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Characterizing Life-Cycle Dynamics of Annual Days of Work, Wages, and Cross-Covariances

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Characterizing Life-Cycle Dynamics of Annual Days of Work, Wages, and Cross-Covariances[*]

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Abstract

This paper investigates the dispersions in days worked and wages by adapting a novel semi-parametric specification that minimizes assumptions about life-cycle labor income dynamics. Data for Italy shows a substantial increase in income inequality after age 50 for males over the time span from 1985 to 2012, which is remarkably driven by the variations in days worked rather than wages. Results show that this increase is determined by permanent changes in the number of days worked. I also introduce an empirical strategy to decompose the cross-covariances of wages and working days to quantify the permanent and transitory responses of days worked to wage shocks. A one-percent increase in permanent wages increases the permanent days worked by 0.8% at the age of 28, while this increase is about 0.3% at the age of 55. Despite the strong reaction of days of work to wage shocks early in careers, the correlation coefficients are small, indicating that only a small share of variation in permanent days worked – which shapes the permanent income inequality – is explained by the changes in wages.

JEL codes: C33, D3, J21, J31.
Keywords: life-cycle dynamics, income inequality, wage inequality, annual days worked, older workers, contemporaneous covariance of wages and days.

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1. Introduction

Recent evidence shows that hours worked have been the main driving factor of the labor income inequality in the bottom half of the income distribution in the United States (Heathcote et al. 2020). Individuals who are exposed to interrupted employment spells can lag behind their counterparts in terms of skills and human capital developed by means of *learning by doing* and *on-the-job-training* (Davis and Von Wachter 2011; Heathcote et al. 2020), which can permanently increase income inequality.

A vast body of literature has studied the determinants of income and wage inequalities, while labor supply inequality and its components have been largely overlooked.[1] It is equally important to explore the patterns and sources of inequality in labor supply over the life cycle to gain a thorough grasp of life-cycle labor market dynamics, income risk, and insurance mechanisms, which are also useful for calibrating welfare (Kaplan 2012).

This paper comprehensively investigates the life-cycle dynamics of dispersions in annual days of work and wages for Italian male workers. For this purpose, I adopt fully age-dependent econometric models that minimize the assumptions about the life-cycle labor income dynamics, and I use population-representative administrative data. My study makes three primary contributions to the literature on income dynamics and life-cycle inequality.

First, it provides a novel evidence by characterizing the life-cycle profiles of permanent and transitory inequalities in annual days of work. Such decomposition is particularly important in understanding the sources of inequality across different age groups, especially in the context of an aging workforce. If the dispersion in days worked is generated by the temporary shifts, the potential consequences are rather mild and the situation might not necessarily be a concern of welfare state. However, if the latter dispersion widens permanently across individuals throughout their careers the situation might require a policy intervention.

Very few studies investigate the inequality in labor supply in terms of its permanent and transitory components (Lillard 1978; Abowd and Card 1989; Haider 2001). Some other studies discuss and consider the persistence of the dispersion in hours worked over the life cycle in their structural models of labor supply (see e.g. among others, Kaplan 2012; Heathcote et al. 2014) and provide descriptive evidence (e.g. Erosa et al. 2016). To the best of my knowledge, this paper is the first study to reveal the life-cycle patterns of permanent and transitory components of the dispersion in labor supply with an empirical framework

[1] Early key contributions were made by Lillard and Willis (1978), Lillard and Weiss (1979), Hause (1980), MaCurdy (1982), and Abowd and Card (1989). After the seminal study of Moffitt and Gottschalk (1995), which employed a variance-component model to characterize the variances of permanent and transitory components of income inequality, many studies revealed the trends in those two components, mostly over time, for different countries; see Dickens (2000) and Kalwij and Alessie (2007) for the United Kingdom, Haider (2001), Meghir and Pistaferri (2004), Kopczuk et al. (2010), Moffitt and Gottschalk (2012), De-Backer et al. (2013) for the United States, Cappellari (2004), Cappellari and Leonardi (2016) for Italy, Baker and Solon (2003) for Canada, Bingley et al. (2013) for Denmark, and Sologon and Van Kerm (2018) for Luxembourg.

that is appropriate to investigate the life-cycle dynamics.[2]

Second, I provide evidence on the life-cycle wage inequality and its permanent and transitory components. While the life-cycle wage and income inequalities have been examined by many studies, only a handful of them did so by employing fully age-dependent models (e.g. Karahan and Ozkan 2013; Blundell et al. 2015).

Third, I introduce an empirical framework to uncover the permanent and transitory reactions of days worked against wage shocks over careers. The latter empirical strategy estimates the age-specific covariances between the permanent (and transitory) changes in wages and days worked over the life cycle by exploiting the empirical cross-covariance structure of the two.[3] If permanent and transitory components exist in both days and wages, it is plausible to expect that the covariance of wages and days also contains these components. The estimated permanent and transitory covariances of wages and days worked help us understand the relationship between the two and also allow us to predict key statistics, namely correlation and OLS coefficients, to quantify this relationship in an economically meaningful way.

The cross-covariance decomposition is not entirely new in this literature. The influential study by Abowd and Card (1989) investigates the contemporaneous covariance between the annual earnings and annual hours of work. They show that the changes in the covariances of earnings and hours are mainly driven by the variations of hours at fixed wage rates. This finding contradicts the classical life-cycle labor supply models which suggest that individual productivity has a bigger impact on earnings than it has on hours.

Despite distinct developments in the literature on income dynamics—e.g. availability of administrative records and improved econometric specifications—there is no new evidence on the aforementioned aspect of income dynamics. This paper fills this gap by employing a state-of-the-art model, whereas using administrative data in which the measurement error in the labor supply measure, annual days of work, is minimal. One of the biggest obstacles of working with the cross-covariance of wages and days (or hours) is the presence of division bias. In fact, the latter covariance is frequently reported negative in the literature (Krueger et al. 2010), which is also the main reason that Abowd and Card (1989) work with a more general measure, the covariance of earnings and hours. To tackle the downward bias between daily wages and annual days of work, I compute empirical cross-covariance matrix between weekly wages and days worked.[4]

[2] Checchi et al. (2016) study the time trends of the inequality in hours of work across countries, but their empirical study is solely based on the decomposition of earnings inequality into wages and hours worked. Nevertheless, their findings show that in the United Kingdom and Germany, the dispersions in hours explain up to 40% of the earnings inequality. Other studies focus on the trends in average hours worked (see, e.g., Alesina et al. 2005; Blundell et al. 2013).

[3] The covariance of wages and hours has been used in the literature to estimate intertemporal labor supply elasticity of substitution (see, e.g., Altonji 1986 and Bredemeier et al. 2019) or used in structural micro- and macro-economic models (Heathcote et al. 2014; Blundell et al. 2016).

[4] In section 4, I discuss this choice in detail and show that the empirical variance-covariance structures of daily and weekly wages are almost identical over the life cycle, while their cross-products with days of work are significantly different.

I conduct the empirical analysis using a large-scale random sample from the archives of the Italian Social Security Institute (*Istituto Nazionale di Previdenza Sociale*, hereafter INPS) spanning the 1985–2012 period. The time span and size of the data, and the precise information on labor income and working days make this data set appealing. The study focuses on blue- and white-collar male workers (due to endogenous female labor force participation (Blundell et al. 2015)). In order to reduce the endogenous participation decisions in the labor market, the sample is restricted to individuals between the ages 25 and 60 who hold full-time contracts.[5] I work with percentage changes (log growths) in wages, annual working days, and labor income.[6]

The Italian context is appropriate to study the life-cycle dynamics as the Italian labor market has undergone several reforms over the past 30 years. These reforms eliminated wage indexation (Leonardi et al. 2019), introduced fixed-term contracts (Cappellari and Leonardi 2016), increased flexibility in labor market, reduced retirement benefits for subsequent generations (Bottazzi et al. 2006). The existing evidence shows that during these three decades the permanent wage inequality (Cappellari 2004), wage instability (Cappellari and Leonardi 2016), income and consumption inequalities (Jappelli and Pistaferri 2010) have risen in Italy. Yet the explicit evidence on life-cycle dynamics of labor supply and wage inequalities are missing.[7]

The findings of this paper are as follows. The log income inequality is U-shaped over the life-cycle. This life-cycle profile of income inequality is consistent with the evidence in the literature for other developed countries.[8] A cross-section decomposition reveals on average that the variance of log growth of working days (0.26) follows a U-shaped pattern over life-cycle and completely dominates the total variance of log growth of income, whereby the variance of log wage growth is only 0.03. As shown in Abowd and Card (1989), this difference between the variances of two processes suggests that the changes in productivity are not an important determinant in shaping the changes in life-cycle income inequality.

Moreover, the entire life-cycle variation in the days worked is driven by the bottom of the distribution (i.e. 50/10 ratio) and by the within-period variations in the extensive margin. Taken together, these findings suggest that the dispersion in annual days of work is not driven by high-productive individuals who keep working more than the median, but it is

[5]I perform several sensitivity tests in section 6 which also include a replication of findings with a sample of narrower age interval and workers who are more attached to the labor market.

[6]In section 5, I also provide results on income inequality and compare these results with the evidence in literature. This is done to check the external validity of the results presented in this paper on wage and days worked. In the end, the log income inequality is a product of log wage inequality, log days worked inequality and their covariances.

[7]Cappellari (2004) shows that, with a specific focus on the time trends, the wage inequality is caused mostly by the permanent component in Italy. Cappellari and Leonardi (2016) study the effects of tenure and the existence of fixed-term contracts (which was introduced to the market during the late 1990s) on wage instability (known as the variance of transitory wage shocks). Their findings suggest that workers who hold fixed-term contracts are subject to significantly higher wage instability than workers with permanent contracts.

[8]For example, see Karahan and Ozkan (2013) for the United States, Blundell et al. (2015) for Norway, and Sanchez and Wellschmied (2020) for Germany.

rather an outcome of interrupted employment spells (Kaplan 2012).

The results from the variance-component model show that the model fits perfectly to the empirical variance-covariance structure of days worked. The findings reveal that the U-shaped pattern in the variance of days worked over the life cycle is determined by the variations in the permanent shifts. A permanent shift of one standard deviation changes the annual days of work of a 26-year-old worker by about 47%. The corresponding number falls as with individuals increasing age and drops to 25% at the age of 48, while from the age of 50 to 60 it steeply rises to about 45%. High productivity, promotions, sorting, and settling into long-term employment may explain the decline in permanent dispersions in early life. Older workers suffer more from a decline in productivity (Kotlikoff and Gokhale 1992), health shocks, and unemployment shocks (Ichino et al. 2017) as they may have firm-specific human capital, all of which may account for the increase in permanent inequality in later life. Considering that the estimation sample consists of full-time employed workers, increase in permanent inequality in days worked after age 50 also points to lack of labor demand for elderly, and age discrimination.

Although the relative contribution of wage inequality to the income inequality is small, the results on wages are not trivial. Permanent wage inequality follows a very wide U-shaped over life-cycle. The variance of permanent wage shocks is 0.012 at the age of 50 and it rapidly increases to 0.026 through age 60, indicating that older workers face higher wage risk.[9] I also show that wage-induced variations account for 33% of the total variation in the annual days of work.

The results from cross-covariance decomposition show that the covariance between the permanent changes in wages and days is the highest with 0.018 at the age of 26. The latter covariance decreases to 0.005 by the age of 33, and it follows a flat pattern until the end of careers. The estimated covariances between the transitory changes in wages and days of work occur between the range of 0.003–0.005 until the age of 47, after which they decline smoothly to -0.003. The negative covariance indicates a wealth effect (Heathcote et al. 2014). Accordingly, older workers' consumption of leisure is more expensive and the accumulated wealth throughout their careers might enable them to temporarily reduce the number of days worked against transitory wage shocks.[10]

The implied OLS coefficients indicate that an average 1% increase in permanent wages permanently increases the days of work by about 0.8% at the age of 28. The responses of individuals' days worked to permanent changes in wages decline to 0.4% through to the age of 32, before remaining stable through to the end of careers. These estimates of life-cycle responses of days worked to changes in lifetime wages broadly correspond to the definition of *life-cycle Marshallian elasticities* described by Attanasio et al. (2018). On the other hand,

[9] The evidence in the literature shows that permanent wage shocks are partially insurable and they affect the consumption of individuals (Blundell et al. 2008; Heathcote et al. 2014; Blundell et al. 2016).

[10] A recent study by Powell (2020) estimates the transitory labor supply responses to transitory income shocks using the 2008 tax rebates in the United States. His estimates reveal that households reduce labor supply temporarily in response to rebate income.

despite the strong reaction of days of work to permanent wage shocks early in careers, the implied correlation coefficient is quite low at 0.3 at the age of 28, decreasing to 0.1 through the age of 60. This suggests that although permanent wage shifts have a strong impact on days of work, these shifts only account for a small share of the total variations in permanent changes in annual days worked.

In terms of policy implications, this work sheds light on the ongoing discussion in Italy about older workers' well-being. Among OECD countries, Italy had one of the worst records in terms of its elderly employment rate (aged 55 and above), which was 40% in 2002 (Leombruni and Villosio 2005). Although unemployment in this age category reached 50% in 2016, it was still 10 percentage points short of the total OECD average (OECD 2020). Moreover, according to the INPS, poverty and unemployment proportionally increased in the space of six years (from 2008 to 2014) within the age group of 55–65.[11] Concerns regarding older workers' well-being in labor markets are not limited to Italy. A recent report by the OECD (OECD 2017) documents increasing individual and household income inequality through to the end of careers for OECD countries and discusses the consequences of reduced income during the late career stage for post-retirement income, welfare, and health.

The remainder of the paper is organized as follows. Section 2 outlines the econometric specification, before section 3 provides information on the data and sample selection. In section 4, I present the empirical variance-covariance structures of variables and explain the estimation method. I discuss the results in section 5. Section 6 employs a sensitivity analysis, and finally section 7 concludes.

2. Econometric Model

Two well-known determinants of income risk are permanent and transitory income inequalities. In theory, permanent inequality can increase due to changes in demand for skilled labor, technological developments, long-term unemployment, and health shocks. On the other hand, transitory inequality can rise due to fluctuations in the market, unexpected job displacements, declines in union power, bonuses, and overtime shifts. The life-cycle variation in these components attracts particular attention from labor, household, and macroeconomists since they are directly linked to consumption inequality, returns to ability (or human capital investments), and labor market fluctuations.

A long line of literature dating back to the late-1970s addresses the characterization of labor income. A lively debate has been ongoing among economists about the true labor income processes.[12] Some studies (Lillard and Willis 1978; Hause 1980; Guvenen 2007) show that labor income contains individual-specific heterogeneous growth – often referred to as heterogeneous income profiles (HIP) – while others (MaCurdy 1982; Abowd and Card

[11] Accordingly, the INPS proposed a policy to the Italian government concerning the workers in that age group. The legislation proposed to establish a minimum income amounting to €500 per month for households with at least one member at least 55 years old. Although the government has acknowledged concerns regarding older workers the proposal was rejected over cost concerns (link to the website).

[12] See Meghir and Pistaferri (2011) for a literature review on the subject.

1989; Meghir and Pistaferri 2004) show that labor income is the sum of permanent (random walk) and transitory (low-order autoregressive) components, referred to as restricted income profiles (RIP). In the RIP models, the effects of permanent shocks last during the entire working span of individuals once they appear, and the effects of transitory shocks fade out with some persistence. Hryshko (2012) rejects the presence of heterogeneous growth in labor income. In this paper, I set up an econometric specification that is similar to Meghir and Pistaferri (2004) and Hryshko (2012) and consider the RIP models.

We know so far that the individual idiosyncratic labor income risk is age-dependent over the life cycle, and it is crucial to have age-varying specifications to estimate accurate patterns of the permanent (or highly persistent) and transitory income inequalities (Karahan and Ozkan 2013; Blundell et al. 2015; Hoffmann 2019). In my empirical analysis, permanent innovations are specified as a random walk process, while the transitory innovations are specified as a low-order autoregressive process. My econometric model draws these innovations from age-specific distributions without imposing any parametric assumption on the life-cycle patterns, which allows me to estimate permanent and transitory components accurately over a working life.

This is important since individuals may respond differently to permanent and transitory shocks depending the stage of the life cycle at which these shocks appear. For example, permanent wage shocks are partially insurable and a certain share of them translate into consumption (Blundell et al. 2008; Heathcote et al. 2014; Blundell et al. 2016), while transitory shocks are perfectly insurable as long as individuals are not liquidity-constrained. However, the response to transitory shocks can differ if these shocks hit individuals at later stages (when they have a shorter horizon). Moreover, the insurability of permanent shocks can differ among age groups. For example, accumulated wealth might enable individuals to be better prepared against these shocks during later life (Karahan and Ozkan 2013). Nevertheless, evidence shows that even late-in-career liquidity constraints exist (see e.g. Basten et al. 2014).

I now outline the income, wage and working-day processes and the moment restrictions that will be used later in the estimation procedure.

2.1. Wages

Let the wage process, w_{it}, be as follows

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

$$\pi_{it} = \pi_{it-1} + \xi_{it}; \;\; \xi_{it} \sim iid(0, \sigma^2_{\xi_{(t-c)}}) \tag{2}$$

$$\upsilon_{it} = (1 - \phi L)^{-1}\epsilon_{it}; \;\; \epsilon_{it} \sim iid(0, \sigma^2_{\epsilon_{(t-c)}}) \tag{3}$$

where i stands for an individual, t denotes the time period, $c = c(i)$ stands for the birth cohort of i, $(t - c)$ represents the age of individual i in year t. α_i is the initial wage level of individual i (which varies based on unobserved individual ability and early-life human capital investments). The permanent component π_{it} is assumed to follow a unit root process; ξ_{it} is a permanent innovation with age-specific variance $\sigma^2_{\xi_{(t-c)}}$; the transitory component υ_{it} is assumed to follow low-order autoregressive process, AR(1), ϵ_{it} is transitory innovation with age-specific variance $\sigma^2_{\epsilon_{(t-c)}}$. L is the lag operator; and ϕ is the autoregressive parameter, which estimates the persistence of transitory changes. The permanent and transitory components are assumed to be orthogonal to each other at every lags and leads.

Equations (1)–(3) could be used to estimate the permanent-transitory components for log wages in levels, as undertaken by several studies in the literature (e.g. Baker and Solon 2003; Cappellari 2004; Moffitt and Gottschalk 2012). However, the results can vary based on the initial conditions of econometric specifications when working with levels (Hryshko 2012).[13] Therefore, I conduct the empirical analysis by using the first differences of individual log wages (see, among others, Meghir and Pistaferri 2004; Hryshko 2012).

All studies in the literature work with the residualized earnings or wages to decompose variance into permanent and transitory components, which I follow in this paper. At the first stage, I produce the individual log wage growth deviations from cohort- and period-specific means, which can be adequately summarized as the sum of permanent (π) and transitory (υ) components. . For this purpose, I regress the raw growth of log wage on time dummies by each cohort. Let the unexplained component of log wage growth – the residualized log wage growth – be Δw_{it} and it is assumed to be decomposable into permanent and transitory components. Therefore, Equations (1)–(3) become

$$\Delta w_{it} = \delta_t[\Delta\pi_{it} + \Delta\upsilon_{it}]; \;\; E(\Delta\pi_{it}\Delta\upsilon_{it}) = 0; \;\; i = 1, ..., N; \;\; t = t_c, ...T_c, \tag{4}$$

$$\Delta\pi_{it} = \xi_{it}, \;\; \xi_{it} \sim iid(0, \sigma^2_{\xi_{(t-c)}}) \tag{5}$$

$$\Delta\upsilon_{it} = (1-\phi L)^{-1}\Delta\epsilon_{it}, \;\; \epsilon_{it} \sim iid(0, \sigma^2_{\epsilon_{(t-c)}}) \tag{6}$$

where $\Delta = (1 - L)$, δ_t is the time-specific factor loading, which captures the aggregate shifts

[13] For example, when transitory component is specified as AR(1), $Var(\tau_{it}) = \rho^2 Var(\tau_{it-1}) + \sigma^2_e$, it requires an additional moment restriction for the initial condition of the process since the variance of year t is a function of the variance of year $t-1$. Cappellari (2004) tackles this issue by specifying a parameter for the first years that cohorts are observed in his data and he shifts this parameter with cohort-specific factor loadings.

in wage distribution,[14] Equation (5) is obtained from Equation (2), and therefore permanent innovations ξ_{it} only appear on the diagonal of the variance-covariance matrix and can be identified independently from the transitory component (see Meghir and Pistaferri 2011 for discussion). Theoretical moment restrictions of Equations (4)–(6) are as follows

$$\begin{aligned} E[\Delta w_{it}\Delta w_{it'}] &= \delta_t^2[\sum_{t-c=26}^{60} \sigma^2_{\xi_{(t-c)}} + \sigma^2_{\epsilon_{(t-c)}} + (1-\phi)^2[\sigma^2_{\epsilon_{(t-c-1)}} \times I(t-c-1 \geq 26) \\ &+ \phi^2\sigma^2_{\epsilon_{(t-c-2)}} \times I(t-c-2 \geq 26) + \phi^4\sigma^2_{\epsilon_{(t-c-3)}} \times I(t-c-3 \geq 26) \\ &+ ... + \phi^{66}\sigma^2_{\epsilon_{(t-c-34)}} \times I(t-c-34 \geq 26)]] \;\; if \;\; t = t', \end{aligned} \tag{7}$$

$$\begin{aligned} E[\Delta w_{it}\Delta w_{it'}] &= \delta_t\delta_{t'}[\sum_{s=1}^{26}\sum_{t-c=26}^{60-s} \phi^{s-1}[-(1-\phi)\sigma^2_{\epsilon_{(t-c)}} + (1-\phi)^2[\phi\sigma^2_{\epsilon_{(t-c-1)}} \times I(t-c-1 \geq 26) \\ &+ \phi^3\sigma^2_{\epsilon_{(t-c-2)}} \times I(t-c-2 \geq 26) + \phi^5\sigma^2_{\epsilon_{(t-c-3)}} \times I(t-c-3 \geq 26) \\ &+ ... + \phi^{65}\sigma^2_{\epsilon_{(t-c-33)}} \times I(t-c-33 \geq 26)]]] \;\; if \;\; t' - t = s \geq 1, \end{aligned} \tag{8}$$

where $t = t'$ represents the diagonal of the variance-covariance matrix, hence the variance. $t' - t = s$ represents the leads and it can range from 1 to 26 (the first year in the sample is 1986 and the last year is 2012). ϕ is the autoregressive parameter that estimates the persistence of transitory changes. $I(. \geq 26)$ is an indicator function that allows only the variances of ages that can be observed in the data to contribute in the estimation of given age (for example, it drops the variance and the ϕ associated with this variance if the age is lower than 26, which is the first age that I observe in the final sample). As can be seen in Equation (7), for a given age, the total variance is the sum of the variance of permanent innovation, $\sigma^2_{\xi_{(t-c)}}$, the variance of transitory innovation, $\sigma^2_{\epsilon_{(t-c)}}$, and the variances of transitory innovations of all previous ages available in the data but with an exponentially decreasing contribution. Equation (8) shows the moment restrictions placed in leads, which

[14] Although it is common in the literature (see, e.g., Cappellari 2004) to use different sets of time shifters for each component, my model includes only one set of time shifters associated with the entire wage distribution. If the data used in the analysis were from a survey, say the PSID, which is frequently used for the United States, the latter would have been too restrictive given that the income processes calculated from surveys include a measurement error as a part of transitory incomes, and thus transitory component might change over time completely differently than the permanent component. For example, Altonji et al. (2002) estimates a tremendous amount of measurement error when estimating income dynamics with PSID. Since my analysis is carried out with administrative data in which the measurement error is minimal, having one set of time-shifters in the model is fairly reasonable (see also Hyslop 2001 for a similar specification). The reason I introduce this restriction on the time-shifters is to produce results that are comparable across decompositions of different processes. Without it, the estimation procedure generates negative variances in some cases, which is a very common issue in this literature (see Baker and Solon 2003 for discussion). Nevertheless, in section 6, I present results on income decompositions obtained from an econometric specification in which each component is assigned to different set of time-shifters, and compare these results with the ones obtained from the main specification. This comparison shows that the restriction on the time-shifters does not change the results, at least in the setup of this study.

include only the transitory innovations.[15]

In order to strengthen the identification strategy, the variance of transitory component at the age of 60 is assumed to be the same with the variance at the age of 59. Without this adjustment, $\sigma^2_{\epsilon_{(60)}}$ could not have been identified in the model since there is no data after the age of 60 to estimate its persistence. Although this adjustment is not necessary for identifying permanent innovations, I use the same specification on the permanent component, given that transitory changes are deviations from permanent ones and the lack of grouping at the age of 60 in the variance of permanent component could have affected the estimation results.

2.2. Annual days worked

The permanent and transitory components of days (hours) worked have been mainly overlooked in this particular literature with the exception of studies by Lillard (1978), Abowd and Card (1989) and Haider (2001). Perhaps one of the main reasons for this is the endogenous nature of labor supply decisions. In this study, the estimation sample will comprise individuals who always hold full-time labor contracts, which to some degree attenuate the endogeneity in labor supply choices. As I will explain in detail in section 3, the sample selection will also include other criteria regarding the labor market attachment of individuals. I will also show how well the model fits the empirical variance-covariance structure of annual days worked when I present the results.

Although this study is the first to provide a fully age-dependent characterization of permanent and transitory shifts in the dispersions in labor supply, the permanent (or persistent) nature of the dispersions in annual hours worked over the life cycle has been discussed and taken into account by several studies that employ structural life-cycle models of labor supply (see, e.g., among others, Kaplan 2012; Heathcote et al. 2014; Erosa et al. 2016). As discussed by Heathcote et al. (2014), the inequality in hours worked should increase over the life cycle due the accumulation of permanent shifts, similar to the case of wages. Nevertheless, the permanent and transitory components of the variations in days worked contain both wage-induced variations (endogenous component) and variations induced by exposure to involuntary spells of unemployment (exogenous component) (Lillard 1978).

First, using the same econometric model outlined above, I decompose the variations in annual days worked into permanent and transitory components, allowing the wage-induced variations to take place in both the latter and the former. The theoretical moment restrictions for this decomposition are as follows.

[15] For convenient, I do not show all the moment restrictions of every age and every lead in Equations (7) and (8), but they are available upon request.

$$
\begin{aligned}
E[\Delta d_{it}\Delta d_{it'}] &= \Gamma_t^2[\sum_{t-c=26}^{60} \sigma^2_{\gamma_{(t-c)}} + \sigma^2_{u_{(t-c)}} + (1-\phi)^2[\sigma^2_{u_{(t-c-1)}} \times I(t-c-1 \geq 26) \\
&+ \phi^2\sigma^2_{u_{(t-c-2)}} \times I(t-c-2 \geq 26) + \phi^4\sigma^2_{u_{(t-c-3)}} \times I(t-c-3 \geq 26) \\
&+ ... + \phi^{66}\sigma^2_{u_{(t-c-34)}} \times I(t-c-34 \geq 26)]] \ \ if \ \ t = t', \qquad (9)
\end{aligned}
$$

$$
\begin{aligned}
E[\Delta d_{it}\Delta d_{it'}] &= \Gamma_t\Gamma_{t'}[\sum_{s=1}^{26}\sum_{t-c=26}^{60-s} \phi^{s-1}[-(1-\phi)\sigma^2_{u_{(t-c)}} + (1-\phi)^2[\phi\sigma^2_{u_{(t-c-1)}} \times I(t-c-1 \geq 26) \\
&+ \phi^3\sigma^2_{u_{(t-c-2)}} \times I(t-c-2 \geq 26) + \phi^5\sigma^2_{u_{(t-c-3)}} \times I(t-c-3 \geq 26) \\
&+ ... + \phi^{65}\sigma^2_{u_{(t-c-33)}} \times I(t-c-33 \geq 26)]]] \ \ if \ \ t' - t = s \geq 1, \qquad (10)
\end{aligned}
$$

where $t' - t = s$, $s \geq 0$, Δd_{it} is the residualized log growth in annual working days, Γ_t is time-specific factor loadings that capture the calendar time effect in the distribution of log day growth, $\sigma^2_{\gamma_{(t-c)}}$ is the variance of permanent changes in annual days worked, $\sigma^2_{u_{(t-c)}}$ is the variance of transitory changes in annual days worked, and ϕ is the autoregressive parameter that estimates the persistence of transitory changes.

The estimates from Equations (9) and (10) will also be used in computing the correlation and OLS coefficients to further investigate the extent to which the changes in wages affect the changes in days worked.

2.2.1. Controlling for the wage-induced variations in days worked

I now demonstrate an econometric specification in which I control for the contribution of the labor supply function in the total variations in annual days of work. Let us consider the annual days of work as follows:

$$
\Delta d_{it} = \Gamma_t[\underbrace{\Theta(\Delta w_{it})}_{\text{endogenous component}} + \underbrace{\gamma_{it} + (1-\phi L)^{-1}\Delta u_{it}}_{\text{exogenous component}}]; \qquad (11)
$$

where $\Theta(\Delta w_{it})$ is the labor supply function, which includes both permanent and transitory responses of days worked to permanent and transitory variations in wages. At this point, I only control for the total labor supply function, but, later in the paper, I will explicitly investigate how permanent (transitory) shifts in wages affect the permanent (transitory) days worked over the life-cycle. Δw_{it} is introduced to the right-hand side of Equation (11) as an observable, namely the empirical variance-covariance matrix of wages. To simplify the process, I assign only one parameter, Θ, to the latter. This empirical exercise is solely conducted to quantify the relative contribution of the wage-induced variations in the variation of days worked. It is also assumed that wages, Δw_{it}, permanent changes in days worked, γ_{it}, and transitory changes in days worked, u_{it}, are not correlated with each other.

The final moment restrictions as follows:

$$\begin{aligned} E[\Delta d_{it}\Delta d_{it'}] &= \Gamma_t^2[\Theta^2 E[\Delta w_{it}\Delta w_{it'}] \\ &+ \sum_{t-c=26}^{60} \sigma^2_{\gamma_{(t-c)}} + \sigma^2_{u_{(t-c)}} + (1-\phi)^2[\sigma^2_{u_{(t-c-1)}} \times I(t-c-1 \geq 26) \\ &+ \phi^2\sigma^2_{u_{(t-c-2)}} \times I(t-c-2 \geq 26) + \phi^4\sigma^2_{u_{(t-c-3)}} \times I(t-c-3 \geq 26) \\ &+ ... + \phi^{66}\sigma^2_{u_{(t-c-34)}} \times I(t-c-34 \geq 26)]] \;\; if \;\; t = t'; \end{aligned} \tag{12}$$

$$\begin{aligned} E[\Delta d_{it}\Delta d_{it'}] &= \Gamma_t\Gamma_{t'}[\Theta^2 E[\Delta w_{it}\Delta w_{it'}] \\ &+ \sum_{s=1}^{26}\sum_{t-c=26}^{60-s} \phi^{s-1}[-(1-\phi)\sigma^2_{u_{(t-c)}} + (1-\phi)^2[\phi\sigma^2_{u_{(t-c-1)}} \times I(t-c-1 \geq 26) \\ &+ \phi^3\sigma^2_{u_{(t-c-2)}} \times I(t-c-2 \geq 26) + \phi^5\sigma^2_{u_{(t-c-3)}} \times I(t-c-3 \geq 26) \\ &+ ... + \phi^{65}\sigma^2_{u_{(t-c-33)}} \times I(t-c-33 \geq 26)]]] \;\; if \;\; t' - t = s \geq 1. \end{aligned} \tag{13}$$

I will compare the estimates from Equations (9)–(10) with the estimates from Equations (12)–(13) to understand how the life-cycle dynamics of permanent and transitory variations in days worked change once the variations in wages are taken into account.

2.3. Cross-covariance between the changes in wages and changes in days worked

In this section, I set up an empirical strategy to formally investigate the life-cycle dynamics of the impacts of wage shocks (permanent and transitory) on the variations in annual days of work (permanent and transitory). To do so, I exploit the variations between the empirical cross-covariance of wages and days worked. In this literature it is widely accepted that the changes in the wages are exogenous and considered as shocks (Krueger et al. 2010). Therefore, I place the days worked in leads in the covariance matrix and estimate the effects of exogenous variations in wages on the long- and short-run variations in days by decomposing the cross-covariances into permanent and transitory components.

Abowd and Card (1989) use the cross-covariances between the changes in annual hours worked and annual earnings to estimate a common component between the two. As they report in their study, the cross-covariances between the changes in hourly wages and hours worked are uniformly negative in their data, and thus they focus on a more general measure to examine the co-movements of earnings and hours worked. The covariance and correlation between wages and hours (or days) worked are very commonly reported as negative in the literature for different countries. Although one could think of the latter negative correlations as an outcome of the income effect dominating the substitution effect, the division bias in these correlations should be taken into account before making such a conclusion. I will show later in the paper how I tackle the downward bias in the cross-covariances between the wages and days worked.

Let the cross-covariance process between the wages and annual days of work as follows:

$$\begin{aligned}
\Delta w_{it}\Delta d_{it'} &= [\xi_{it} + (1-\phi L)^{-1}\Delta\epsilon_{it}][\gamma_{it'} + (1-\phi L)^{-1}\Delta u_{it'}], &(14)\\
E[\xi_{it}\epsilon_{it}] &= E[\xi_{it}u_{it'}] = E[\gamma_{it'}\epsilon_{it}] = E[\gamma_{it'}u_{it'}] = 0, &(15)\\
E[\xi_{it}\gamma_{it'}] &= \sigma_{\xi\gamma_{(t-c)}}; E[\epsilon_{it}u_{it'}] = \sigma_{\epsilon u_{(t-c)}}, &(16)
\end{aligned}$$

where $t^{'} - t = s$, $s >= 0$, Δw_{it} and $\Delta d_{it'}$ are the residualized log wage growth and residualized log day growth, respectively, $\sigma_{\xi\gamma_{(t-c)}}$ is the covariance between the permanent wage ξ_{it} and the days worked γ_{it} at age $t-c$ in year t, $\sigma_{\epsilon u_{(t-c)}}$ is the covariance between the transitory wage ϵ_{it} and transitory days worked u_{it}. As in the previous specifications, I allow these covariances to vary in age to capture the life-cycle profile of this process. By assumption, as shown in Equation (15), all permanent shifts (wages and days) are uncorrelated with all transitory shifts (wages and days).

To reflect the labor supply responses to the changes in wages, the wage process is placed in t dimension, and the days worked take place in $t^{'}$ dimension.

As can be seen in Equation (14), there is only one autoregressive parameter assigned to transitory wages and days worked due to the difficulties in identification of two different parameters, even though the two can be persistent at different levels. This restriction on the number of autoregressive parameters will be addressed in section 6, where I show that the restriction does not change the results in a meaningful way.

Following Equations (14)–(16), the theoretical moment restrictions of the co-movements of log wage and log day growths become

$$\begin{aligned}
E[\Delta w_{it}\Delta d_{it'}] &= \psi_t^2[\sum_{t-c=26}^{60} \sigma_{\xi\gamma_{(t-c)}} + \sigma_{\epsilon u_{(t-c)}} + (1-\phi)^2[\sigma_{\epsilon u_{(t-c-1)}} \times I(t-c-1 \geq 26)\\
&+ \phi^2\sigma_{\epsilon u_{(t-c-2)}} \times I(t-c-2 \geq 26) + \phi^4\sigma_{\epsilon u_{(t-c-3)}} \times I(t-c-3 \geq 26)\\
&+ ... + \phi^{66}\sigma_{\epsilon u_{(t-c-34)}} \times I(t-c-34 \geq 26)]] \;\; if \;\; t = t^{'}, &(17)
\end{aligned}$$

$$\begin{aligned}
E[\Delta w_{it}\Delta d_{it'}] &= \psi_t\psi_{t'}[\sum_{s=1}^{26}\sum_{t-c=26}^{60-s} \phi^{s-1}[-(1-\phi)\sigma_{\epsilon u_{(t-c)}} + (1-\phi)^2[\phi\sigma_{\epsilon u_{(t-c-1)}} \times I(t-c-1 \geq 26)\\
&+ \phi^3\sigma_{\epsilon u_{(t-c-2)}} \times I(t-c-2 \geq 26) + \phi^5\sigma_{\epsilon u_{(t-c-3)}} \times I(t-c-3 \geq 26)\\
&+ ... + \phi^{65}\sigma_{\epsilon u_{(t-c-33)}} \times I(t-c-33 \geq 26)]]] \;\; if \;\; t^{'} - t = s \geq 1, &(18)
\end{aligned}$$

where ψ_t is the time shifters that capture the aggregate changes in the co-movements of wages and days over time.

2.3.1. Computation of OLS and correlation coefficients

Although the estimates of permanent and transitory covariances between the wages and days worked provide certain interesting information about the sign and strength of their relationships, they are not interpretable in a straightforward manner. Therefore, I compute OLS and correlation coefficients for the permanent wages and days worked, as well as for the transitory wages and days worked. For this purpose, I will use the estimates obtained from Equations (7)–(8) for the variances of the wage components (thus the standard deviations can be also calculated accordingly), estimates obtained from Equations (9)–(10) for the variances of the components in days worked, and estimates from Equations (17)–(18) for the permanent and transitory covariances.

The correlation coefficients will be calculated by using the following formula:

$$\hat{\rho}^{P}_{(t-c)} = \hat{\sigma}_{\xi\gamma_{(t-c)}}/(\sqrt{\hat{\sigma}^2_{\xi_{(t-c)}}} * \sqrt{\hat{\sigma}^2_{\gamma_{(t-c)}}}), \tag{19}$$

$$\hat{\rho}^{T}_{(t-c)} = \hat{\sigma}_{\epsilon u_{(t-c)}}/(\sqrt{\hat{\sigma}^2_{\epsilon_{(t-c)}}} * \sqrt{\hat{\sigma}^2_{u_{(t-c)}}}), \tag{20}$$

where $\hat{\rho}^{P}_{(t-c)}$ and $\hat{\rho}^{T}_{(t-c)}$ are the age-specific correlation coefficients of permanent and transitory correlations, respectively.

In a simple linear regression (with a constant), the β coefficient is simply equal to the covariance of independent and dependent variables divided by the variance of independent variable. Therefore, I can calculate these OLS coefficients for each age, using the estimates of variance decompositions of wages and the results on the cross-covariance decompositions between the wages and days worked. The formula of these calculations can be illustrated as follows:

$$\hat{\beta}^{P}_{(t-c)} = \hat{\sigma}_{\xi\gamma_{(t-c)}}/\hat{\sigma}^2_{\xi_{(t-c)}} \tag{21}$$

$$\hat{\beta}^{T}_{(t-c)} = \hat{\sigma}_{\epsilon u_{(t-c)}}/\hat{\sigma}^2_{\epsilon_{(t-c)}}. \tag{22}$$

where $\hat{\beta}^{P}_{(t-c)}$ and $\hat{\beta}^{T}_{(t-c)}$ are the age-specific OLS coefficients of permanent and transitory correlations, respectively.

2.4. Labor Income

Many studies in the literature have investigated labor income and its components. The permanent and transitory changes in labor income receive particular attention from labor economists as these changes are linked to consumption inequality and welfare of households. Some of these studies also employ age-specific specifications to characterize the variations in permanent and transitory incomes (e.g. Karahan and Ozkan 2013; Blundell et al. 2015). As previously discussed , the main focus of this study is on wages and annual days worked as the income inequality is defined by the variations of the two. However, I will also estimate the life-cycle patterns of inequalities in permanent and transitory incomes to compare them with existing studies, and position the main findings of this study in the literature.

The same econometric specification is used for the log growths in income where permanent components follow a random walk process and the transitory components are specified as the AR(1) process. The mathematical notation for the income decomposition can be found in Online Appendix.

3. Data

The data used in this study are from the archives of the INPS and cover the period from 1985 to 2012. The data randomly draw social security records from a one out of 90 samples of employees who were born on the 10th March, June, September, and December of each year. The data only contain information on private sector workers because the INPS assesses retirement benefits for these employees. As a result, individuals who leave the private sector for self-employment or the public and agricultural sectors cannot be tracked. This is one of the common restrictions of using administrative data. Another restriction is the limited information on individuals' observable characteristics (e.g. missing education data). In this study, the data provide information on annual taxable labor income, year of birth, gender, type of contract (permanent, temporary), occupation, annual days worked, and weeks worked per year.

The main target group of this study is white- and blue-collar male workers holding full-time contracts in the private sector. Accordingly, seasonal workers, apprentices, and managers (*dirigente*) are excluded from the sample. To reduce the effect of endogenous labor supply decisions at the early (e.g. pursuing an education) and late stages (e.g. early retirement) of the life cycle, I follow other studies in the literature and restrict the sample to workers who are between the ages of 25 and 60. Moreover, since the focus of this paper is solely on the life-cycle dynamics, the working sample is constructed based on the year of individuals' birth. Each birth cohort is allowed to be observed for at least ten years (Baker and Solon 2003; Cappellari and Leonardi 2016). The oldest cohort in my working sample is 1934 (51 years old in 1985) and the youngest is 1978 (34 years old in 2012).[16] Cohorts from 1952 to 1960 are fully observed in 1985–2012.

As a final restriction, I keep only individuals who are observed in the data at least five consecutive years with positive income and working days (Blundell et al. 2015).[17] There are two reasons for such a restriction: first, it creates a consistent working sample comprising individuals who continuously participate in the labor market (Baker and Solon 2003; Cappellari and Leonardi 2016); and second, as stated by Meghir and Pistaferri (2011), it eases the separate identification of permanent and transitory components. In the final working

[16]As stated above, my aim is to observe each birth cohort for at least ten years. Therefore, given that 1985 is the first year in the data and 60 is the oldest age, $1985 - 60 = 1925$, so $1925 + 9 = 1934$ is the oldest cohort in the sample. Given that the last year in the data is 2012 and the youngest age is 25, $2012 - 25 = 1987$, $1987 - 9 = 1978$ is the youngest cohort.

[17]Labor income is adjusted based on 2013 prices.

sample, individuals are on average observed consecutively for 13.68 years with a standard deviation of 6.62, varying from 5 to 28 consecutive years. Ultimately, the final sample is an unbalanced panel comprising 734,918 individuals with 10,962,026 person-year observations spanning 1985–2012. Table 1 reports the summary statistics of the structure of the estimation sample by cohort.

Table 1: Sample Size by Birth–Cohort

Cohort	**Person**	**Person–Year**	**Age–Range**	**Year–Range**
1934	8,008	65,577	51-60	1985-1994
1935	8,743	76,981	50-60	1985-1995
1936	8,715	80,178	49-60	1985-1996
1937	9,581	92,071	48-60	1985-1997
1938	10,914	108,972	47-60	1985-1998
1939	11,716	121,034	46-60	1985-1999
1940	11,940	128,929	45-60	1985-2000
1941	11,095	125,981	44-60	1985-2001
1942	11,305	136,254	43-60	1985-2002
1943	11,466	143,723	42-60	1985-2003
1944	12,034	158,785	41-60	1985-2004
1945	11,931	167,250	40-60	1985-2005
1946	15,564	229,594	39-60	1985-2006
1947	16,267	253,528	38-60	1985-2007
1948	16,689	274,341	37-60	1985-2008
1949	15,976	272,876	36-60	1985-2009
1950	16,128	285,795	35-60	1985-2010
1951	15,496	287,942	34-60	1985-2011
1952	15,516	297,543	33-60	1985-2012
1953	15,663	304,053	32-59	1985-2012
1954	16,375	317,951	31-58	1985-2012
1955	16,653	326,088	30-57	1985-2012
1956	17,127	330,935	29-56	1985-2012
1957	17,743	342,147	28-55	1985-2012
1958	17,934	343,952	27-54	1985-2012
1959	18,832	361,290	26-53	1985-2012
1960	19,711	370,918	25-52	1985-2012
1961	19,915	365,566	25-51	1986-2012
1962	20,567	368,171	25-50	1987-2012
1963	20,827	364,596	25-49	1988-2012
1964	22,208	378,333	25-48	1989-2012
1965	22,383	368,765	25-47	1990-2012
1966	21,876	346,505	25-46	1991-2012
1967	21,320	324,729	25-45	1992-2012
1968	21,616	313,864	25-44	1993-2012
1969	20,878	290,714	25-43	1994-2012
1970	20,769	276,957	25-42	1995-2012
1971	20,500	261,943	25-41	1996-2012
1972	19,907	242,113	25-40	1997-2012
1973	19,441	226,903	25-39	1998-2012
1974	19,382	213,130	25-38	1999-2012
1975	18,029	188,069	25-37	2000-2012
1976	17,010	167,603	25-36	2001-2012
1977	15,282	140,650	25-35	2002-2012
1978	13,886	118,727	25-34	2003-2012
Total	734,918	10,962,026	25-60	1985-2012

3.1. Descriptive statistics

In the final sample, on average the pre-tax income is 27,000 Euro, with 272 annual days of work, 47 weeks worked per year, the daily wage is 97 Euro, the weekly wage is 560 Euro, and on average individuals work 5.7 days per week. Fig. 1 highlights the descriptive statistics of pre-tax log income, log wages (daily and weekly), log days, and log weeks over the life cycle. Daily wages are calculated by dividing the total pre-tax labor income in a given year by the total annual days of work. Annual days of work are defined in this paper as the sum of days worked (they might be from several jobs in one year) of workers in each year. The data also contain the number of weeks worked per year by default, and thus the calculation of weekly wages is also possible (total labor income divided by the number of weeks in a given year). This extra information on the weeks worked per year will play a key role in tackling the division bias between daily wages and annual days of work.

The patterns observed in Fig. 1 are consistent with all aspects of the life-cycle wage profile. Average wages increase throughout the working span, although this increase slows during the late stage. Average working days grow from the age of 25 to 45, before they subsequently start to slowly decrease, which can be explained by the fact that during the late stage of the life cycle individuals are exposed to higher levels of productivity and health shocks. The standard deviation of log wages increases with wavy cyclical fluctuations over the life cycle, indicating that—in a descriptive context—the dispersion across individuals rises as they get older. On the other hand, the standard deviation of log days is in a U-shape through the working span. A similar U-shaped pattern in the variance of annual working hours over the lifetime is documented by Kaplan (2012) and Blundell et al. (2015).

As will be explained in detail below, this study works with the growth in variables (in other words, the first differences in logs). Fig. 2 shows the life-cycle patterns of log growths in all variables used in this study. Taking the first differences excludes the observations at the age of 25 and in 1985. The average log wages growth presented in the figure is rather flat, as is its standard deviation, with the exception of the increase after the age of 50. The log growths in income, days, and weeks decrease during the early stage and remain relatively flat from the age of 33 to 48, before they start decreasing again after the age of 50, which generates an increase in their standard deviations. Although this study works with the second moments of these variables, the life-cycle profiles in Fig. 2 show that even the first moments of income growth co-move with the first moments of days and weeks worked. Moreover, the standard deviations of log growths in income, days and weeks worked are at similar levels and move together throughout the life cycle.

3.2. Further investigation into the variation in annual days of work

3.2.1. 90/10 and 50/10 ratios

Thus far, I have presented how similar the variations in days worked (standard deviations) are to the variations in income. While the similarities between variations in income and days worked are interesting, it is important to understand the potential sources of the

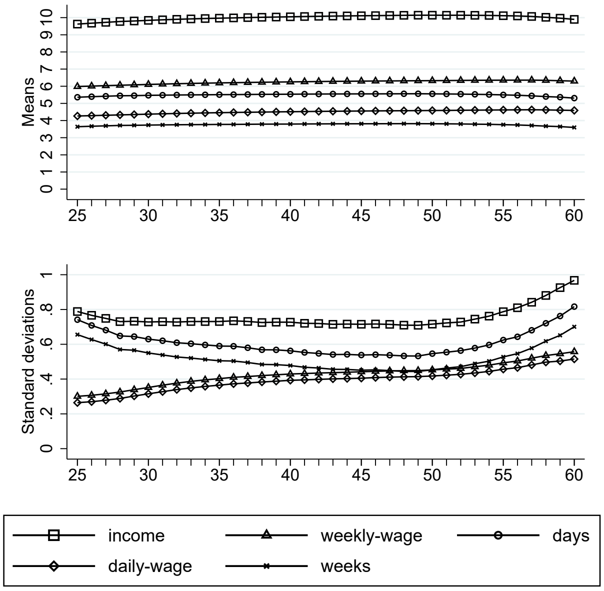

Fig. 1: Descriptive statistics of income, wages, days worked, and weeks worked.
Notes: The figure at the top highlights the average income, weekly wages, daily wages, annual days worked, and weeks worked per year over the life cycle. The figure at the bottom highlights the standard deviations of these variables. Both figures are obtained from the final estimation sample. All variables are in their natural logarithms.

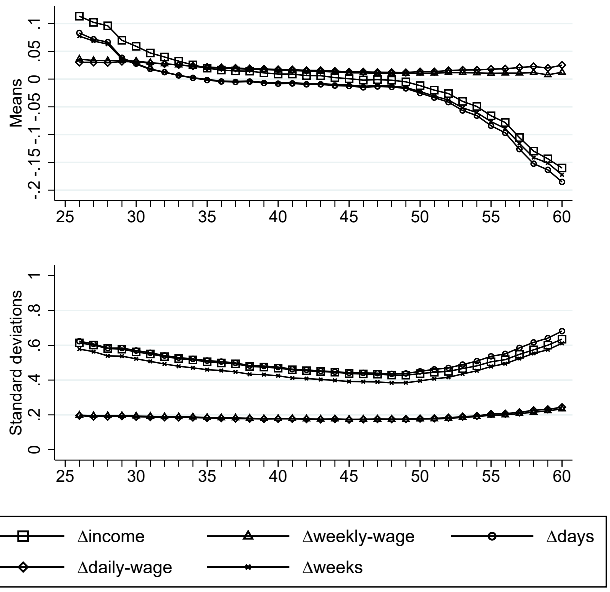

Fig. 2: Descriptive statistics of log growths in income, wages, days worked, and weeks worked.
Notes: The figure at the top highlights the averages of income, weekly wages, annual days worked, daily wages, and weeks worked per year over the life cycle. The figure at the bottom highlights the standard deviations of these variables. Both figures are obtained from the final estimation sample. All variables are in their natural logarithms.

variation in days worked. In Fig. 3, I present an alternative measure for the inequality in days worked, namely the 90/50 and 50/10 ratios in the distribution of annual days of work. The results are striking as the entire variation in the days worked (throughout the life cycle) is driven by the variations in the bottom half of the distribution (50/10 ratio), while the 90/50 ratio is very close to 1 and follows a flat pattern. This indicates that the total variation in days worked is not driven by some high-productive individuals who keep working more days than the median and increasing the dispersion in the number of working days (Kaplan 2012). The life-cycle variations in the days worked presented in Fig. 3 are very similar to those reported by Kaplan (2012) for the hours worked in the United States. The resemblance between the days and hours worked is reassuring for the use of days worked as a proxy to labor supply.

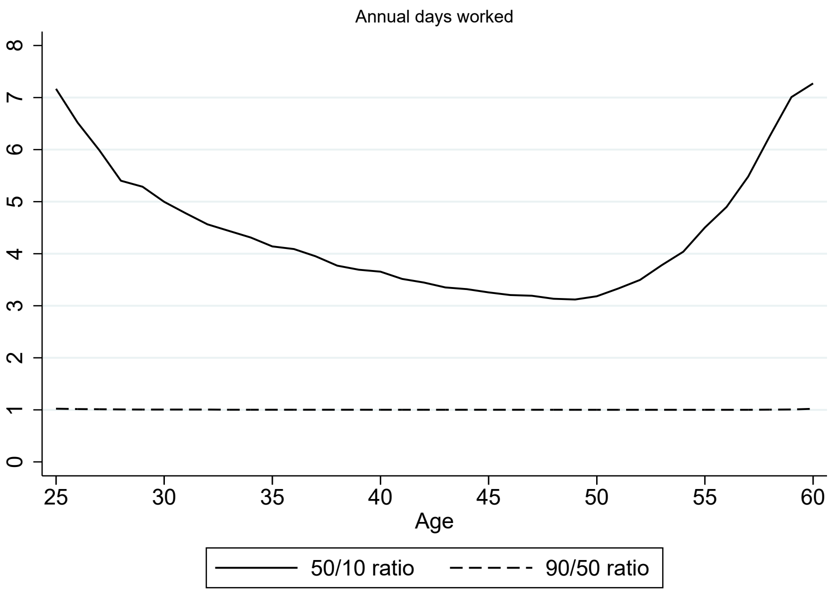

Fig. 3: Annual days worked by 50/10 and 90/50 ratios.
Notes: The solid line shows the 50/10 ratio, which is computed by dividing the median number of days worked by the annual days of work of individuals who are in either the 10th or lower percentiles of the distribution in a given age. The dash line shows the 90/10 ratio, which it is computed by dividing the annual days of work of individuals who are in either the 90th or higher percentiles of the distribution by the median number of days worked in a given age.

3.2.2. Extensive and intensive margins

I now investigate—through a cross-sectional decomposition—the extent to which the variations in days worked are driven at the extensive and intensive margins. As I have previously explained in this section, the data that I use contains information on annual days of work and the number of weeks worked per year by default. Ultimately, the total number of days worked in a given year is the sum of the total number of weeks worked per year multiplied by the number of days worked per week. I calculate the average number of days worked per week manually by dividing the total number of days worked by the total number of weeks worked. After taking the logarithm of days worked, the variance of log annual days of work becomes:

$$Var(log[days_{it}]) = \overbrace{Var(log[weeks\ worked\ per\ year])}^{\text{extensive margin}} + \overbrace{Var(log[days\ worked\ per\ week])}^{\text{intensive margin}}$$
$$+ \quad 2 * Cov(log[weeks\ worked\ per\ year], log[days\ worked\ per\ week]); \quad (23)$$

where the first item on the right-hand side of Equation (23) represents the variations at the extensive margin, the second item represents the variations at the intensive margin, and the third item is the covariance between the two.[18] This cross-sectional decomposition enables quantifying the relative contribution of the extensive and intensive margin-based variations in the total number of days worked. Fig. 4 presents the life-cycle profile of this decomposition. The figure at the top shows the results in levels, while the figure at the bottom shows the results in first differences.

As can be clearly seen, the variation in the weeks worked per year shapes the variation in the days worked. More specifically, the relative contribution of the variation of weeks worked to the total log variance of days worked is on average around 72%, indicating that the inequality in the number of days worked is mainly driven by the unemployment spells within a year.

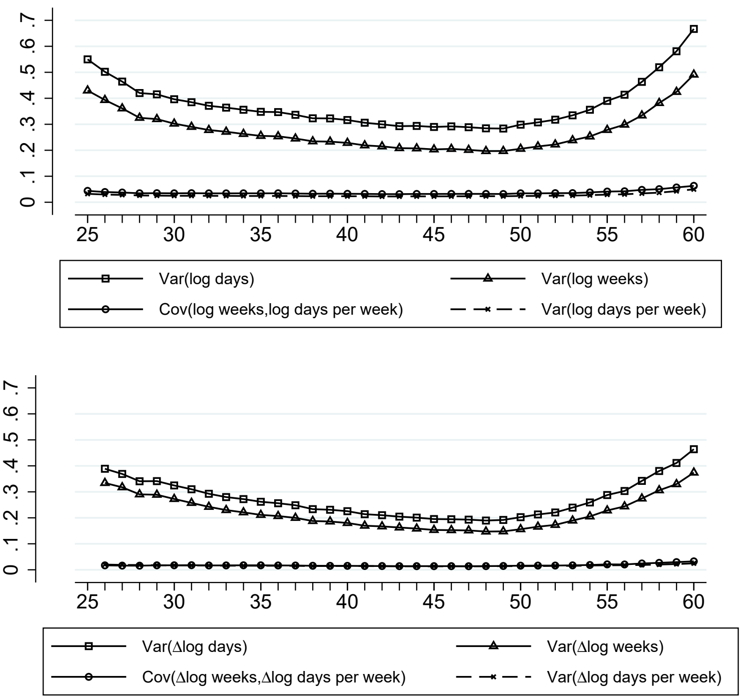

Fig. 4: Cross-sectional decomposition of annual days worked.
Notes: The figure at the top highlights the cross-sectional decomposition in levels over the life cycle. The figure at the bottom highlights cross-sectional decomposition in first differences over the life cycle. Both figures are obtained from Equation (23) explained in subsubsection 3.2.2.

[18]See Kaplan (2012) for the same decomposition for the annual hours of work.

4. Empirical Moments and Covariance Structures

I produce cohort-specific empirical covariance matrices $m^g_{tt'}$, $m^w_{tt'}$, $m^d_{tt'}$ and $m^{wd}_{tt'}$ for the log income growth, log wage growth, log day growth, and the cross-products of log wage and log day growths, respectively, to estimate the parameters of the theoretical moments that are presented in section 2.

$$m^g_{tt'} = \sum_{i=1}^{N} \Delta r_{it} \Delta r_{it'} / \sum_{i=1}^{N} k_{it} k_{it'}, \tag{24}$$

$$m^w_{tt'} = \sum_{i=1}^{N} \Delta x_{it} \Delta x_{it'} / \sum_{i=1}^{N} k_{it} k_{it'}, \tag{25}$$

$$m^d_{tt'} = \sum_{i=1}^{N} \Delta \eta_{it} \Delta \eta_{it'} / \sum_{i=1}^{N} k_{it} k_{it'}, \tag{26}$$

$$m^{wd}_{tt'} = \sum_{i=1}^{N} \Delta x_{it} \Delta \eta_{it'} / \sum_{i=1}^{N} k_{it} k_{it'}, \tag{27}$$

where $t <= t^{'}$, Δr_{it}, Δx_{it}, and $\Delta \eta_{it}$ are the empirical counterparts of Δg_{it}, Δw_{it} and Δd_{it}, respectively, k is equal to 1 if individual i is observed in year t, and otherwise 0. As previously stated, I work with unbalanced panel data in which individuals can enter and exit over the years.[19] If individual i is not observed in a given year, that individual's contribution to the variance and covariances is zero for the period involving that year. Therefore, it is reassuring to have sample selection criteria that only keep individuals in the sample who are observed for at least five consecutive years.

4.1. Descriptive Moments

In the final sample, there are 9,714 moments installed in each of the covariance matrices ($m^g_{tt'}$, $m^w_{tt'}$, $m^d_{tt'}$ and $m^{wd}_{tt'}$). Fig. 5 and Fig. 6 highlight the empirical second moments and auto-covariance structures, respectively, of log growths in income (upper left), days worked (upper right), weekly and daily wages (lower left), and cross-covariances of wages and days worked (lower right) over the life cycle.

The common feature of all four graphs in Fig. 6 is that after the second lag, the auto-covariances are very close to zero. This is consistent with the reported patterns in the literature and it fulfills the necessary conditions to identify the permanent and transitory components when working with first differences (e.g. Altonji et al. 2002; Meghir and Pistaferri 2004; Hryshko 2012).

In Fig. 5, we see that the variances of log growths in income and days worked are very similar in terms their levels and U-shaped patterns, while the variance of log growth in wages rather occurs at s much lower level, increasing after the age of 50. As we see in Fig. 5 and Fig. 6, the empirical second moments and auto-covariance structures of weekly

[19] See Baker and Solon (2003) for a discussion on estimating auto-covariance structures with unbalanced panel data sets.

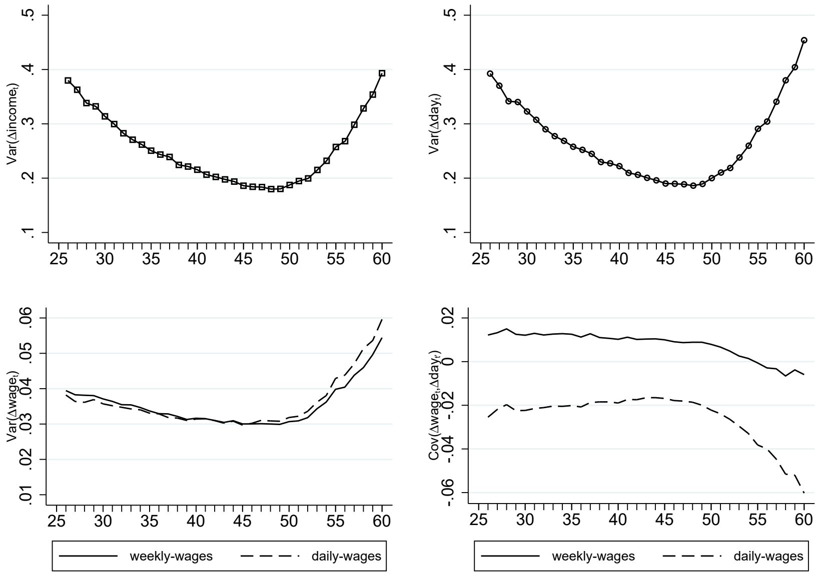

Fig. 5: Empirical moments over the life cycle.
Notes: The upper left figure displays the second moments of the residualized log income growth. The upper right figure highlights second moments of the residualized log days growth. The bottom left figure displays the second moments of the residualized log daily and weekly growth. The bottom right figure displays the diagonal of residualized covariances between log wage growths (daily and weekly wages) and log day growth over the life cycle.

and daily wages are almost identical, although their cross-products with the annual days of work are significantly different. While the covariance of daily wages and days worked vary from -0.02 to -0.06, the covariances between the weekly wages and days worked have a positive sign until the age of 56, then they fall to -0.007 at the age of 60. This is the case because the covariances between the daily wages and annual days of work are subject to division bias, which reduces the correlation between the two (Borjas 1980). Therefore, the decomposition of cross-covariances will take place between the weekly wages and days worked when estimating the parameters of Equations (17) and (18).

4.2. Estimation method

I estimate the parameters of the model outlined in the previous section by using the 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 the empirical covariance matrix that were obtained from data and the theoretical covariance matrix structure implied by my model.

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

$$\Theta = \underset{\Theta}{\operatorname{argmin}} \; [m - f(\Theta)]W[m - f(\Theta)]', \tag{28}$$

where $f(\Theta)$ is the theoretical covariance structure; m—as explained previously—is the em-

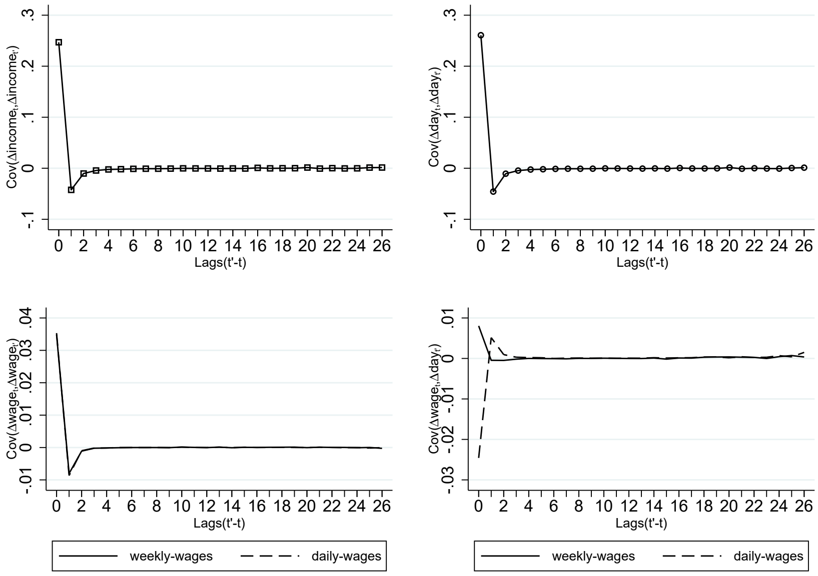

Fig. 6: Empirical moments over the lags.
Notes: The figure shows the empirical autocovariances of log income growth (upper left), log day growth (upper right), log wage growths (bottom left) and cross-covariance between log wage and log day growths over the lags (bottom right).

pirical 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, Ω_c is the number of years for which cohort c is observed, and W is a positive definite weighting matrix.

Chamberlain (1984) shows that choosing W as an inverse matrix of 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 the second and fourth moments. In the light of other studies in the literature, I choose the weighting matrix, W, as an identity matrix. Therefore, this estimation method is called *equally weighted minimum distance estimation* (EWMD), which is tantamount to the non-linear least squares. However, non-linear least squares methods produce a biased estimated covariance matrix of Θ due to the heteroskedasticity and autocorrelation in m. To tackle this issue, standard errors robust to these problems are obtained by using the fourth-moments matrix F (Cappellari 2004). $Var(\Theta) = (G'G)^{-1}G'FG(G'G)^{-1}$, where G is the gradient matrix utilized at the solution of Equation (22).

5. Results

In this section I will discuss the estimation results from models presented in section 2. The discussion in this section will take place based on the results displayed in figures, while the tables with the full list of parameter estimates with robust standard errors are available in Online Appendix.

5.1. Wages

Fig. 7 and Fig. 9 report the results on weekly and daily wages, respectively. These results are obtained by using Equations (7) and (8). Both permanent and transitory inequalities in daily and weekly wages are similar in terms of their levels and trends. The results show that the variance of permanent weekly wage shocks is 0.027 at the age of 26, which represents the permanent inequality in wages at the beginning of one's career. What follows is a sharp decrease to 0.018 at the age of 27, after which the variance of permanent wages smoothly decreases to 0.011 until the age of 49. As we see from these figures, the sharp increase in the total empirical variance of wages after the age of 50 is explained by the rise of permanent wage inequality, indicating that workers are subject to a higher level of uninsurable wage risk during the late stages of their careers. It is noteworthy that the effect of permanent changes in wages by definition lasts forever. Therefore, to better visualize the life-cycle profile of these shocks, I display the sum of them in Fig. 8.[20]

On the other hand, the variance of transitory weekly wage shocks is stable even after the age of 50, except for the peak at the age of 60. The estimated persistence of transitory wage shocks, ϕ, is very low (0.14), suggesting that on average only 2% of these shocks survive to the next year.

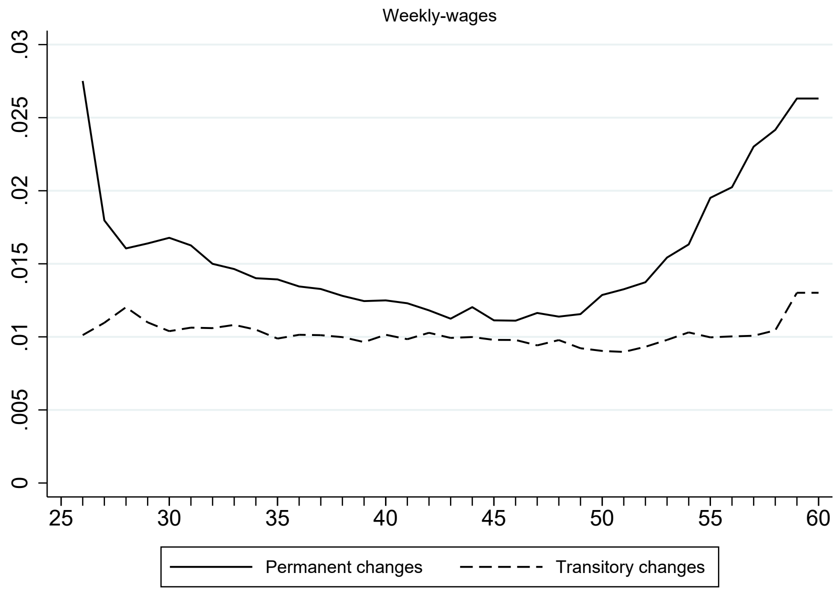

Fig. 7: Variance decomposition of weekly-wages over the life cycle.
Notes: The figure shows the estimation results of variance decomposition obtained from the econometric specifications outlined in subsection 2.1. The solid line is used for variance of permanent changes in weekly wages, $\sigma^2_{\xi_{(t-c)}}$, and the dashed lines for variance of transitory changes in weekly wages, $\sigma^2_{\epsilon_{(t-c)}}$. Full parameter estimates are reported in Table 3.

[20]This presentation of permanent shocks are equivalent of presentations when working with levels.

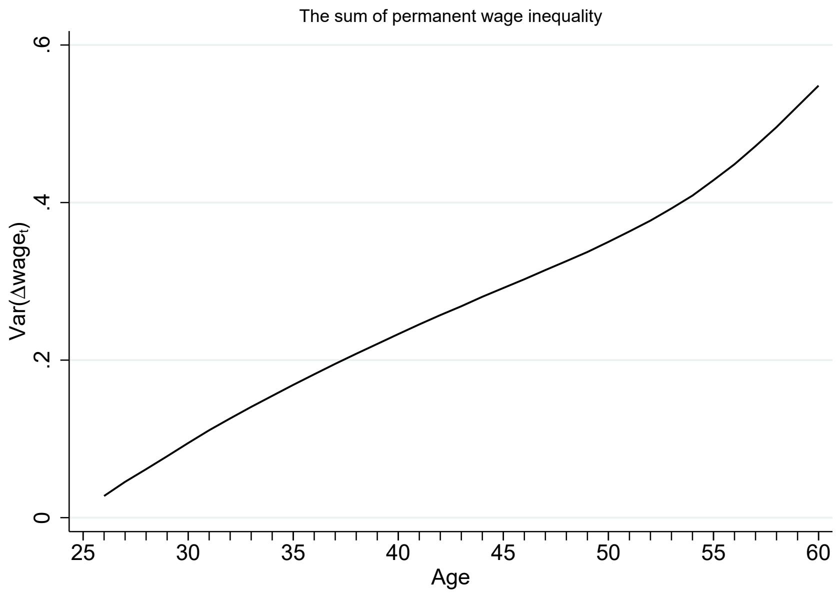

Fig. 8: Variance of permanent weekly wage shocks.
Notes: The figure displays the sum of the estimated variances of permanent shifts in weekly wages over the life-cycle.

5.2. Annual days of work

The results estimated from Equations (9) and (10) are reported in Fig. 10, showing that the variance of permanent changes in days worked follows a wide U-shaped pattern over the life cycle. In Fig. 11, I show that the model fits perfectly to the empirical variance-covariance structure of days worked. The permanent variance in the number of days worked starts from 0.22 at the age of 26 and decreases to 0.065 through to the age of 48. Subsequently, it rapidly increases after 50 and reaches 0.21 at the age of 60. This finding is economically large, indicating that a permanent shift of one standard deviation changes the annual days of work of a 55-year-old by about 42%, while the corresponding number is only 26% for a 45-year-old. The existence of such large-scale permanent inequalities that can alter the labor supply of individuals who are very close to retirement is in line with the concerns regarding the well-being of older workers.

On the other hand, the estimated variance of transitory changes in days worked is smaller than the variance of permanent ones, and their life-cycle patterns also differ. The variance of transitory changes is 0.081 at the age of 26 and it decreases to 0.037 at the age of 52. Afterwards, it increases to 0.057 through to the age of 60. The estimated autoregressive parameter is 0.25, which suggests that only 6% of transitory shifts in annual working days still affect the days worked after two years.

The contribution of the variance of permanent changes in days worked to the total income inequality is by far greater than that of the variance of permanent wage shocks. This suggests that the traditional approach in this literature that focuses only on the labor income inequality is incomplete, and that a more comprehensive characterization of income inequal-

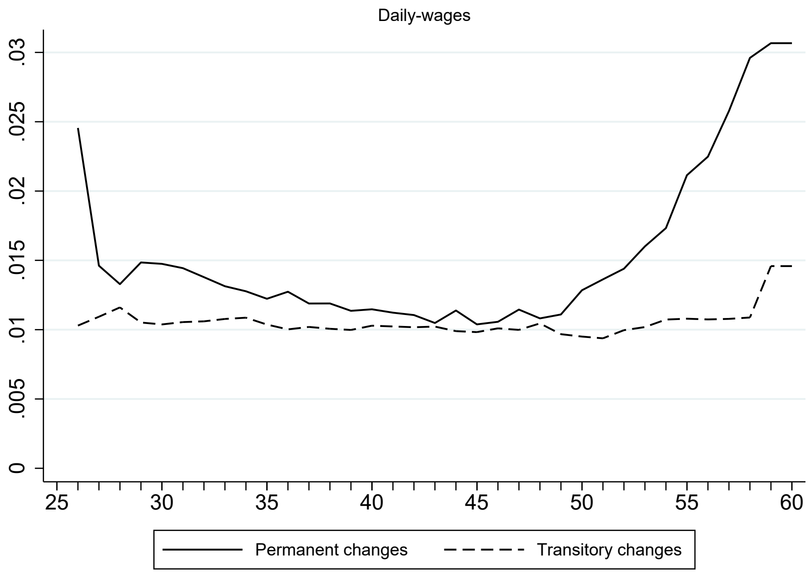

Fig. 9: Variance decomposition of daily-wages over the life cycle.
Notes: The figure shows the estimation results of variance decomposition obtained from the econometric specifications outlined in subsection 2.1. The solid line is used for variance of permanent changes in daily-wages, $\sigma^2_{\xi_{(t-c)}}$, and the dashed lines for variance of transitory changes in daily-wages, $\sigma^2_{\epsilon_{(t-c)}}$. Full parameter estimates are reported in Table 5.

ity that takes into account the dispersions in annual days (or hours) of work and in wages separately is necessary. From a policy point of view, dealing with labor supply inequality requires different policy interventions (e.g. insurance, government transfers, incentivizing firms) than dealing with wage inequality (e.g. collective bargaining).

5.2.1. Results after controlling for the wage induced variations

As previously discussed, unlike the case with wages, the variation in days worked has an endogenous component (e.g. responses to variations in wages), as well as an exogenous component (e.g. labor demand, involuntary unemployment spells). The results obtained from Equations (12)–(13) are presented in Fig. 12. The figure on the left shows the results once the labor supply function is controlled for, and the figure on the right shows the main findings on days worked presented in the last section, obtained from Equations (9)–(10). On the one hand, in line with theoretical expectations, controlling for the wage-induced variations in days worked reduces the levels of the estimated variances of permanent and transitory changes in annual days of work. On the other hand, the relative contribution of the wage-induced variations in days is only about 33%, which indicates that the exogenous component is the main driving factor of the total variations in days worked.

Taken together with the cross-sectional decompositions presented in section 3, the findings on the annual days worked inequality suggest that the unemployment spells induced by labor demand shape the permanent dispersion in the life-cycle labor supply.

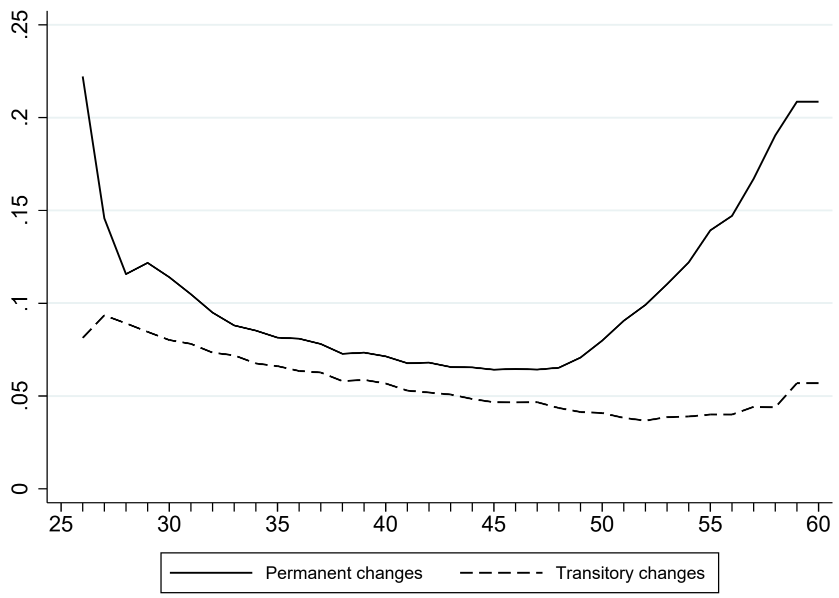

Fig. 10: Variance decomposition of days worked over the life cycle.
Notes: The figure shows the estimation results of variance decomposition obtained from the econometric specifications outlined in Equations (9)–(10). The solid line is used for variance of permanent changes in days worked, $\sigma^2_{\gamma_{(t-c)}}$, and the dashed lines for variance of transitory changes in days worked, $\sigma^2_{u_{(t-c)}}$. Full parameter estimates are reported in Table 2.

5.3. Decomposition of cross-covariances between weekly wages and days worked

Thus far, I have separately investigated the components of dispersions in wages and working days over the life cycle. I now present the results—estimated from the Equations (17) and (18)—on the interactions of weekly wages and working days. Recall that—as explained in subsection 2.3—working days are placed in leads of the empirical covariance matrix used in this estimation procedure to reflect the labor supply responses to wage shocks.

The results for the decomposition of the cross-covariances are presented in Fig. 13. The estimated covariances between the permanent wages and days worked are always positive throughout the life cycle. We see that early in one's career the latter covariance is higher with 0.018 at the age of 26, declining to 0.005 through to the age of 35, and it follows a relatively flat pattern around 0.005 until the age of 60. On the other hand, the estimated covariances for the transitory wages and days worked smoothly declining over one's career, with a negative sign after the age of 53. The coefficient estimates for ages 52 (-0.0001) and 53 (0.0003) are small and not significantly different than zero.[21] The slightly negative covariance between wages and days worked at the end of careers can be explained by the accumulated wealth of individuals through the life cycle and the fact that the consumption of leisure is more expensive for older individuals. The estimated autoregressive parameter for the persistence of the wage-induced transitory changes in days worked is 0.44.

Fig. 14 displays the computed OLS and correlations coefficients between wages and days worked. The figure on the top shows the findings on the permanent wages and days worked,

[21] In Online Appendix, Table 4 reports the robust standard errors.

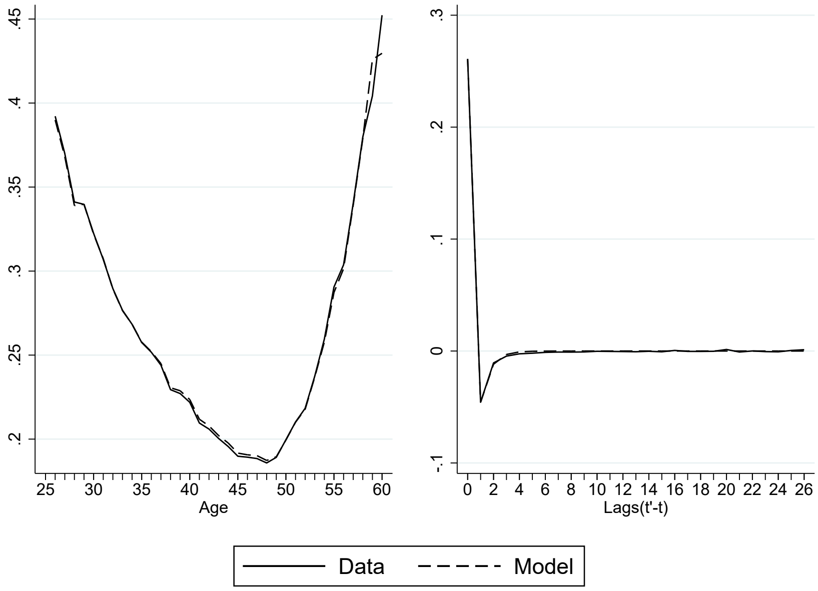

Fig. 11: Model fit over the life cycle.

while the figure at the bottom shows the results on the transitory wages and days worked. The correlation coefficients are obtained from Equations (19)–(20), whereas the OLS coefficients are obtained from Equations (21)–(22). Although these statistics are obtained with *back-of-the-envelope-calculations*, they provide important information on the labor supply reactions to different type of wage shocks.

Since wages and days of work are in logs, the interpretation of these OLS coefficients can be made as follows. A one-percent increase in permanent wages increases the days worked permanently by 0.8% at the age of 28. The reaction of days worked to the changes in permanent wages decreases to 0.4% by the age of 33 and remains rather stable until the age of 53. The smallest OLS coefficient is computed at the age 58 with 0.15%. In a broad sense, these estimates fall in definitions of Marshallian elasticities of labor supply described by Blundell and MaCurdy (1999) and Attanasio et al. (2018), as these parameters are obtained from individuals permanent reactions of labor supply to the permanent shifts in wages (thus the change in lifetime wages). It is also noteworthy that the cross-covariance of wages and days include (within-period) variations in both the intensive and extensive margins. Recent studies have shown that the extensive margin accounts for a large portion of aggregate labor supply (Keane and Wasi 2016; Erosa et al. 2016; Attanasio et al. 2018).

In terms of the computed correlations of permanent wages and days of work, even at the age of 28—when the permanent labor supply reaction is at its peak—the correlation coefficient is 0.3. This finding suggests that despite the strong reaction of days worked to the changes in permanent wages early in one's career, the changes in permanent wages fail to explain the total variation in days worked. These correlations occur at around 0.1 through to the end of one's career, indicating very weak correlations.

The temporary reactions of days worked to the transitory changes in wages are about

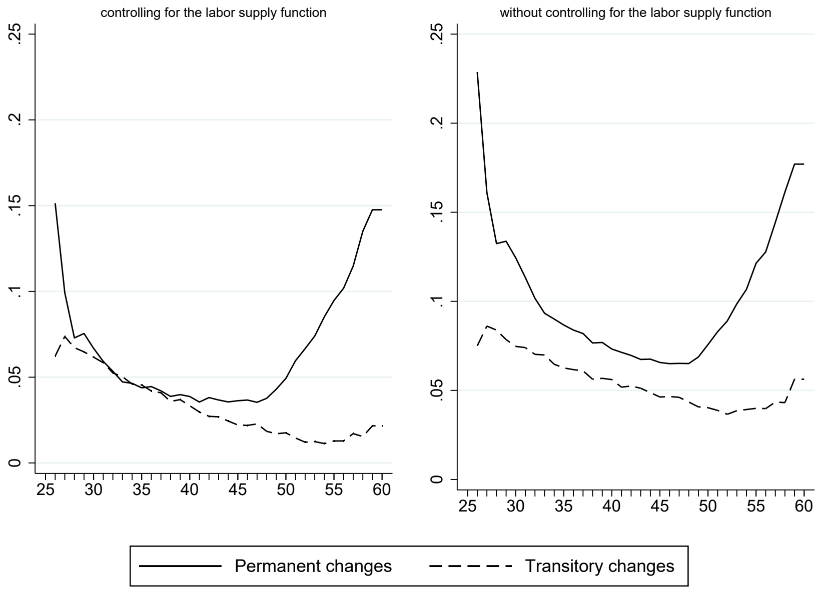

Fig. 12: Decomposition of annual days of worked.
Notes: The figure on left shows the results of variance decomposition of days worked after controlling for the labor supply functions as explained in Equations (12) and (13). The estimated Θ^2 is 2.434. The figure on right is the same with Fig. 10.

0.5% between the ages of 27 and 33. While the corresponding reactions slightly decrease through to the age of 50 and decline to 0.3%, they are negative after the age of 53, indicating a wealth effect. Similar to the correlations between the permanent changes, the correlation coefficients of transitory changes in wages and days worked are very low and they occur around 0.015 until the age of 51. Since both OLS and correlation coefficients are functions of the covariances between wages and days of work, the estimated correlations after the age of 53 are also negative.

5.4. Income

Finally, I present the results on the labor income decomposition, which are presented in Fig. 15. The results are very similar to those presented for the annual days of work. This is unsurprising as I have previously shown that the empirical variances of income and days worked are almost identical. This finding is in line with the results of the study by Abowd and Card (1989), in which they show that the variations in the co-movements of earnings and hours worked occur at a fixed wage rate, explained by the variations in annual hours of work.

The estimated patterns for the permanent and transitory components of income over the life cycle accord with the evidence in literature. Karahan and Ozkan (2013)—using data from the United States—and Blundell et al. (2015)—using data from Norway—find U-shaped patterns for the variance of permanent component of income. Furthermore, Sanchez and Wellschmied (2020) ascertain that the decline in permanent income inequality early in life is due to less-dispersed positive persistent shocks, whereas the increase in later life is

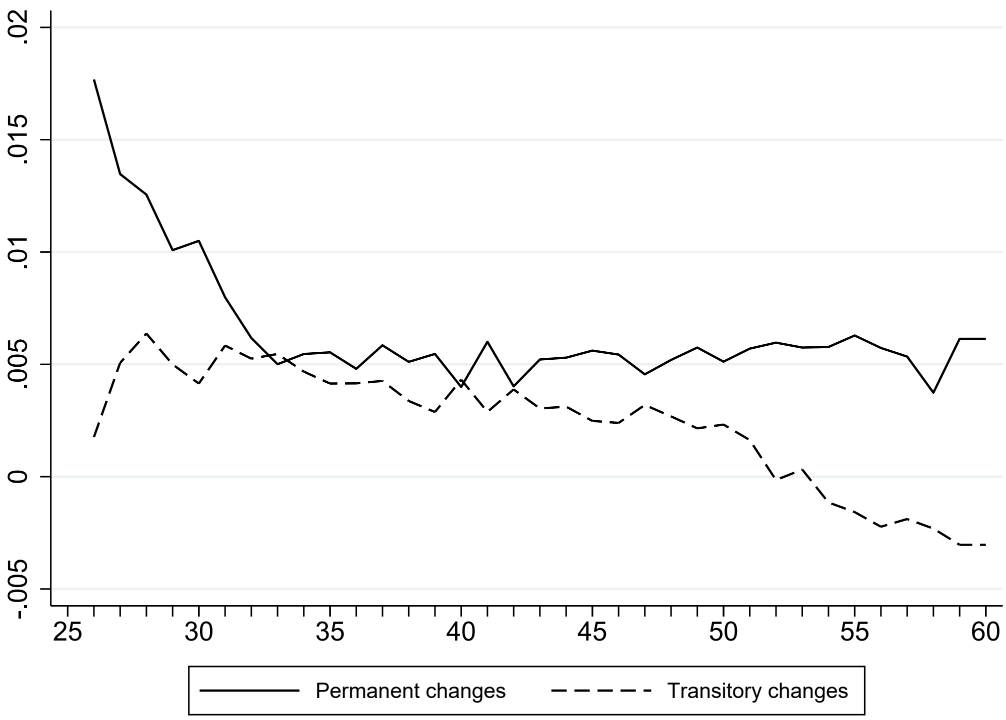

Fig. 13: Covariance decomposition over the life cycle.
Notes: The figure shows the estimation results of covariance decomposition obtained from the econometric specifications outlined in subsection 2.3. The solid line is used for covariance of permanent changes in weekly wages and days of work, $\sigma_{\xi\gamma_{(t-c)}}$, the dashed line for covariance of transitory changes in weekly wages and days of work, $\sigma_{\epsilon u_{(t-c)}}$. Full parameter estimates are reported in Table 4.

driven by more-dispersed negative persistent shocks.

6. Sensitivity Checks

In this section, I provide several sensitivity tests to check whether the results presented thus far are robust to different sample selections and econometric specifications.

6.1. Inclusion of component-specific time shifters

As I explained in footnote 14, the econometric specifications employed throughout this study contain only time shifters that take into account the calendar time effects in the entire distributions of the dependent variables. I introduce component-specific time shifters into the model and estimate Equations (34)–(35) to decompose income inequality into permanent and transitory components.

The results are presented in Fig. 16, suggesting that the difference in the results obtained from the main specification and those with component-specific factor loadings is negligible. This can be attributed to the dataset used in this study, in which the measurement error is minimal in income variable.

6.2. Restricted sample

In this section, I provide a robustness exercise in terms of the sample selection restrictions. One concern might be the effect of the endogenous labor supply participation decisions

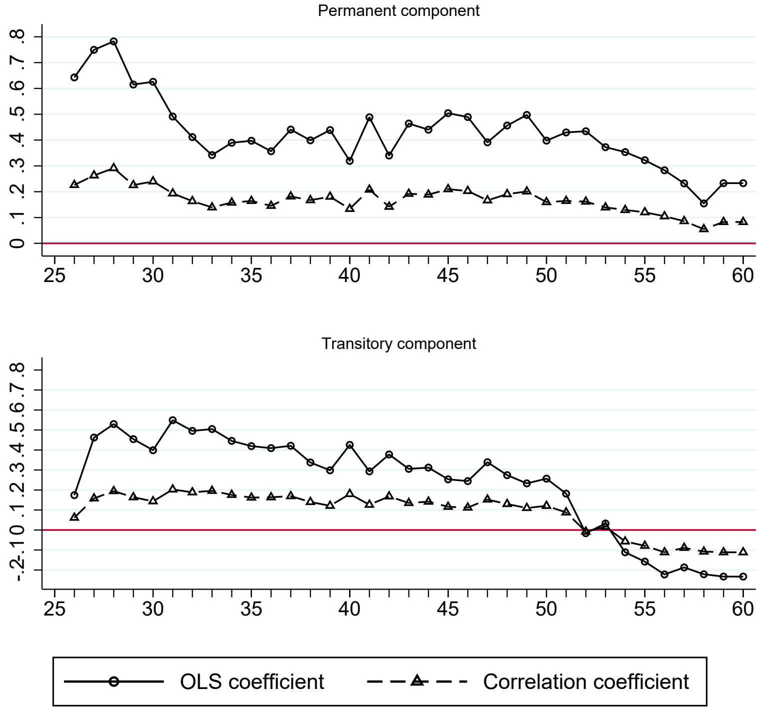

Fig. 14: Predicted OLS and correlation coefficients over the life-cycle.
Notes: The figure at the top shows the results obtained from Equations (21) and (19) for the OLS and correlation coefficients, respectively. The figure at the bottom shows the results for the transitory component, obtained from Equations (22) and (20).

over the life cycle, especially for the findings on older workers. I replicate the main analysis of this paper using a sample comprising individuals who are observed at least ten consecutive years with positive income and working days in the data. I also place a restriction on the analysis to workers between the ages of 30–55. Finally, using information from an additional dataset, I exclude the individuals who ever benefited from the social safety net program (*Cassa Integrazione Guadagni*, hereafter CIG). CIG programs compensate up to 80% of salaries of the workers who experience reductions in hours due to demand, revenue, or other economic shocks to the firms.[22] The information on CIG is available between 1996 and2012 in the data, and there are 27,144 individuals in my main sample who benefit from CIG at some point in their careers. Although the latter number is very small with respect to the sample size of this study, these compensations can create a *mechanical* relationship between the wages and days worked. Nevertheless, it is worth noting that CIG programs only cover employed workers and not involuntary lay-offs.

In the final restricted sample, the oldest cohort is 1939 and the youngest one is 1973. The sample comprises 374,520 individuals with 6,204,649 individual-year observations. On average, individuals are observed for 18.18 (standard deviation of 5.52) consecutive years, ranging from 10 to 28 years.

[22]See Giupponi and Landais (2018) for detail information on CIG programs.

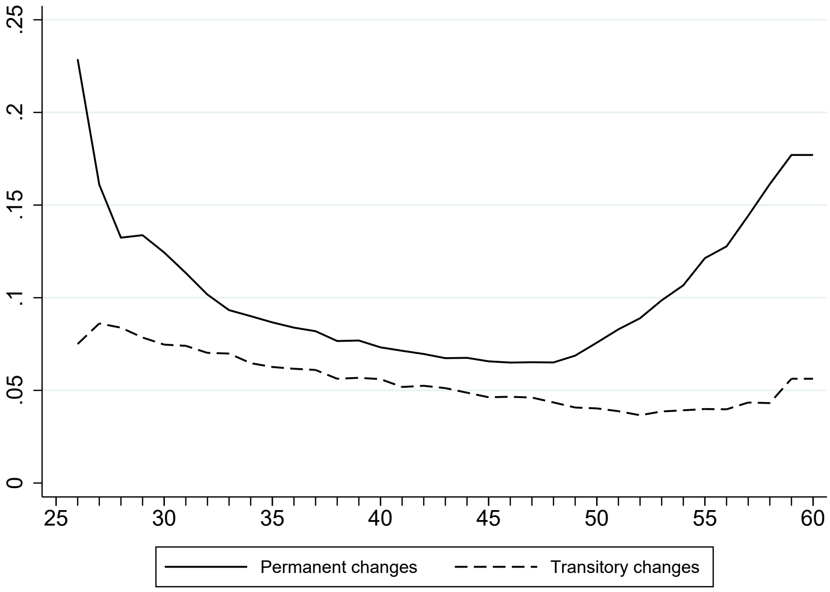

Fig. 15: Variance decomposition of income over the life cycle.
Notes: The figure shows the estimation results of variance decomposition obtained from the econometric specifications outlined in Equations (34) and (35). The solid line is used for variance of permanent changes in income, $\sigma^2_{\zeta_{(t-c)}}$, and the dashed lines for variance of transitory changes in income, $\sigma^2_{\varphi_{(t-c)}}$. Full parameter estimates are reported in Table 6.

The results obtained from the restricted sample are displayed in Fig. 17.[23] Apart from the slight decrease in the levels of permanent wage and working-day inequalities—mostly for the prime-age workers—the patterns are the same as the results in the main estimation sample for the corresponding ages.

6.3. Predicted values of ϕ^w and ϕ^d

As previously stated, the theoretical moment restrictions derived for the cross-covariance of log wage and log day growths are missing the separate identifications for the autoregressive parameters of wage and day processes. Let us consider that the transitory component is specified as an AR(1) process, but with wage and days worked specific autoregressive parameters. The cross-covariance process of Δw_{it} and $\Delta d_{it'}$ should be as follows:

$$\begin{aligned} \Delta w_{it}\Delta d_{it'} &= [\xi_{it} + (1-\phi_w L)^{-1}\Delta\epsilon_{it}][\gamma_{it'} + (1-\phi_d L)^{-1}\Delta u_{it'}], && (29) \\ E[\xi_{it}\epsilon_{it}] &= E[\xi_{it}u_{it'}] = E[\gamma_{it'}\epsilon_{it}] = E[\gamma_{it'}u_{it'}] = 0, && (30) \\ E[\xi_{it}\gamma_{it'}] &= \sigma_{\xi\gamma_{(t-c)}}; E[\epsilon_{it}u_{it'}] = \sigma_{\epsilon u_{(t-c)}}, && (31) \end{aligned}$$

where ϕ_w and ϕ_d are the autoregressive parameters of transitory changes in wage and days, respectively. Subsequently, the moment restrictions would be:

[23] The full list of parameter estimates is available upon request.

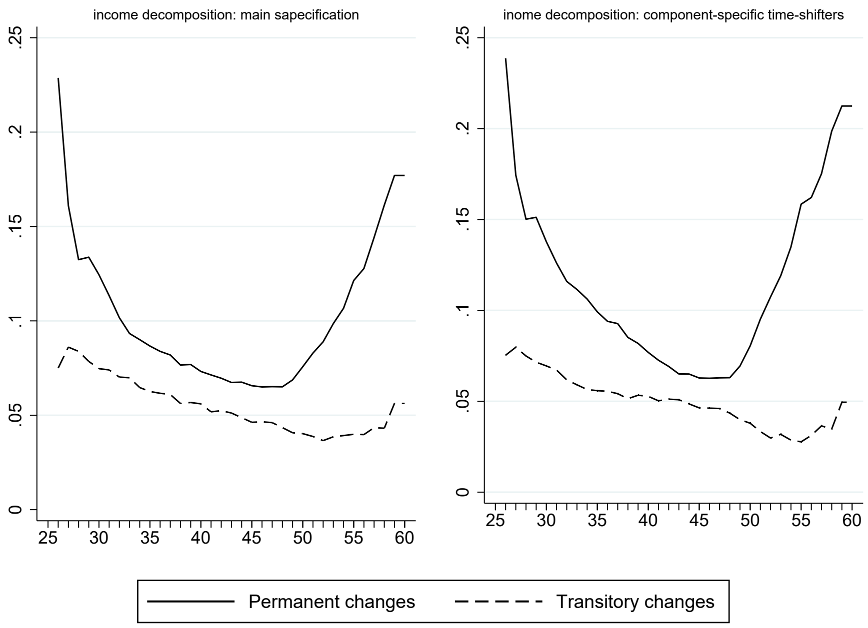

Fig. 16: Variance decomposition of income over the life cycle.
Notes: This figures compares the results obtained from main specification that includes only one set of time shifters (figure on left) with the results obtained from a specification in which component-specific time shifters are employed (figure on right). Full parameter estimates are reported in Table 7.

$$\begin{aligned} E[\Delta w_{it}\Delta d_{it'}] &= \psi_t^2[\sum_{t-c=26}^{60} \sigma_{\xi\gamma_{(t-c)}} + \sigma_{\epsilon u_{(t-c)}} + (1-\phi_w)(1-\phi_d)[\sigma_{\epsilon u_{(t-c-1)}} \times I(t-c-1 \geq 26) \\ &+ \phi_w\phi_d\sigma_{\epsilon u_{(t-c-2)}} \times I(t-c-2 \geq 26) + \phi_w^2\phi_d^2\sigma_{\epsilon u_{(t-c-3)}} \times I(t-c-3 \geq 26) \\ &+ ... + \phi_w^{33}\phi_d^{33}\sigma_{\epsilon u_{(t-c-34)}} \times I(t-c-34 \geq 26)]] \;\; if \;\; t = t', \end{aligned} \tag{32}$$

$$\begin{aligned} E[\Delta w_{it}\Delta d_{it'}] &= \psi_t\psi_{t'}[\sum_{s=1}^{26}\sum_{t-c=26}^{60-s} \phi_d^{s-1}[-\sigma_{\epsilon u_{(t-c)}} \\ &+ (1-\phi_d)(1-\phi_w)[\phi_d\sigma_{\epsilon u_{(t-c-1)}} \times I(t-c-1 \geq 26) \\ &+ \phi_d^2\phi_w\sigma_{\epsilon u_{(t-c-2)}} \times I(t-c-2 \geq 26) + \phi_d^3\phi_w^2\sigma_{\epsilon u_{(t-c-3)}} \times I(t-c-3 \geq 26) \\ &+ ... + \phi_d^{33}\phi_w^{32}\sigma_{\epsilon u_{(t-c-33)}} \times I(t-c-33 \geq 26)]]] \;\; if \;\; t' - t = s \geq 1, \end{aligned} \tag{33}$$

where ψ_t is the time shifters that capture the aggregate changes in the co-movements of wages and days over time. Using the moments outlined in Equations (32)–(33) ϕ_w cannot be identified. Therefore, in the main specification—Equations (17)–(18)—there is only one autoregressive parameter assigned to both transitory shocks in wages and days. To ascertain whether the latter restriction has any impact on the estimates of $\sigma_{\xi\gamma_{(t-c)}}$ and $\sigma_{\epsilon u_{(t-c)}}$, I estimate the Equations (32)–(33) using the predicted values of autoregressive parameters

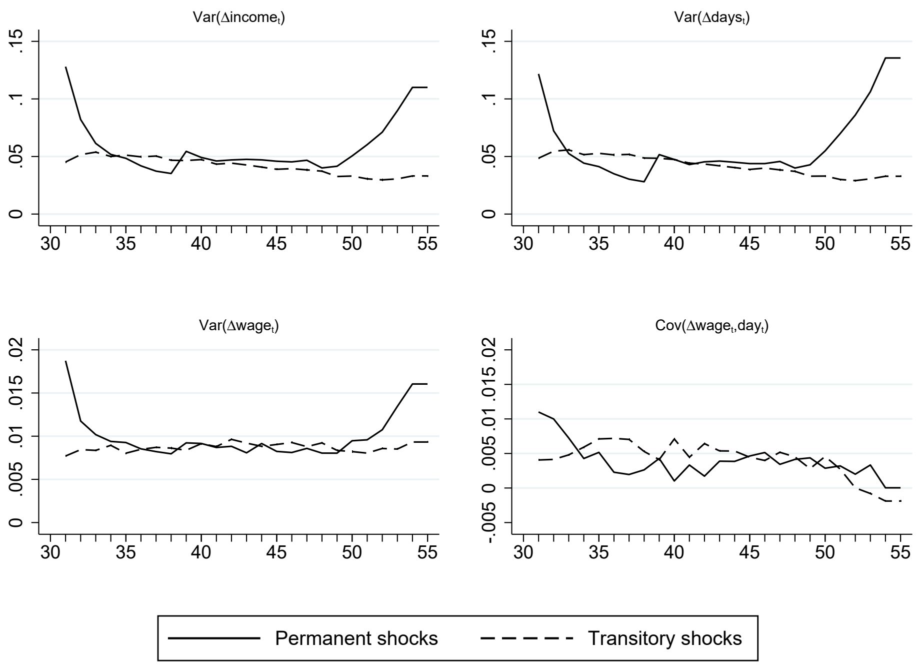

Fig. 17: Variance and covariance decompositions over the life cycle.
Notes: The figure shows the estimation results of variance decomposition obtained from the econometric specifications outlined in section 2. The solid lines are used for variance of permanent changes and the dashed lines for variance of transitory changes. The estimates are obtained from the restricted sample discussed in subsection 6.2. The upper left figure shows the results for income, the upper-right figure for days worked, the bottom left figure for wage, and the bottom right figure for covariance decomposition of wages and days worked.

$\hat{\phi}^w$ (0.140) and $\hat{\phi}^d$ (0.256) obtained from separate estimations on log wage and log day growths (using the moment restrictions in Equations (7)–(10)).

Fig. 18 shows the comparison between the results estimated from Equations (17)–(18) on the left and those estimated from Equations (32)–(33) on the right, using the predicted values.[24] The results obtained with the predicted values of autoregressive parameters are perfectly in line with those obtained from the main specification, reassuring that the restriction on the number of autoregressive parameters in the main model does not alter the estimates of $\sigma_{\xi\gamma_{(t-c)}}$ and $\sigma_{\epsilon u_{(t-c)}}$.

7. Concluding Remarks

In this study, I have analyzed the life-cycle inequalities in the log growths of annual days of work, wage and income for Italian male workers. Using large-scale administrative data containing minimum measurement error, I have shown that the total log income inequality is shaped entirely by the dispersion in annual days worked. The findings reveal that the permanent shifts account for the decrease in variations in days worked early in life and the increase late in life, which also coincide with the life-cycle permanent income inequality. Uncovering this empirical fact is important—especially for older workers—as dealing

[24]The full list of parameter estimates is available upon request.

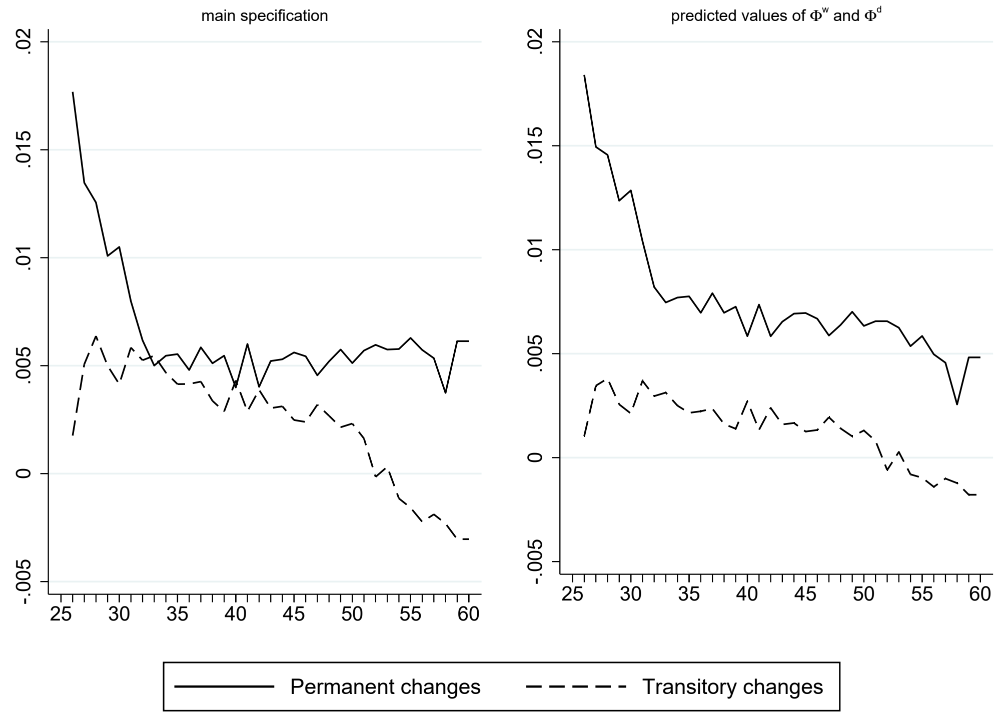

Fig. 18: Covariance decompositions over the life-cycle.
Notes: The figure on left shows the estimation results of covariance decomposition obtained from the main econometric specification outlined in subsection 2.3, while the figure on right reports the results obtained from econometric specification explained in subsection 6.3. The solid lines are used for covariance of permanent changes in wages and days worked, and the dashed lines for covariance of transitory changes in wages and days worked.

with wage inequality requires different policy interventions (e.g. collective bargaining) than dealing with inequality in labor supply (e.g. incentivizing firms to increase labor demand).

I have assessed that wage-induced fluctuations account for a limited part (33%) of the variations in days worked, and that the variations in annual days of work are driven by the individuals at the bottom of the distribution. The results show that the dominant factor is the variations at the (within-period) extensive margin.

In terms of the life-cycle wage inequality, the results have demonstrated that an increase in wage inequality late in careers is generated by the increase in the permanent wage inequality. While the results show that older workers are subject to higher wage risk, the share of the increase in permanent wage inequality after the age of 50 is almost negligible with respect to the increase in the permanent inequality of days worked.

In addition, this paper contributes to the long-lasting literature on the labor supply responses to wage shocks. This contribution also includes a new methodology that can estimate labor supply elasticities with minimum data requirements. The findings show that early in the life cycle permanent wage shocks strongly affect the life-cycle annual days of work, while their impact is relatively weaker at the end of careers. Despite the latter impact, even in early life, the dispersion in permanent annual days worked cannot be explained by the wage shocks as the correlations between the permanent wages and days worked are small.

There are also some limitations in this study. For example, it is not possible to link spouses in INPS data, and thus the analysis is missing the household incomes and labor supply. However, there is evidence of assortative mating based on income, a phenomenon according to which the income profiles of spouses tend to resemble each other. While Hryshko et al. (2017) show that there is no major impact of assortative mating on income inequality in the United States, the estimates of Eika et al. (2019) show that assortative mating to some extent accounts for the cross-sectional income inequality in households for several developed countries. In the event of assortative mating, the inequality observed in my study for Italian male workers could provide only an under-estimation of the inequality of gross family income. Another limitation is the fact that the INPS data does not contain information on hours of work. In theory, this makes a difference from the existing literature and causes certain limitations for the analysis of labor supply (e.g. the analysis is missing transitory changes—e.g. overtime shifts within a day—in hours worked). Nevertheless, the results from cross-section decomposition indicate that the main source of the variation in days worked is the dispersion in weeks worked per year. Moreover, the life-cycle profile of days worked displayed in this paper is in line with the life-cycle profile of hours of work reported by other studies in the literature (e.g. Kaplan 2012; Blundell et al. 2015).

Overall, the results of this paper are in line with the emerging concerns regarding older workers in Italy. However, issues about unequal aging in the workplace are not limited to Italy. A recent OECD report discusses the concerns about earnings and household income inequalities throughout the life cycle across OECD countries, as well as their impact on post-retirement incomes, health outcomes, and individual welfare (OECD 2017). The OECD report also indicates that the next generations will be subject to greater inequality with respect to previous cohorts of the same age groups. My study reveals that permanent labor supply risk is more pronounced close to retirement even for full-time workers who have had stable employment spells throughout their careers. Future research could seek to pin down the exact sources of labor supply shocks and provide a guide to policy-makers and governments on how to prevent such dispersion in labor supply at older ages (through e.g. government transfers, insurance, or training programs).

Given the future retirement ages targeted by developed countries, it is important to comprehend wage and labor supply risks to which individuals are subject in the later stage of their careers to institute sustainable pension systems and safeguard the transition to retirement without compromising individuals' welfare.

References

Abowd, John M., and David Card. 1989. On the covariance structure of earnings and hours changes. *Econometrica* 57, no. 2:411–445.

Alesina, Alberto, Edward Glaeser, and Bruce Sacerdote. 2005. Work and leisure in the united states and europe: why so different? *NBER macroeconomics annual* 20:1–64.

Altonji, Joseph G. 1986. Intertemporal substitution in labor supply: Evidence from micro data. *Journal of Political Economy* 94, no. 3:S176–S215.

Altonji, Joseph G., Ana Paula Martins, and Aloysius Siow. 2002. Dynamic factor models of consumption, hours and income. *Research in Economics* 56, no. 1:3–59.

Altonji, Joseph G., and Lewis M. Segal. 1996. Small-sample bias in gmm estimation of covariance structures. *Journal of Business & Economic Statistics* 14, no. 3:353–366.

Attanasio, Orazio, Peter Levell, Hamish Low, and Virginia Sánchez-Marcos. 2018. Aggregating elasticities: Intensive and extensive margins of women's labor supply. *Econometrica* 86, no. 6:2049–2082.

Baker, Michael and Gary Solon. 2003. Earnings dynamics and inequality among canadian men, 1976-1992: Evidence from longitudinal income tax records. *Journal of Labor Economics* 21, no. 2:289–321.

Basten, Christoph, Andreas Fagereng, and Kjetil Telle. 2014. Cash-on-hand and the duration of job search: Quasi-experimental evidence from Norway. *The Economic Journal* 124, no. 576:540–568.

Bingley, Paul, Lorenzo Cappellari, and Niels Westergård-Nielsen. 2013. Unemployment insurance, wage dynamics and inequality over the life cycle. *The Economic Journal* 123, no. 568:341–372.

Blundell, Richard, Antoine Bozio, and Guy Laroque. 2013. Extensive and intensive margins of labour supply: Work and working hours in the us, the uk and france. *Fiscal Studies* 34, no. 1:1–29.

Blundell, Richard, Michael Graber, and Magne Mogstad. 2015. Labor income dynamics and the insurance from taxes, transfers, and the family. *Journal of Public Economics* 127:58–73.

Blundell, Richard and Thomas MaCurdy. 1999. Labor supply: A review of alternative approaches. In *Handbook of labor economics*, vol. 3. Elsevier, 1559–1695.

Blundell, Richard, Luigi Pistaferri, and Ian Preston. 2008. Consumption inequality and partial insurance. *American Economic Review* 98, no. 5:1887–1921.

Blundell, Richard, Luigi Pistaferri, and Itay Saporta-Eksten. 2016. Consumption inequality and family labor supply. *American Economic Review* 106, no. 2:387–435.

Borjas, George J. 1980. The relationship between wages and weekly hours of work: The role of division bias. *The Journal of Human Resources* 15, no. 3:409–423.

Bottazzi, Renata, Tullio Jappelli, and Mario Padula. 2006. Retirement expectations, pension reforms, and their impact on private wealth accumulation. *Journal of Public Economics* 90, no. 12:2187–2212.

Bredemeier, Christian, Jan Gravert, and Falko Juessen. 2019. Estimating labor supply elasticities with joint borrowing constraints of couples. *Journal of Labor Economics* 37, no. 4:1215–1265.

Cappellari, Lorenzo. 2004. The dynamics and inequality of Italian men's earnings long-term changes or transitory fluctuations? *Journal of Human Resources* 39, no. 2:475–499.

Cappellari, Lorenzo and Marco Leonardi. 2016. Earnings instability and tenure. *The Scandinavian Journal of Economics* 118, no. 2:202–234.

Chamberlain, Gary. 1984. Panel data. *Handbook of econometrics* 2:1247–1318.

Checchi, Daniele, Cecilia García-Peñalosa, and Lara Vivian. 2016. Are changes in the dispersion of hours worked a cause of increased earnings inequality? *IZA Journal of European Labor Studies* 5, no. 1:15.

Davis, Steven J and Till Von Wachter. 2011. Recessions and the costs of job loss. *Brookings Papers on Economic Activity* :1.

DeBacker, Jason, Bradley Heim, Vasia Panousi, Shanthi Ramnath, and Ivan Vidangos. 2013. Rising inequality: transitory or persistent? new evidence from a panel of us tax returns. *Brookings Papers on Economic Activity* 2013, no. 1:67–142.

Dickens, Richard. 2000. The evolution of individual male earnings in Great Britain: 1975–95. *The Economic Journal* 110, no. 460:27–49.

Eika, Lasse, Magne Mogstad, and Basit Zafar. 2019. Educational assortative mating and household income inequality. *Journal of Political Economy* 127, no. 6:2795–2835.

Erosa, Andrés, Luisa Fuster, and Gueorgui Kambourov. 2016. Towards a micro-founded theory of aggregate labour supply. *The Review of Economic Studies* 83, no. 3:1001–1039.

Giupponi, Giulia and Camille Landais. 2018. Subsidizing labor hoarding in recessions: The employment & welfare effects of short time work. *CEPR Discussion Paper* , no. DP13310.

Guvenen, Fatih. 2007. Learning your earning: Are labor income shocks really very persistent? *American Economic Review* 97, no. 3:687–712.

Haider, Steven J. 2001. Earnings instability and earnings inequality of males in the United States: 1967–1991. *Journal of Labor Economics* 19, no. 4:799–836.

Hause, John C. 1980. The fine structure of earnings and the on-the-job training hypothesis. *Econometrica: Journal of the Econometric Society* 48, no. 4:1013–1029.

Heathcote, Jonathan, Fabrizio Perri, and Giovanni L. Violante. 2020. The rise of US earnings inequality: Does the cycle drive the trend? *Review of Economic Dynamics* 37:S181 – S204. URL http://www.sciencedirect.com/science/article/pii/S1094202520300429.

Heathcote, Jonathan, Kjetil Storesletten, and Giovanni L. Violante. 2014. Consumption and labor supply with partial insurance: An analytical framework. *American Economic Review* 104, no. 7:2075–2126.

Hoffmann, Florian. 2019. Hip, rip, and the robustness of empirical earnings processes. *Quantitative Economics* 10, no. 3:1279–1315.

Hryshko, Dmytro. 2012. Labor income profiles are not heterogeneous: Evidence from income growth rates. *Quantitative Economics* 3, no. 2:177–209.

Hryshko, Dmytro, Chinhui Juhn, and Kristin McCue. 2017. Trends in earnings inequality and earnings instability among US couples: How important is assortative matching? *Labour Economics* 48:168–182.

Hyslop, Dean R. 2001. Rising us earnings inequality and family labor supply: The covariance structure of intrafamily earnings. *American Economic Review* 91, no. 4:755–777.

Ichino, Andrea, Guido Schwerdt, Rudolf Winter-Ebmer, and Josef Zweimüller. 2017. Too old to work, too young to retire? *The Journal of the Economics of Ageing* 9:14–29.

Jappelli, Tullio and Luigi Pistaferri. 2010. Does consumption inequality track income inequality in italy? *Review of Economic Dynamics* 13, no. 1:133–153.

Kalwij, Adriaan S., and Rob Alessie. 2007. Permanent and transitory wages of british men, 1975–2001: year, age and cohort effects. *Journal of Applied Econometrics* 22, no. 6:1063–1093.

Kaplan, Greg. 2012. Inequality and the life cycle. *Quantitative Economics* 3, no. 3:471–525.

Karahan, Fatih and Serdar Ozkan. 2013. On the persistence of income shocks over the life cycle: Evidence, theory, and implications. *Review of Economic Dynamics* 16, no. 3:452–476.

Keane, Michael P and Nada Wasi. 2016. Labour supply: the roles of human capital and the extensive margin. *The Economic Journal* 126, no. 592:578–617.

Kopczuk, Wojciech, Emmanuel Saez, and Jae Song. 2010. Earnings inequality and mobility in the united states: evidence from social security data since 1937. *The Quarterly Journal of Economics* 125, no. 1:91–128.

Kotlikoff, Laurence J., and Jagadeesh Gokhale. 1992. Estimating a firm's age-productivity profile using the present value of workers' earnings. *The Quarterly Journal of Economics* 107, no. 4:1215–1242.

Krueger, Dirk, Fabrizio Perri, Luigi Pistaferri, and Giovanni L Violante. 2010. Cross-sectional facts for macroeconomists. *Review of Economic Dynamics* 13, no. 1:1–14.

Leombruni, Roberto and Claudia Villosio. 2005. Employability of older workers in Italy and Europe. *Available at SSRN 886674* .

Leonardi, Marco, Michele Pellizzari, and Domenico Tabasso. 2019. Wage compression within the firm: Evidence from an indexation scheme. *The Economic Journal* 129, no. 624:3256–3291.

Lillard, Lee A. 1978. Estimation of permanent and transitory response functions in panel data: a dynamic labor supply model. In *Annales de l'insee*. JSTOR, 367–394.

Lillard, Lee A., and Yoram Weiss. 1979. Components of variation in panel earnings data: American scientists 1960-70. *Econometrica: Journal of the Econometric Society* 47, no. 2:437–454.

Lillard, Lee A., and Robert J Willis. 1978. Dynamic aspects of earning mobility. *Econometrica: Journal of the Econometric Society* 46, no. 5:985–1012.

MaCurdy, Thomas E. 1982. The use of time series processes to model the error structure of earnings in a longitudinal data analysis. *Journal of Econometrics* 18, no. 1:83–114.

Meghir, Costas and Luigi Pistaferri. 2004. Income variance dynamics and heterogeneity. *Econometrica* 72, no. 1:1–32.

———. 2011. Earnings, consumption and life cycle choices. *Handbook of labor economics* 4:773–854.

Moffitt, Robert and Peter Gottschalk. 1995. Trends in the covariance of earnings in the united states: 1969–1987. *Institute for Research on Poverty, Discussion Paper* , no. 1001.

Moffitt, Robert A., and Peter Gottschalk. 2012. Trends in the transitory variance of male earnings methods and evidence. *Journal of Human Resources* 47, no. 1:204–236.

OECD. 2017. Preventing ageing unequally. *OECD Publishing*, Paris.

———. 2020. Employment rate by age group (indicator), URL https://doi.org/10.1787/084f32c7-en.

Powell, David. 2020. Does labor supply respond to transitory income? Evidence from the economic stimulus payments of 2008. *Journal of Labor Economics* 38, no. 1:1–38.

Sanchez, Manuel and Felix Wellschmied. 2020. Modeling life-cycle earnings risk with positive and negative shocks. *Review of Economic Dynamics* 37:103 – 126.

Sologon, Denisa M., and Philippe Van Kerm. 2018. Modelling earnings dynamics and inequality: foreign workers and inequality trends in Luxembourg, 1988–2009. *Journal of the Royal Statistical Society: Series A (Statistics in Society)* 181, no. 2:409–440.

A. **Online Appendix**

A.1. Econometric model for income decomposition

The final theoretical moment restrictions for income decomposition are as follows:

$$\begin{aligned} E[\Delta g_{it}\Delta g_{it'}] &= \Omega_t^2[\sum_{t-c=26}^{60} \sigma^2_{\zeta(t-c)} + \sigma^2_{\varphi(t-c)} + (1-\phi)^2[\sigma^2_{\varphi(t-c-1)} \times I(t-c-1 \geq 26) \\ &+ \phi^2\sigma^2_{\varphi(t-c-2)} \times I(t-c-2 \geq 26) + \phi^4\sigma^2_{\varphi(t-c-3)} \times I(t-c-3 \geq 26) \\ &+ ... + \phi^{66}\sigma^2_{\varphi(t-c-34)} \times I(t-c-34 \geq 26)]] \;\; if \;\; t = t', \end{aligned} \quad (34)$$

$$\begin{aligned} E[\Delta g_{it}\Delta g_{it'}] &= \Omega_t\Omega_{t'}[\sum_{s=1}^{26}\sum_{t-c=26}^{60-s} \phi^{s-1}[-(1-\phi)\sigma^2_{\varphi(t-c)} + (1-\phi)^2[\phi\sigma^2_{\varphi(t-c-1)} \times I(t-c-1 \geq 26) \\ &+ \phi^3\sigma^2_{\varphi(t-c-2)} \times I(t-c-2 \geq 26) + \phi^5\sigma^2_{\varphi(t-c-3)} \times I(t-c-3 \geq 26) \\ &+ ... + \phi^{65}\sigma^2_{\varphi(t-c-33)} \times I(t-c-33 \geq 26)]]] \;\; if \;\; t' - t = s \geq 1, \end{aligned} \quad (35)$$

where $t' - t = s$, $s \geq 0$, Δg_{it} is the residualized log labor income growth, Ω_t is time-specific factor loadings that capture the calendar time effect in the distribution of log income growth, $\sigma^2_{\zeta(t-c)}$ is the variance of permanent innovations in income, and $\sigma^2_{\varphi(t-c)}$ is the variance of transitory innovations in income.

A.2. Tables

Table 2: Parameter estimates on annual days of work

Permanent component			Transitory component			Time-shifters		
Parameters	Coeff.	S.E.	Parameters	Coeff.	S.E.	Parameters	Coeff.	S.E.
			ϕ	.256	.002			
$\sigma^2_{\gamma 26}$	.222	.003	σ^2_{u26}	.081	.001	Γ_{1986}	1.00	.
$\sigma^2_{\gamma 27}$	.145	.002	σ^2_{u27}	.093	.001	Γ_{1987}	.998	.006
$\sigma^2_{\gamma 28}$	.115	.002	σ^2_{u28}	.089	.001	Γ_{1988}	1.00	.007
$\sigma^2_{\gamma 29}$	.121	.002	σ^2_{u29}	.084	.001	Γ_{1989}	1.08	.007
$\sigma^2_{\gamma 30}$	.114	.002	σ^2_{u30}	.080	.001	Γ_{1990}	1.06	.007
$\sigma^2_{\gamma 31}$	.104	.001	σ^2_{u31}	.078	.001	Γ_{1991}	1.09	.007
$\sigma^2_{\gamma 32}$	.094	.001	σ^2_{u32}	.073	.001	Γ_{1992}	1.15	.008
$\sigma^2_{\gamma 33}$	.088	.001	σ^2_{u33}	.071	.001	Γ_{1993}	1.10	.008
$\sigma^2_{\gamma 34}$	.085	.001	σ^2_{u34}	.067	.001	Γ_{1994}	1.21	.009
$\sigma^2_{\gamma 35}$	.081	.001	σ^2_{u35}	.066	.001	Γ_{1995}	1.12	.008
$\sigma^2_{\gamma 36}$	.080	.001	σ^2_{u36}	.063	.001	Γ_{1996}	1.11	.008
$\sigma^2_{\gamma 37}$	.078	.001	σ^2_{u37}	.062	.001	Γ_{1997}	1.14	.008
$\sigma^2_{\gamma 38}$	.072	.001	σ^2_{u38}	.058	.001	Γ_{1998}	1.17	.008
$\sigma^2_{\gamma 39}$	.073	.001	σ^2_{u39}	.058	.001	Γ_{1999}	1.18	.009
$\sigma^2_{\gamma 40}$	.071	.001	σ^2_{u40}	.056	.001	Γ_{2000}	1.18	.009
$\sigma^2_{\gamma 41}$	.067	.001	σ^2_{u41}	.052	.001	Γ_{2001}	1.20	.009
$\sigma^2_{\gamma 42}$	.068	.001	σ^2_{u42}	.051	.001	Γ_{2002}	1.20	.009
$\sigma^2_{\gamma 43}$	.065	.001	σ^2_{u43}	.050	.001	Γ_{2003}	1.20	.009
$\sigma^2_{\gamma 44}$	.065	.001	σ^2_{u44}	.048	.001	Γ_{2004}	1.21	.009
$\sigma^2_{\gamma 45}$	.064	.001	σ^2_{u45}	.046	.001	Γ_{2005}	1.22	.009
$\sigma^2_{\gamma 46}$	.064	.001	σ^2_{u46}	.046	.001	Γ_{2006}	1.23	.009
$\sigma^2_{\gamma 47}$	.064	.001	σ^2_{u47}	.046	.001	Γ_{2007}	1.18	.009
$\sigma^2_{\gamma 48}$	.065	.001	σ^2_{u48}	.043	.001	Γ_{2008}	1.20	.009
$\sigma^2_{\gamma 49}$	.070	.001	σ^2_{u49}	.041	.001	Γ_{2009}	1.30	.009
$\sigma^2_{\gamma 50}$	.079	.001	σ^2_{u50}	.040	.001	Γ_{2010}	1.30	.010
$\sigma^2_{\gamma 51}$	.090	.001	σ^2_{u51}	.038	.001	Γ_{2011}	1.26	.010
$\sigma^2_{\gamma 52}$	.099	.002	σ^2_{u52}	.036	.001	Γ_{2012}	1.32	.010
$\sigma^2_{\gamma 53}$	.110	.002	σ^2_{u53}	.038	.001			
$\sigma^2_{\gamma 54}$	.122	.002	σ^2_{u54}	.038	.001			
$\sigma^2_{\gamma 55}$	.139	.002	σ^2_{u55}	.040	.001			
$\sigma^2_{\gamma 56}$	.147	.002	σ^2_{u56}	.040	.001			
$\sigma^2_{\gamma 57}$	.167	.003	σ^2_{u57}	.044	.001			
$\sigma^2_{\gamma 58}$	.190	.004	σ^2_{u58}	.043	.001			
$\sigma^2_{\gamma 59}$	.208	.004	σ^2_{u59}	.056	.002			
$\sigma^2_{\gamma 60}$	.208	.004	σ^2_{u60}	.056	.002			

Notes: Table 2 reports the estimation results on the variance decomposition of annual days of work from econometric model outlined in Equations (9)–(10). Robust standard errors are computed from the fourth moments as explained in subsection 4.2.

Table 3: Parameter estimates on weekly-wages

Permanent component			Transitory component			Time-shifters		
Parameters	Coeff.	S.E.	Parameters	Coeff.	S.E.	Parameters	Coeff.	S.E.
			ϕ	.140	.002			
$\sigma^2_{\xi_{26}}$	.027	.0006	$\sigma^2_{\epsilon_{26}}$	.010	.0004	δ_{1986}	1	.
$\sigma^2_{\xi_{27}}$	.017	.0004	$\sigma^2_{\epsilon_{27}}$	.010	.0003	δ_{1987}	.989	.008
$\sigma^2_{\xi_{28}}$	.016	.0003	$\sigma^2_{\epsilon_{28}}$	.012	.0004	δ_{1988}	.975	.009
$\sigma^2_{\xi_{29}}$	.016	.0003	$\sigma^2_{\epsilon_{29}}$	.010	.0003	δ_{1989}	1.01	.009
$\sigma^2_{\xi_{30}}$	.016	.0003	$\sigma^2_{\epsilon_{30}}$	.010	.0003	δ_{1990}	.957	.008
$\sigma^2_{\xi_{31}}$	.016	.0003	$\sigma^2_{\epsilon_{31}}$	.010	.0003	δ_{1991}	.960	.008
$\sigma^2_{\xi_{32}}$	.014	.0003	$\sigma^2_{\epsilon_{32}}$	.010	.0003	δ_{1992}	.974	.008
$\sigma^2_{\xi_{33}}$	.014	.0003	$\sigma^2_{\epsilon_{33}}$	.010	.0003	δ_{1993}	1.02	.009
$\sigma^2_{\xi_{34}}$	.014	.0003	$\sigma^2_{\epsilon_{34}}$	.010	.0003	δ_{1994}	1.05	.010
$\sigma^2_{\xi_{35}}$	.013	.0003	$\sigma^2_{\epsilon_{35}}$	.009	.0002	δ_{1995}	.958	.009
$\sigma^2_{\xi_{36}}$	.013	.0003	$\sigma^2_{\epsilon_{36}}$	.010	.0002	δ_{1996}	.930	.008
$\sigma^2_{\xi_{37}}$	.013	.0003	$\sigma^2_{\epsilon_{37}}$	.010	.0003	δ_{1997}	.948	.009
$\sigma^2_{\xi_{38}}$	.012	.0003	$\sigma^2_{\epsilon_{38}}$	.009	.0002	δ_{1998}	1.16	.014
$\sigma^2_{\xi_{39}}$	.012	.0002	$\sigma^2_{\epsilon_{39}}$	.009	.0002	δ_{1999}	1.19	.013
$\sigma^2_{\xi_{40}}$	.012	.0003	$\sigma^2_{\epsilon_{40}}$	.010	.0003	δ_{2000}	1.12	.012
$\sigma^2_{\xi_{41}}$	.012	.0003	$\sigma^2_{\epsilon_{41}}$	.009	.0003	δ_{2001}	1.03	.010
$\sigma^2_{\xi_{42}}$	.011	.0003	$\sigma^2_{\epsilon_{42}}$	.010	.0004	δ_{2002}	1.05	.012
$\sigma^2_{\xi_{43}}$	.011	.0002	$\sigma^2_{\epsilon_{43}}$	.009	.0003	δ_{2003}	1.03	.012
$\sigma^2_{\xi_{44}}$	.012	.0004	$\sigma^2_{\epsilon_{44}}$	.009	.0004	δ_{2004}	1.00	.013
$\sigma^2_{\xi_{45}}$	.011	.0002	$\sigma^2_{\epsilon_{45}}$	.009	.0003	δ_{2005}	1.05	.010
$\sigma^2_{\xi_{46}}$	.011	.0003	$\sigma^2_{\epsilon_{46}}$	.009	.0003	δ_{2006}	1.01	.010
$\sigma^2_{\xi_{47}}$	.011	.0003	$\sigma^2_{\epsilon_{47}}$	.009	.0002	δ_{2007}	.982	.009
$\sigma^2_{\xi_{48}}$	.011	.0003	$\sigma^2_{\epsilon_{48}}$	.009	.0003	δ_{2008}	.983	.009
$\sigma^2_{\xi_{49}}$	.011	.0003	$\sigma^2_{\epsilon_{49}}$	.009	.0002	δ_{2009}	1.07	.009
$\sigma^2_{\xi_{50}}$	.012	.0003	$\sigma^2_{\epsilon_{50}}$	.009	.0003	δ_{2010}	1.09	.010
$\sigma^2_{\xi_{51}}$	.013	.0003	$\sigma^2_{\epsilon_{51}}$	.008	.0003	δ_{2011}	1.07	.010
$\sigma^2_{\xi_{52}}$	.013	.0003	$\sigma^2_{\epsilon_{52}}$	.009	.0004	δ_{2012}	1.08	.010
$\sigma^2_{\xi_{53}}$	.015	.0004	$\sigma^2_{\epsilon_{53}}$	.009	.0003			
$\sigma^2_{\xi_{54}}$	.016	.0005	$\sigma^2_{\epsilon_{54}}$	.010	.0006			
$\sigma^2_{\xi_{55}}$	.019	.0007	$\sigma^2_{\epsilon_{55}}$	.009	.0007			
$\sigma^2_{\xi_{56}}$	.020	.0007	$\sigma^2_{\epsilon_{56}}$	.010	.0004			
$\sigma^2_{\xi_{57}}$	.023	.0010	$\sigma^2_{\epsilon_{57}}$	.010	.0006			
$\sigma^2_{\xi_{58}}$	.024	.0009	$\sigma^2_{\epsilon_{58}}$	.010	.0005			
$\sigma^2_{\xi_{59}}$	.026	.0008	$\sigma^2_{\epsilon_{59}}$	.013	.0010			
$\sigma^2_{\xi_{60}}$	.026	.0008	$\sigma^2_{\epsilon_{60}}$	.013	.0010			

Notes: Table 3 reports the estimation results for the variance decomposition of weekly-wages obtained from econometric model outlined in Equations (7) and (8). Robust standard errors are computed from the fourth moments as explained in subsection 4.2.

Table 4: Parameter estimates on cross-covariance decomposition of wages and days worked

Permanent component			Transitory component			Time-shifters		
Parameters	Coeff.	S.E.	Parameters	Coeff.	S.E.	Parameters	Coeff.	S.E.
			ϕ	.444	.022			
$\sigma_{\xi\gamma_{26}}$	.017	.0015	$\sigma_{\epsilon u_{26}}$	.001	.0011	ψ_{1986}	1	.
$\sigma_{\xi\gamma_{27}}$	.013	.0012	$\sigma_{\epsilon u_{27}}$	.005	.0010	ψ_{1987}	.917	.027
$\sigma_{\xi\gamma_{28}}$	.012	.0011	$\sigma_{\epsilon u_{28}}$	.006	.0010	ψ_{1988}	.869	.029
$\sigma_{\xi\gamma_{29}}$	.010	.0009	$\sigma_{\epsilon u_{29}}$	.004	.0007	ψ_{1989}	.596	.036
$\sigma_{\xi\gamma_{30}}$	.010	.0009	$\sigma_{\epsilon u_{30}}$	.004	.0006	ψ_{1990}	.573	.035
$\sigma_{\xi\gamma_{31}}$	.007	.0007	$\sigma_{\epsilon u_{31}}$	.005	.0006	ψ_{1991}	.632	.033
$\sigma_{\xi\gamma_{32}}$	.006	.0006	$\sigma_{\epsilon u_{32}}$	.005	.0005	ψ_{1992}	.565	.037
$\sigma_{\xi\gamma_{33}}$	.005	.0005	$\sigma_{\epsilon u_{33}}$	.005	.0005	ψ_{1993}	.895	.030
$\sigma_{\xi\gamma_{34}}$	.005	.0005	$\sigma_{\epsilon u_{34}}$	.004	.0005	ψ_{1994}	.896	.031
$\sigma_{\xi\gamma_{35}}$	.005	.0005	$\sigma_{\epsilon u_{35}}$	.004	.0005	ψ_{1995}	.753	.032
$\sigma_{\xi\gamma_{36}}$	.004	.0005	$\sigma_{\epsilon u_{36}}$	.004	.0004	ψ_{1996}	.631	.035
$\sigma_{\xi\gamma_{37}}$	.005	.0005	$\sigma_{\epsilon u_{37}}$	.004	.0004	ψ_{1997}	.589	.036
$\sigma_{\xi\gamma_{38}}$	.005	.0005	$\sigma_{\epsilon u_{38}}$	.003	.0004	ψ_{1998}	.728	.034
$\sigma_{\xi\gamma_{39}}$	.005	.0005	$\sigma_{\epsilon u_{39}}$	.002	.0004	ψ_{1999}	.746	.035
$\sigma_{\xi\gamma_{40}}$	.003	.0004	$\sigma_{\epsilon u_{40}}$	.004	.0004	ψ_{2000}	.757	.034
$\sigma_{\xi\gamma_{41}}$	.006	.0005	$\sigma_{\epsilon u_{41}}$	.002	.0004	ψ_{2001}	.700	.034
$\sigma_{\xi\gamma_{42}}$	.004	.0004	$\sigma_{\epsilon u_{42}}$	.003	.0004	ψ_{2002}	.734	.035
$\sigma_{\xi\gamma_{43}}$	.005	.0005	$\sigma_{\epsilon u_{43}}$	.003	.0004	ψ_{2003}	.750	.033
$\sigma_{\xi\gamma_{44}}$	.005	.0005	$\sigma_{\epsilon u_{44}}$	.003	.0004	ψ_{2004}	.861	.032
$\sigma_{\xi\gamma_{45}}$	.005	.0005	$\sigma_{\epsilon u_{45}}$	.002	.0004	ψ_{2005}	1.24	.035
$\sigma_{\xi\gamma_{46}}$	.005	.0005	$\sigma_{\epsilon u_{46}}$	.002	.0004	ψ_{2006}	1.17	.034
$\sigma_{\xi\gamma_{47}}$	.004	.0005	$\sigma_{\epsilon u_{47}}$	.003	.0004	ψ_{2007}	1.10	.034
$\sigma_{\xi\gamma_{48}}$	.005	.0005	$\sigma_{\epsilon u_{48}}$	.002	.0004	ψ_{2008}	1.31	.037
$\sigma_{\xi\gamma_{49}}$	.005	.0005	$\sigma_{\epsilon u_{49}}$	.002	.0004	ψ_{2009}	1.66	.043
$\sigma_{\xi\gamma_{50}}$	.005	.0005	$\sigma_{\epsilon u_{50}}$	.002	.0004	ψ_{2010}	1.67	.044
$\sigma_{\xi\gamma_{51}}$	.005	.0006	$\sigma_{\epsilon u_{51}}$	.001	.0004	ψ_{2011}	1.63	.044
$\sigma_{\xi\gamma_{52}}$	.005	.0006	$\sigma_{\epsilon u_{52}}$	-.0001	.0004	ψ_{2012}	1.57	.044
$\sigma_{\xi\gamma_{53}}$	.005	.0006	$\sigma_{\epsilon u_{53}}$	.0003	.0005			
$\sigma_{\xi\gamma_{54}}$	.005	.0006	$\sigma_{\epsilon u_{54}}$	-.001	.0005			
$\sigma_{\xi\gamma_{55}}$	.006	.0007	$\sigma_{\epsilon u_{55}}$	-.001	.0005			
$\sigma_{\xi\gamma_{56}}$	.005	.0007	$\sigma_{\epsilon u_{56}}$	-.002	.0005			
$\sigma_{\xi\gamma_{57}}$	.005	.0008	$\sigma_{\epsilon u_{57}}$	-.001	.0006			
$\sigma_{\xi\gamma_{58}}$	.003	.0010	$\sigma_{\epsilon u_{58}}$	-.002	.0008			
$\sigma_{\xi\gamma_{59}}$	.006	.0012	$\sigma_{\epsilon u_{59}}$	-.003	.0011			
$\sigma_{\xi\gamma_{60}}$	.006	.0012	$\sigma_{\epsilon u_{60}}$	-.003	.0011			

Notes: Table 4 reports the estimation results on decomposition of covariances between the weekly-wages and days worked from econometric model outlined in (17)–(18). Robust standard errors are computed from the fourth moments as explained in subsection 4.2.

Table 5: Parameter estimates on daily-wages

Permanent component			Transitory component			Time-shifters		
Parameters	Coeff.	S.E.	Parameters	Coeff.	S.E.	Parameters	Coeff.	S.E.
			ϕ	.113	.002			
$\sigma^2_{\xi_{26}}$	.024	.0006	$\sigma^2_{\epsilon_{26}}$	.010	.0004	δ_{1986}	1	.
$\sigma^2_{\xi_{27}}$	.014	.0004	$\sigma^2_{\epsilon_{27}}$	.010	.0003	δ_{1987}	.997	.008
$\sigma^2_{\xi_{28}}$	.013	.0003	$\sigma^2_{\epsilon_{28}}$	.011	.0004	δ_{1988}	.994	.009
$\sigma^2_{\xi_{29}}$	.014	.0003	$\sigma^2_{\epsilon_{29}}$	.010	.0003	δ_{1989}	1.12	.010
$\sigma^2_{\xi_{30}}$	.014	.0003	$\sigma^2_{\epsilon_{30}}$	.010	.0003	δ_{1990}	1.10	.010
$\sigma^2_{\xi_{31}}$	.014	.0003	$\sigma^2_{\epsilon_{31}}$	.010	.0003	δ_{1991}	1.06	.009
$\sigma^2_{\xi_{32}}$	.013	.0003	$\sigma^2_{\epsilon_{32}}$	.010	.0003	δ_{1992}	1.04	.010
$\sigma^2_{\xi_{33}}$	.013	.0003	$\sigma^2_{\epsilon_{33}}$	.010	.0003	δ_{1993}	1.02	.010
$\sigma^2_{\xi_{34}}$	.012	.0003	$\sigma^2_{\epsilon_{34}}$	.010	.0003	δ_{1994}	1.07	.011
$\sigma^2_{\xi_{35}}$	.012	.0003	$\sigma^2_{\epsilon_{35}}$	.010	.0002	δ_{1995}	.942	.010
$\sigma^2_{\xi_{36}}$	.012	.0003	$\sigma^2_{\epsilon_{36}}$	.010	.0002	δ_{1996}	.917	.009
$\sigma^2_{\xi_{37}}$	.011	.0003	$\sigma^2_{\epsilon_{37}}$	.010	.0003	δ_{1997}	.949	.011
$\sigma^2_{\xi_{38}}$	.011	.0003	$\sigma^2_{\epsilon_{38}}$	.010	.0002	δ_{1998}	1.14	.015
$\sigma^2_{\xi_{39}}$	.011	.0002	$\sigma^2_{\epsilon_{39}}$	.009	.0002	δ_{1999}	1.17	.014
$\sigma^2_{\xi_{40}}$	.011	.0003	$\sigma^2_{\epsilon_{40}}$	.010	.0003	δ_{2000}	1.11	.013
$\sigma^2_{\xi_{41}}$	.011	.0003	$\sigma^2_{\epsilon_{41}}$	.010	.0003	δ_{2001}	1.02	.012
$\sigma^2_{\xi_{42}}$	.011	.0003	$\sigma^2_{\epsilon_{42}}$	.010	.0004	δ_{2002}	1.03	.013
$\sigma^2_{\xi_{43}}$	.010	.0002	$\sigma^2_{\epsilon_{43}}$	.010	.0003	δ_{2003}	1.01	.012
$\sigma^2_{\xi_{44}}$	.011	.0004	$\sigma^2_{\epsilon_{44}}$	.009	.0004	δ_{2004}	.982	.013
$\sigma^2_{\xi_{45}}$	.010	.0002	$\sigma^2_{\epsilon_{45}}$	.009	.0003	δ_{2005}	1.00	.014
$\sigma^2_{\xi_{46}}$	.010	.0003	$\sigma^2_{\epsilon_{46}}$	.010	.0003	δ_{2006}	.983	.012
$\sigma^2_{\xi_{47}}$	.011	.0003	$\sigma^2_{\epsilon_{47}}$	.009	.0002	δ_{2007}	.941	.010
$\sigma^2_{\xi_{48}}$	.010	.0003	$\sigma^2_{\epsilon_{48}}$	.010	.0003	δ_{2008}	.936	.010
$\sigma^2_{\xi_{49}}$	.011	.0003	$\sigma^2_{\epsilon_{49}}$	.009	.0002	δ_{2009}	.995	.010
$\sigma^2_{\xi_{50}}$	.012	.0003	$\sigma^2_{\epsilon_{50}}$	.009	.0003	δ_{2010}	1.03	.010
$\sigma^2_{\xi_{51}}$	.013	.0003	$\sigma^2_{\epsilon_{51}}$	.009	.0003	δ_{2011}	1.01	.012
$\sigma^2_{\xi_{52}}$	.014	.0003	$\sigma^2_{\epsilon_{52}}$	.009	.0004	δ_{2012}	1.02	.011
$\sigma^2_{\xi_{53}}$	.016	.0004	$\sigma^2_{\epsilon_{53}}$	.010	.0003			
$\sigma^2_{\xi_{54}}$	.017	.0005	$\sigma^2_{\epsilon_{54}}$	.010	.0006			
$\sigma^2_{\xi_{55}}$	.021	.0007	$\sigma^2_{\epsilon_{55}}$	.010	.0007			
$\sigma^2_{\xi_{56}}$	.022	.0007	$\sigma^2_{\epsilon_{56}}$	.010	.0004			
$\sigma^2_{\xi_{57}}$	.025	.0010	$\sigma^2_{\epsilon_{57}}$	.010	.0006			
$\sigma^2_{\xi_{58}}$	.029	.0009	$\sigma^2_{\epsilon_{58}}$	.010	.0005			
$\sigma^2_{\xi_{59}}$	.030	.0008	$\sigma^2_{\epsilon_{59}}$	.014	.0010			
$\sigma^2_{\xi_{60}}$	.030	.0008	$\sigma^2_{\epsilon_{60}}$	.014	.0010			

Notes: Table 5 reports the estimation results for the variance decomposition of daily-wages obtained from econometric model outlined in Equations (7) and (8). Robust standard errors are computed from the fourth moments as explained in subsection 4.2.

Table 6: Parameter estimates on income

Permanent component			Transitory component			Time-shifters		
Parameters	Coeff.	S.E.	Parameters	Coeff.	S.E.	Parameters	Coeff.	S.E.
			ϕ	.266	.002			
$\sigma^2_{\zeta_{26}}$	.228	.003	$\sigma^2_{\varphi_{26}}$	.075	.001	Ω_{1986}	1	.
$\sigma^2_{\zeta_{27}}$	.161	.002	$\sigma^2_{\varphi_{27}}$	.086	.001	Ω_{1987}	.996	.006
$\sigma^2_{\zeta_{28}}$	.132	.002	$\sigma^2_{\varphi_{28}}$	.083	.001	Ω_{1988}	.995	.006
$\sigma^2_{\zeta_{29}}$	.133	.002	$\sigma^2_{\varphi_{29}}$	.078	.001	Ω_{1989}	1.04	.007
$\sigma^2_{\zeta_{30}}$	.124	.002	$\sigma^2_{\varphi_{30}}$	.074	.001	Ω_{1990}	1.02	.006
$\sigma^2_{\zeta_{31}}$	.113	.001	$\sigma^2_{\varphi_{31}}$	.074	.001	Ω_{1991}	1.05	.006
$\sigma^2_{\zeta_{32}}$	.101	.001	$\sigma^2_{\varphi_{32}}$	.070	.001	Ω_{1992}	1.09	.007
$\sigma^2_{\zeta_{33}}$	.093	.001	$\sigma^2_{\varphi_{33}}$	.069	.001	Ω_{1993}	1.09	.007
$\sigma^2_{\zeta_{34}}$	.090	.001	$\sigma^2_{\varphi_{34}}$	.064	.001	Ω_{1994}	1.17	.007
$\sigma^2_{\zeta_{35}}$	.086	.001	$\sigma^2_{\varphi_{35}}$	.062	.001	Ω_{1995}	1.10	.007
$\sigma^2_{\zeta_{36}}$	.083	.001	$\sigma^2_{\varphi_{36}}$	.061	.001	Ω_{1996}	1.10	.007
$\sigma^2_{\zeta_{37}}$	.081	.001	$\sigma^2_{\varphi_{37}}$	.061	.001	Ω_{1997}	1.11	.007
$\sigma^2_{\zeta_{38}}$	.076	.001	$\sigma^2_{\varphi_{38}}$	.056	.001	Ω_{1998}	1.18	.008
$\sigma^2_{\zeta_{39}}$	.076	.001	$\sigma^2_{\varphi_{39}}$	.056	.001	Ω_{1999}	1.19	.008
$\sigma^2_{\zeta_{40}}$	.073	.001	$\sigma^2_{\varphi_{40}}$	.056	.001	Ω_{2000}	1.20	.008
$\sigma^2_{\zeta_{41}}$	.071	.001	$\sigma^2_{\varphi_{41}}$	.051	.001	Ω_{2001}	1.19	.008
$\sigma^2_{\zeta_{42}}$	.069	.001	$\sigma^2_{\varphi_{42}}$	.052	.001	Ω_{2002}	1.18	.008
$\sigma^2_{\zeta_{43}}$	.067	.001	$\sigma^2_{\varphi_{43}}$	.051	.001	Ω_{2003}	1.18	.008
$\sigma^2_{\zeta_{44}}$	.067	.001	$\sigma^2_{\varphi_{44}}$	.048	.001	Ω_{2004}	1.19	.008
$\sigma^2_{\zeta_{45}}$	.065	.001	$\sigma^2_{\varphi_{45}}$	.046	.001	Ω_{2005}	1.21	.008
$\sigma^2_{\zeta_{46}}$	.065	.001	$\sigma^2_{\varphi_{46}}$	.046	.001	Ω_{2006}	1.21	.008
$\sigma^2_{\zeta_{47}}$	.065	.001	$\sigma^2_{\varphi_{47}}$	.046	.001	Ω_{2007}	1.17	.008
$\sigma^2_{\zeta_{48}}$	.065	.001	$\sigma^2_{\varphi_{48}}$	.043	.001	Ω_{2008}	1.19	.008
$\sigma^2_{\zeta_{49}}$	.068	.001	$\sigma^2_{\varphi_{49}}$	.040	.001	Ω_{2009}	1.31	.009
$\sigma^2_{\zeta_{50}}$	.075	.001	$\sigma^2_{\varphi_{50}}$	.040	.001	Ω_{2010}	1.29	.009
$\sigma^2_{\zeta_{51}}$	.082	.001	$\sigma^2_{\varphi_{51}}$	.038	.001	Ω_{2011}	1.26	.009
$\sigma^2_{\zeta_{52}}$	.088	.001	$\sigma^2_{\varphi_{52}}$	.036	.001	Ω_{2012}	1.31	.009
$\sigma^2_{\zeta_{53}}$	.098	.001	$\sigma^2_{\varphi_{53}}$	.038	.001			
$\sigma^2_{\zeta_{54}}$	.106	.002	$\sigma^2_{\varphi_{54}}$	.039	.001			
$\sigma^2_{\zeta_{55}}$	.121	.002	$\sigma^2_{\varphi_{55}}$	.039	.001			
$\sigma^2_{\zeta_{56}}$	.127	.002	$\sigma^2_{\varphi_{56}}$	.039	.001			
$\sigma^2_{\zeta_{57}}$	.144	.002	$\sigma^2_{\varphi_{57}}$	.043	.001			
$\sigma^2_{\zeta_{58}}$	.161	.003	$\sigma^2_{\varphi_{58}}$	.043	.001			
$\sigma^2_{\zeta_{59}}$	.177	.003	$\sigma^2_{\varphi_{59}}$	.056	.002			
$\sigma^2_{\zeta_{60}}$	.177	.003	$\sigma^2_{\varphi_{60}}$	.056	.002			

Notes: Table 6 reports the estimation results for the variance decomposition of labor income from econometric model outlined in (34)–(35). Robust standard errors are computed from the fourth moments as explained in subsection 4.2.

Table 7: Parameter estimates on labor income

Permanent component			Transitory component			Time-shifters					
Parameters	Coeff.	S.E.	Parameters	Coeff.	S.E.	Parameters	Coeff.	S.E.	Parameters	Coeff.	S.E.
			ϕ	.288	.002	Ω^p_{1986}	1.00	.	Ω^t_{1986}	1.00	.
$\sigma^2_{\zeta_{26}}$	.238	.012	$\sigma^2_{\varphi_{26}}$	.075	.004	Ω^p_{1987}	.963	.044	Ω^t_{1987}	1.02	.037
$\sigma^2_{\zeta_{27}}$	.174	.009	$\sigma^2_{\varphi_{27}}$	.079	.005	Ω^p_{1988}	.981	.037	Ω^t_{1988}	1.00	.031
$\sigma^2_{\zeta_{28}}$	.150	.007	$\sigma^2_{\varphi_{28}}$	.074	.004	Ω^p_{1989}	.961	.037	Ω^t_{1989}	1.10	.032
$\sigma^2_{\zeta_{29}}$	.151	.007	$\sigma^2_{\varphi_{29}}$	.071	.004	Ω^p_{1990}	1.03	.037	Ω^t_{1990}	1.01	.030
$\sigma^2_{\zeta_{30}}$	.137	.007	$\sigma^2_{\varphi_{30}}$	.069	.004	Ω^p_{1991}	1.06	.037	Ω^t_{1991}	1.04	.030
$\sigma^2_{\zeta_{31}}$	.126	.006	$\sigma^2_{\varphi_{31}}$	.067	.004	Ω^p_{1992}	.970	.035	Ω^t_{1992}	1.16	.032
$\sigma^2_{\zeta_{32}}$	.115	.006	$\sigma^2_{\varphi_{32}}$	.061	.003	Ω^p_{1993}	1.34	.044	Ω^t_{1993}	.871	.030
$\sigma^2_{\zeta_{33}}$	.111	.005	$\sigma^2_{\varphi_{33}}$	.059	.003	Ω^p_{1994}	1.09	.039	Ω^t_{1994}	1.19	.034
$\sigma^2_{\zeta_{34}}$	.106	.005	$\sigma^2_{\varphi_{34}}$	.056	.003	Ω^p_{1995}	1.23	.042	Ω^t_{1995}	.990	.032
$\sigma^2_{\zeta_{35}}$	.099	.005	$\sigma^2_{\varphi_{35}}$	.055	.003	Ω^p_{1996}	1.14	.040	Ω^t_{1996}	1.04	.032
$\sigma^2_{\zeta_{36}}$	.093	.005	$\sigma^2_{\varphi_{36}}$	.055	.003	Ω^p_{1997}	1.09	.039	Ω^t_{1997}	1.11	.033
$\sigma^2_{\zeta_{37}}$	.092	.005	$\sigma^2_{\varphi_{37}}$	.054	.003	Ω^p_{1998}	1.21	.043	Ω^t_{1998}	1.14	.035
$\sigma^2_{\zeta_{38}}$	.085	.004	$\sigma^2_{\varphi_{38}}$	.051	.003	Ω^p_{1999}	1.24	.044	Ω^t_{1999}	1.14	.035
$\sigma^2_{\zeta_{39}}$	.081	.004	$\sigma^2_{\varphi_{39}}$	.053	.003	Ω^p_{2000}	1.31	.045	Ω^t_{2000}	1.10	.035
$\sigma^2_{\zeta_{40}}$	.076	.004	$\sigma^2_{\varphi_{40}}$	.052	.003	Ω^p_{2001}	1.19	.042	Ω^t_{2001}	1.16	.035
$\sigma^2_{\zeta_{41}}$	.072	.004	$\sigma^2_{\varphi_{41}}$	.050	.003	Ω^p_{2002}	1.25	.044	Ω^t_{2002}	1.11	.034
$\sigma^2_{\zeta_{42}}$	.069	.003	$\sigma^2_{\varphi_{42}}$	.051	.003	Ω^p_{2003}	1.28	.044	Ω^t_{2003}	1.09	.034
$\sigma^2_{\zeta_{43}}$	.065	.003	$\sigma^2_{\varphi_{43}}$	.050	.003	Ω^p_{2004}	1.27	.043	Ω^t_{2004}	1.11	.034
$\sigma^2_{\zeta_{44}}$	.064	.003	$\sigma^2_{\varphi_{44}}$	.048	.003	Ω^p_{2005}	1.42	.048	Ω^t_{2005}	1.02	.035
$\sigma^2_{\zeta_{45}}$	.062	.003	$\sigma^2_{\varphi_{45}}$	.046	.002	Ω^p_{2006}	1.41	.047	Ω^t_{2006}	1.03	.034
$\sigma^2_{\zeta_{46}}$	.062	.003	$\sigma^2_{\varphi_{46}}$	.046	.002	Ω^p_{2007}	1.36	.045	Ω^t_{2007}	1.01	.033
$\sigma^2_{\zeta_{47}}$	.062	.003	$\sigma^2_{\varphi_{47}}$	.046	.002	Ω^p_{2008}	1.19	.042	Ω^t_{2008}	1.16	.036
$\sigma^2_{\zeta_{48}}$	.062	.003	$\sigma^2_{\varphi_{48}}$	.043	.002	Ω^p_{2009}	1.60	.052	Ω^t_{2009}	1.05	.035
$\sigma^2_{\zeta_{49}}$	.069	.003	$\sigma^2_{\varphi_{49}}$	.039	.002	Ω^p_{2010}	1.53	.050	Ω^t_{2010}	1.08	.035
$\sigma^2_{\zeta_{50}}$	.080	.004	$\sigma^2_{\varphi_{50}}$	.037	.002	Ω^p_{2011}	1.47	.048	Ω^t_{2011}	1.08	.034
$\sigma^2_{\zeta_{51}}$	.095	.005	$\sigma^2_{\varphi_{51}}$	.033	.002	Ω^p_{2012}	1.51	.050	Ω^t_{2012}	1.15	.036
$\sigma^2_{\zeta_{52}}$	.107	.005	$\sigma^2_{\varphi_{52}}$	.029	.002						
$\sigma^2_{\zeta_{53}}$	.119	.006	$\sigma^2_{\varphi_{53}}$	.031	.002						
$\sigma^2_{\zeta_{54}}$	.134	.007	$\sigma^2_{\varphi_{54}}$	.028	.002						
$\sigma^2_{\zeta_{55}}$	.158	.008	$\sigma^2_{\varphi_{55}}$	.027	.002						
$\sigma^2_{\zeta_{56}}$	.162	.008	$\sigma^2_{\varphi_{56}}$	.031	.002						
$\sigma^2_{\zeta_{57}}$	.175	.009	$\sigma^2_{\varphi_{57}}$	.036	.002						
$\sigma^2_{\zeta_{58}}$	.198	.011	$\sigma^2_{\varphi_{58}}$	.034	.002						
$\sigma^2_{\zeta_{59}}$	.212	.011	$\sigma^2_{\varphi_{59}}$	.049	.003						
$\sigma^2_{\zeta_{60}}$	.212	.011	$\sigma^2_{\varphi_{60}}$	.049	.003						

Notes: Table 7 reports the estimation results on the variance decomposition of labor income. Results are obtained from econometric specification in which permanent and transitory components is associated with time-shifters, Ω^p_t and Ω^t_t, respectively, the rest remains the same as in Equations (34)–(35). Robust standard errors are computed from the fourth moments as explained in subsection 4.2.