gap resists year by year. An increase in π_t, on the other hand, mixes the rank of individuals in the income distribution and this mixing process repeats every year.

We also include cohort-specific factor loadings into our model in order to capture the variations in inequality across birth-cohorts

$$y_{it} = p_t \gamma_c \mu_{it} + \pi_t \varphi_c \upsilon_{it}, \tag{5}$$

$$Var(y_{it}) = p_t^2 \gamma_c^2 \sigma_\mu^2 + \pi_t^2 \varphi_c^2 \sigma_\upsilon^2, \tag{6}$$

where γ_c and φ_c are the cohort shifters on permanent and transitory components, respectively[5]. Cohort shifters on permanent component, γ_c, are associated with the entire process alongside time shifters, while the cohort shifters, φ_c, are only associated with the initial condition of transitory component. The latter specification, the details are provided below, is necessary for the identification of transitory component since transitory shocks are specified as an autoregressive process[6] (Baker and Solon (2003); Sologon and Van Kerm (2014); Cappellari and Leonardi (2016)).

Next we specify the components of inequality. Following the previous studies (Abowd and Card (1989); Moffitt and Gottschalk (1995); Dickens (2000); Sologon and Van Kerm (2014)) we estimate permanent component, μ_{it}, as a random walk process that varies with age

[5]Both cohort shifters are normalized to 1 at birth-cohort 1953 for identification.
[6]See Appendix-B for the moment restrictions and identification of parameters.

$$
\begin{aligned}
\mu_{it} &= \mu_{i(c+25)} \sim iid(0, \sigma^2_{\mu_{c+25}}), \;\; if \; t = c + 25, \\
\mu_{it} &= \mu_{i,t-1} + \phi_{it}, \qquad\qquad\qquad if \;\; t > c + 25, \\
\phi_{it} &\sim iid(0, \sigma^2_{\phi_{t-c}}), \;\; E(\mu_{i,t-1}, \phi_{it}) = 0.
\end{aligned} \tag{7}
$$

Random walk specification in permanent earnings, also known as "restricted income profiles" (RIP) in the literature, captures highly persistent income shocks that individuals are exposed to during their life-cycles. While many of the studies in corresponding literature specify random walk process with a constant variance, we follow a procedure similar to Dickens (2000); Sologon and Van Kerm (2014) and allow the variance of random walk process, ϕ_{it}, to vary at age level. Blundell et al. (2015) found that allowing age-specific heterogeneity in the variances of components of income inequality is essential to estimate accurately the income dynamics of labor market.

As for the transitory component, a low-order autoregressive moving average process, ARMA (1,1), is set in our model (MaCurdy (1982); Moffitt and Gottschalk (1995); Dickens (2000); Haider (2001); Sologon and Van Kerm (2014)). While the majority in the literature specify the variance of transitory component as a constant (Moffitt and Gottschalk (1995); Dickens (2000); Haider (2001)) and some of them allow it to follow a linear (Moffitt and Gottschalk (2012)) or a quartic function in age (Baker and Solon (2003); Sologon and Van Kerm (2014)), we once again let the variance of transitory component to vary at age level

$$\begin{aligned} \upsilon_{it} &= \rho\upsilon_{i,t-1} + \zeta_{it} + \theta\zeta_{i,t-1}, \\ \upsilon_{i0} &\sim (0, \eta_c\sigma_0^2), \quad if \;\; t = c + 25, \\ \zeta_{it} &\sim (0, \sigma^2_{\zeta_{t-c}}), \quad if \;\; t > c + 25, \end{aligned} \tag{8}$$

where the moving average parameter, θ, captures the sharp fall of first lag autocovariance and the autoregressive parameter, ρ, represents the persistence of the transitory shocks, υ_{i0} is the initial condition of ARMA (1,1) process with a cohort-specific variance, η_c stands for the cohort-specific factor loadings capture the aggregate alterations in the distribution of transitory incomes. Transitory shocks, ζ_{it}, are white-noise with zero mean and age-specific variance. To the best of our knowledge we are the first study that provides an unrestricted life-cycle profile of transitory shocks.

In order to strengthen the identification of age-specific shocks in permanent, ϕ_{it}, and transitory, ζ_{it}, components, we group these shocks by two age-year between the ages of 26 and 57, and by three age-year for the ages 58-59-60. This type of adjustments are commonly used in the literature (see also Sologon and Van Kerm (2014)).

At the last stage, we include the rare-shocks into our model. To do so, a dummy variable generated based on the in- and out-movements of individuals in the labor market. More specifically, the dummy, r, is equal to 1 at the beginning and end of each spell of each individual, otherwise is equal to 0. The finalized version of our variance-component model becomes

$$Var(y_{it}) = p_t^2\gamma_c^2\sigma_\mu^2 + \pi_t^2\varphi_c^2\sigma_\upsilon^2 + \sigma_r^2 I(r = \underline{\tau} | r = \bar{\tau}), \tag{9}$$

where σ_r^2 stands for the variance of rare-shocks and is uncorrelated with permanent and transitory components by assumption, I is an indicator function, $\underline{\tau}$ and $\bar{\tau}$ stand for the labor market entry and exit, respectively. In the results section, we shall highlight different results obtained from different econometric specifications that do not involve rare-shocks and discuss these findings by comparing them to our baseline model which has been presented in this section.

4 Estimation Method

We estimate the parameters of our model outlined in the previous section by using GMM minimum distance estimation (Chamberlain (1984); Abowd and Card (1989)). This method estimates the parameters of interest by minimizing the squared distance between the sample moments of empirical covariance-matrix that obtained from our working sample and the theoretical covariance-matrix structure implied by our model.

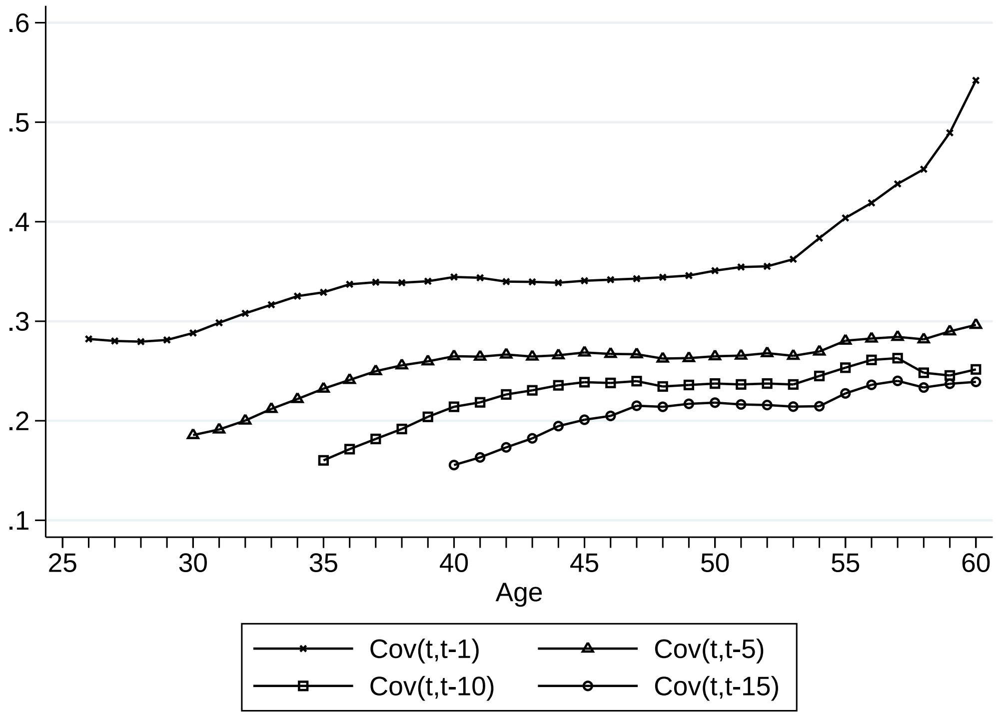
Suppose that Θ represents the parameters of interest to be estimated so the minimum distance estimator minimizes the distance function by choosing Θ:

$$\Theta = \underset{\Theta}{\operatorname{argmin}} \; [m - f(\Theta)]W[m - f(\Theta)]', \tag{10}$$

where $f(\Theta)$ is the theoretical covariance structure, m is the empirical counterpart of $f(\Theta)$ and is a vector with dimension of $(\sum_c \Omega_c(\Omega_c + 1)/2) \times 1$ derived by assembling m_c over cohorts, $m_c = vech(M_c)$, M_c is the empirical covariance-matrix for birth-cohort c and Ω_c is the number of years that cohort c is observed, W is a positive definite weighting matrix.

Chamberlain (1984) shows that choosing W as an inverse matrix of income's fourth moments is the asymptotically optimal choice to weight the minimization problem. Nevertheless, as discussed by Altonji and Segal (1996) the latter choice on the weighting matrix produces biased estimates due to the correlation in sampling errors between second and fourth moments. Therefore, in the light of other studies in the literature, we choose the weighting matrix, W, as an identity matrix. This estimation method is called *Equally Weighted Minimum Distance Estimation* (EWMD) which is tantamount to non-linear least squares. However, non-linear least squares methods produce biased estimated covariance matrix of Θ because of the heteroskedasticity and autocorrelation in m. Therefore, at the last stage by using the fourth-moments we estimate standard errors robust to these problems (Cappellari (2004)).

Figure 3: **Income covariances over the life-cycle**



4.1 Descriptive Moments

We obtain 10,632 sample moments by stacking 45 m_c vectors into the aggregate vector m. In Figure 3, we plot the covariance structure of log-income residuals, y_{it}, obtained by the demeaning process which has been explained in Equation 1[7]. The figure highlights the covariances with different time interval widths: 1, 5, 10, 15. The longer the width is the closer the covariances to the variance of permanent component since the effects of transitory shocks fade over time. The latter descriptive evidence is informative in terms of explaining the source of the accelerating pattern in the log-income variance after age 50 (see Figure 1). We see a smoothly increasing pattern for the covariances with 5th, 10th and 15th lags, which indicates that the peak after age 50 in the variance is driven by the transitory shocks.

5 Results

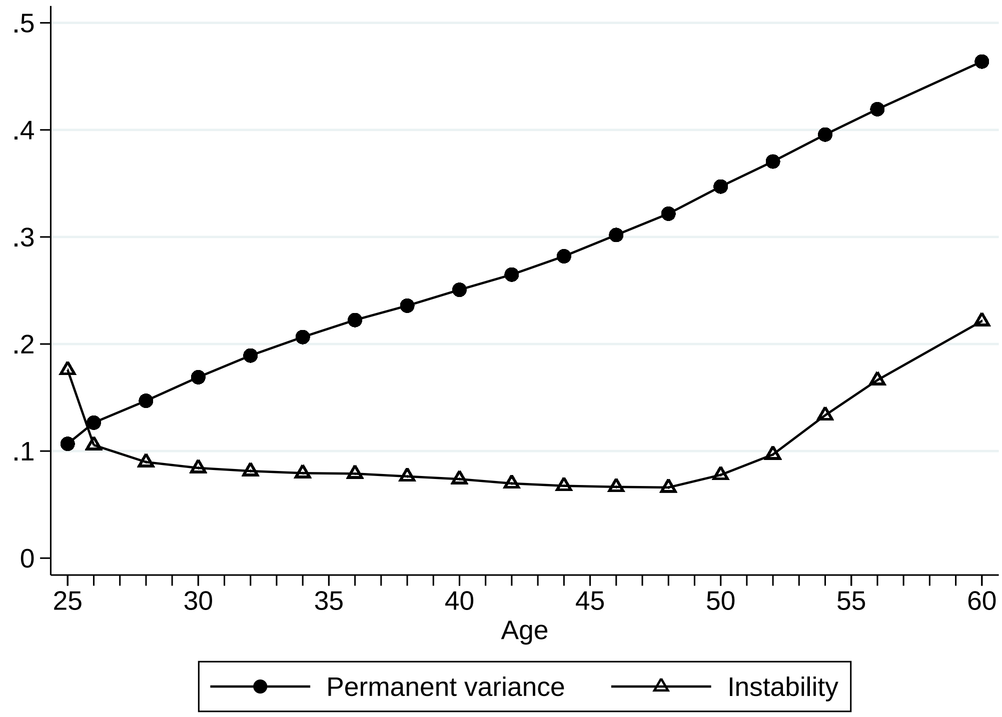
In this section we start off presenting the results of our baseline model, afterwards we will compare these results with the other econometric specifications and discuss the differences among them. Table 2 highlights the full parameter estimates. Columns 2 and 3 contain the estimates and robust standard errors correspond to those estimations for our baseline model Equation 9, respectively. Since the parameter estimates are not so intuitive on their own, we display estimated variance-decompositions with graphs to have a better interpretation.

Figure 4 displays the variance-decomposition of the baseline model. The

[7]For the clarity purposes we present only the covariances because the inclusion of the variance into the graph increases the scale of y axis and thus reduces the vision on the longer lag covariances. The variance, however, is the same with the one plotted in Figure 1.

variance of permanent component increases smoothly over the life-cycle as one would expect to observe such pattern from the variance of random walk process. This increasing trend in the variance of permanent shocks is mostly considered as an outcome of human capital investments of individuals (i.e. return to education, training programs etc.).

Figure 4: **Variance-decomposition over the life-cycle**



As for the variance of transitory component, also known as "income instability", it follows a U-shaped pattern which is consistent with the previous findings in the literature. Despite the relatively big fall between the ages of 25 and 26 it is on smooth decrease as the individuals age until age 50. The variance of transitory innovations is equal to .077 at age 50 and starts increasing significantly through the end of the life-cycle, reaches to .221 at age

60 which is almost 3 times greater in magnitude than the variance of age 50[8].

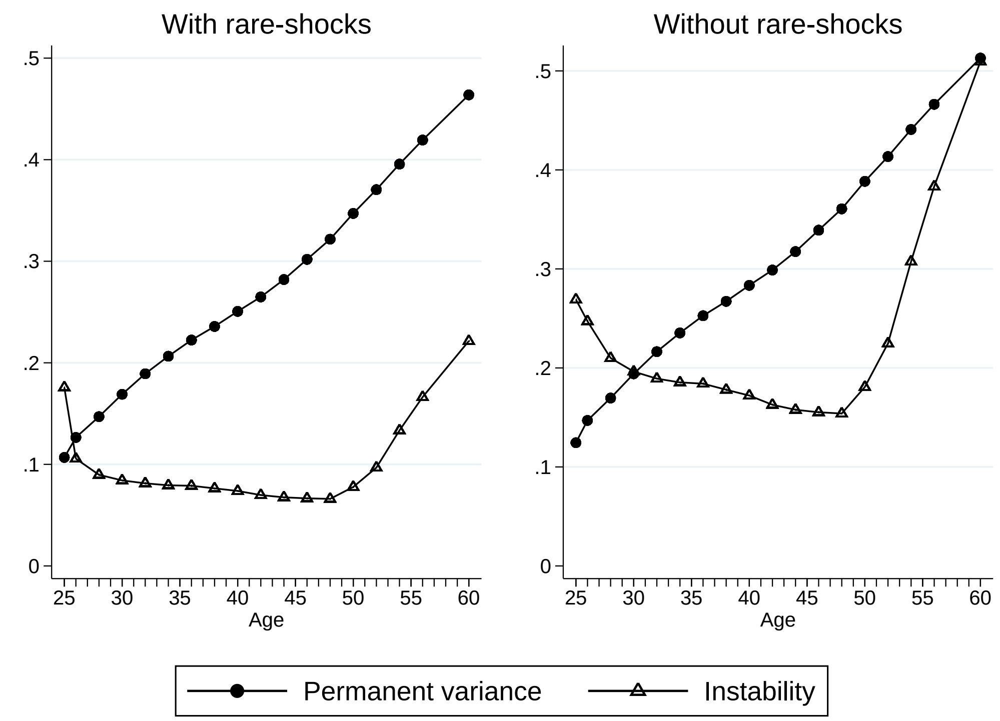
We know from Figure 2 that the increase in cumulative income inequality between the ages of 50 and 60 is associated with the increase in the variance of annual weeks of work. However, what we could not understand from that figure was that this increase in the variance of working weeks whether is an outcome of voluntary decisions made by workers. Since we do not observe any fraction in the permanent variance but we do observe a significant increase in income instability after 50, the reduction in the annual weeks of work should not be coming from voluntary decisions of older workers. We count on our rich econometric specification on the latter interpretation because our permanent component is specified flexible enough to capture such fractions should the workers voluntarily reduce their working weeks as they get older.

5.1 Results From Other Econometric Specifications

We now provide additional results obtained from different econometric specifications. First, using the same working sample we restrict our baseline model and exclude the rare-shocks from the estimation process. We will refer this model as "restricted model". Second, we restrict both our working sample by dropping the first and last observations of each individual as Baker and Solon (2003) do and our baseline model by extracting the rare-shocks. We will call this model "restricted sample". Our purpose is to see how influential the in- and out-movements of workers on the estimation of variances of permanent-transitory components.

[8]We estimated the model with a restriction in the working sample at age 50. The estimated variance of transitory shocks follows exactly the same pattern we obtain in Figure 4 until age 50. The latter robustness check is done to be sure that the increase after age 50 is not an outcome of an end of data issue. Results are available based on a request.

Figure 5: **Variance-decomposition over the life-cycle with and without rare-shocks**



5.1.1 Restricted Model

We present the results of restricted model that contains all the parameters of Equation 9 but the rare-shocks. The 4th and 5th columns of Table 2 show the full parameter estimates of our restricted model.

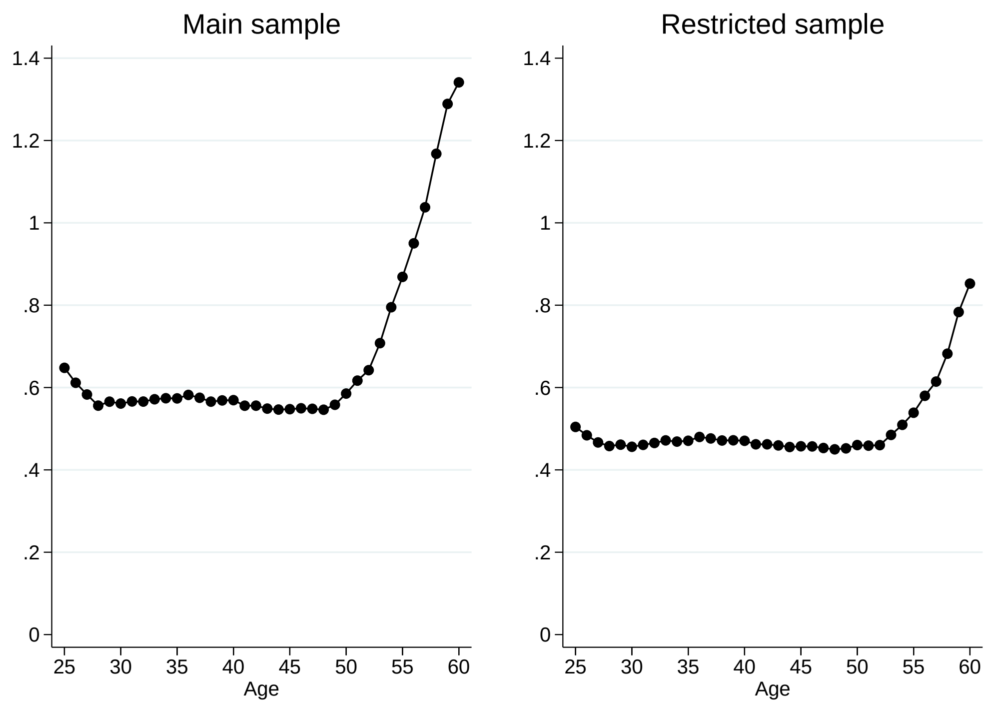
To be able to see the differences clearly between the results, we display the results of our baseline and restricted models together in Figure 5. The first graph in Figure 5 is the same with Figure 4, while the second one is the variance-decomposition of restricted model that does not take into account the rare-shocks. There is an incontrovertible difference in the estimated income instabilities between two graphs. In the absence of rare-shocks income instability is overestimated at any stage of the life-cycle. Especially the peak after age 50 in income instability is far greater if the rare shocks are not included. The variance of transitory shocks is equal to .180 at age 50 and reaches to .510 at age 60. Therefore, although the transitory component in our restricted model still has arguably the most flexible econometric specification in the literature, our findings suggest that the presence of rare-shocks in the estimation process is essential to estimate genuine income instability.

5.1.2 Restricted Sample

For the restricted sample, before starting to analyze the results a couple of things need to be clarified. As mentioned above, we drop the first and last observations of each individual because Baker and Solon (2003) state that this is a consistent way of estimating instability. Sometimes individuals rush into labor market just to initiate their career and accept a job offer that they are not really into in contemplation of changing the job soon. This situation can thus generate more volatile incomes at corresponding ages. Also the last observation of the individuals can be misleading since they are close to flow into the retirement and this may reduce their productivity or be a reason to accept low-paid jobs just to be able to stay in the labor market. Therefore, following the latter reasoning we apply this sample selection criteria on our working sample. However, having this restriction on the selection procedure has several consequences. First, once the first and last observations of individuals are dropped we happen to lose the first (1985) and last (2012) years of our data as well. Thereby we also lose two

birth-cohorts (1934 and 1978). Moreover, since we only keep the individuals who have at least 5 consecutive years of observation in our data, the entire spells of individuals who are observed only for 5 and 6 consecutive years in

Figure 6: **Variance of log-incomes over the life-cycle: main sample vs. restricted sample**

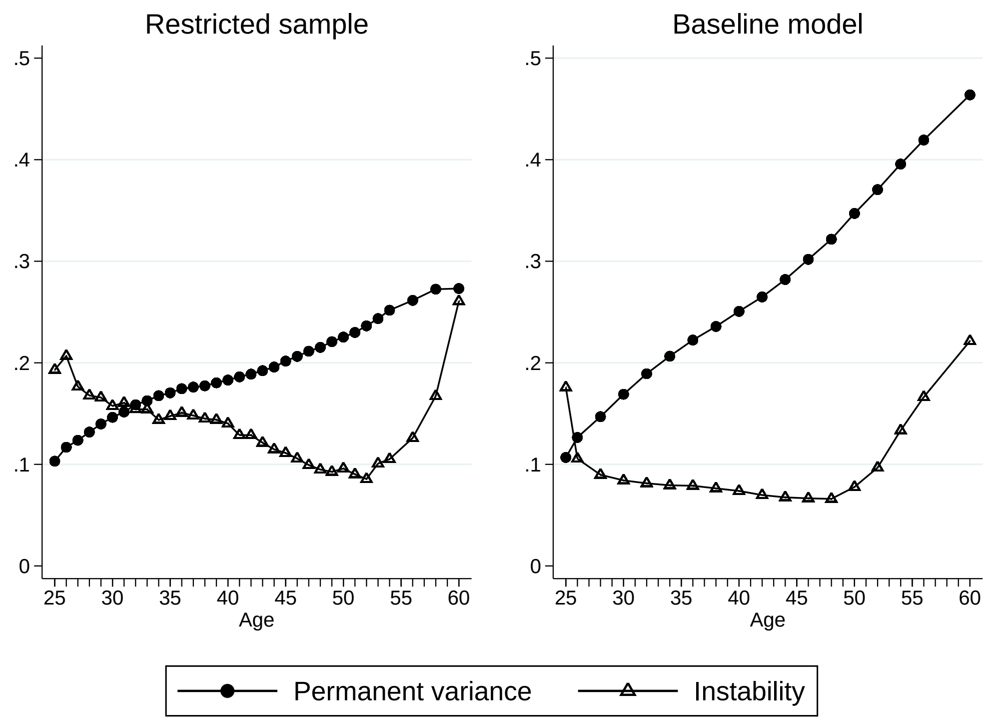


our unrestricted sample are dropped too. As a result, our restricted working sample consists of 658,690 individuals with 9,456,783 person-year observation, spanning the years 1986-2011.

Figure 6 displays the variance of log-incomes over the life-cycle for both unrestricted (on the left side) and restricted samples (on the right side). As can be seen obviously from Figure 6, after applying additional selection criteria on the sample selection there is a remarkable amount of a reduction in levels of cumulative income inequality, while its pattern remains the same. Nevertheless, the variance of log-incomes in Figure 6 is still a simple descriptive statistics and is very heterogeneous due to the time- and cohort-effects.

Once again, we estimate a variance-component model by using a very similar

Figure 7: **Variance-decomposition over the life-cycle: restricted sample vs. unrestricted sample with rare-shocks**



but even more flexible econometric specification than our baseline model[9]. Table 3 shows the full parameter estimates on our restricted sample. Rare-shocks are not included into the estimation process since our aim is to see either estimating rare-shocks or dropping the first and last observations of individuals is a better approach to estimate income inequality without inflated by the in- and out- movements at the early and late stages of the life-cycle.

Figure 7 displays the estimated variances of permanent and transitory

[9]Having a new working sample did not allow us to use the same econometric specification with our baseline model, however, we were fortunate enough to set even more flexible model than our baseline specification in terms of the use of age-specific shocks. Permanent and transitory components are still specified as random walk and ARMA(1,1) processes, respectively. Both processes allowed to vary in age to capture the true life-cycle effects as in our baseline model. However, this time only the last six age-years are grouped by two (55-56, 57-58, 59-60) in the variances of random walk and ARMA(1,1). Moreover, cohort shifters are used only on the transitory component.

components of the model described above (on the left) and of our unrestricted model (on the right) that has already been shown in the Figure 4 and Figure 5. As are the previous results, permanent variance is on a smooth increase through the life-cycle while instability follows a U-shaped pattern. Although the patterns of estimated variances are consistent across the graphs plotted within Figure 7, the levels of estimates vary depending on how the rare-shocks are dealt with. In Figure 7, for the restricted sample on the left, we see a reduction in the level of estimated permanent variance respect to the graph on the right side, which is not surprising considering the fact that by applying the additional selection criteria we have dropped the entire spells of individuals who were observed for 5 or 6 consecutive years in our unrestricted working sample, and the absence of these short period spells led us to estimate a lower level of permanent variance. As for the instability, on the other hand, between the ages 26 and 50 estimated instability from restricted sample on average is almost two times greater in magnitude than the instability estimated with unrestricted model, though the increasing pattern after age 50 is pretty similar between two graphs.

As a conclusion, although dropping the first and last observations of individuals seems partially a better option than not taking into account the rare-shocks at all, our results suggest that estimating permanent-transitory components along with the variance of rare-shocks still provides more accurate results in terms of estimating genuine instability over the life-cycle without even excluding any information from the selected sample.

6 Summary and Conclusions

In this paper, we used a large-scale administrative panel data spanning twenty eight years of period between 1985 and 2012, and decomposed the annual income inequality of Italian males aged 25 to 60. We contributed to the well-established literature of earnings dynamics and inequality with an up-to-date evidence for Italy by focusing on the life-cycles and with a flexible econometric specification that relaxes some of the parametric restrictions on the estimation of instability.

We shown that there is a significant increase in the aggregate inequality at the late stage of life-cycle, namely for the workers between ages of 50 and 60. A similar pattern has been plotted for the variance of annual weeks of work which indicated that, in the light of previous work of Abowd and Card (1989), the former increase is mostly an outcome of the latter. We emphasized the importance of understanding the extent to which changes in the working weeks is driven by the voluntary decisions of workers. All the results we estimated from different econometric specification implied that the accelerating increase in the income inequality for older workers is driven by the increase in the variance of transitory shocks which can be attributed as an outcome of involuntary decision of workers on their working weeks. Although in theory transitory shocks are considered insurable if individuals can lend and borrow freely and also if there is no liquidity-constrains, it is still in question to what extend real market conditions reflect that theory.

We also demonstrated that even with a rich econometric model, as the one we used in this paper, not taking account of repetitive labor market entries and exits at the early and late stage of life-cycle inflates the estimates on the variance of transitory shocks. We compared two different methods suggested to deal with this issue in the literature, dropping fist and last observations of individuals by Baker and Solon (2003) and inclusion of rare-shocks by Manovskii et al. (2015), both methods of which are effective. Nevertheless, including additional restriction on the sample selection causes to lose considerable amount of valid information. Thus our favored model is the one includes rare-shocks into the estimation process.

References

Abowd, J. M. and D. Card (1989). On the covariance structure of earnings and hours changes. *Econometrica 57*(2), 411–445.

Altonji, J. G. and L. M. Segal (1996). Small-sample bias in gmm estimation of covariance structures. *Journal of Business & Economic Statistics 14*(3), 353–366.

Baker, M. and G. Solon (2003). Earnings dynamics and inequality among canadian men, 1976-1992: Evidence from longitudinal income tax records. *Journal of Labor Economics 21*(2), 289–321.

Basten, C., A. Fagereng, and K. Telle (2014). Cash-on-hand and the duration of job search: Quasi-experimental evidence from norway. *The Economic Journal 124*(576), 540–568.

Bingley, P., L. Cappellari, and N. Westergård-Nielsen (2013). Unemployment insurance, wage dynamics and inequality over the life cycle. *The Economic Journal 123*(568), 341–372.

Blundell, R., M. Graber, and M. Mogstad (2015). Labor income dynamics and the insurance from taxes, transfers, and the family. *Journal of Public Economics 127*, 58–73.

Blundell, R., L. Pistaferri, and I. Preston (2008). Consumption inequality and partial insurance. *The American Economic Review 98*(5), 1887–1921.

Cameron, S. and J. Tracy (1998). Earnings variability in the united states: an examination using matched-cps data. *Columbia University and Federal Reserve Bank of New York*.

Cappellari, L. (2004). The dynamics and inequality of italian mens earnings long-term changes or transitory fluctuations? *Journal of Human Resources 39*(2), 475–499.

Cappellari, L. and M. Leonardi (2016). Earnings instability and tenure. *The Scandinavian Journal of Economics 118*(2), 202–234.

Celik, S., C. Junh, K. McCue, and J. Thompson (2012). Recent trends in earnings volatility: Evidence from survey and administrative data. *The B.E. Journal of Economic Analysis & Policy 12*(2(contributions), Article 1.

Chamberlain, G. (1984). Panel data. *Handbook of econometrics 2*, 1247–1318.

Cunha, F. and J. Heckman (2016). Decomposing trends in inequality in earnings into forecastable and uncertain components. *Journal of labor economics 34*(S2), S31–S65.

DeBacker, J., B. Heim, V. Panousi, S. Ramnath, and I. Vidangos (2013). Rising inequality: transitory or persistent? new evidence from a panel of us tax returns. *Brookings Papers on Economic Activity 2013*(1), 67–142.

Dickens, R. (2000). The evolution of individual male earnings in great britain: 1975–95. *The Economic Journal 110*(460), 27–49.

Friedman, M. (1957). *The Permanent Income Hypothesis*, pp. 20–37. Princeton University Press.

Haider, S. J. (2001). Earnings instability and earnings inequality of males in the united states: 1967–1991. *Journal of labor Economics 19*(4), 799–836.

Hause, J. C. (1980). The fine structure of earnings and the on-the-job training hypothesis. *Econometrica: Journal of the Econometric Society*, 1013–1029.

Huggett, M., G. Ventura, and A. Yaron (2011). Sources of lifetime inequality. *The American Economic Review 101*(7), 2923–2954.

Kalwij, A. S. and R. Alessie (2007). Permanent and transitory wages of british men, 1975–2001: year, age and cohort effects. *Journal of Applied Econometrics 22*(6), 1063–1093.

Krueger, D., F. Perri, L. Pistaferri, and G. L. Violante (2010). Cross-sectional facts for macroeconomists. *Review of Economic dynamics 13*(1), 1–14.

Lillard, L. A. and Y. Weiss (1979). Components of variation in panel earnings data: American scientists 1960-70. *Econometrica: Journal of the Econometric Society*, 437–454.

Lillard, L. A. and R. J. Willis (1978). Dynamic aspects of earning mobility. *Econometrica: Journal of the Econometric Society*, 985–1012.

MaCurdy, T. E. (1982). The use of time series processes to model the error structure of earnings in a longitudinal data analysis. *Journal of econometrics 18*(1), 83–114.

Manovskii, I., D. Hryshko, M. Daly, et al. (2015). Reconciling estimates of earnings processes in growth rates and levels. In *2015 Meeting Papers*, Number 1395. Society for Economic Dynamics.

Meghir, C. and L. Pistaferri (2004). Income variance dynamics and heterogeneity. *Econometrica 72*(1), 1–32.

Meghir, C. and L. Pistaferri (2011). Earnings, consumption and life cycle choices. *Handbook of labor economics 4*, 773–854.

Moffitt, R. and P. Gottschalk (1995). Trends in the covariance of earnings in the united states: 1969-1987. *Institute for Research on Poverty, Discussion Paper* (1001).

Moffitt, R. A. and P. Gottschalk (2012). Trends in the transitory variance of male earnings methods and evidence. *Journal of Human Resources 47*(1), 204–236.

Sologon, D. M. and P. Van Kerm (2014). Earnings dynamics, foreign workers and the stability of inequality trends in luxembourg 1988-2009. *Luxembourg Institute of Socio-Economic Research (LISER) Working Paper Series 3*.

Appendix-A

Table 2: **Full parameter estimates of income inequality**

	Baseline Model		W/out rare-shocks	
	Estimate	SE	Estimate	SE
Permanent component:				
$\sigma^2_{\mu_{25}}$	.106	.002	.124	.002
Age-specific shocks:				
$\sigma^2_{\phi_{26-27}}$	.019	.0008	.022	.0009
$\sigma^2_{\phi_{28-29}}$	.020	.0007	.022	.0008
$\sigma^2_{\phi_{30-31}}$	.022	.0007	.024	.0008
$\sigma^2_{\phi_{32-33}}$	.020	.0007	.022	.0008
$\sigma^2_{\phi_{34-35}}$	.017	.0007	.019	.0008
$\sigma^2_{\phi_{36-37}}$	.015	.0008	.017	.0008
$\sigma^2_{\phi_{38-39}}$	.013	.0008	.014	.0009
$\sigma^2_{\phi_{40-41}}$	.014	.0009	.016	.0009
$\sigma^2_{\phi_{42-43}}$	.014	.001	.015	.001
$\sigma^2_{\phi_{44-45}}$	.017	.001	.018	.001
$\sigma^2_{\phi_{46-47}}$	.019	.001	.021	.001
$\sigma^2_{\phi_{48-49}}$	.019	.001	.021	.001
$\sigma^2_{\phi_{50-51}}$	.025	.001	.027	.001
$\sigma^2_{\phi_{52-53}}$	.023	.001	.025	.001
$\sigma^2_{\phi_{54-55}}$	.025	.002	.027	.002
$\sigma^2_{\phi_{56-57}}$	.023	.003	.025	.003
$\sigma^2_{\phi_{58-59-60}}$	.044	.006	.046	.007
Cohort shifters:				
γ_{34}	.714	.014	.730	.014
γ_{35}	.726	.015	.739	.014
γ_{36}	.740	.015	.752	.015
γ_{37}	.779	.014	.791	.014
γ_{38}	.829	.014	.840	.014
γ_{39}	.816	.014	.826	.014
γ_{40}	.855	.014	.864	.014
γ_{41}	.863	.014	.872	.014
γ_{42}	.877	.014	.885	.014
γ_{43}	.903	.014	.910	.014
γ_{44}	.901	.014	.930	.014
γ_{45}	.926	.013	.932	.013
γ_{46}	.918	.012	.924	.012

Continued on next page

Table 2 – continued from previous page

	Baseline Model		W/out rare-shocks	
	Estimate	SE	Estimate	SE
γ_{47}	.927	.012	.932	.011
γ_{48}	.919	.011	.923	.011
γ_{49}	.922	.011	.926	.011
γ_{50}	.946	.011	.950	.011
γ_{51}	.970	.011	.972	.011
γ_{52}	.989	.011	.999	.011
γ_{54}	1.00	.011	1.00	.011
γ_{55}	1.03	.011	1.03	.011
γ_{56}	1.04	.011	1.03	.011
γ_{57}	1.08	.012	1.08	.011
γ_{58}	1.07	.012	1.07	.011
γ_{59}	1.10	.011	1.09	.011
γ_{60}	1.13	.012	1.12	.012
γ_{61}	1.15	.012	1.15	.012
γ_{62}	1.16	.012	1.15	.012
γ_{63}	1.16	.013	1.16	.012
γ_{64}	1.16	.012	1.16	.012
γ_{65}	1.18	.013	1.18	.013
γ_{66}	1.19	.013	1.19	.013
γ_{67}	1.20	.014	1.20	.014
γ_{68}	1.20	.014	1.19	.014
γ_{69}	1.22	.015	1.21	.015
γ_{70}	1.23	.015	1.22	.015
γ_{71}	1.26	.016	1.25	.016
γ_{72}	1.27	.017	1.26	.016
γ_{73}	1.24	.016	1.23	.016
γ_{74}	1.28	.017	1.27	.017
γ_{75}	1.30	.019	1.29	.018
γ_{76}	1.30	.019	1.28	.019
γ_{77}	1.29	.020	1.28	.020
γ_{78}	1.36	.023	1.34	.022
Time shifters:				
p_{85}	1.00	.	1.00	.
p_{86}	1.05	.005	.987	.004
p_{87}	1.08	.005	1.01	.004
p_{88}	1.06	.006	.990	.004
p_{89}	1.04	.006	.975	.005
p_{90}	1.05	.006	.982	.005
p_{91}	1.05	.006	.991	.005
p_{92}	1.06	.007	.977	.006
p_{93}	1.04	.007	1.00	.006
p_{94}	1.07	.007	.988	.006
p_{95}	1.05	.008	.971	.007

Continued on next page

Table 2 – continued from previous page

	Baseline Model		W/out rare-shocks	
	Estimate	SE	Estimate	SE
p_{96}	1.03	.008	.963	.007
p_{97}	1.02	.008	.936	.007
p_{98}	.992	.008	.902	.007
p_{99}	.956	.009	.887	.007
p_{00}	.939	.009	.888	.008
p_{01}	.940	.009	.890	.008
p_{02}	.943	.009	.878	.008
p_{03}	.930	.009	.869	.008
p_{04}	.919	.010	.870	.009
p_{05}	.921	.010	.871	.009
p_{06}	.914	.010	.865	.009
p_{07}	.884	.010	.836	.009
p_{08}	.881	.010	.834	.009
p_{09}	920	.011	.870	.009
p_{10}	.916	.011	.866	.010
p_{11}	.921	.011	.871	.010
p_{12}	.897	.011	.880	.010
Transitory component:				
ρ	.494	.004	.490	.004
θ	-.250	.002	-.251	.002
σ_0^2	.175	.014	.270	.016
Age-specific shocks:				
$\sigma^2_{\zeta_{26-27}}$	.010	.005	.247	.006
$\sigma^2_{\zeta_{28-29}}$	.090	.004	.210	.005
$\sigma^2_{\zeta_{30-31}}$	.084	.004	.196	.004
$\sigma^2_{\zeta_{32-33}}$	.081	.004	.190	.004
$\sigma^2_{\zeta_{34-35}}$	.080	.004	.185	.004
$\sigma^2_{\zeta_{36-37}}$	.079	.004	.184	.004
$\sigma^2_{\zeta_{38-39}}$	.076	.003	.178	.004
$\sigma^2_{\zeta_{40-41}}$	.073	.003	.172	.004
$\sigma^2_{\zeta_{42-43}}$	.070	.003	.162	.004
$\sigma^2_{\zeta_{44-45}}$	.067	.003	.157	.003
$\sigma^2_{\zeta_{46-47}}$	.066	.003	.155	.003
$\sigma^2_{\zeta_{48-49}}$	.066	.003	.154	.004
$\sigma^2_{\zeta_{50-51}}$	.077	.004	.180	.004
$\sigma^2_{\zeta_{52-53}}$	.096	.005	.224	.005
$\sigma^2_{\zeta_{54-55}}$	.133	.006	.307	.007
$\sigma^2_{\zeta_{56-57}}$	.166	.008	.383	.009
$\sigma^2_{\zeta_{58-59-60}}$	.221	.011	.510	.013
Cohort shifters:				
η_{34}	1.30	.162	1.122	.110

Continued on next page

Table 2 – continued from previous page

	Baseline Model		W/out rare-shocks	
	Estimate	SE	Estimate	SE
η_{35}	1.20	.150	1.07	.106
η_{36}	.943	.136	.907	.100
η_{37}	.963	.136	.907	.100
η_{38}	.857	.124	.816	.089
η_{39}	.649	.111	.671	.082
η_{40}	.690	.116	.714	.086
η_{41}	.543	.112	.588	.082
η_{42}	.790	.122	.783	.089
η_{43}	.743	.126	.747	.092
η_{44}	.480	.100	.562	.075
η_{45}	.443	.104	.522	.078
η_{46}	.478	.093	.572	.070
η_{47}	.522	.091	.596	.068
η_{48}	.653	.098	.697	.073
η_{49}	.629	.098	.703	.075
η_{50}	1.00	.122	.967	.089
η_{51}	.882	.112	.868	.082
η_{52}	.926	.115	.923	.086
η_{54}	1.27	.135	1.19	.097
η_{55}	1.24	.128	1.17	.094
η_{56}	1.29	.130	1.23	.094
η_{57}	1.47	.145	1.35	.103
η_{58}	1.60	.150	1.48	.107
η_{59}	1.84	.170	1.66	.118
η_{60}	1.94	.177	1.71	.121
η_{61}	1.00	.091	1.28	.093
η_{62}	.884	.082	1.27	.093
η_{63}	.640	.061	.966	.073
η_{64}	.620	.058	.938	.070
η_{65}	.567	.054	.863	.064
η_{66}	.521	.050	.792	.060
η_{67}	.468	.045	.710	.054
η_{68}	.582	.055	.872	.065
η_{69}	.534	.050	.800	.060
η_{70}	.527	.050	.796	.060
η_{71}	.589	.055	.883	.065
η_{72}	.513	.050	.772	.057
η_{73}	.488	.046	.733	.054
η_{74}	.585	.055	.880	.064
η_{75}	.578	.055	.875	.064
η_{76}	.570	.054	.861	.064
η_{77}	.530	.050	.807	.060
η_{78}	.540	.052	.818	.063

Continued on next page

Table 2 – continued from previous page

	Baseline Model		W/out rare-shocks	
	Estimate	SE	Estimate	SE
Time shifters:				
π_{85}	1.00	.	1.00	.
π_{86}	1.55	.029	1.13	.012
π_{87}	1.71	.040	1.17	.014
π_{88}	1.75	.043	1.17	.015
π_{89}	1.85	.045	1.24	.015
π_{90}	1.89	.045	1.26	.015
π_{91}	1.96	.047	1.31	.015
π_{92}	2.02	.050	1.35	.016
π_{93}	2.02	.050	1.35	.016
π_{94}	2.12	.051	1.42	.017
π_{95}	2.20	.054	1.47	.018
π_{96}	2.07	.051	1.39	.017
π_{97}	2.26	.056	1.51	.019
π_{98}	2.31	.057	1.55	.019
π_{99}	2.32	.058	1.55	.020
π_{00}	2.09	.052	1.40	.019
π_{01}	2.14	.053	1.43	.019
π_{02}	2.16	.054	1.45	.019
π_{03}	2.07	.052	1.39	.018
π_{04}	2.13	.053	1.42	.018
π_{05}	2.12	.053	1.41	.018
π_{06}	2.10	.052	1.40	.018
π_{07}	2.00	.050	1.34	.017
π_{08}	2.19	.054	1.46	.018
π_{09}	2.13	.052	1.42	.018
π_{10}	2.23	.054	1.49	.018
π_{11}	2.27	.055	1.51	.019
π_{12}	2.12	.044	1.51	.019
Rare shocks:				
σ_r^2	.113	.004	.	.

Table 3: **Full parameter estimates of income inequality from restricted sample**

	Restricted sample	
	Estimate	SE
Permanent component:		
$\sigma^2_{\mu_{25}}$	.103	.001
Age-specific shocks:		
$\sigma^2_{\phi_{26}}$	.013	.0008
$\sigma^2_{\phi_{27}}$	.006	.0008
$\sigma^2_{\phi_{28}}$	.008	.0007
$\sigma^2_{\phi_{29}}$	.008	.0007
$\sigma^2_{\phi_{30}}$	.006	.0007
$\sigma^2_{\phi_{31}}$	.005	.0006
$\sigma^2_{\phi_{32}}$	.007	.0006
$\sigma^2_{\phi_{33}}$	.004	.0006
$\sigma^2_{\phi_{34}}$	.005	.0007
$\sigma^2_{\phi_{35}}$	.002	.0007
$\sigma^2_{\phi_{36}}$	.004	.0007
$\sigma^2_{\phi_{37}}$	.001	.0007
$\sigma^2_{\phi_{38}}$	.003	.0007
$\sigma^2_{\phi_{39}}$	.002	.0007
$\sigma^2_{\phi_{40}}$	.003	.0007
$\sigma^2_{\phi_{41}}$	.002	.0007
$\sigma^2_{\phi_{42}}$	.003	.0007
$\sigma^2_{\phi_{42}}$	.003	.0007
$\sigma^2_{\phi_{43}}$	.005	.0008
$\sigma^2_{\phi_{44}}$	.004	.0008
$\sigma^2_{\phi_{45}}$	.005	.0008
$\sigma^2_{\phi_{46}}$	.003	.0009
$\sigma^2_{\phi_{47}}$	.005	.0009
$\sigma^2_{\phi_{48}}$	.004	.0009
$\sigma^2_{\phi_{49}}$	.004	.001
$\sigma^2_{\phi_{50}}$	.006	.001
$\sigma^2_{\phi_{51}}$	.007	.001
$\sigma^2_{\phi_{52}}$	.008	.001
$\sigma^2_{\phi_{53}}$	.009	.001
$\sigma^2_{\phi_{54}}$	.010	.001
$\sigma^2_{\phi_{55-56}}$	.003	.001
$\sigma^2_{\phi_{57-58}}$	.003	.002
$\sigma^2_{\phi_{59-60}}$	.0006	.005
Time shifters:		
p_{86}	1.00	.

Continued on next page

Table 3 – continued from previous page

	Restricted sample	
	Estimate	SE
p_{87}	1.06	.004
p_{88}	1.04	.004
p_{89}	1.04	.005
p_{90}	1.06	.005
p_{91}	1.09	.005
p_{92}	1.10	.005
p_{93}	1.15	.006
p_{94}	1.15	.006
p_{95}	1.17	.006
p_{96}	1.16	.006
p_{97}	1.16	.006
p_{98}	1.15	.007
p_{99}	1.14	.007
p_{00}	1.14	.007
p_{01}	1.16	.007
p_{02}	1.15	.007
p_{03}	1.14	.007
p_{04}	1.14	.007
p_{05}	1.15	.008
p_{06}	1.15	.008
p_{07}	1.10	.008
p_{08}	1.09	.008
p_{09}	1.13	.008
p_{10}	1.13	.008
p_{11}	1.05	.008
Transitory component:		
ρ	.551	.004
θ	-.262	.002
σ_0^2	.193	.014
Age-specific shocks:		
$\sigma^2_{\zeta_{26}}$	.206	.006
$\sigma^2_{\zeta_{27}}$	.176	.005
$\sigma^2_{\zeta_{28}}$	.167	.005
$\sigma^2_{\zeta_{29}}$	.165	.005
$\sigma^2_{\zeta_{30}}$	.157	.005
$\sigma^2_{\zeta_{31}}$	.160	.005
$\sigma^2_{\zeta_{32}}$	.154	.004
$\sigma^2_{\zeta_{33}}$	.154	.004
$\sigma^2_{\zeta_{34}}$	.143	.004
$\sigma^2_{\zeta_{35}}$	.147	.004
$\sigma^2_{\zeta_{36}}$	.150	.004
$\sigma^2_{\zeta_{37}}$	.148	.004

Continued on next page

Table 3 – continued from previous page

	Restricted sample	
	Estimate	SE
$\sigma^2_{\zeta_{38}}$	.145	.004
$\sigma^2_{\zeta_{39}}$	.143	.004
$\sigma^2_{\zeta_{40}}$	.140	.004
$\sigma^2_{\zeta_{41}}$	.128	.004
$\sigma^2_{\zeta_{42}}$	.128	.004
$\sigma^2_{\zeta_{43}}$	.121	.004
$\sigma^2_{\zeta_{44}}$	.114	.003
$\sigma^2_{\zeta_{45}}$	.111	.003
$\sigma^2_{\zeta_{46}}$	.105	.003
$\sigma^2_{\zeta_{47}}$	.099	.003
$\sigma^2_{\zeta_{48}}$	.094	.003
$\sigma^2_{\zeta_{49}}$	.092	.003
$\sigma^2_{\zeta_{50}}$	.096	.003
$\sigma^2_{\zeta_{51}}$	.090	.003
$\sigma^2_{\zeta_{52}}$	.085	.003
$\sigma^2_{\zeta_{53}}$	.100	.004
$\sigma^2_{\zeta_{54}}$	.105	.004
$\sigma^2_{\zeta_{55-56}}$	.126	.004
$\sigma^2_{\zeta_{57-58}}$	.167	.005
$\sigma^2_{\zeta_{59-60}}$	.260	.009
Cohort shifters:		
η_{35}	.627	.125
η_{36}	.461	.123
η_{37}	.526	.108
η_{38}	.734	.114
η_{39}	.496	.096
η_{40}	.660	.107
η_{41}	.506	.103
η_{42}	.738	.112
η_{43}	.770	.114
η_{44}	.563	.091
η_{45}	.677	.100
η_{46}	.637	.095
η_{47}	.725	.095
η_{48}	.739	.100
η_{49}	.615	.091
η_{50}	.937	.110
η_{51}	1.00	.113
η_{52}	1.02	.116
η_{54}	1.13	.120
η_{55}	1.21	.120

Continued on next page

Table 3 – continued from previous page

	Restricted sample	
	Estimate	SE
η_{56}	1.12	.115
η_{57}	1.35	.132
η_{58}	1.41	.134
η_{59}	1.47	.134
η_{60}	1.70	.151
η_{61}	1.58	.140
η_{62}	1.56	.141
η_{63}	1.13	.106
η_{64}	1.13	.105
η_{65}	.958	.090
η_{66}	.908	.085
η_{67}	.864	.082
η_{68}	.966	.088
η_{69}	.999	.091
η_{70}	1.03	.097
η_{71}	.977	.091
η_{72}	.919	.087
η_{73}	.791	.076
η_{74}	.875	.084
η_{75}	.825	.082
η_{76}	.810	.083
η_{77}	.714	.078
Time shifters:		
π_{86}	1.00	.
π_{87}	1.13	.013
π_{88}	1.17	.017
π_{89}	1.16	.018
π_{90}	1.23	.018
π_{91}	1.29	.019
π_{92}	1.28	.018
π_{93}	1.42	.020
π_{94}	1.41	.020
π_{95}	1.32	.019
π_{96}	1.38	.020
π_{97}	1.39	.020
π_{98}	1.44	.021
π_{99}	1.45	.022
π_{00}	1.32	.020
π_{01}	1.35	.020
π_{02}	1.33	.020
π_{03}	1.36	.021
π_{04}	1.40	.021
π_{05}	1.40	.020

Continued on next page

Table 3 – continued from previous page

	Restricted sample	
	Estimate	SE
π_{06}	1.38	.021
π_{07}	1.37	.021
π_{08}	1.34	.021
π_{09}	1.57	.023
π_{10}	1.60	.023
π_{11}	1.65	.025

Figure 8: **Variance-decomposition over time, for males 40 years old: baseline model.**

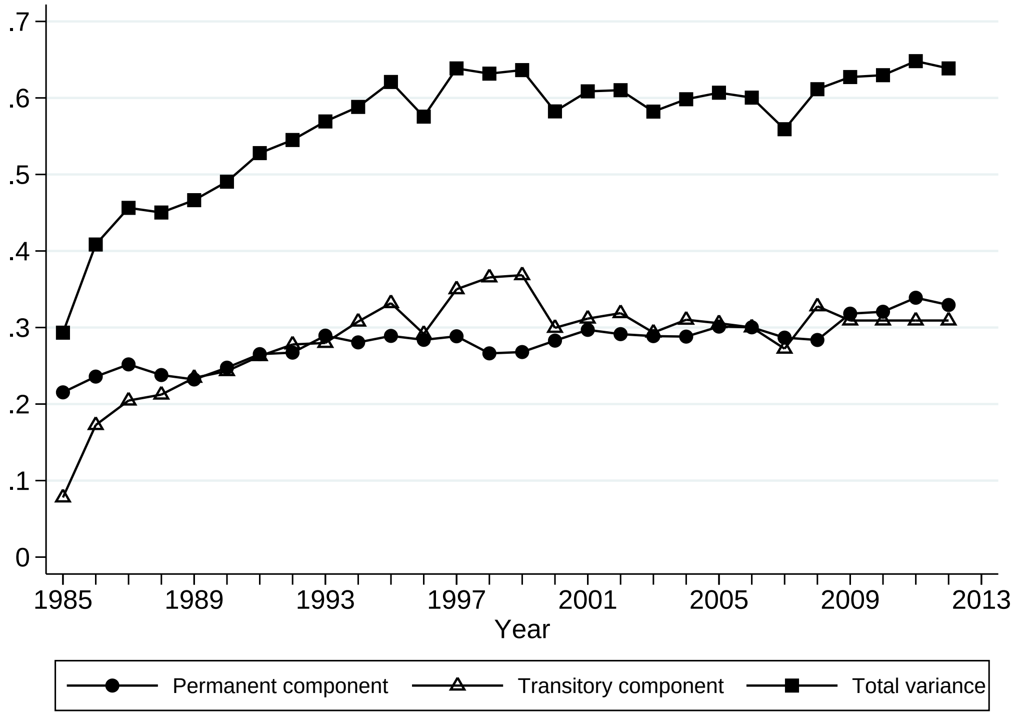


Figure 8 displays the variance decomposition over time obtained by our baseline model. In the figure we highlight the trends in permanent and transitory shocks only for the males at age 40. We plot the decomposition only for 40 years old workers since they are approximately in the middle of their working life. The first thing to note in the figure is the increasing pattern in the total variance from 1985 to 1997. Afterwards, it stays rather stable. We see that the changes in the total variance, including the increase between 1985-1997, are mostly driven by the changes in the transitory component while permanent component follows a stable pattern over the years with a slightly upward trend.

Appendix-B: Identification of the Parameters

Moment restrictions on the permanent component:

$$E(\mu_{ict}\mu_{ic(t-k)}) = \gamma_c^2 p_t p_{t-k}[\sigma_{\mu_{25}} + \sum_{a=26}^{a=60} \sigma^2_{\phi_a}]. \quad (11)$$

Moment restrictions on the transitory component is as follows:

$$\begin{aligned}
E(\upsilon_{ict}\upsilon_{ic(t-k)}) &= \pi_t\pi_{t-k}[\eta_c\sigma_0^2], \;\; if\; k = 0 \; and \; t = t_{0c} \quad (12)\\
E(\upsilon_{ict}\upsilon_{ic(t-k)}) &= \pi_t\pi_{t-k}[\sigma^2_{\zeta_a}(1+\theta^2+2\rho\theta) + E(\upsilon_{i(t-1)}\upsilon_{i(t-1)})\rho^2], \;\; if \;\; k = 0 \; and \; t > t_{0c}\\
E(\upsilon_{ict}\upsilon_{ic(t-k)}) &= \pi_t\pi_{t-k}[E(\upsilon_{i(t-1)}\upsilon_{i(t-k)})\rho + \theta\sigma^2_{\zeta_a}], \;\; if \;\; k = 1 \; and \; t > t_{0c}\\
E(\upsilon_{ict}\upsilon_{ic(t-k)}) &= \pi_t\pi_{t-k}[E(\upsilon_{i(t-1)}\upsilon_{i(t-k)})\rho], \;\; if \;\; k > 1 \; and \; t > t_{0c},
\end{aligned}$$

where t_{0c} is the first year cohort c is observed, index-a stands for the age which is equivalent to $t - c$ (year minus cohort).

Separate identification of the parameters for two income components in the baseline model is achieved by using orthogonality assumption between permanent and transitory components; $E(\mu_{it}\upsilon_{it}) = 0$. Orthogonality implies that the overall moment restriction to be matched to empirical moments is the sum of moments restrictions for permanent and transitory components. Permanent component is specified as a random walk process. The coefficient $\sigma^2_{\mu_{25}}$ captures the variance at age 25 (e.g. variation in human capitals accumulated during the years prior to age 25), $\sigma^2_{\phi_{t-c}}$ captures the variance of permanent shocks for subsequent ages. Transitory component, on the other hand, is specified as ARMA (1,1) process. Initial condition of ARMA, σ_0^2, is the variance in the first calender year a cohort is observed, which is associated with the cohort shifters (η_c). $\sigma^2_{\zeta_{t-c}}$ is the variances in subsequent ages, AR parameter, ρ, captures the persistence of the transitory shocks and MA coefficient, θ, captures the sharp decrease over the first period of transitory shocks.