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Employment Time and the Cyclicality of Earnings Growth

By Eran B. Hoffmann and Davide Malacrino

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Abstract

We study how the distribution of earnings growth evolves over the business cycle in Italy. We distinguish between two sources of annual earnings growth: changes in employment time (number of weeks of employment within a year) and changes in weekly earnings. Changes in employment time generate the tails of the earnings growth distribution, and account for the increased dispersion and negative skewness in the distribution of earnings growth in recessions. In contrast, the cross-sectional distribution of weekly earnings growth is symmetric and stable over the cycle. Thus, models that rely on cyclical idiosyncratic risk, should separately account for the employment margin in their earnings process to avoid erroneous conclusions. We propose such a process, based on the combination of simple employment and wage processes with few parameters, and show that it captures the procyclical skewness in changes in earnings growth and other important features of its distribution.

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1 Introduction

A long strand of literature has studied and quantified the individual labor earnings process, and in particular the risk in earnings growth.[1] In a recent paper, Guvenen, Ozkan, and Song (2014) (GOS from now on) use a large administrative dataset from the US Social Security Administration and find that recessions have an asymmetric impact on the distribution of individual earnings growth: large decreases in earnings become more common and large increases less common during recessions, while the distribution of small changes remains stable over the cycle.

A common interpretation of these results is that the downside risk to individual permanent income increases during recessions. This type of cyclical asymmetry in earnings risk has important implications for a wide range of economic outcomes. Indeed, a growing number of papers rely on this interpretation for studying consumption and wealth dynamics, designing public policy, asset pricing and improving monetary policy.[2]

However, annual earnings growth is the outcome of two distinct components. Consider the decomposition of individual i's (log) annual earnings growth Δy_{it}, into the change in the (log) employment time Δx_{it}, measured in weeks, and the change in (log) weekly earnings Δw_{it}:

$$\Delta y_{it} = \Delta x_{it} + \Delta w_{it}. \tag{1}$$

Decomposition (1) implies that a change in earnings could be the outcome of either a change in employment time or changes in weekly earnings (or both). The dataset used by GOS does not contain observations of the time spent in employment within a given year, or the weekly earnings when employed, and thus does not allow this decomposition.[3]

In this paper, we apply decomposition (1) to measure the contribution of changes in employment time and changes in weekly earnings in shaping the earnings growth distribution. We view the distinction between the employment margin and the wage margin (captured here by weekly earnings) as important for three main reasons. First, the two sources of variation have different policy implications. For example, unemployment insurance may effectively insure against drops in employment time, but not insure at all against declines in wages. Similarly, wage insurance policies, such as the one suggested by LaLonde (2007), can only reduce the adverse consequences of falls in wages.

[1] See for instance MaCurdy (1982), Abowd and Card (1989), Meghir and Pistaferri (2004), Storesletten, Telmer, and Yaron (2004b), Guvenen (2009), Arellano, Blundell, and Bonhomme (2017).

[2] DeNardi, Fella, and Pardo (2016) and McKay (2017) study consumption and wealth dynamics. McKay and Reis (2016) design an optimal unemployment insurance rule. Constantinides and Ghosh (2014) and Schmidt (2016) study the role of idiosyncratic risk in asset pricing. Berger, Dew-Becker, Schmidt, and Takahashi (2016) study modified Taylor rules.

[3] The Master Earnings File (MEF) data from the US Social Security Administration used by GOS and by others is based on reported income from W-2 tax forms. See for example Song and Manchester (2007), von Wachter, Song, and Manchester (2011) and French and Song (2014). For a discussion of advantages and limitations of these data see Kopczuk, Saez, and Song (2010).

Second, in some applications one of the margins is considered exogenous from the perspective of the worker while the other is considered a response margin. The canonical real business cycles model, for instance, assumes that households take wages as given and respond by adjusting extensive labor supply.[4] Finally, the persistence of changes to these two components may be very different. Unemployment spells are typically measured in months, while wage changes have a persistent component, which last for many years.[5] Estimating the earnings process without acknowledging the separate roles of the employment margin and wage margin may therefore be misleading.

We divide our analysis in three parts. First, we show that most of the cross-sectional variation in annual earnings growth in Italy is due to changes in employment rather than changes in weekly earnings. In particular, changes in the number of weeks of employment generate the tails of the distribution (see Figure 1 for a decomposition of a single cross-section), both in recessions and in expansions.

Second, we study how the cross-sectional distribution of annual earnings growth and its components evolve over time. We provide visual and statistical evidence of a strong association between the distribution of changes in employment time and that of annual earnings growth. In particular, the third moments of the distributions, which capture asymmetry, are highly correlated over time and are both procyclical. In contrast, the distribution of changes in weekly earnings around its mean shows little asymmetry and is stable over the cycle.

Third, our findings suggest that the employment margin needs to be carefully modeled, separately from the weekly earnings. Thus, we propose a model of an earnings process based on the combination of an *employment process* and a *wage process*. The employment process, which is driven by random transitions between labor market states, is enough to generate the tails of the annual earnings distribution, and their cyclical movements. The wage process is the sum of a Gaussian permanent component, and a transitory shock, which generates a symmetric wage growth distribution. We demonstrate that this model captures the key features of the earnings growth distribution in Italy with only few parameters. Using data from the US, we offer additional suggestive evidence that this process captures the cyclical movements of the earnings growth distribution.

We conduct most of our analysis using a large administrative panel dataset from the Italian social security institute (INPS), which covers the period 1985-2012. This dataset includes observations of annual earnings and weeks of employment within every given year for each worker, allowing us to perform decomposition (1) at the worker-year level.

We show non-parametrically that the tails of the annual earnings growth distribution (below the 10th and above the 90th percentile) are almost entirely driven by employment changes:

[4] For instance, Hansen (1985) and Rogerson (1988) model households as choosing employment, and taking wages as given.

[5] See for example Rothstein (2011) for evidence on unemployment duration and Low, Meghir, and Pistaferri (2010) for structural evidence on the persistence of wage shocks.

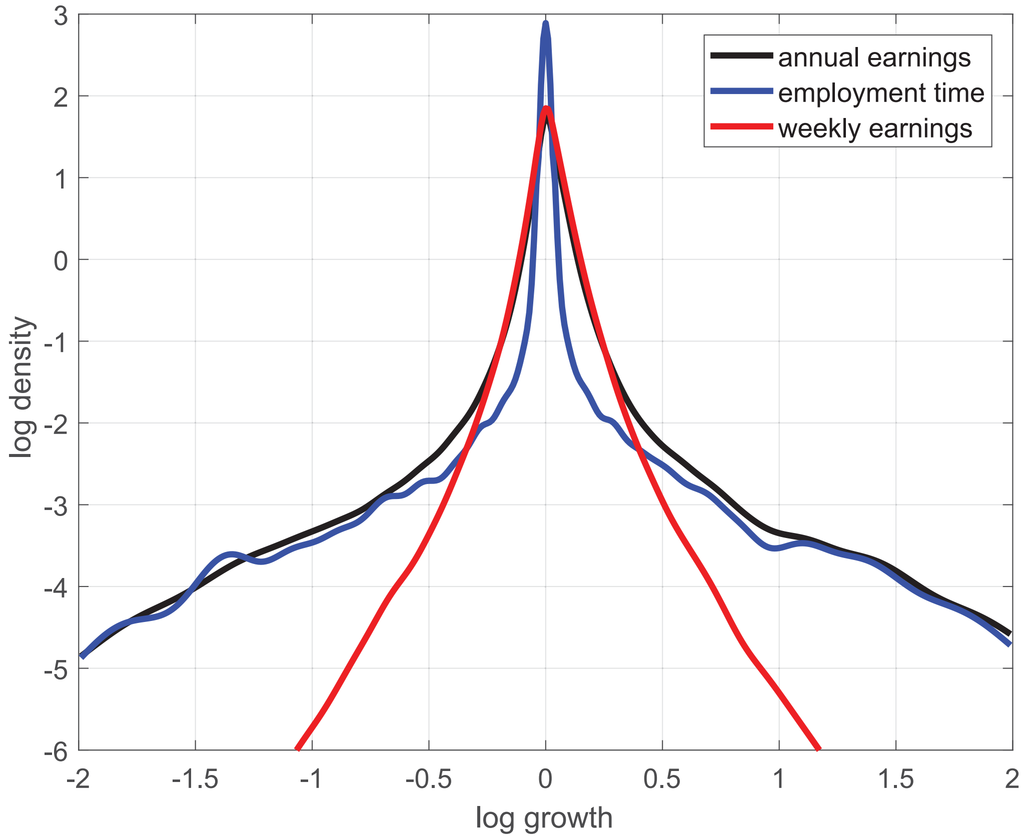

Figure 1: Decomposition of Annual Earnings Growth Distribution

Notes: Log densities of one-year growth of annual earnings and its components. Based on a representative sample of males 25-60 that includes 300,000 observations (approximately 6.5% of all male workers in the private sector in that age range), for the year 2002. Employment time is the number of weeks of work within a year. Weekly earnings is the annual earnings divided by employment time.

Workers who are employed for 52 weeks in a given year are 12 times less likely than those who are employed for less than 52 weeks to experience a change in their earnings larger than the 90th percentile in the following year. Similarly, workers who are employed for 52 weeks in a given year are 20 times less likely than those who are not to have experienced a change smaller than the 10th percentile from the previous year. When measured in logs, changes in employment time generate more than four-fifths of the variance in annual earnings growth. We conclude that employment time is the primary source of variation in earnings growth across individuals within any given year.

Our main contribution is providing evidence for the dominant role of employment time in generating the cyclical patterns in earnings growth. To this end, we construct time series of the first three moments of earnings growth and each of its components using the INPS dataset. To address the growing interest in the asymmetric features of the earnings growth distribution, we devote particular attention to the third moment of the cross sectional distributions. The time series of the third moment of changes in employment time is visually similar to that of annual earnings growth, both in magnitude and in pattern. In contrast, the time series of the third moment of changes in weekly earnings is relatively flat and close to zero.

We confirm the visual evidence with a statistical test using the constructed time series. We define the cyclicality of a cross-sectional moment as its contemporaneous correlation with GDP growth. The third moment of annual earnings growth is highly procyclical: Its correlation with GDP growth is 0.66 and significant. However, when controlling for the third moment of changes in employment time, the correlation drops to a non-significant -0.12. This result offers further evidence that employment time is the source of the procyclical skewness of earnings growth.

To evaluate the persistence structure of earnings growth, we repeat the decomposition at a five-year horizon. We find that the variance of five-year changes in weekly earnings is twice as high as that of one-year changes (0.051 compared to 0.024), while the variance of the five-year changes in employment time is approximately the same as the one-year changes (about 0.11). This suggests that weekly earnings have an important persistent component, while changes in employment time are for the most part transitory.

We also explore the impact of tax and transfers on the earnings growth distribution and the differences between workers who switch jobs and those who do not. Tax and transfers can have an insurance effect on labor earnings dynamics (Blundell, Graber, and Mogstad, 2015). Therefore, we look at the effects of unemployment benefits and income taxes on the distribution of earnings growth. We find that the Italian tax and transfer system reduced the variance and the asymmetry of earnings growth, especially following the 2007 recession. For example, in 2009, the post-tax earnings growth variance (third moment) was 0.15 (-0.04) compared to 0.20 (-0.11) pre-tax. Most of this effect comes from the unemployment benefits, while the income tax only has a marginal role, consistent with our evidence that non-employment spells determine most large changes in earnings.

Other studies document that workers who switch jobs ("switchers") and workers who do not ("stayers") have a different earnings growth distribution (e.g. Topel and Ward, 1992). This is also true in our data. The variance of earnings growth of switchers is over twice as large as the that of stayers (0.40 compared to 0.16 in 2009), and the third central moment is more negative in recessions (-0.13 compared to -0.08 in 2009). However, we find that almost all of the difference is due to workers who experience changes in employment time. Switchers and stayers who do not experience spells of non-employment have similar earnings growth distributions.[6]

These findings suggest that the distributions of changes in employment time and weekly earnings differ in shape, cyclicality, persistence, and response to policy. Hence, special attention

[6] For example, in 2009 the difference in variance (third moment) between switchers and stayers was 0.240 (-0.051), but the difference between switchers and stayers who were employed for 52 weeks both in 2009 and 2008 was only 0.007 (0.001).

should be given to modeling the two margins as separate processes. Not doing so is likely to lead to erroneous conclusions about the underlying dynamics of annual earnings, and may ultimately lead to misleading inference in richer models of consumption and wealth.

Therefore, we propose a model of individual earnings with the goal to demonstrate that the combination of an employment process and a wage process, with few parameters, can capture the cross-sectional and cyclical features of the earnings growth distribution and its components, without the need to assume complex distributions for the persistent shocks.

The employment process is driven by random transitions between discrete labor market states at a monthly frequency, in the spirit of the Diamond-Mortensen-Pissarides job search model. The wage process is the sum of a Gaussian permanent component and a transitory shock, which generates a *symmetric* wage growth distribution. Through a numerical example calibrated to match key moments from Italy, we demonstrate that the model captures the shape of the annual earnings growth distribution as well as its procyclical left skewness.

The model provides an intuitive explanation for the procyclical skewness of annual earnings growth. During recessions, the separation rate (the probability to transition from employment to unemployment within a given month) goes up and the hiring rate (the probability to transition from unemployment to employment) goes down. A high separation rate increases the number of workers who experience a reduction in employment time, while a low hiring rate extends the duration of non-employment spells. Together, these two factors make large negative changes in the number of weeks of employment more common in recesssions and generate the negative skewness in the their cross-sectional distribution.

Finally, we use labor market flows from the US, based on matched monthly CPS files, to evaluate the main mechanism of the model. We feed the labor market flows from the data into the model and recover the model implied cross-sectional distributions of changes in employment time. The time series of the model implied third moment follows the timing and magnitude of the time series of the third moment of earnings growth. We view that as suggestive evidence that this mechanism alone is quantitatively enough to replicate the observed procyclical skewness of annual earnings growth.

The rest of the paper is organized as follows. Section 2 discusses the related literature. Section 3 describes the theoretical framework behind the decomposition of earnings growth into changes in the employment time and changes in weekly earnings. Section 4 presents the data. Sections 5 reports and discusses the evidence on the role of employment time. Section 6 proposes a model for the earnings process. Section 7 concludes.

2 Related Literature

This paper directly contributes to a strand of literature that explores the cyclical properties of the idiosyncratic earnings process. Storesletten, Telmer, and Yaron (2004b) explore the relationship between the state of the aggregate economy and the dispersion of idiosyncratic earnings shocks to households based on PSID. They use a structural model and find that the variance of the persistent idiosyncratic shocks to earnings in recessions is twice as high as in expansions. Guvenen, Ozkan, and Song (2014) study individual earnings growth in the US and find that the first and third moments of the cross-sectional distribution of earnings growth are procyclical while the second moment is not. Based on this evidence, they use a structural model to estimate an earnings process with time-varying non-Gaussian persistent shocks.

We provide a new interpretation for the statistical findings of GOS based on data from Italy. We first confirm that earnings growth in Italy exhibit similar cyclical patterns, then decompose individual earnings growth into changes in employment time and changes in weekly earnings. This decomposition reveals a dominant role for employment time in generating the procyclical skewness of earnings growth. This suggests that careful modeling of the employment process is needed before estimating cyclical non-Gaussian shocks to the permanent earnings.

In contrast to our results, Busch, Domeij, Guvenen, and Madera (2016) argue that skewness in wage growth is responsible for skewness of annual earnings growth in German data. While some institutional differences between the Italian and the German labor market might be responsible for part of the different results, we believe that most of them can be accounted for by two differences in methods. First, we focus on measurement of the third central moment while they base their results on a quantile based measure of skewness. We view the third moment as better fitted for this analysis because it lends itself to a natural decomposition, which quantile based measures lack. Second, we focus on a more direct statistical test of the sources of cyclicality, while they argue by comparing magnitudes of coefficients across two separate regressions.[7]

The idea that random transitions between labor market states can generate the tails of the earnings growth distribution is also suggested by Hubmer (2018). Our paper differs in both methods and focus. Hubmer (2018) proposes a calibrated structural life-cycle model with displacement risk and shows that it captures non-Gaussian features of the cross-sectional distribution of earnings growth. In contrast, we provide direct non-parametric evidence that changes in employment time are driving the observed shape of the distribution of earnings growth. Also, Hubmer (2018) focuses on the life cycle properties of earnings growth, while our main focus is on the cyclical properties of the distribution. Therefore, we see our results as complementary to his.

Many studies rely on time-varying idiosyncratic risk to explain household behavior and, through aggregation, its impact on the macro economy. Constantinides and Duffie (1996) propose an explanation for the equity premium puzzle that relies on persistent idiosyncratic risk in the earnings process. They argue that an earnings process that has highly persistent shocks with time varying variance that is correlated with growth can generate large risk premia. Sto-

[7] Notice that Busch et al. (2016) measure of the cyclicality of quantile differences (L9050,L5010), as presented in their Table III, is substantially smaller for wages than for total earnings. This suggests that, at best, wages can explain only part of the skewness in annual earnings.

resletten, Telmer, and Yaron (2007) revise Constantinides and Duffie (1996) by adding a life cycle savings problem and find a weaker role of idiosyncratic risk in explaining the equity premium puzzle. Krebs (2007) finds that the welfare costs of business cycles are much higher when considering that the idiosyncratic displacement risk is countercyclical. Recently Constantinides and Ghosh (2014) and Schmidt (2016) study the impact of idiosyncratic downside risk during recessions to explain asset prices. However, their key assumption that the shape of earnings shocks carries over to consumption is only valid if these shocks are persistent. Other studies explain consumption behavior in an environment with idiosyncratic risk. Storesletten, Telmer, and Yaron (2004a) use idiosyncratic risk to explain why consumption inequality is increasing over the life-cycle, but not as much as income inequality. Low, Meghir, and Pistaferri (2010) study welfare programs in an environment with idiosyncratic employment and wage risks and find that job arrival and job destruction, in addition to wage shocks, have large effects on household welfare. Their interpretation of risk to employment is the closest to our interpretation of employment risk.

We inform this literature by performing a direct decomposition of the variation in annual earnings into employment time and weekly earnings. Even though our analysis does not quantify what share of these variations constitute risk rather than anticipated changes, we do measure the relative size of the total variation. We find that employment time is the primary source of the cross-section variance of earnings growth (measured in logs) and is the source of cyclical variations. These findings suggest that the employment margin needs to be carefully modeled, separately from wage changes. If not, one could draw erroneous conclusions about the underlying dynamics of annual earnings, especially when it comes to higher order moments and nonlinearities and ultimately lead to misleading inferences about the implications of richer models of earnings dynamics for consumption and wealth.

Finally, this paper builds on a literature that studies changes in job creation and job destruction over the business cycle using labor market flows data. Abowd and Zellner (1985), Blanchard and Diamond (1989) and more recently Shimer (2012) provide methods to recover labor market flows from survey data, and point to a pronounced countercyclicality in the separation rate, and procyclicality in the hiring rate. In this paper we document similar patterns of cyclicality in transition rates. We show that the cyclical properties of the separation rate and the hiring rate explain the negative skewness of earnings growth in recessions. In a recent contribution to this literature, Hall and Schulhofer-Wohl (2015) explore a richer definition of labor market states, that includes short- and long-term unemployment and temporary employment. These definitions could further our understanding of the employment process underlying our results.

3 Decomposing Earnings Growth

In this section we discuss the decomposition of annual earnings into employment time and weekly earnings and provide some useful definitions for the rest of the analysis.

3.1 The Components of Earnings

Annual earnings can be separated into three components: employment time in weeks (weeks spent in employment spells, sometimes referred to as the extensive margin), hours worked per week (sometimes referred to as the intensive margin) and the mean wage per hour worked. For individual i at time t, these three components form the following accounting identity:

$$Y_{it} = X_{it} \cdot H_{it} \cdot \tilde{W}_{it} \tag{2}$$

where Y_{it} is annual earnings, X_{it} is employment time in weeks, H_{it} is average hours worked per week and $\tilde{W}_{it}$ is the mean hourly wage.[8]

By taking logs and first differencing, we get the following decomposition:

$$\Delta y_{it} = \Delta x_{it} + \Delta h_{it} + \Delta \tilde{w}_{it} \tag{3}$$

where lowercase denotes logged values, and Δ is the difference between year t and year $t-1$.

In many cases, a direct observation of all three components is absent. The US administrative data from the SSA used by GOS, for instance, contain observations of Δy, but not of any of its components. In the INPS data used in this paper, earnings growth, Δy, and changes in employment time, Δx, are observed, but changes in number of hours worked per week and hourly wages are not. Given this limitation of the data, we adopt the decomposition in equation (1), in which the mean hours per week and the hourly wage are combined, $\Delta w = \Delta h + \Delta \tilde{w}$, and refer to it as changes in weekly earnings:

$$\Delta y_{it} = \Delta x_{it} + \Delta w_{it}$$

A change in weekly earnings is less straightforward to interpret than a change in mean hourly earnings ($\Delta \tilde{w}$). Weekly earnings confound a potentially endogenous decision margin (hours per week) with the hourly wage, thus Δw cannot be read as a change in "prices" as do hourly wages. Nonetheless, Δw captures changes over a frequency that is typical of employment contracts, often denominated in weekly, monthly or even annual terms rather than hourly pay. In addition, labor economists have found responses in the intensive margin of male workers to be smaller than adjustments in the extensive margin.[9] Thus, we do not believe that intensive margin responses crucial for the validity of any of the results in our paper.

[8] To give an example, a worker who worked for 39 weeks, 40 hours per week (on average) and earned \$20 an hour (on average), would earn \$31.2K in a given year. i.e $X_{it} = 39$, $H_{it} = 40$, $\tilde{W}_{it} = \$20$ and $Y_{it} = 39 \cdot 40 \cdot \$20 = \$31,200$.

[9] Most recently, Blundell, Bozio, and Laroque (2011) find that the elasticity of labor supply on the extensive

3.2 Decomposing Moments of the Cross-Sectional Distribution

In our analysis, we are interested in quantifying the role of Δx in generating both the cross-sectional moments of the distribution of Δy and their variations with the business cycle. More specifically, we would like to measure the contribution of each component to the first three central moments, since these are measures commonly used to describe distributions.

We denote the jth central moment of the cross-sectional distribution as $m_j(\cdot)$, and $m_{k,l}(\cdot,\cdot)$ as the cross-term of order k and l, that is:

$$m_{k,l}(a,b) \equiv \mathrm{E}^i \left[(a - m_1(a))^k (b - m_1(b))^l\right] \tag{4}$$

for any two random variables a and b, and where the superscript i indicates that the expected value is taken with respect to individuals in a single cross section. Here are the decompositions of the first three central moments.

Mean. The first moment of the distribution has a additive decomposition:

$$m_1(\Delta y) = m_1(\Delta x) + m_1(\Delta w) \tag{5}$$

Variance. The second central moment of Δy can be decomposed to a sum of the second moments of its components and an additional cross term.

$$m_2(\Delta y) = m_2(\Delta x) + 2m_{1,1}(\Delta x, \Delta w) + m_2(\Delta w) \tag{6}$$

The cross term for the variance decomposition is two times the covariance. If the covariance is small in magnitude (such as in the case when Δx and Δw are mean-independent) we can measure the approximate contribution of each component as their share of the variance.

Third Moment. The third central moment expands to four terms:

$$m_3(\Delta y) = m_3(\Delta x) + 3m_{2,1}(\Delta x, \Delta w) + 3m_{1,2}(\Delta x, \Delta w) + m_3(\Delta w) \tag{7}$$

In the analysis that follows we will refer to the sum $3m_{2,1}(\Delta x, \Delta w) + 3m_{1,2}(\Delta x, \Delta w)$ as the cross term of the third moment. The decomposition of the third central moment of earnings growth is the sum of the third central moment of its components plus this cross term.

4 Data

We rely mainly on two data sources: Italian social security data (INPS), and Current Population Survey (CPS) data for the United States.[10]

margin is higher than on the intensive margin across countries. Chetty (2012) argues that even a small adjustment cost can explain the rigidity of labor supply on the intensive margin. Notice that in some cases, particularly during recessions, changes in the extensive margin may be involuntary.

[10] We also use moments of annual earnings growth provided by GOS, the timeseries of GDP growth and CPI from NIPA tables (US), and similar statistics from the Italian National Institute of Statistics (Italy).

4.1 Italy: INPS Data

The Italian social security administration (*Istituto Nazionale di Previdenza Sociale* or INPS) collects data on employer and employee relationships in order to compute social contributions and pension benefits. We use a sample dataset covering the period 1985-2012, based on workers who were born in 24 randomly selected birth dates from the universe of all the Italian employees in the non-farm private sector, who are insured at INPS.[11] The data represents a 6.6 percent sample of this population.

The basic observation in the data is a job relationship with a private employer within a calendar year. For every job relationship we observe the number of weeks of employment and the contributive earnings which include both salary and non-salary components.[12] The earnings from each job relationship are top-coded in accordance with a daily cap of €650 in 2013 (equivalent to individual annual earnings of more than €200K). We find this cap affects at most 0.5 percent of all matched observations. In our main analysis we exclude these observations. In Appendix A, we show that adding back the observations does not change our analysis.[13]

We obtain an individual level panel including joint observations of annual earnings and weeks of work by performing the following steps. First, we combine information from multiple jobs for the same individual by summing over all records associated with the same worker in a given year. This gives us the annual earnings of that worker. We adjust earnings using CPI and compute the difference in logs to get earnings growth Δy_{it}. Second, we calculate employment time as the number of weeks worked – the minimum between 52 weeks and the sum of all weeks worked across all jobs within a calendar year.[14] We take the difference in logs across every two consecutive years in which the worker is observed to get the changes in employment time Δx_{it}. Lastly, we take the difference between annual earnings growth, and changes in employment time, to recover weekly earnings growth Δw_{it}:

$$\Delta w_{it} \equiv \Delta y_{it} - \Delta x_{it}$$

[11] We use the LoSai dataset made available by the Italian Ministry of Labor and Social Policy (*Ministero Italiano del lavoro e delle politiche sociali* or MLPS). More information can be found at www.cliclavoro.gov.it

[12] Contributive earnings include the earnings used to compute individual contributions to the social security system (*imponibile previdenziale*) and are different from the taxable earnings (*imponibile fiscale*) as the social security contributions are included in the former but excluded in the latter. While over-time pay is included, some lump sum payments, such as severance payments, are excluded.

[13] Ideally, one would like to include the (unobserved) top-coded earnings in the data and check if the main results are affected. This is not possible, so we perform an exercise where we assigning extreme values of the earnings (outside the observed range) to the top-coded observations and replicate some of our results to assess possible consequences of a top coding. The results of our exercise reveal that the effects are likely to be small. See Appendix A for a discussion of the results.

[14] If a worker held two jobs at the same time we would not capture it with this data. However, for a sub sample of workers we are also able observe the exact number of months worked, correctly accounting for overlapping jobs. We redo our calculations on this subsample and find that our results are quantitatively very similar and qualitatively unchanged.

For comparability to the literature, we restrict the sample to 25-60 years old male workers, who have a records both in year t and $t-1$ with earnings above the 2.5 percentile of the income distribution, and who have worked for at least 3 weeks in a given year.[15] This choice also helps mitigate concerns with measurement error. Suppose that work is compensated at a daily rate. Then a worker who worked for two weeks and two days would have a reported three weeks of work and have a measured weekly earnings that is lower then the same worker had he worked for the full three weeks. Fortunately, this type of measurement error is bounded and falls as a percentage of the weekly earnings with the number of weeks of work (1/number of weeks). For example, a worker who works for two weeks has a maximal measurement error of 50 percent, but a worker that works for 10 weeks has a maximal measurement error of 10 percent.

We also restrict the sample to employees whose main work contract is full time.[16] Including part-time workers does not change the main results, and dropping these observations reduces the concerns that variation in average weekly earnings could be in fact driven by large changes in hours worked within a week.

We are left with an unbalanced panel of 974,686 workers over 27 years with a total of more than 9 million individual-year observations. In every particular two year period, we have 335,000 observations on average. Workers appear in the sample for 9.7 years on average, and the median worker spends 8 years in the sample. More descriptive statistics about the age and the level of annual earnings, weekly earnings and employment time are reported in Table 1 where all years are pooled together.[17] Mean annual earnings are €27,988 and most workers are employed for the full year (the median worker is employed for 52 weeks). More precisely, 77% of the workers in the sample work for 52 weeks,[18] and to 80% work 50 weeks or more. For comparison, according to the CPS, in the United States 68.9% of prime aged males work 52 weeks, and the figure rises to 82.90% if one only considers individuals working at the time of the interview, those who we think are the relevant sample to compare to ours.[19] Weekly earnings range between €321 at the 10th percentile to €896 at the 90th percentile. Annual earnings growth (in log points) is more dispersed than weekly earnings growth: the standard

[15] The 2.5 percentile is equivalent to an annual income of €800 in 2012 (alternative choices do not affect the results significantly). These sample restrictions are equivalent to the sample restrictions in GOS. Removing workers who have worked less than 3 weeks (0.25% of the full sample) corresponds to that definition, and possibly reduces the measurement error in weekly earnings. The removed workers are likely to be individuals receiving payments relative to work done in previous years, accounted in the current year for accounting reasons. 60% of these workers are actually recorded with 0 weeks of work, leaving only 0.1% of the full sample working 1 or 2 weeks.

[16] Full-time and part-time employment is specified at the record level. We define main work contract to be the one associated with the highest share of overall earnings in a year.

[17] See Appendix A for summary statistics for selected years. Year by year statistics are available from the authors upon request. In the appendix table A.2, we also report more statistics for all the years in the sample.

[18] The share of workers in the sample who work for 52 weeks is 77.2% if we only include people with more than two weeks worked, and 77.3% if we also restrict the sample to include only non-top-coded observations

[19] We obtained these statistics pooling all available CPS interviews from 1962 to 2016

deviation of Δy is more than twice the standard deviation of Δw (0.40 and 0.17 respectively).

Table 1: Summary Statistics – INPS Panel Data

	Mean	Std.Dev.	P10	P50	P90
Age	40.71	9.04	29.00	40.00	54.00
Annual Earnings	27,988	18,919	12,181	23,905	45,565
Employment Time (Weeks)	48.20	9.77	36.00	52.00	52.00
Weekly Earnings	572	360	321	474	896
Δ Earnings (Δy)	0.01	0.40	-0.20	0.01	0.22
Δ Employment Time (Δx)	-0.01	0.38	-0.10	0.00	0.08
Δ Weekly Earnings (Δw)	0.02	0.17	-0.10	0.01	0.15
Observations: 9,293,543					

Notes: The sample is restricted to 25-60 years old males with at least one record at the Italian social security administration between 1985 and 2012. Earnings data are in 2013 euros. Δ terms are in logs. *Source:* INPS data provided by MLPS.

One concern is that measurement errors in employment time will carry over to weekly earnings (also known as "division bias"), and will generate a mechanical negative correlation. However, weeks of work are measured accurately in the INPS data, and we excluded observations with particularly low number of weeks of work, which may lead to large measurement errors. Also, if there were substantial measurement errors in employment time, it would have increased the variance of changes in weekly earnings. We measure the standard deviations of weekly earnings at 17 percent, and it is thus not likely to be a threat to this measurement exercise.

Since our analysis emphasizes the role of changes in employment time in explaining earnings growth, we present some additional descriptive statistics of the employment time dynamics in the Appendix. In particular, Table A.5 reports the autocovariance structure of employment time and employment time changes. We also report the decomposition of the variance of changes in employment into within worker and between workers components. The former component accounts for 86 percent of the variance, and the latter for 14 percent.

4.1.1 Earnings growth in Italy and the US

Figure 2 compares the log-density of earnings growth, Δy_{it}, in Italy and the United States, for the year 1996.[20] Both distributions display similar heavy left and right tails. The Italian distribution is less dispersed and (in 1996) more symmetric. These similarities imply that the forces driving the particular shape of the distribution are not unique to the United States, and support the validity of the analysis using the Italian data.

[20] The density data for the United States is taken from Guvenen, Karahan, Ozkan, and Song (2015).

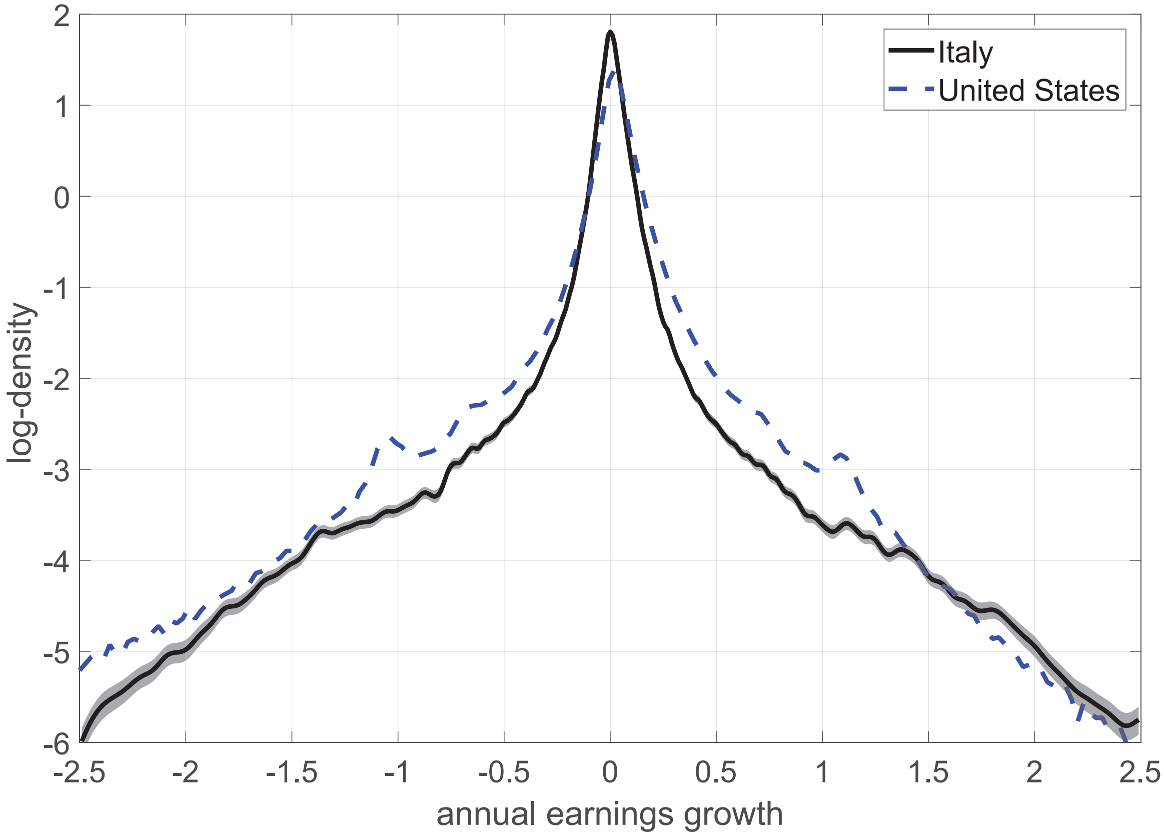

Figure 2: Log-Density of Annual Earnings Growth, Italy and US 1996

Sources: Italy – INPS (as described in the main text). United States – Guvenen et al. (2015). All samples are restricted to males 25-60 years old.

4.2 Current Population Survey

Our analysis of the US labor market flows is based on matched monthly files of the Current Population Survey. Details of these data are discussed in Appendix A.

5 Evidence on the Role of Employment Time

In this section we decompose individual level annual earnings growth into changes in employment time and changes in weekly earnings using the INPS data. We divide our analysis in this section into two parts: evidence from the cross-sectional distribution of earnings growth, and evidence on cyclical patterns of earnings growth.

5.1 Evidence from the Cross Section

Figure 1 in the introduction displays the log densities of earnings growth and weekly earnings for the year 2002. The graph shows that the distribution of weekly earnings growth has thinner tails than that of annual earnings growth, and that the distribution of changes in employment time matches the tails of the distribution of annual earnings growth. Here we expand this analysis, and provide additional non-parametric evidence for the role of employment time.

Our preferred way to explore the role of the employment time in the cross-sectional distribution, is to look at the distribution of earnings growth for workers who have a certain amount of employment time in a given year. In particular we look at the distribution of earnings growth for three groups, and compare them to the full sample for the reference year ($t = 2002$):

(A) Workers employed for 52 weeks in year $t - 1$ (Figure 3 panel (a))

(B) Workers employed for 52 weeks in year t (Figure 3 panel (b))

(C) Workers employed for 52 weeks in both year $t - 1$ and year t (Figure 3 panel (c))

Panel (a) in figure 3 shows the distribution of earnings growth for group A. Since workers in this group were employed for 52 weeks in year $t-1$, their changes in employment time cannot be positive. That is, positive growth in earnings for this group can only be generated by increases in their weekly earnings. The right tail of the distribution of group A is considerably thinner than that of the full sample, while retaining the shape and magnitude of the left tail. This implies that the right tail of the distribution is generated almost entirely by workers who are in the complimentary group – those that were employed for less than 52 weeks in year $t - 1$. Figure 3 panel (b) is the mirror image of panel (a). Members of group B, who were employed for 52 weeks in year t, are unlikely to experience a drop in earnings larger the 10th percentile of the full sample distribution (dashed line). The bottom panel of Figure 3 completes the picture. Workers in group C, who were employed for the full 104 weeks of 2001 and 2002, are unlikely to have experienced large positive *or* negative earnings growth during this period.

To quantify this visual evidence we compare the probability of experiencing large or small earnings growth in each of the groups, and report results in Table 2. Columns (1) and (2) report the 10th and 90th percentile of the full-sample distribution of earnings growth.[21] For each group we compute the probability of experiencing earnings growth below the 10th and above the 90th percentile. The probability of a worker in group A to experience a rise in earnings of greater than the 90th percentile, reported in column (7), is less than 2.1 percent in 2002 (and never above 4.3 percent). Group A includes more than 80 percent of workers in that year, implying that those *not* working for 52 weeks in year $t - 1$, are approximately 20

[21] As in GOS, we find that the 10th and the 90th percentiles are both procyclical (in the two recessions of 1993 and 2009 both quantiles drop by 10 to 20 log-points), while the median moves little over the cycle (see Appendix Table A.1 for the median and other statistics).

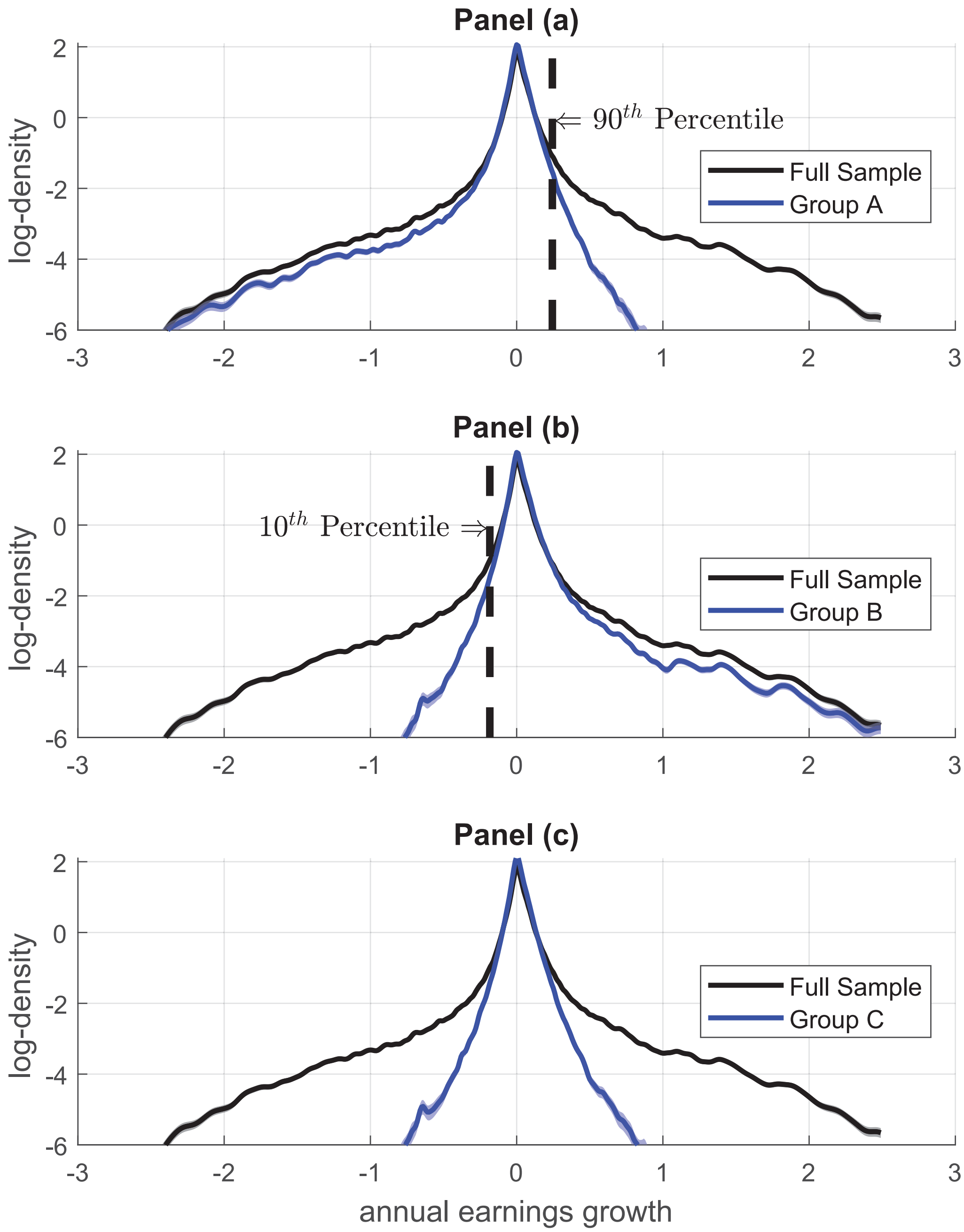

Figure 3: Log-densities of Earnings Growth in Italy 2002, Group A, B, C

Notes: Black line - full-sample distribution, 25-60 years old males in all panels. Panel (a): blue line, sample restricted to workers who have worked for 52 weeks in year 2001 (group A). Panel (b): blue line, sample restricted to workers who have worked for 52 weeks in year 2002 (group B). Panel (c): blue line, sample restricted to workers who have worked for 52 weeks in both years 2001 *and* 2002 (group C). *Source:* INPS data provided by MLPS.

times more likely to experience large earnings growth.[22] Similarly, those *not* employed for 52 weeks in year t (the complimentary group for B) are about 19 times more likely to experience earnings growth lower than the 10th percentile (see Table 2 column (5)).

Since the analysis so far was completely non-parametric, and is invariant to any monotone transformation of earnings growth (90th percentile remains the 90th percentile), we view it as the most convincing evidence. Changes in employment time are responsible for the tails of the distribution. However, letting log changes be the metric for the size of changes (as is typical in the literature), we can also quantifying the relative magnitudes by variance decomposition. Variance decomposition for the year 2002 shows a large role for employment time:

$$\underset{0.158}{\mathrm{var}(\Delta y)} = \underset{0.150}{\mathrm{var}(\Delta x)} + \underset{-0.014}{2\mathrm{cov}(\Delta x, \Delta w)} + \underset{0.023}{\mathrm{var}(\Delta w)} \tag{8}$$

where the number below each term is its estimated value.

In 2002, the variance of employment time is 0.158, implying a standard deviations of 40 percent, compared to a variance of 0.022, or a standard deviation of 15 percent for weekly earnings.

Table 3 provides values of decomposition (6) for all the years in the sample. Two results for equation (8) and Table 3 are notable. First, the variance of changes in employment time is greater than four-fifths of the variance of annual earnings growth in all years in the sample. Second, the cross-term, twice the covariance of the two components, is small and negative throughout most of sample period. Together these two results imply that the variance of log earnings growth is mostly driven by changes in employment time rather than changes in weekly earnings.

A similar decomposition for the third moment (See table A.3) reveals a similar pattern, with the sign and magnitude of the third moment of employment time growth tracking closely those of earnings growth. Moreover, the magnitude of the third moment of weekly earnings growth is mostly one order of magnitude smaller than that of annual earnings growth and employment time growth, with the only exceptions of year 1998 and 1999, when the third moment of annual earnings growth is notably close to zero and (exceptionally) positive.

[22] By construction, 10 percent of the workers experience a rise in earnings above the 90th percentile. Since 80% of all workers are in group A, the probability of experiencing earnings growth above the 90th percentile for the complementary group can be found by solving:

$$0.021 \times 0.8 + p \times 0.2 = 0.1 \Rightarrow p = 0.416$$

so that the workers who are not in group A are 0.416/0.021=19.8 times more likely to experience large earnings growth.

Table 2: Conditional Probabilities of Large Changes in Earnings

	Percentiles of Δy			$\mathbb{P}$("drop")			$\mathbb{P}$("jump")		
Year	P10	P90	group:	A	B	C	A	B	C
(1)	(2)	(3)		(4)	(5)	(6)	(7)	(8)	(9)
1986	-0.159	0.196		0.076	0.026	0.026	0.038	0.078	0.039
1987	-0.134	0.228		0.076	0.026	0.026	0.039	0.080	0.041
1988	-0.122	0.241		0.080	0.031	0.031	0.034	0.079	0.035
1989	-0.138	0.223		0.082	0.032	0.033	0.037	0.079	0.037
1990	-0.143	0.214		0.079	0.028	0.028	0.038	0.081	0.040
1991	-0.155	0.233		0.076	0.021	0.021	0.037	0.082	0.039
1992	-0.215	0.191		0.076	0.015	0.015	0.035	0.080	0.038
1993	-0.272	0.141		0.070	0.013	0.013	0.043	0.087	0.047
1994	-0.222	0.175		0.074	0.016	0.016	0.032	0.080	0.034
1995	-0.163	0.195		0.078	0.027	0.028	0.031	0.076	0.032
1996	-0.179	0.187		0.077	0.021	0.021	0.032	0.078	0.033
1997	-0.135	0.240		0.075	0.023	0.023	0.035	0.078	0.037
1998	-0.174	0.216		0.081	0.024	0.025	0.031	0.077	0.032
1999	-0.157	0.244		0.079	0.026	0.027	0.025	0.074	0.026
2000	-0.159	0.267		0.078	0.028	0.028	0.021	0.075	0.022
2001	-0.179	0.272		0.080	0.023	0.024	0.021	0.074	0.022
2002	-0.184	0.245		0.075	0.021	0.021	0.021	0.074	0.022
2003	-0.181	0.277		0.076	0.020	0.021	0.014	0.067	0.014
2004	-0.184	0.233		0.073	0.017	0.017	0.023	0.072	0.024
2005	-0.228	0.214		0.071	0.013	0.012	0.024	0.076	0.025
2006	-0.164	0.266		0.076	0.019	0.019	0.017	0.069	0.018
2007	-0.167	0.270		0.073	0.020	0.020	0.022	0.071	0.023
2008	-0.201	0.249		0.070	0.015	0.015	0.021	0.074	0.023
2009	-0.424	0.176		0.070	0.004	0.004	0.032	0.086	0.036
2010	-0.252	0.250		0.066	0.010	0.010	0.019	0.070	0.020
2011	-0.246	0.228		0.066	0.011	0.011	0.018	0.067	0.019
2012	-0.340	0.164		0.063	0.007	0.007	0.027	0.073	0.029

Notes: conditional probabilities of a large drop (columns 3 to 5) or a large jump (columns 6 to 8) in annual earnings for selected groups of workers. A *drop* is defined as a change in annual earnings below the 10th percentile of the unconditional distribution of earnings growth. A *jump* is defined as a change in annual earnings above the 90th percentile of the unconditional distribution of earnings growth. Group A includes workers who had 52 weeks of employment in year $t-1$, group B includes workers who had 52 weeks of employment in year t, group C includes workers with 52 weeks of employment both in year t and in year $t-1$. *Source:* INPS data provided by MLPS.

Table 3: Variance Decomposition of Earnings Growth, Italy 1986-2012

Year	$m_2(\Delta y)$ (1)		$m_2(\Delta x)$ (2)		$m_2(\Delta w)$ (3)		$2m_{1,1}(\Delta x, \Delta w)$ (4)	
1986	0.126	(0.001)	0.113	(0.001)	0.024	(0.000)	-0.012	(0.000)
1987	0.131	(0.001)	0.118	(0.001)	0.024	(0.000)	-0.012	(0.000)
1988	0.131	(0.001)	0.118	(0.001)	0.024	(0.000)	-0.011	(0.000)
1989	0.126	(0.001)	0.116	(0.001)	0.024	(0.000)	-0.014	(0.000)
1990	0.125	(0.001)	0.116	(0.001)	0.022	(0.000)	-0.014	(0.000)
1991	0.137	(0.001)	0.128	(0.001)	0.023	(0.000)	-0.016	(0.000)
1992	0.148	(0.001)	0.143	(0.001)	0.023	(0.000)	-0.019	(0.000)
1993	0.147	(0.001)	0.131	(0.001)	0.025	(0.000)	-0.009	(0.000)
1994	0.149	(0.001)	0.139	(0.001)	0.025	(0.000)	-0.015	(0.000)
1995	0.140	(0.001)	0.131	(0.001)	0.022	(0.000)	-0.013	(0.000)
1996	0.141	(0.001)	0.133	(0.001)	0.021	(0.000)	-0.014	(0.000)
1997	0.141	(0.001)	0.135	(0.001)	0.021	(0.000)	-0.016	(0.000)
1998	0.156	(0.001)	0.145	(0.001)	0.025	(0.000)	-0.014	(0.000)
1999	0.156	(0.001)	0.145	(0.001)	0.024	(0.000)	-0.012	(0.000)
2000	0.166	(0.001)	0.153	(0.001)	0.025	(0.000)	-0.013	(0.000)
2001	0.167	(0.001)	0.156	(0.001)	0.025	(0.000)	-0.014	(0.000)
2002	0.158	(0.001)	0.150	(0.001)	0.023	(0.000)	-0.014	(0.000)
2003	0.164	(0.001)	0.159	(0.001)	0.023	(0.000)	-0.017	(0.000)
2004	0.156	(0.001)	0.146	(0.001)	0.022	(0.000)	-0.012	(0.000)
2005	0.167	(0.001)	0.148	(0.001)	0.024	(0.000)	-0.006	(0.000)
2006	0.165	(0.001)	0.147	(0.001)	0.022	(0.000)	-0.004	(0.000)
2007	0.158	(0.001)	0.140	(0.001)	0.023	(0.000)	-0.004	(0.000)
2008	0.168	(0.001)	0.143	(0.001)	0.023	(0.000)	0.001	(0.000)
2009	0.203	(0.001)	0.168	(0.001)	0.028	(0.000)	0.007	(0.000)
2010	0.193	(0.001)	0.159	(0.001)	0.029	(0.000)	0.005	(0.000)
2011	0.195	(0.001)	0.160	(0.001)	0.027	(0.000)	0.007	(0.000)
2012	0.197	(0.001)	0.167	(0.001)	0.027	(0.000)	0.004	(0.000)

Notes: the variance of earnings growth (1), is decomposed into the variance of changes in employment time (2), the variance of changes in weekly earnings (3) and a cross-term (4). Standard deviations of each component are reported in parentheses. Sample includes all 25-60 years old males who appear in the data for two consecutive years. *Source:* INPS data provided by MLPS.

5.2 Time Series Evidence

Since employment time has a dominant role in shaping the tails of the cross-sectional annual earnings growth distribution, we are now interested in measuring its contribution to the cyclicality of annual earnings. We start by confirming that recessions affect the shape of the distribution of annual earnings growth. Figure 4 shows the cross-sectional distribution of annual earnings growth in Italy for 2002 (expansion year) and 2009 (recession year). In recessions, the right tail of the distribution (large increases) goes down while the left tail (large decreases) goes up. Since the central part of the distribution remains stable, the overall skewness of the distribution becomes more negative. The similarity of this impact of a recession in Italy to that documented by GOS suggests a common mechanism.

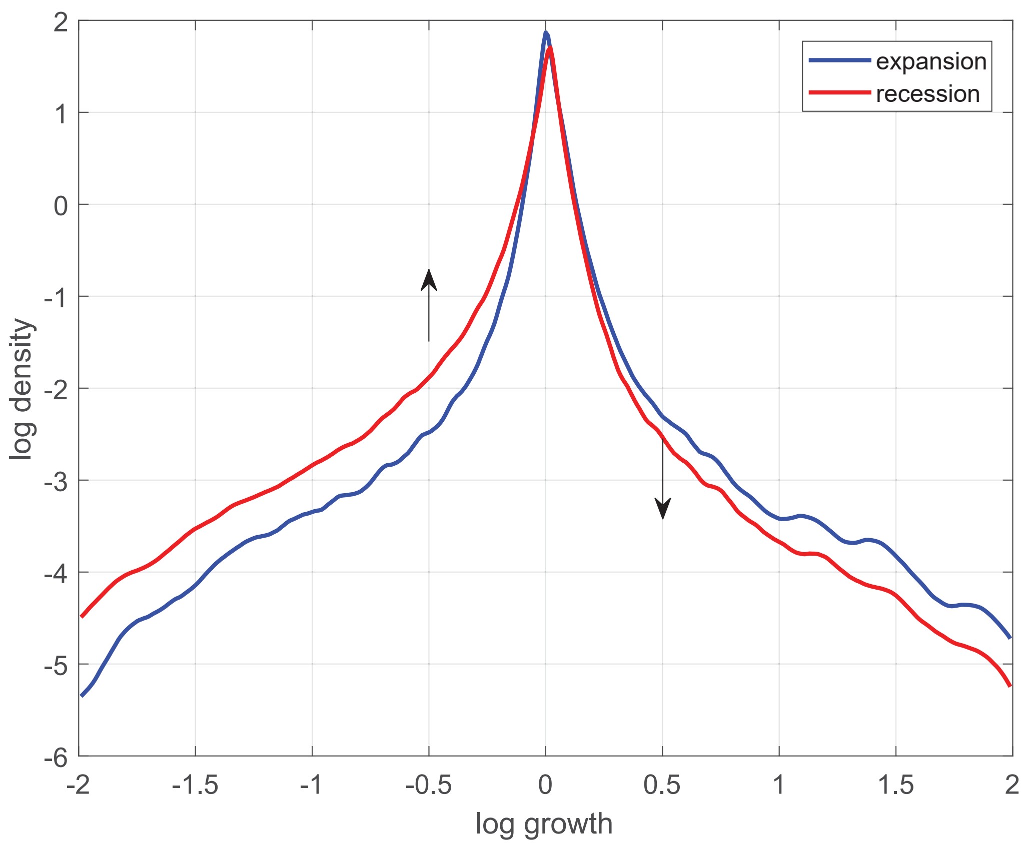

Figure 4: Annual Earnings Growth in Expansion and Recession, Italy 2002 and 2009

Notes: Annual earnings growth is measured as the difference in logs. The sample includes 25-60 years old males in Italy. *Source:* INPS data provided by MLPS.

We continue by presenting the decompositions of the first three central moments of earnings growth over the sample period in Figure 5.

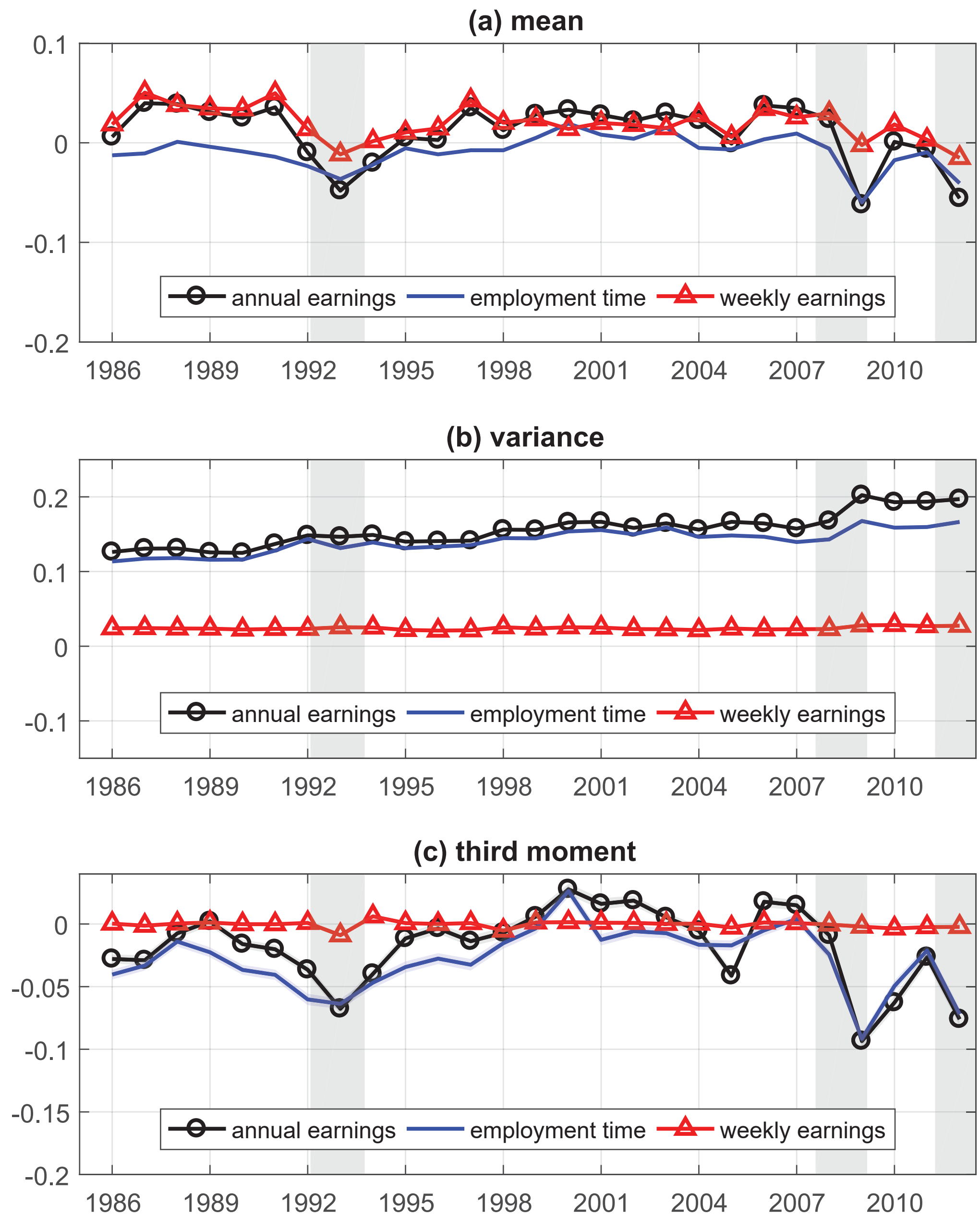

Figure 5: Moment Decomposition of Annual Earnings Growth, Italy 1986-2012

Notes: Panels (a) through (c) present the time series of moments of the cross-sectional distributions. Panel (a) presents decomposition of the mean, panel (b) presents decomposition of the variance and panel (c) presents decomposition of the third central moment. In each panel, there are three lines: annual earnings (black), employment time (blue) and weekly earnings (red). All variables are measured as difference in logs. The sample includes 25-60 years old males in Italy. Shaded areas represent recessions. *Source:* INPS data provided by MLPS.

Panel (a) shows the decomposition of the mean earnings growth. The mean change in employment time remains negative throughout most of the sample period. It reaches a low of -0.07 at 2009, in the midst of the Great Recession. The mean change in weekly earnings is on average a positive 0.02 during expansions. It drops during recessions, reaching a low of -0.02 in 2012. The dynamic behavior of the means suggests that cyclicality of mean earnings growth reflects cyclical properties of both employment time and weekly earnings.

The variance of earnings growth is decomposed in panel (b), visually repeating the variance decomposition reported in Table 3. The variance of earnings growth and the variance of changes employment time follow a long-term increasing trend. This trend is particularly evident after the beginning of the Great Recession in 2007. There appears to be some amount of counter cyclicality in the variance earnings growth and changes in employment time, but both seem to be less pronounced than the long-term trend. The time series of the variance of changes in weekly earnings is relatively flat, with a period of higher variance in the late 1990s early 2000s. The variance of changes in employment time is visually associated with the variance of earnings growth.

Panel (c) presents the decomposition of the third central moment. Controlling for the mean and variance, the third central moment captures the asymmetry of the distribution. The third moment of annual earnings growth and of changes in employment time follow the same path, both in magnitude and in pattern. They are both clearly pro-cyclical, dropping to a negative -0.1 in 2009, during the global economic slowdown. The third moment of changes in weekly earnings is relatively flat and close to zero. We interpret these results as employment time being the primary source for the observed cyclical asymmetry of annual earnings growth.

We confirm the visual evidence with a statistical test using the constructed time series of moments. Table 4 presents the statistical test. We define the cyclicality of a cross-sectional moment as its contemporaneous correlation with GDP growth. The third moment of annual earnings growth in Italy is highly procyclical (see column 1), which is similar to the findings of GOS for the United States. However, when controlling for the third moment of changes in employment time in the regression, the correlation disappears (see column 2). This results offer further suggestive evidence that employment time is the source of the cyclical skewness of earnings growth. Appendix C provides additional statistical tests.

5.3 Earnings Growth at Longer Horizons

We also evaluate the decomposition of earnings growth at longer horizon. GOS argue that comparing the distribution of five-years earnings growth to the distribution of one-year earnings growth is informative on the persistence of earnings shocks. Therefore, we supplement the one-year earnings growth decomposition with a decomposition of the first three moments of the

Table 4: Statistical Test of Source of Cyclicality

Dependent variable	Third moment of annual earnings growth	
	(1)	(2)
GDP Growth	**0.659**	-0.120
	(0.124)	(0.086)
Third moment of changes in employment time		**1.020**
		(0.091)
R-squared	0.43	0.86
Observations	27	27

Notes: The dependent variable is the third moment of annual earnings growth (columns 1 and 2). All time series are detrended with a linear trend and standardized. Regressors include contemporaneous GDP growth (log difference of real GDP from ISTAT) and the third moment of the distribution of changes in employment time. Data covers the years 1986-2012. Bold text indicates significance at the 0.95 level. Standard errors are computed using Newey-West estimator with two lags.

five-year earnings growth distribution.[23]

Figure 6 presents the time series of the mean, variance, and third moment in a way that is comparable to Figure 5. The mean earnings growth at longer horizons, which is presented in panel (a), moves together with the mean changes in weekly earnings. In contrast to the one-year results, the mean of changes in employment time does not contribute much to the five-year earnings growth. The variance decomposition in panel (b) reveals that changes in weekly earnings account for a larger share of the variance of five-years earnings growth. Changes in employment time still generate most of the variance and are responsible for the secular upward trend and mild countercyclicality. But the variance of five-years changes in employment time is roughly the same as the variance of one-year changes in employment time, while the variance of five-years weekly earnings growth (0.05) is roughly double the variance of one-year weekly earnings growth (0.025). Panel (c) shows that the role of employment time in generating the asymmetric response to recession is as important at the longer horizon as it was for the one-year earnings growth. The third moment of five-year changes in employment closely follows the third moment of earnings growth, both in magnitude and in pattern, and is visibly lower after the beginning of the slump in mid-2007. As in the one-year case, the third moment of changes in weekly earnings is flat and close to zero.

These results have implications for the persistence of the changes in earnings growth and its

[23] Following GOS, we define the n-years earnings growth as $\Delta_n y_t = y_t - y_{t-n}$ where y_t is the logged annual earnings at year t. Similarly, the changes in employment time and weekly earnings are defined as $\Delta_n x_t = x_t - x_{t-n}$ and $\Delta_n w_t = w_t - w_{t-n}$, taking the log differences between the annual values.

components. Under a simple permanent/transitory framework the increase in the variance of weekly earnings growth with the time horizon suggests that shocks to weekly earnings have a considerable permanent component while the absence of an increase in the variance of changes in employment time suggests that most of the variation in employment time is transitory.[24] Since the distribution of weekly earnings growth appears to be symmetric and acyclical, this suggests that the cyclicality in annual earnings growth is mostly coming from transitory shocks that affect labor supply, rather than permanent shocks to earnings.

5.4 Job Stayers and Job Switchers

Economists have documented differences in the mean earnings growth between workers who switch jobs and workers that stay with the same employer (Topel and Ward, 1992; Bagger, Fontaine, Postel-Vinay, and Robin, 2014; Low and Pistaferri, 2015). Recently Guvenen, Karahan, Ozkan, and Song (2015) show significant differences in the second, third and fourth moments of earnings growth between job stayers and job switchers. Specifically, job stayers face a standard deviation of earnings growth that is approximately half that of job switchers and their group's earnings distribution has a less negative third central moment. In this subsection we document that most of these differences disappear once we restrict attention to workers who did not experience large drops or increases in employment time, and therefore the differences are related to spells of non-employment.

Guvenen, Karahan, Ozkan, and Song (2015) define a worker to be a "job stayer" if a given employer provides the largest share of his annual earnings (out of all his job relationships in a year) in years $t-1$ through $t+2$, and if the same employer provides at least 80% of his total annual earnings in years t and t + 1. They define as "job switchers" those workers who are not a job stayers. We adopt a similar definition, and consider as switchers all workers whose main employer (the employer that provide most of their earnings) changes between year $t-1$ and year t.

Figure 7 shows the first, second and third moments of the earnings growth distribution for stayers and switchers. Panels (a), (b), and (c) show the time series of the mean, variance, and third moment of job stayers and job switchers. These results are similar to those in Guvenen et al. (2015): the variance of earnings growth for switchers is twice as large as the that of stayers and the third central moment of switchers is more negative than of stayers. Panels (d), (e), and (f) restricts attention to workers who were employed for 52 weeks in both years

[24] Let $z_t = \eta_t + e_t$ be a permanent/transitory process, in which $\eta_t = \eta_{t-1} + u_t$ is the permanent component and e_t and u_t are independent shocks with mean zero and variance σ_e^2 and σ_u^2. The variance of the one-year growth is $\text{Var}[\Delta z_t] = \sigma_u^2 + 2\sigma_e^2$. The variance of the five-years growth is $\text{Var}[\Delta_5 z_t] = 5\sigma_u^2 + 2\sigma_e^2$. Therefore the difference $\text{Var}[\Delta_5 z_t] - \text{Var}[\Delta z_t]$ is four time the variance of the permanent component. Using this result and the variance of one- and five-years weekly earnings growth suggest a permanent component with standard deviations of 7% and transitory component with standard deviations of 10%. Since the variance of one- and five-years changes in employment time is roughly the same, this suggests a negligible permanent component.

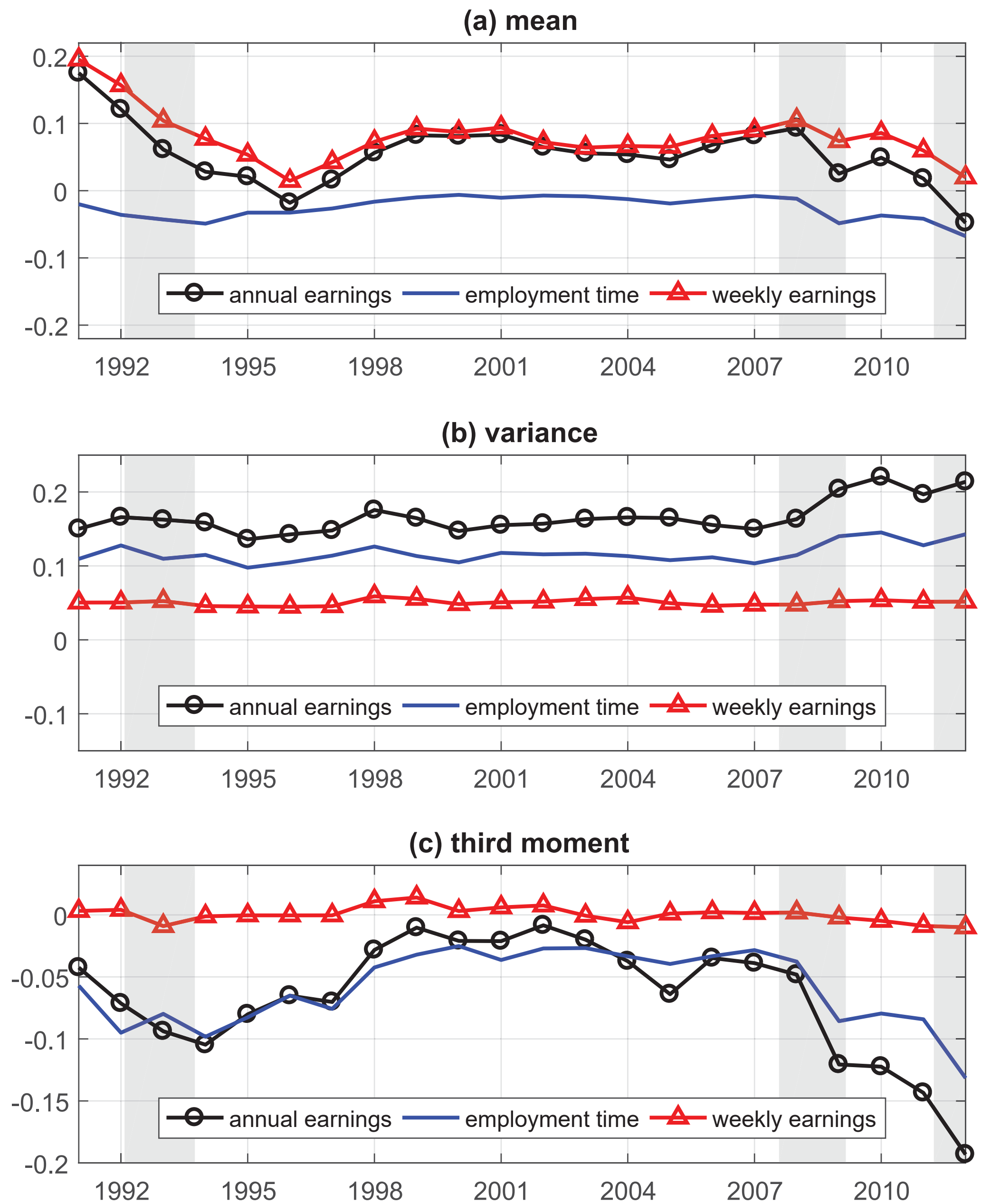

Figure 6: Moment Decomposition of Five-Year Earnings Growth

Notes: Panels (a) through (c) present the time series of moments of the cross-sectional distributions of five-year changes in annual earnings (black, round marker), employment time (blue, smooth), and weekly earnings (red, triangles). Panel (a) presents decomposition of the mean, panel (b) presents decomposition of the variance and panel (c) presents decomposition of the third central moment. All variables are measured as difference in logs. The sample includes 25-60 years old males in Italy. Shaded areas represent recessions. *Source:* INPS data provided by MLPS.

t and $t-1$. Within this group the differences narrow significantly, becoming quantitatively negligible. Hence, the difference between the groups observed in the left panels is driven by the composition of workers within the two groups: switchers experience more spells of non-employment and therefore the variance of their earnings growth is higher.

Another interesting observation is that during recessions switchers have a lower mean earnings growth, while in expansion they have a higher earnings growth. When looking at continuously employed workers, this difference almost disappears. This difference points to cyclical changes in the composition of job switchers who are laid off, who quit and find a new job, and who are "poached" by other employers while on the job that was highlighted in the literature (see for example Postel-Vinay and Robin (2002); Holzheu (2018)).

5.5 Effects of Income Tax and Unemployment Benefits

In a recent paper, Blundell, Graber, and Mogstad (2015) show that the Norwegian tax system plays a crucial role in reducing the magnitude and persistence of income shocks, especially among low educated and young Norwegian. To reach this conclusion they use a rich collection of administrative data that allows them to compute each Norwegian tax payer's labor income before and after tax and transfers. To assess the impact of tax and transfers on the distribution of earnings growth, we perform a similar exercise on the Italian data.

Our data includes only social security income (*reddito contributivo*), which is used to compute social security contributions. Social security income is sometimes different from the fiscal income (*reddito fiscale*), which is used to compute income taxes, but the two measures are in generally close to each other.[25] The Italian personal income tax (*Imposta sulle Persone Fisiche*, IRPEF) changed several times over our sample period.[26] Marginal tax rates very between 10% for low income brackets to peaks of 65% for the highest brackets in the 1980s. Moreover, the transfer system in Italy depends on a complex combination of information on the tax payers' household as well as various measures of wealth, that we cannot completely pin down from our data. However, starting in 1997 we direclty observe a combination of transfers paid by the social security administration to workers who spend some time in unemployment in any given year. Since all these payments are also part of the taxable income, we build two new measures of income. The first is the sum of labor earnings and unemployment benefits. The second is a post-tax measure of income obtained by applying the marginal tax schedule to the previous sum.

Figure 8 presents the mean, variance and third central moment of changes in the logs of the three measures between 1997 and 2012. The tax system reduces systematically the variance

[25] One main difference is that fiscal income excludes the contributions that are paid to the social security system by the employee. The fiscal income is also also excludes severance payments and some forms of non monetary compensations which are included in the social security income. It does include non-labor income that the social security income doesn't include.

[26] Table A.4 in the appendix summarizes these changes

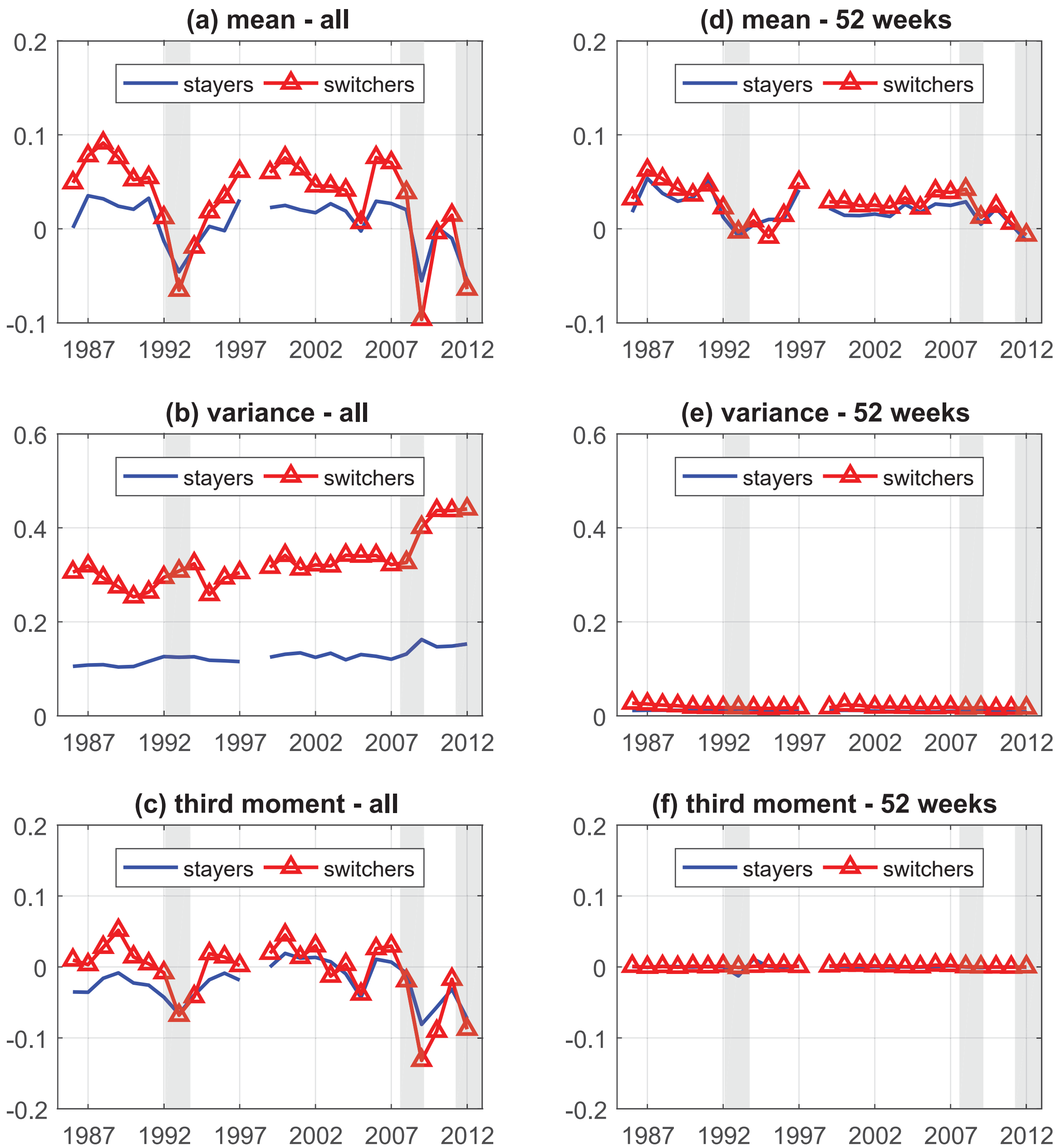

Figure 7: Job Stayers and Job Switchers, Italy 1986-2012

Notes: Panels (a), (b), and (c) present the time series of mean, variance and third central moment of the cross-sectional distributions of annual earnings growth for “stayers” and “switchers” over the full sample. Panels (d), (e), and (f) present the time series of the same statistics, only for workers employed 52 weeks both in year $t-1$ and t. The sample includes 25-60 years old males from Italy and covers the period 1986 to 2012. Shaded areas represent recessions. Year 1998 is omitted as in that year the INPS recording system was reformed and it is not possible to precisely define stayers and switchers. *Source:* INPS data provided by MLPS.

of income growth. Especially following the 2007 economics downturn, the combination of unemployment benefit transfers and income taxes systematically reduce the aggregate variance of earnings growth by 25%, from 0.2 to 0.15. Similarly, the third central moment of earnings growth increase following 2007 reflecting an insuring effect of the system during economic downturns. The mechanism through which this is achieved is illustrated in Figure 9: the left tail of the earnings growth distribution becomes thinner once unemployment benefits are accounted for. Consistent with our findings that most large negative shocks correspond to large declines in employment time (often mirrored by unemployment spells), the unemployment benefits are effective in reducing the consequent drop in earnings, making the distribution less left-skewed.

5.6 Earnings Growth Over the Life Cycle

In our analysis so far we have described the distribution of earnings growth by pooling together workers of different age group. However, it is well known that individual earnings follow a predictable age profile: workers' labor earnings rise when young and fall when old. This predictable component can potential inflate the dispersion of the distribution, and could contribute to the cyclical patterns if there is some systematic differences in the response to aggregate shocks across age groups.

To evaluate this concern we conduct a robustness check. We remove a time-age fixed effect from annual earnings, employment time, and weekly earnings, at the worker level. Then, we use the residuals to replicate Figures 1 and 5. Detailed results are reported in Appendix D. The age profile, while important in describing the life-cycle patterns of earnings, has little to no effect on the results of this paper.

5.7 Summary: Evidence from Italy

In this section we present direct evidence indicating that changes in employment time drive the cyclical properties of the distribution of annual earnings growth. First, changes in employment time generate the tails of the earnings growth distribution. Second, the cyclical asymmetry of the earnings growth distribution, measured by its third moment, is generated by cyclical changes in the distribution of changes in employment time. In contrast, we find that changes in weekly earnings have a minor role in driving the tails of annual earnings growth, and that their distribution around the mean is acyclical. We also find that the distribution of changes in weekly earnings displays only small deviations from symmetry. Changes in weekly earnings are also much more persistent than changes in employment time, and therefore may have a larger impact on individual permanent income.

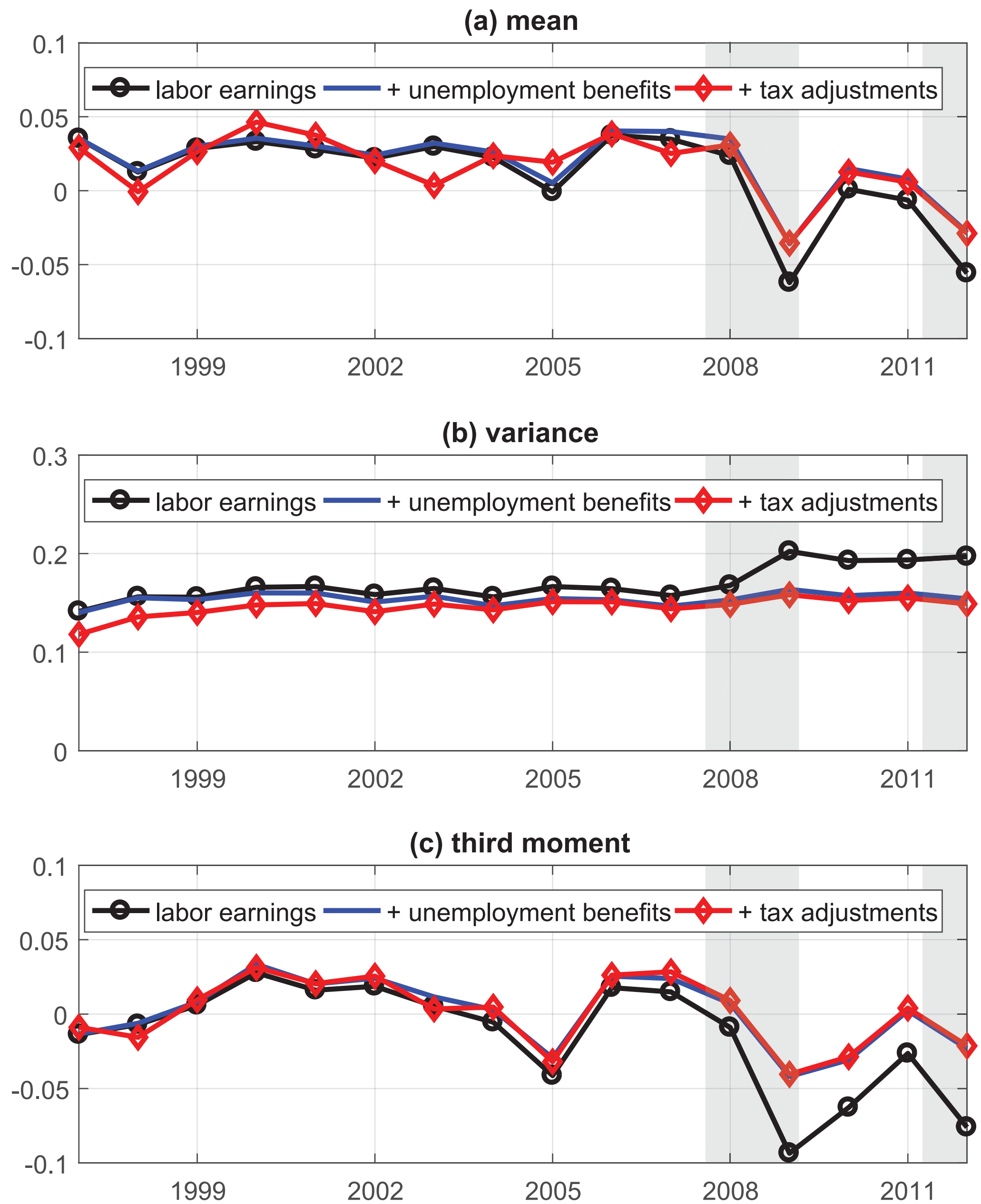

Figure 8: Moments of Annual Earnings Growth, Pre and Post Taxes, Italy 1997-2012

Notes: The mean, variance and third central moments of the cross-sectional distributions of annual labor earnings growth (black line, circle markers), annual earnings growth plus unemployment related transfers before tax (blue line, no markers) and after tax adjustment (red line, diamond markers). Unemployment related transfers are available only starting in 1997. The sample includes 25-60 years old males in Italy. Shaded areas represent recessions. *Source:* INPS data provided by MLPS.

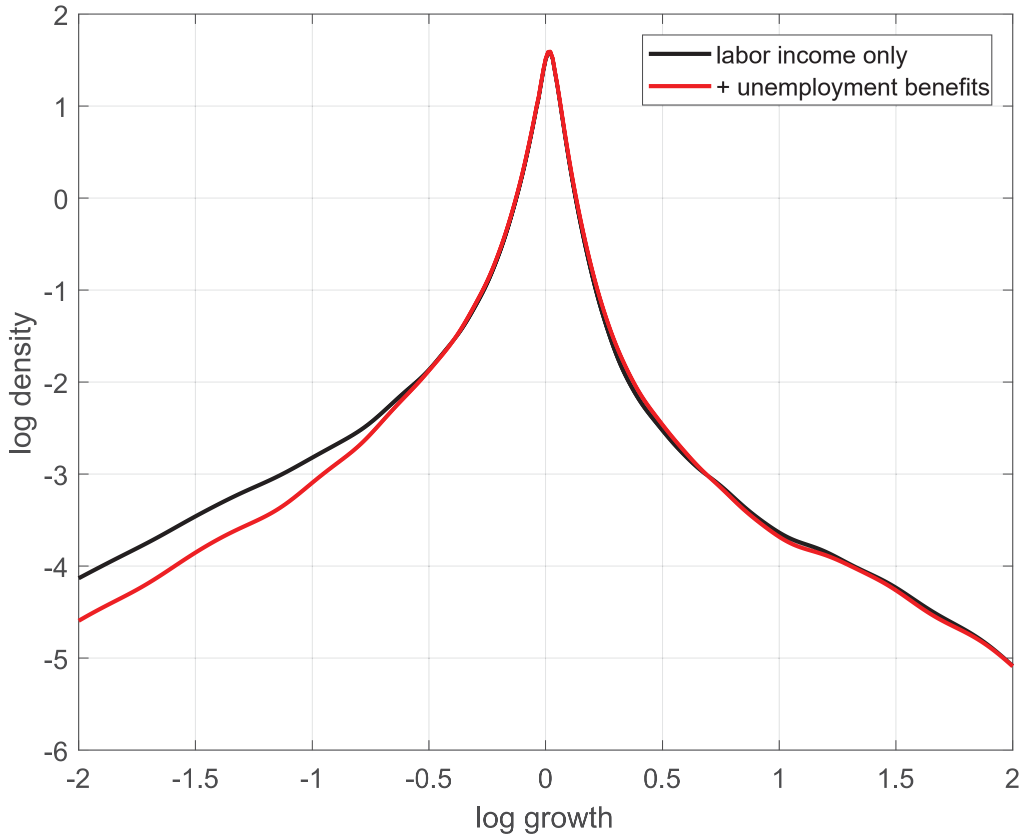

Figure 9: Effect of Unemployment Benefits in the 2009 Cross-section

Notes: Log-density of the distribution of earnings growth before (black) and after (red) adding the unemployement benefits in 2009. The sample includes 25-60 years old males in Italy. *Source:* INPS data provided by MLPS.

6 Implications: A Proposed Earnings Process

So far we have established a set of features of the earnings growth distribution based on its decomposition into changes in employment time and in weekly earnings. Namely, we have shown that changes in employment time are responsible for the tails of the distribution and are the source of cyclical asymmetry, while the distribution of changes in weekly earnings around its mean is symmetric and acyclical. This evidence suggests the need to carefully model the employment margin separately from the wage margin.

In this section we propose a parsimonious model of the earnings process that is consistent with these features. Other recent studies of the earnings process emphasize asymmetries in persistent earnings shocks to capture the procyclical skewness of the earnings growth distribution. However, our analysis shows that most of the tails are generated by workers who reduce or increase their employment time, and these changes account for the cyclical patterns in earnings growth. We therefore propose a different model that captures the procyclical skewness of changes in employment time, as well as other important features, without the explicit assumption of asymmetric persistent shocks.

The key idea is that annual earnings is the combination of two processes: an employment process and a wage process. The employment process is driven by random transitions between discrete labor market states. This type of process is consistent with the Diamond-Mortensen-Pissarides framework of labor search and matching process, which is a standard macroeconomic view of labor markets.[27] The wage process is subject to independent permanent and transitory shocks that generate a symmetric wage growth distribution. This is a common assumption in the literature studying the idiosyncratic earnings process, dating back to MaCurdy (1982). We aim to show that the combination of these two simple processes, with few parameters, can capture the cyclical patterns in the data without the need to assume more complex distributions for the persistent earnings shocks.

The employment process captures the procyclical skewness in changes in employment time through cyclical changes in the transition rates between labor market states. In the beginning of recessions, the separation rate (transitions from employment to unemployment) increases and the hiring rate (transitions from unemployment to employment) declines. The higher separation rate leads more workers to transition to unemployment, and the lower hiring rate leads to longer average duration of unemployment spells. As a result, more workers experience a large drop in employment time in the beginning of recessions. For the majority of workers who stay employed, changes in employment time remain effectively zero. Therefore, the distribution of changes in employment time becomes more negatively skewed. As the number of unemployed workers increases, the number of workers who experience large increases in employment time gradually increases, and the distribution of the changes in employment time becomes more symmetric.

In the rest of the section we formally define the employment and wage processes and show that they can generate the qualitative features of earnings growth distribution and its components using a numerical example. We then provide additional suggestive evidence, based on labor market flows from the US, that the proposed mechanism can generate the timing and magnitude of the observed cyclical movements in the earnings growth distribution reported by GOS.

6.1 The Employment Process

Employment follows a discrete-time Markov chain. Every month m, a worker is in one of two labor market states: employment (E) or unemployment (U). The probability of a worker who is in state i in month $m-1$ to transition to state j in month m is $P_{i,j}(m)$. These probabilities

[27] Other recent papers have explored a similar idea (Hubmer, 2018; Holzheu, 2018) aiming at reproducing the cross-sectional properties of the earnings growth distribution. Our model aims at capturing both the cross-sectional properties and the the cyclical properties of the distribution.

are time varying, but common to all workers at time m, and are summarized in the transition probability matrix $P(m)$. Annual employment time at every month m is defined as the number of months spent in state E out of months $\{m, m+1, ..., m+11\}$.

To capture the cyclicality in transition rates, we consider a transition probability matrix that can take one of two possible values: $P(m) = P^E$ if the economy is in expansion in month m and $P(m) = P^R$ if the economy is in recession in month m. By convention, year t starts at month $m = 12t$ and ends at month $12t+11$. The employment time X_{it} is therefore the number of months spent in employment between month $12t$ and $12t + 11$.

6.2 Wage Process

The log wage w_{it} of worker i at year t is the sum $w_{it} = \eta_{it} + e_{it}$, where η_{it} is the permanent component and e_{it} is a transitory shock. The transitory shock e_{it} is exponentially distributed with parameter b, $e_{it} \sim \text{Exponential}(b)$. The permanent component has a unit root, and is therefore the sum $\eta_{it} = \eta_{it-1} + u_{it}$ of lagged permanent component and a permanent shock u_{it}. The permanent shock is assumed to be normally distributed according to $u_{it} \sim N(\mu_t, \sigma^2)$, where μ_t is time varying mean wage growth.

This wage process specification captures three important features observed in the Italian data and documented in the literature. First, the distribution of weekly earnings growth around its mean is acyclical. This is reflected in only allowing the mean of the permanent shock, μ_t, to vary over time. Second, the transitory shocks are non-Gaussian, which helps to capture the shape of the weekly earnings growth distribution in the data. We pick the exponential distribution for the transitory shocks, and hence the transitory component in the change in wages, Δe_{it}, follows the Laplace distribution. This distribution captures the "straight tails" in the distribution of weekly earnings growth that are apparent in Figure 1. While this is a technical assumption that can be overlooked, we believe that it does capture an important feature of the weekly earnings growth distribution. Lastly, our assumption that the permanent shocks are Gaussian follows Arellano, Blundell, and Bonhomme (2017), who document that most of the non-Gaussianity observed in earnings growth is in its transitory component and that permanent shocks have only small departures from Gaussianity.

6.3 A Numerical Example

We pick parameter values for the employment and wage processes to match moments of unemployment and the wage growth distribution. The employment process is determined by the value of the separation rate and the hiring rate in recession and expansion. Hobijn and Şahin (2009) study labor market flows in OECD countries and find the separation rate in Italy to be 1 percent on average in a sample that covers the period 1988-2004. We therefore set the separation rate in expansion to be 1 percent. We also set the separation rate in recessions to be slightly higher at 1.25 percent. These numbers reflect an average employment spell duration of 6 to 9 years and capture the long duration of typical job relationships in Italy. Male unemployment rate was 6.27 percent in 2005 and 12.13 percent in 2014.[28]. We therefore set the job finding rate to 15 percent in expansion to match the 2005 rate at steady state and 9 percent in recession to match the 2014 rate in steady state. The average unemployment spell in the simulated economy is therefore 6 to 11 months, capturing the high share of workers who are unemployed for more than 12 months in Italy.[29]

The wage process is defined by the parameter b of the transitory shock and the parameter σ of the permanent shock. To set these parameters, we match the standard deviations of weekly earnings growth at the one-year and five-years horizon. The variance is approximately 0.025 at the one-year horizon, and increase to 0.05 in the five-years horizon. To set the parameters, we use the following two equations:

$$\mathrm{Var}[\Delta w_{it}] = \sigma^2 + 2b^2,$$

$$\mathrm{Var}[\Delta_5 w_{it}] = 5\sigma^2 + 2b^2.$$

The dispersion of the permanent shock is therefore set to $\sigma = 0.07$, and the parameter of the transitory shock is $b = 0.10$, which implies a standard deviation of 10 percent.

We then simulate 100,000 worker histories over a 10 years period, in which the 8th and 9th years are recession years.[30] The simulation allows us to both look at the cross-sectional distributions and reproduce the decomposition in Figure 1, and see the effects of a recession by comparing cross-sections at year 8 and year 10.

Figure 10 shows a decomposition of the annual earnings growth at an expansion year (7th year in the simulation) in a similar way to the decomposition in Figure 1. The simulated distribution captures the main visual features of the distribution in the data, including heavy tails of the distribution of changes in employment time, and straight lags of the distribution of changes in weekly earnings.

Figure 11 compares the distribution of earnings growth in years 8 and 10 of the simulation (recession and recovery) to show what happens in recessions. In the recession year the left tail of the distribution of annual earnings growth is higher and the right tail lower, while the distribution of small earnings growth is relatively stable. This is reflected in negative skewness of the distribution in recessions.

6.4 Suggestive Evidence from US Labor Market Flows

The numerical example shows that the suggested earnings process is able to replicate the qualitative features of the Italian data. But since we do not directly observe high frequency

[28] Source: http://dati.istat.it/Index.aspx

[29] See Hobijn and Şahin (2009) for cross-country comparison of employment and unemployment duration. Most unemployed workers in Italy have been unemployed for more than 12 months.

[30] Years 1 through 7, and year 10 are expansion years.

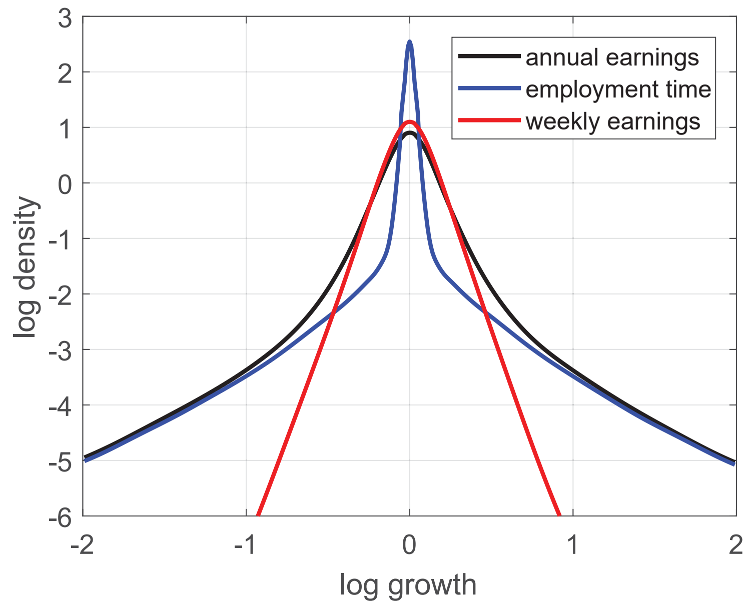

Figure 10: Numerical Example – Decomposition of Earnings Growth

Notes: Cross-sectional distribution of one-year log growth of annual earnings, employment time, and weekly earnings based on simulations of the earnings process described in the main text.

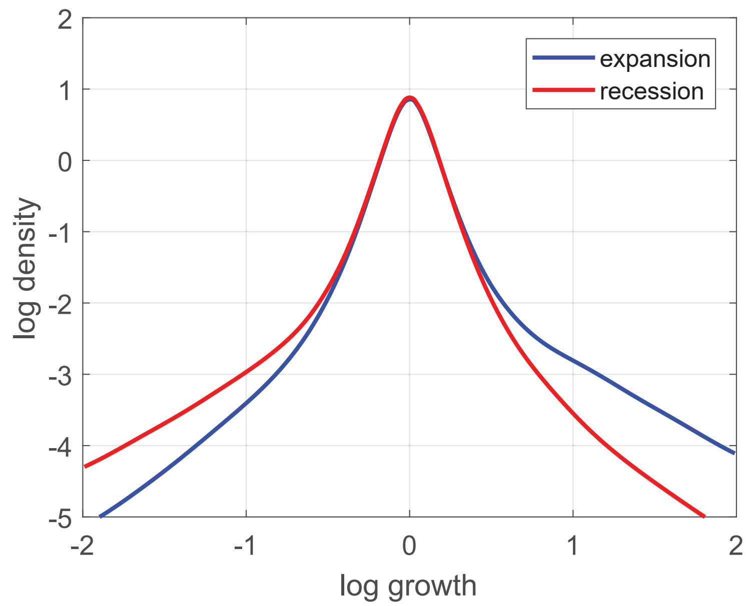

Figure 11: Simulation – Recession and Expansion

Notes: Cross-sectional distribution of annual earnings growth in recession and expansion. Data simulated from the numerical example.

flows between labor market states in Italy, we cannot evaluate the ability of the mechanism to quantitatively produce the timing and magnitude of the cyclical fluctuations that we report in Section 5. Instead, we assess the quantitative implications of the model using labor market flows data from the US.

We conduct this analysis using data from the US for two main reasons. First, labor market flows data are available through the panel aspect of the CPS, and have been widely used in previous studies. Labor flows data allow to directly measure the employment process. Similar data are not available for Italy. Second, GOS document their statistical facts on earnings growth in the US. Measuring labor flows in the US and evaluating our model against their findings provides additional suggestive evidence that the mechanism of the model is also important in countries other than Italy.

In the data, workers often separate from employers into "not-in-the-labor-force" state, and workers in that state often transition directly into employment. We find that this state is fundamentally different from unemployment, and so warrants an additional state in the employment process. Therefore, we augment the employment process with a third "not-in-the-labor-force" (N) state and take into account the flows into and out of this state (see Appendix B for details). Nonetheless, for the sake of simplicity, we focus our discussion on the role of the transitions between employment and unemployment, which are the biggest flows observed in the data.

Figure 12 shows the transition rates between labor market states over the sample period, from February 1976 to December 2015. Several details are are worth noting. The diagonal panels (E to E, U to U and N to N) reveal the persistence of each state. Unemployment is less persistent than both employment and not-in-labor-force states. The transitions from employment to not-in-labor-force and back, that are sometimes neglected in search and matching models, are non-trivial. Over 1 percent of employed workers exit the labor force each month, and around 8 percent of workers outside the labor force transition directly into employment each month. The long-term increasing trend in E to N transitions reflects the decrease in the labor force participation among prime working age men (for discussion of this trend see Hall, 2014). The transition rates also reveal that the flows from outside of the labor force into unemployment are also substantial and highly countercyclical, and so contribute to the increase in unemployment in recessions (for discussion of the contribution of the participation margin to the unemployment rate see Elsby, Hobijn, and Şahin, 2015).

The most important detail to our analysis is the cyclicality of the separation rate (E to U) and hiring rate (U to E). During recessions, the transition rate from employment to unemployment (top middle panel) increases and the transition from unemployment to employment (middle left panel) declines. This is consistent across all the recessions in our sample. Furthermore, the effect of the recession is slow to wear off, and separation and hiring rates take several years to return to their pre-recession levels, even following relatively mild recessions.

To evaluate the model, we feed the transitions probabilities and labor market state shares into the augmented employment process and compute the model implied distributions of changes in employment time. We do so for each month in the sample, using a method explained

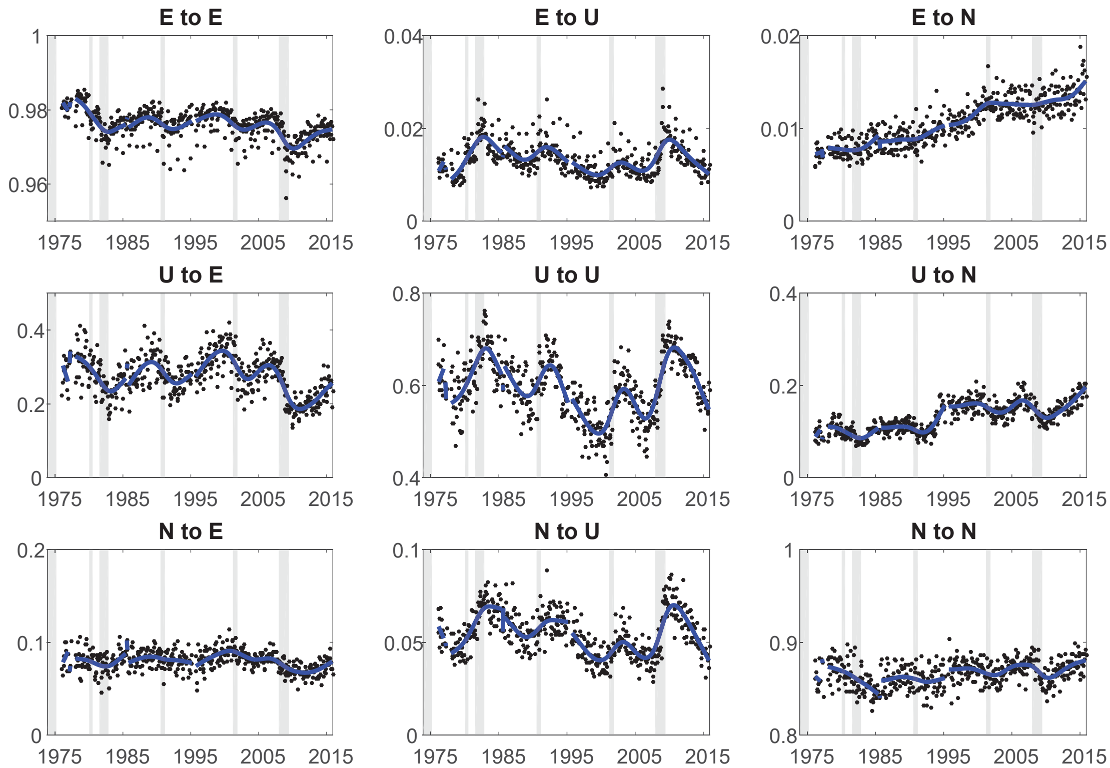

Figure 12: Labor Market Transition Rates, United States 1976-2015

Notes: Labor market states are Employment (E), Unemployment (U) and Not-in-Labor-Force (N). The sample includes all males 25-60 years old. Dots are monthly point estimates; solid lines are HP-filtered time series with parameter 14,400. Transition rates between states i and state j are measured as the share of workers that are in state i at month $t-1$ who are at state j at month t. All estimates weighted using 'final person weight'. *Source:* IPUMS-CPS (Flood, King, Ruggles, and Warren, 2015).

in Appendix B.[31] We then compute the third moment of these distributions for each cross-sections. A success of is the model generates a third moment that is similar to the third moment of earnings growth provided by GOS, and therefore is consistent with the stylized fact that we documented for Italy.

Figure 13 presents the third moment of employment time implied by the model (blue line), and the actual third moment of earnings growth calculated by GOS (black line, round marker). The time series show that the model implied third moment of changes in employment time match the timing and the magnitude of the time series of third moment of earnings growth. This is a surprising results since the model parameters target the labor market flows from CPS and not the cross-sectional moments, and they are based on different datasets. We interpret

[31] Due to changes in indexing in the CPS, several month pairs could not be matched. As a result, the implied distribution could not be calculated in those months and the preceding and following 12 months.

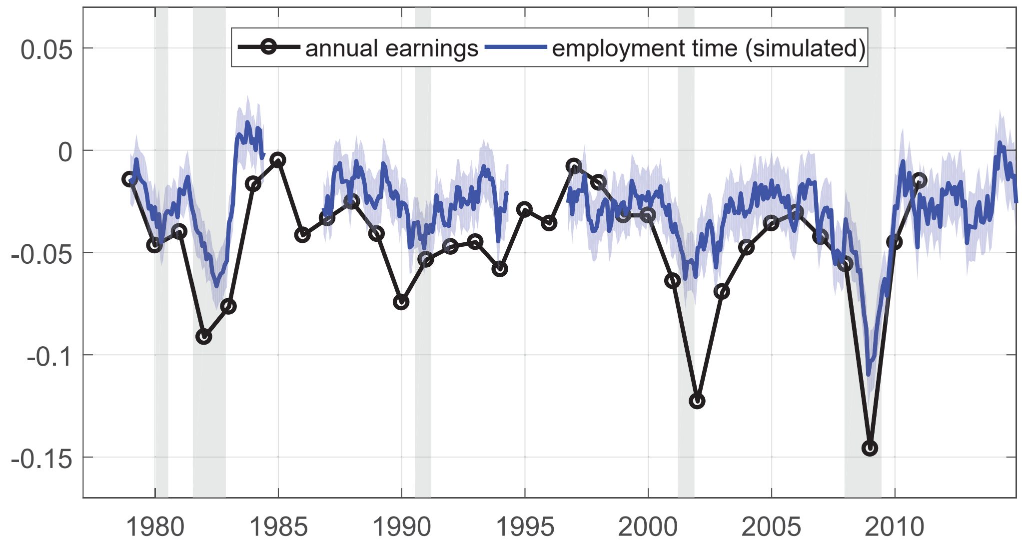

Figure 13: Third Moment of Annual Earnings Growth & Changes in Employment Time (Model)

Notes: The third central moment of annual earnings growth (black) and model implied distribution of changes in employment time (blue). Shaded area shows a 0.95 confidence intervals (computed using 500 bootstrap replications for employment time). *Sources:* Guvenen, Ozkan, and Song (2014) and IPUMS-CPS (Flood et al., 2015).

this as suggestive evidence for the importance of the fluctuation in transition rates in generating left skewness during recessions.

7 Conclusion

In this paper we study the evolution of the earnings growth distribution over time using administrative data from Italy. We decompose earnings growth into changes in employment time (the number of weeks of work within a year) and weekly earnings. We show that (i) employment changes drive the tails of the earnings growth distribution and (ii) fluctuations in employment explain the co-movement of moments of earnings growth and business cycles. In particular, changes in employment generate the procyclical skewness of earnings growth.

This set of results suggests a new interpretation for the procyclical skewness in the earnings growth distribution found by Guvenen, Ozkan, and Song (2014). In particular, it suggests that the aggregate factors that affect the number of workers who lose their jobs and the duration of unemployment spells are also responsible for the observed cyclicality in earnings growth.

In many economic applications the source of earnings growth is important. We find that the distributions of changes in employment time and weekly earnings differ in shape, cyclicality, persistence, and are affected differently by policy. Changes in employment time also explain most of the differences between switchers and stayers. These findings highlight the need to carefully model the employment margin separately from the wage margin, especially in studies of consumption and wealth or public policy.

Therefore, we propose a parsimonious model of earnings as the sum of an employment process and a wage process. The employment process is based on random transitions between labor market states, and the wage process is subject to permanent and transitory shocks that generate a symmetric wage growth distribution. Using a numerical example, we show that such a process can capture the key features of the earnings growth distribution, despite having no asymmetric persistent shocks. Failing to model the employment margin may lead to draw erroneous conclusions on the underlying processes, and in particular, to overstate the magnitude and the persistence of the downside risk in recessions.

While the focus of this paper is on decomposing "earnings growth" and not "earnings risk", we view this analysis as a step towards better understanding the latter. A proper study of the risk component of labor earnings requires a structural model in which changes in earnings can be the result of endogenous choices (for example see Low et al., 2010; Lise, 2012). Further research should also analyze the the interaction between the employment and the wage process, found to be important in other studies (e.g. Davis and von Wachter, 2011; Saporta-Eksten, 2014).

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A Data Appendix

In this appendix we report additional statistics about the INPS data and the CPS data.

A.1 Italy: Additional Summary Statistics.

In Table A.1 we report summary statistics for the years 1992, 2002 and 2012 of the sample. Similar statistics for all the years in our sample are available from the authors upon request. In Table A.2 we report mean, standard deviation, 10th, 50th and 90th percentile of the main variables of interest (annual and monthly earnings growth as well as employment time growth) in all years of our sample. Table A.3 reports the decomposition of the third central moment in Italy year by year.

Additional information about the INPS data can be found on the website of the Italian Ministry of Labor.

A.2 Italy: Top-coding

The INPS data is top coded at a rate based on daily earnings for each job. In 2012, the income is top coded at €645 per day. In previous years the maximum value is obtained from the occupation specific index on pre-tax retribution provided by ISTAT (the Italian Statistical Institute) available here. At each year, approximately 0.5 percent of the worker-year observations are affected by top-coding. In our main analysis we decide to drop the top-coded observations. In Figure A.1 we assess the sensitivity of some of our results to this choice. In the first column of the figure we replicate the results reported in the main text. In the second column we include the top-coded observations without correcting the reported earnings. In the third column, we assign to every top-coded observation (in year t and year $t-1$) two times the maximum observed weekly earnings, and after recomputing weekly and annual earings growth we plot the time series for the first three moments. In the fourth column we assign the maximum observed weekly earnings to all observations top-coded in year t and twice the maximum to all observations top-coded in year $t-1$. In the last column we assign twice the maximum observed weekly earnings to all observations top-coded in year t and the maximum to all observations top-coded in year $t-1$.

The series relative to annual earnings are virtually unaffected, and when looking at the third moment the employment time keeps tracking their evolution very closely. The series of weekly earnings are still remarkably close to the original one, although we observe a bump in the variance between 1998 and 2000, a period during which the INPS recording procedures where reformed, and similarly we observe some fluctuations in the third moments in the same years. This might reflect the fact that during these years there are some errors in the records that produced anomalous weekly earnings that ended up being top-coded for this reason. Other than that, it is still visually clear that the movements in the weekly earnings growth ditribution are hardly capable of have a relevant quantitative role in driving the evolution of the annual earnings growth moments over time.

A.3 Italy: the Italian Income Tax

Table A.4 reports the marginal tax rates in Italy from 1985 to 2012. The data have been collected from the website http://www.kitech.it/servizi_online.aspx, that collects these data for Italian professional accountants.

A.3.1 Italy: Employment Time Statistics

Employment time is persistent at the individual level. The estimated autocovariance in log employment time is positive and significant up to the tenth lag. In contrast, changes in employment time display negative autocovariance. Table A.5 reports the estimated autocovariances of log-weeks worked (panel a) and the growth in log-weeks worked (panel b) up to ten lags. Our estimates are similar to those reported by Abowd and Card (1989) for annual growth in log hours worked, who compute the autocovariance structure for annual hours and hourly earnings using PSID. However, while Abowd and Card (1989) higher order autocovariance estimates fluctuate around zero, our estimates stays negative and significant up to the nineth lag, although becoming economically small. This is expected as our sample is more than one *thousand* times larger than theirs.

We decompose the variance of changes in employment into within worker and between workers components. We do so in the following way. First, we calculate the change in employment time after controlling for year fixed effects, denoted $\Delta x_{res,it}$. Then we compute the mean change for each worker, $\Delta\bar{x}_{res,i} = \sum_{t_{min,i}}^{t_{max,i}} x_{res,it}/(t_{max,i} - t_{min,i})$, where $t_{min,i}$ and $t_{max,i}$ denote the time of the first and last observation of worker i. We can then define the within-worker residual $u_{it} = \Delta x_{res,it} - \Delta\bar{x}_{res,i}$. The variance of changes in employment time can then be decomposed into the within-worker variance, calculated as the variance of $\Delta\bar{x}_{res,i}$, and between-worker variance, calculated as the variance of u_{it}.

We find that the within-worker effects account for 86 percent of the variance of changes in employment time, while the between-worker effects account for the remainder 14 percent. When we conduct a similar decomposition of the variance in levels of employment time, we find that the between worker effect accounts for 40 percent of the overall variance.

A.4 United States: Moments from GOS

Guvenen, Ozkan, and Song (2014) provide time series of moments that are used in our analysis. They are based on a large panel dataset on earnings histories from the US Social Security Administration records, the Master Earnings File (MEF). The moments are computed from a 10 percent sample of males, 25-60 years old, covering the period 1978-2011. As this dataset is

Table A.1: Summary Statistics for Selected Years

	Year 1992					
	Obs	Mean	Std.Dev.	P10	P50	P90
Age	339,296	40.62	9.42	28.00	40.00	54.00
Annual Earnings	339,296	29,116.23	19,357.03	12,969.15	24,977.62	47,073.21
Employment Time (Weeks)	339,296	48.10	9.78	36.00	52.00	52.00
Earnings Rate (Weekly Earnings)	339,296	598.15	369.45	334.78	498.81	929.89
Δ Earnings (Δy)	339,296	-0.01	0.39	-0.22	0.00	0.19
Δ Employment Time (Δx)	339,296	-0.02	0.38	-0.14	0.00	0.06
Δ Earnings Rate (Δw)	339,296	0.01	0.16	-0.10	0.01	0.14
	Year 2002					
	Obs	Mean	Std.Dev.	P10	P50	P90
Age	347,323	39.99	8.85	29.00	39.00	53.00
Annual Earnings	347,323	27,841.43	19,277.20	12,117.09	23,410.70	45,880.26
Employment Time (Weeks)	347,323	48.33	9.54	37.00	52.00	52.00
Earnings Rate (Weekly Earnings)	347,323	568.56	367.79	316.73	464.68	902.67
Δ Earnings (Δy)	347,323	0.02	0.40	-0.18	0.01	0.25
Δ Employment Time (Δx)	347,323	0.00	0.39	-0.08	0.00	0.12
Δ Earnings Rate (Δw)	347,323	0.02	0.16	-0.10	0.01	0.15
	Year 2012					
	Obs	Mean	Std.Dev.	P10	P50	P90
Age	374,901	42.41	8.83	30.00	42.00	55.00
Annual Earnings	374,901	27,218.92	19,088.43	9,914.40	23,416.86	45,795.07
Employment Time (Weeks)	374,901	46.98	11.21	29.00	52.00	52.00
Earnings Rate (Weekly Earnings)	374,901	563.79	355.65	312.32	468.48	899.84
Δ Earnings (Δy)	374,901	-0.05	0.45	-0.34	-0.02	0.17
Δ Employment Time (Δx)	374,901	-0.04	0.41	-0.24	0.00	0.06
Δ Earnings Rate (Δw)	374,901	-0.02	0.17	-0.15	-0.01	0.12

Notes: The sample is restricted to males 25-60 years old who ever had a record at the Italian social security administration between 1984 and 2012. Earnings data are in 2013 euros *Sources:* INPS.

Table A.2: Summary statistics

	Annual Earnings Growth					Employment Time Growth					Weekly Earnings Growth				
Year	Mean	Sd	p10	p50	p90	Mean	Sd	p10	p50	p90	Mean	Sd	p10	p50	p90
1986	0.01	0.13	-0.16	0.01	0.20	-0.01	0.11	-0.06	0.00	0.06	0.02	0.02	-0.09	0.01	0.15
1987	0.04	0.13	-0.13	0.04	0.23	-0.01	0.12	-0.06	0.00	0.06	0.05	0.03	-0.07	0.04	0.18
1988	0.04	0.13	-0.12	0.03	0.24	0.00	0.12	-0.04	0.00	0.08	0.04	0.02	-0.08	0.03	0.17
1989	0.03	0.13	-0.14	0.02	0.22	0.00	0.12	-0.06	0.00	0.04	0.03	0.02	-0.08	0.02	0.17
1990	0.02	0.13	-0.14	0.02	0.21	-0.01	0.12	-0.06	0.00	0.04	0.03	0.02	-0.08	0.03	0.17
1991	0.04	0.14	-0.16	0.04	0.23	-0.01	0.13	-0.10	0.00	0.06	0.05	0.02	-0.07	0.04	0.18
1992	-0.01	0.15	-0.22	0.00	0.19	-0.02	0.14	-0.14	0.00	0.06	0.01	0.02	-0.10	0.01	0.14
1993	-0.05	0.15	-0.27	-0.01	0.14	-0.04	0.13	-0.17	0.00	0.04	-0.01	0.03	-0.13	-0.01	0.11
1994	-0.02	0.15	-0.22	0.00	0.17	-0.02	0.14	-0.12	0.00	0.08	0.00	0.03	-0.11	0.00	0.12
1995	0.00	0.14	-0.16	0.00	0.20	-0.01	0.13	-0.06	0.00	0.06	0.01	0.02	-0.10	0.00	0.14
1996	0.00	0.14	-0.18	0.00	0.19	-0.01	0.13	-0.08	0.00	0.06	0.01	0.02	-0.10	0.01	0.14
1997	0.03	0.14	-0.14	0.03	0.24	-0.01	0.14	-0.06	0.00	0.06	0.04	0.02	-0.07	0.03	0.17
1998	0.02	0.16	-0.17	0.02	0.22	-0.01	0.15	-0.08	0.00	0.06	0.02	0.03	-0.10	0.02	0.15
1999	0.03	0.17	-0.16	0.02	0.24	0.00	0.15	-0.06	0.00	0.10	0.03	0.04	-0.09	0.02	0.15
2000	0.03	0.17	-0.16	0.01	0.27	0.02	0.15	-0.04	0.00	0.14	0.01	0.03	-0.10	0.00	0.15
2001	0.03	0.17	-0.18	0.01	0.27	0.01	0.16	-0.08	0.00	0.21	0.02	0.03	-0.10	0.01	0.16
2002	0.02	0.16	-0.18	0.01	0.24	0.00	0.15	-0.08	0.00	0.12	0.02	0.02	-0.10	0.01	0.15
2003	0.03	0.17	-0.18	0.01	0.28	0.01	0.16	-0.09	0.00	0.17	0.01	0.02	-0.10	0.01	0.14
2004	0.02	0.16	-0.18	0.02	0.23	-0.01	0.15	-0.11	0.00	0.10	0.03	0.02	-0.09	0.02	0.15
2005	0.00	0.17	-0.23	0.01	0.21	-0.01	0.15	-0.13	0.00	0.11	0.01	0.02	-0.12	0.01	0.13
2006	0.04	0.16	-0.16	0.02	0.27	0.00	0.15	-0.10	0.00	0.12	0.03	0.02	-0.08	0.02	0.17
2007	0.03	0.16	-0.17	0.02	0.27	0.01	0.14	-0.08	0.00	0.12	0.03	0.02	-0.09	0.02	0.16
2008	0.02	0.17	-0.20	0.02	0.25	-0.01	0.14	-0.12	0.00	0.10	0.03	0.02	-0.10	0.02	0.17
2009	-0.06	0.20	-0.42	0.00	0.18	-0.06	0.17	-0.31	0.00	0.04	0.00	0.03	-0.16	0.01	0.14
2010	0.00	0.19	-0.25	0.02	0.25	-0.02	0.16	-0.17	0.00	0.12	0.02	0.03	-0.11	0.02	0.16
2011	-0.01	0.19	-0.25	0.00	0.23	-0.01	0.16	-0.14	0.00	0.11	0.00	0.03	-0.12	0.00	0.14
2012	-0.06	0.20	-0.34	-0.02	0.16	-0.04	0.17	-0.24	0.00	0.06	-0.02	0.03	-0.15	-0.01	0.12

Notes: The samples are restricted to males 25-60 years old. *Sources:* INPS.

Table A.3: Third Central Moment Decomposition of Annual Earnings Growth, Italy

Year	$m_3(\Delta y)$ (1)		$m_3(\Delta x)$ (2)		$m_3(\Delta w)$ (3)		Cross (4)	
1986	-0.028	(0.002)	-0.040	(0.002)	0.000	(0.000)	0.012	(0.001)
1987	-0.029	(0.002)	-0.033	(0.002)	-0.001	(0.000)	0.006	(0.001)
1988	-0.007	(0.002)	-0.014	(0.002)	0.000	(0.000)	0.006	(0.001)
1989	0.002	(0.002)	-0.022	(0.002)	0.001	(0.000)	0.023	(0.001)
1990	-0.016	(0.002)	-0.036	(0.002)	-0.000	(0.000)	0.021	(0.001)
1991	-0.020	(0.002)	-0.040	(0.002)	-0.000	(0.000)	0.020	(0.001)
1992	-0.036	(0.002)	-0.060	(0.002)	0.001	(0.000)	0.023	(0.001)
1993	-0.068	(0.002)	-0.064	(0.002)	-0.009	(0.001)	0.005	(0.001)
1994	-0.040	(0.002)	-0.047	(0.002)	0.006	(0.001)	0.001	(0.001)
1995	-0.012	(0.002)	-0.035	(0.002)	0.001	(0.000)	0.022	(0.001)
1996	-0.004	(0.002)	-0.028	(0.002)	-0.000	(0.000)	0.024	(0.001)
1997	-0.014	(0.002)	-0.033	(0.002)	0.001	(0.000)	0.018	(0.001)
1998	-0.007	(0.002)	-0.015	(0.002)	-0.005	(0.001)	0.013	(0.001)
1999	0.006	(0.002)	-0.004	(0.002)	0.001	(0.000)	0.008	(0.001)
2000	0.028	(0.002)	0.026	(0.002)	0.001	(0.001)	0.000	(0.001)
2001	0.016	(0.002)	-0.013	(0.002)	0.001	(0.000)	0.027	(0.001)
2002	0.019	(0.002)	-0.006	(0.002)	0.001	(0.000)	0.024	(0.001)
2003	0.005	(0.002)	-0.008	(0.002)	0.000	(0.000)	0.013	(0.001)
2004	-0.005	(0.002)	-0.016	(0.002)	0.000	(0.000)	0.011	(0.001)
2005	-0.042	(0.002)	-0.017	(0.002)	-0.003	(0.000)	-0.022	(0.001)
2006	0.018	(0.002)	-0.005	(0.002)	0.001	(0.000)	0.022	(0.001)
2007	0.015	(0.002)	0.004	(0.002)	0.001	(0.000)	0.010	(0.001)
2008	-0.008	(0.002)	-0.024	(0.002)	-0.000	(0.000)	0.016	(0.001)
2009	-0.094	(0.002)	-0.092	(0.002)	-0.002	(0.000)	0.000	(0.001)
2010	-0.063	(0.003)	-0.049	(0.002)	-0.004	(0.000)	-0.010	(0.001)
2011	-0.027	(0.003)	-0.022	(0.002)	-0.002	(0.000)	-0.003	(0.001)
2012	-0.076	(0.003)	-0.071	(0.002)	-0.002	(0.000)	-0.002	(0.001)

Notes: the third moment of earnings growth (1), is decomposed into the third moment of changes in employment time (2), the thirm moment of changes in weekly earnings (3) and the cross-term $3m_{2,1}(\Delta x, \Delta w) + 3m_{1,2}(\Delta x, \Delta w)$ (4). Standard deviations of each component are reported in parentheses. Sample includes all 25-60 years old males who appear in the data for two consecutive years. *Source:* INPS data provided by MLPS.

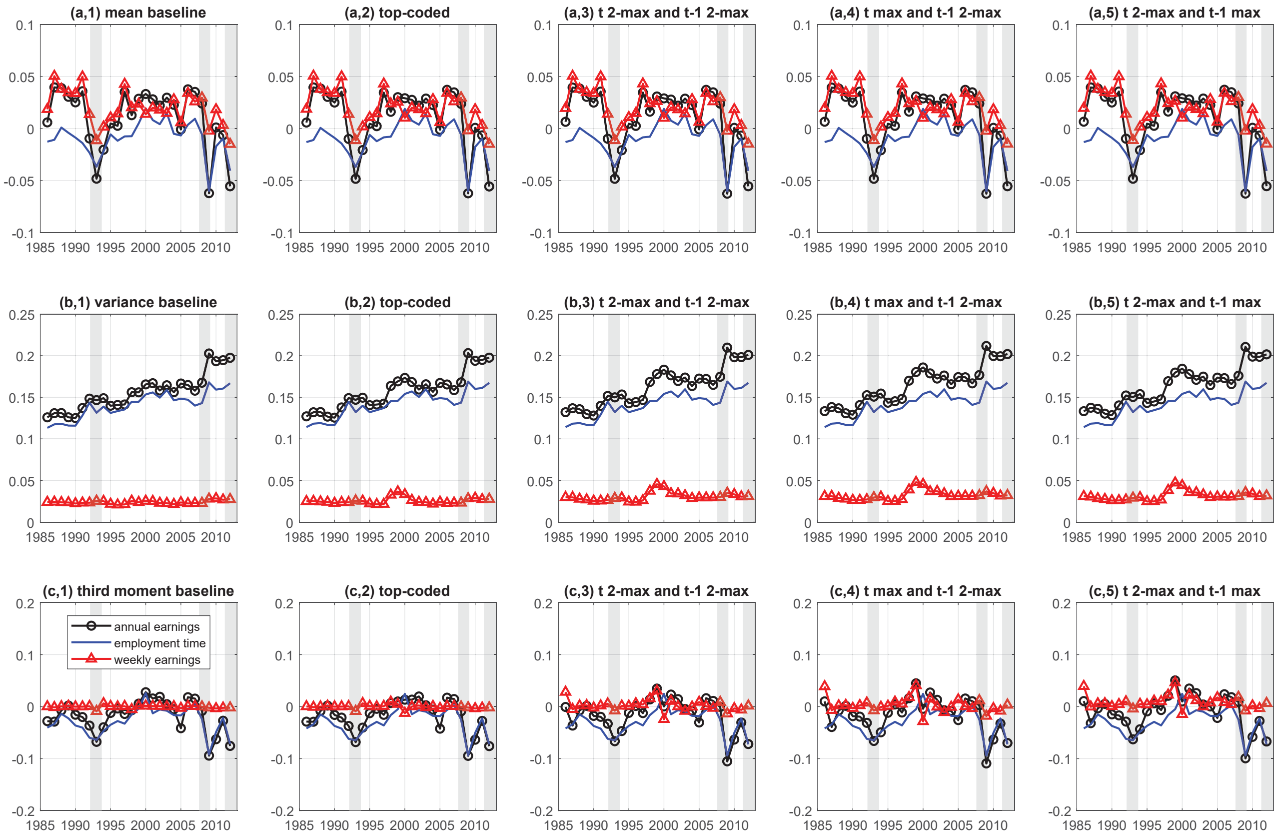

Figure A.1: Sensitivity to Top-coding

Notes: The sample is restricted to males 25-60 years old who ever had a record at the Italian social security administration between 1984 and 2012.
Source: INPS data provided by MLPS.

Table A.4: Brackets and Marginal Tax Rates (MTR) for the Italian Income Tax (IRPEF)

Year(s)	#Bracket:	1	2	3	4	5	6	7	8	9
1984-1985	Bracket	[0-11)	[11-24)	[24-30)	[30-38)	[38-60)	[60-120)	[120-250)	[250-500)	>500
	MTR	18%	27%	35%	37%	41%	47%	56%	62%	65%
1986-1988	Bracket	[0-6)	[6-11)	[11-28)	[28-50)	[50-100)	[100-150)	[150-300)	[300-600)	>600
	MTR	12%	22%	27%	34%	41%	48%	53%	58%	62%
1989	Bracket	[0-6)	[6-12)	[12-30)	[30-60)	[60-150)	[150-300)	>300		
	MTR	10%	22%	26%	33%	40%	45%	50%		
1990	Bracket	[0-6.4)	[6.4-12.7)	[12.7-31.8)	[31.8-63.7)	[63.7-159.1)	[159.1-318.3)	>318.3		
	MTR	10%	22%	26%	33%	40%	45%	50%		
1991	Bracket	[0-6.8)	[6.8-13.5)	[13.5-33.7)	[33.7-67.6)	[67.6-168.8)	[168.8-337.7)	>318.3		
	MTR	10%	22%	26%	33%	40%	45%	50%		
1992-1997	Bracket	[0-7.2)	[7.2-14.4)	[14.4-30)	[30-60)	[60-150)	[150-300)	>300		
	MTR	10%	22%	27%	34%	41%	46%	51%		
1998-1999	Bracket	[0-15)	[15-30)	[30-60)	[60-135)	>135				
	MTR	18.5%	26.5%	33.5%	39.5%	45.5%				
2000	Bracket	[0-20)	[20-30)	[30-60)	[60-135)	>135				
	MTR	18.5%	26.5%	33.5%	39.5%	45.5%				
2001	Bracket	[0-20)	[20-30)	[30-60)	[60-135)	>135				
	MTR	18%	26%	33%	39%	45%				
2002	Bracket	[0-10329.14)	[10329.14-15493.71)	[15493.71-30987.41)	[30987.41-69721.68)	>69721.68				
	MTR	18%	26%	33%	39%	45%				
2003-2004	Bracket	[0-15000)	[15000-29000)	[29000-32600)	[32600-70000)	>70000				
	MTR	23%	29%	31%	39%	45%				
2005-2006	Bracket	[0-26000)	[26000-33500)	[33500-100000)	>100000					
	MTR	23%	33%	39%	43%					
2007-2012	Bracket	[0-15000)	[15000-28000)	[28000-55000)	[55000-75000)	>75000				
	MTR	23%	27%	38%	41%	43%				

Notes: The table collects the income brackets and the marginal tax rates for the Italian Income Tax (IRPEF). Income brackets are expressed in million Italian Liras up to 2001, and in Euros thereafter. 1 Euros is 1936.27 Liras. *Source:* `http://www.kitech.it/servizi_online.aspx`

Table A.5: Employment Time – Autocovariance Structure

(a) Levels

Order Autocov.	Autocovariance	s.e.	t-stat	Observations	Workers
0	0.1258	0.0002	505	9,291	974
1	0.0330	0.0001	240	8,028	853
2	0.0198	0.0001	168	7,000	760
3	0.0174	0.0001	152	6,296	709
4	0.0155	0.0001	138	5,669	661
5	0.0143	0.0001	127	5,088	615
6	0.0135	0.0001	118	4,556	572
7	0.0128	0.0001	110	4,071	529
8	0.0121	0.0001	102	3,626	489
9	0.0116	0.0001	96	3,215	448
10	0.0111	0.0001	89	2,841	412

(b) Growth

Order Autocov.	Autocovariance	s.e.	t-stat	Observations	Workers
0	0.1421	0.0003	548	9,291	974
1	-0.0228	0.0001	-233	8,028	853
2	-0.0049	0.0001	-78	7,000	760
3	-0.0018	0.0001	-29	6,296	709
4	-0.0007	0.0001	-12	5,669	661
5	-0.0006	0.0001	-10	5,088	615
6	-0.0004	0.0001	-5	4,556	572
7	-0.0003	0.0001	-4	4,071	529
8	-0.0003	0.0001	-4	3,626	489
9	-0.0001	0.0001	-2	3,215	448
10	-0.0000	0.0001	-0	2,841	412

Notes: The sample is restricted to 25-60 years old males with at least one record at the Italian social security administration between 1985 and 2012. Panel (a) reports the autocovariance of log-weeks of work, while panel (b) reports the autocovariance of the growth in log-weeks of work. Standard errors and t-statistcs are computed clustering at the individual level. Number of observations and workers are in thousands. *Source:* INPS data provided by MLPS.

based on official W-2 forms reporting taxable labor income, it is generally considered reliable (see Kopczuk, Saez, and Song (2010) for a discussion of advantages and limitations of these data). However it does not contain any information about employment spells or other sources of income (such as from unemployment insurance). For a detailed description of the data and sampling method see Guvenen et al. (2014) section II and references therein. We use the first three moments from their appendix tables A.1 and A.8 for our analysis.

A.5 United States: CPS Data

We use CPS matched monthly files, collected by the Bureau of Labor Statistics and made available on-line by IPUMS-CPS (Flood et al., 2015). We follow a standard procedure to recover the monthly transition probabilities.

Our sample covers the period 1976-2015[32]. We restrict observations to males 25-60 years old for consistency across samples. Each observation is a person-month record, including the employment state in the previous month and the employment state at the current period. All the statistics in this paper are weighted using the "final weight" provided by the BLS. Standard errors are computed using 500 bootstrapped samples. The share of the sample at each of the three states, and additional descriptive statistics are in Table A.6.

We distinguish between three labor market states: Employed (E), Unemployed (U) and Not-in-labor-force (N).

Figure A.2 displays the shares of each state over time. Several details are worth mentioning. The most striking is the large change in employment and unemployment during the 1982-1983 recession and the Great Recession (2008-2009). This shift, translated into individual level changes in employment time, generated large negative shocks to earnings for many workers. In the Great Recession, unemployment share[33] increased to almost twice its peak value in the 40 years sample, reaching 9.2% in January 2010, a month that was officially part of the recovery phase.

It is also important to notice that the share of not-in-labor-force (N) state follows a long-term upward trend. The share of working age males that are not participating in the labor force has increased from around 7.5% at the beginning of the sample to 14.2% at the end of 2015. This rise has been noticed most clearly during the great recession, and has typically been classified as reflecting "discouraged workers", but can also reflect a change in the composition of workers. According to Hall (2014) this pattern is part of a trend that is unrelated to the business cycle. In any case, this trend is quantitatively important and is reflected in our

[32] Due to technical issues with the consistency of household identifiers, all months of 1977, July to October 1985, and May to September 1995 cannot be matched. We exclude these periods and the following and previous 12 months from our analysis.

[33] It is important to notice that unemployment share does not correspond to the unemployment rate – the denominator for the unemployment rate is the civilian labor force (employed plus unemployed) while the share is denominated by the total working age population of males.

Table A.6: Summary Statistics – January Matched CPS

Year	Observations	Age	Employment State		
			E	U	N
1989	21,713	39.8	0.878	0.043	0.079
1990	23,103	39.8	0.873	0.045	0.082
1991	23,253	39.9	0.858	0.055	0.086
1992	23,303	40.0	0.843	0.070	0.087
1993	22,902	40.2	0.846	0.064	0.090
1994	22,757	40.2	0.847	0.058	0.096
1995	23,008	40.4	0.858	0.046	0.095
1996	19,667	40.6	0.854	0.046	0.100
1997	20,208	40.7	0.858	0.043	0.098
1998	20,508	41.0	0.866	0.037	0.097
1999	20,498	41.2	0.873	0.032	0.096
2000	20,870	41.4	0.873	0.030	0.096
2001	20,064	41.6	0.866	0.034	0.100
2002	24,008	41.8	0.842	0.052	0.106
2003	24,181	41.9	0.833	0.053	0.114
2004	23,576	42.0	0.841	0.049	0.111
2005	23,139	42.1	0.838	0.043	0.119
2006	22,781	42.2	0.843	0.039	0.118
2007	22,424	42.3	0.851	0.039	0.110
2008	22,698	42.4	0.847	0.041	0.112
2009	22,760	42.4	0.808	0.076	0.116
2010	22,960	42.4	0.783	0.093	0.124
2011	22,388	42.4	0.789	0.083	0.128
2012	21,996	42.6	0.803	0.069	0.129
2013	21,898	42.7	0.807	0.065	0.128

Notes: Sample includes males 25-60 years old that appear in two consecutive months, and are matched using CPSIDP. Each row refers to January of that year. Age and employment state shares are computed using the final weights provided by the CPS. *Sources:* IPUMS-CPS (Flood et al., 2015).

analysis.

Lastly, there is a considerable amount of seasonality in the data. The series we use are not seasonally adjusted, since seasonality of employment within the year may be quantitatively important as a source of variation. Our analysis is based on moments of annual changes in

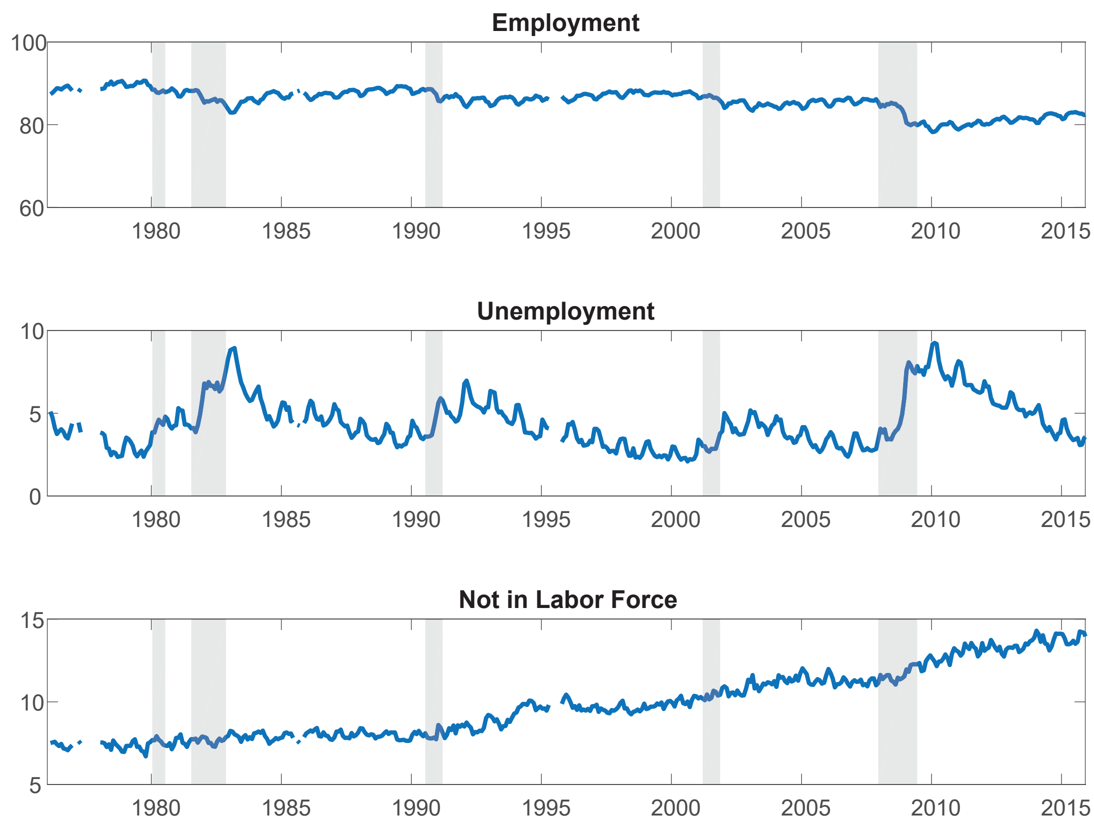

Figure A.2: Labor Market State Shares, US 1976-2015

Notes: Sample includes males 25-60 years old that appear in two consecutive months, and are matched using CPSIDP identifier. *Sources:* IPUMS-CPS (Flood et al., 2015).

employment time, in a monthly frequency, potentially uncovering seasonality in the distribution of changes in employment time.

The monthly CPS questionnaire also asks about weekly wages. We match individuals that appear in two consecutive January surveys to calculate the distribution of changes in weekly earnings. This data suffers from two main limitations. First, the number of observations that are matched is about two thousands, not nearly enough to reliably measure third moment of a distribution (compare this to 300,000 in the INPS data, and five million in the data used by GOS). Second, since this is a self reported value, it may suffer from misreporting and measurement error. Together these limitations result in high estimated standard errors. Thus, in our analysis we will not rely on the point estimates of measures derived from this data. Additional information about IPUMS-CPS is available at cps.ipums.org.

B Extended Employment Process and US Evidence

In this appendix we describe the extended employment process, which we then use to transform the monthly labor flows data from the CPS, into cross-sectional distribution of annual changes in the employment time for every time period in the sample.

B.1 Setup

Time is discrete (a month), and the labor market state follows a first order Markov chain.[34] The individual state at period t is denoted s_t, and takes on one of $\mathcal{S} = \{1, 2, ...S\}$ discrete values (we drop individual i notation in this section, for clarity). The probability of a worker who is in state i at period $t-1$ to transition to state j at period t is given by:

$$P_{i,j}(t) = \mathbb{P}\left(s_t = j | s_{t-1} = i\right).$$

$P(t)$ denotes the time t transition probability matrix (TPM), in which every element (i, j) corresponds to the transition probability $P_{i,j}(t)$. Since elements of the matrix represent probabilities, they all lie in the closed interval $[0, 1]$, and every row sums up exactly to one. We follow the convention that transitions occur at the end of the period, that is, workers spend period t in state s_t.

Let $\tilde{P}(t)$ be the reverse transition probability matrix (rTPM), that is defined as

$$\tilde{P}_{i,j}(t) = P_{i,j}(t)\frac{\mathbb{P}(s_{t-1} = i)}{\mathbb{P}(s_t = j)} = \mathbb{P}\left(s_{t-1} = i | s_t = j\right),$$

where the last equality is given by Bayes' rule. $\tilde{P}(t)$ can be considered as a transition probability matrix for another Markov chain in which time runs backwards. It retains all the Markov properties of the forward process, and it generates statistically identical sequence of transitions, when the time index is reversed.

B.2 The Conditional Annual Employment

Invoking the Markov property and a sequence of TPMs and rTPMs is straightforward to compute the probability of any sequence of states. We are specifically interested in finding the distribution of the number of months worked, which is a counting function over these sequences.

Let $\mathcal{E} \subset \mathcal{S}$ be the set of states which are considered as employment, and $\mathcal{N} = \mathcal{S} \setminus \mathcal{E}$ the non-employment states. Let $\overrightarrow{V}_n(t)$ be the counting process of the number of periods spent in employment out of the n periods from t to $t + n - 1$, that is:

$$\overrightarrow{V}_n(t) = \sum_{\tau=0}^{n-1} \mathbb{1}(s_{t+\tau} \in \mathcal{E}) \tag{9}$$

[34] Technical background on occupation time in Markov chains, and some of the derivations can be found at Sericola (2000).

We also define $\overleftarrow{V}_n(t)$ as the reverse counting process, which counts the number of employment periods between $t-n$ and $t-1$. It retains the same properties as $\overrightarrow{V}_n(t)$.

We are now ready to define the probability functions of the joint distribution of states and employment time, $\overrightarrow{\Pi}_{i,j}(n,k,t)$ and $\overleftarrow{\Pi}_{i,j}(n,k,t)$ are defined by:

$$\overrightarrow{\Pi}_{i,j}(n,k,t) = \mathbb{P}\left(\overrightarrow{V}_n(t) = k, s_{t+n} = j | s_t = i\right), \tag{10}$$

$$\overleftarrow{\Pi}_{i,j}(n,k,t) = \mathbb{P}\left(\overleftarrow{V}_n(t) = k, s_{t-n} = j | s_t = i\right), \tag{11}$$

where $\overrightarrow{\Pi}_{i,j}(n,k,t)$ is the probability of being at state j at time $t+n$, after spending exactly k periods in employment in the period from t to period $t+n-1$, conditional on being at state i at time t (similar interpretation is given to $\overleftarrow{\Pi}_{i,j}(n,k,t)$). The sum of these probabilities over j is the marginal distribution of the number of months employed, conditional on the initial state i. Let the *forward probability mass function* of annual employment be

$$\overrightarrow{\Pi}_i(k,t) = \sum_{j=1}^{S} \Pi_{i,j}(12,k,t). \tag{12}$$

This is the probability of a worker in state i at time t to have k months of employment in the next 12 months. We can also define the *backward probability mass function* $\overleftarrow{\Pi}_i(k)$. Combining the two probability mass functions, we find the unconditional joint distribution of annual employment time:

$$\mathbb{P}(\overleftarrow{V}_{12}(t) = k, \overrightarrow{V}_{12}(t) = l) = \sum_{i,j} \overleftarrow{\Pi}_i(k,t) P_{i,j}(t) \overrightarrow{\Pi}_j(l,t). \tag{13}$$

This equation is a direct application of the Markov assumption made earlier. The last step is to get the probability measure of the difference in logs, $\log \overrightarrow{V}_{12}(t) - \log \overleftarrow{V}_{12}(t)$.

B.3 Computing the Forward Probability Mass Function

The following is an algorithm to compute $\overrightarrow{\Pi}_j(\cdot)$[35]. Without loss of generality, allow the set of employment states $\mathcal{E}$ to be the first states in $\mathcal{S}$, and the following to be the partition of $P(t)$:

$$P(t) = \begin{bmatrix} P_{\mathcal{E}\mathcal{E}}(t) & P_{\mathcal{E}\mathcal{N}}(t) \\ P_{\mathcal{N}\mathcal{E}}(t) & P_{\mathcal{N}\mathcal{N}}(t) \end{bmatrix} \tag{14}$$

In the same way as we partition $P(t)$, we can also partition $\overrightarrow{\Pi}(n,k,t)$, the matrix form of $\overrightarrow{\Pi}_{i,j}(n,k,t)$:

$$\overrightarrow{\Pi}(n,k,t) = \begin{bmatrix} \overrightarrow{\Pi}_{\mathcal{E}\mathcal{E}}(n,k,t) & \overrightarrow{\Pi}_{\mathcal{E}\mathcal{N}}(n,k,t) \\ \overrightarrow{\Pi}_{\mathcal{N}\mathcal{E}}(n,k,t) & \overrightarrow{\Pi}_{\mathcal{N}\mathcal{N}}(n,k,t) \end{bmatrix} \tag{15}$$

[35] $\overleftarrow{\Pi}_i(\cdot)$ is solved using the same algorithm by replacing the TPMs with rTPMs and reversing the sequence order.

We follow these notations with a proposition that recursively solves the forward probability density function of annual earnings.

Proposition 1 *Let* $\{P(t+\tau)\}_{\tau=1\ldots 12}$ *be the sequence of transition probability matrices, and let* $\overrightarrow{\Pi}(n,k,t)$ *be the matrix form of the joint probability mass function as defined in* (15)*, then:*

1. *For every* $n, k > 0$, $\overrightarrow{\Pi}(n,k,t)$ *can be recursively computed by:*

$$\left[\overrightarrow{\Pi}_{\mathcal{E}\mathcal{E}}(n,k,t) \quad \overrightarrow{\Pi}_{\mathcal{E}\mathcal{N}}(n,k,t)\right] = \left[P_{\mathcal{E}\mathcal{E}}(t+1) \quad P_{\mathcal{E}\mathcal{N}}(t+1)\right] \cdot \overrightarrow{\Pi}(n-1,k-1,t+1) \tag{16}$$

$$\left[\overrightarrow{\Pi}_{\mathcal{N}\mathcal{E}}(n,k,t) \quad \overrightarrow{\Pi}_{\mathcal{N}\mathcal{N}}(n,k,t)\right] = \left[P_{\mathcal{N}\mathcal{E}}(t+1) \quad P_{\mathcal{N}\mathcal{N}}(t+1)\right] \cdot \overrightarrow{\Pi}(n-1,k,t+1) \tag{17}$$

2. *If* $k = 0$*, for ever* $n > 0$,

$$\overrightarrow{\Pi}(n,0,t) = \begin{bmatrix} 0 & 0 \\ 0 & P_{\mathcal{N}\mathcal{N}}(t+1) \end{bmatrix} \overrightarrow{\Pi}(n-1,0,t+1) \tag{18}$$

3. *If* $n = 0$*, for every* $k > 0$, $\overrightarrow{\Pi}(0,k,t) = 0$.

4. *If* $n = 0$ *and* $k = 0$, $\overrightarrow{\Pi}(0,0,t) = I_{S\times S}$

Proof. First consider the case where $n > 0$ and $k > 0$. If the state at t is in $\mathcal{E}$, the worker spends that period in employment, and thus need to spend on $k-1$ out of the next $n-1$ periods in employment for employment time to be k. This implies equation (16). If the state at time t is in $\mathcal{N}$, the worker is not employed, and so every path from $t+1$ must have k employment periods within $n-1$ periods. This implies equation 17, completing step 1. If $k = 0$, the only paths that avoid employment are those that start within $\mathcal{N}$ and end up in $\mathcal{N}$. Applying the same logic as that used for step 1, and imposing this restriction on the transition between t and $t+1$ gives us step 2. Step 3 is derived from the definition of $\overrightarrow{\Pi}$: there can be at most n employment period in the next n periods. Thus a path with $n = 0$ and $k > 0$ has zero probability. Finally, if $n = 0$ transitions into a different state are not possible, and thus the probability on the diagonal is 1 ■

Proposition 1 provides initial conditions and a recursion rule to exactly compute the cross-sectional distribution of changes in the extensive margin. The transition probability matrices, that are the only source of variation over time, can be estimated directly and accurately from flows data, by dividing each flow by the stock at the destination state (forward) or origin state (backward).

B.4 Limitation of the Markov Assumption

The Markov assumption is used repeatedly in the solution described above. It allows us to use monthly matches, extracted from a short panel, to explore dynamics over much longer time horizons. This assumption is not without cost, since it imposes strict restrictions on the labor market state process. Namely, it imposes two limitations: ex-ante homogeneity, and no history dependence.

Ex-ante homogeneity is the assumption that the distribution of future realization for two workers who are at the same state follows the same probability distribution. This may be a concern in particular when the data combines observations of workers from different occupations, education levels and age groups. *No history dependence* restricts future realization to depend only on the current state, but not on the path taken to this state. The main concern with restricting history dependence, is that some states tend to have a declining exit rates. It has been documented, for instance, that the rate of job finding declines with the duration of unemployment.[36]

These two limitations however, can be seen as restrictions imposed by the *state space* and by the *observed data* rather than by the Markov assumption. Ideally, having unlimited data, one could construct a rich enough state space to capture the full structure of an heterogeneous and history dependent process. For example, one can stratify the sample into age groups and use age-group specific transition probability matrices. As long as these groups have enough observations to accurately measure flows, we can estimate the transition probability matrices and recover the unconditional distribution using the method above. A longer panel, including observations of annual income over several years, could allow conditioning on a particular path, or capture heterogeneity across income profiles.

B.5 Time Series Evidence

Figure A.3 is an extended version of Figure 13 in the main text. It presents the moments of the implied distributions together with moments of weekly earnings growth from matched January-to-January CPS, and the moments of earnings growth provided by Guvenen, Ozkan, and Song (2014) for our sample period. The patterns that we find in the implied distributions are similar to the ones we find in the administrative data for Italy.

As in Italy, the first three moments in the US display similar patterns. Panel (a) shows the mean change in annual earnings and in the two components. The three time series of means move together and are clearly procyclical. The variance of the implied changes in employment time and weekly earnings growth, presented in panel (b), exhibit an upward trend, similar to the one observed in Italy. This is however surprisingly at odds with a downward trend in the variance of earnings growth provided by GOS. The long-term trend that we find in the variance of changes in employment time can be explained by the increasing trend in the share of worker who are not in the labor force. Panel (c) repeated the third moment in Figure 13, and in addition provides the third moment of changes in weekly earnings based on CPS. The confidence intervals on the third moment of weekly earnings growth is large, due to low sample

[36] This evidence can also be caused by unobserved ex-ante heterogeneity. See Heckman and Borjas (1980), Kiefer (1988) and Meyer (1990) for evidence and discussions on heterogeneity versus path dependence.

size that makes it particularly difficult to estimate higher moments. Still, the time series of the point estimates exhibits little cyclicality, is relatively flat and close to zero, corresponding to the results from Italy. We see that as additional suggestive evidence that as in Italy, employment time is also the primary source of asymmetry in the cross-section of earnings growth in the US.

C Accounting for Cyclicality

In this Appendix we complement the visual evidence presented in the main text with a quantitative exercise. We define the cyclicality of each moment of earnings growth as its contemporaneous correlation with GDP growth (after removal of trend). We apply this definition to the constructed time series from Italy,and check whether changes in employment time can account for the cyclical pattern of earnings growth. The idea is that if controlling for moments of changes in employment time eliminates the correlation between moments of earnings growth and GDP growth, employment time can account for the cyclicality of annual earnings growth. Consistent with the visual evidence in Figures 5 and A.3, we find that changes in employment time can account for the cyclicality of the third moment of earnings growth,suggesting that changes in employment time are generating the distribution of earnings growth.

We perform a regression analysis to determine whether changes in employment time capture the cyclical patterns of moments of employment growth. Consider the detrended and standardized time series of moments of earnings growth Δy, changes in employment time Δx and GDP growth $\hat{g}_t$. Denote $\hat{m}_t^n(\cdot)$ as the detrended and standardized nth moment of the cross-sectional distribution at year t. The unconditional correlation between $\hat{m}_t^n(\Delta y_{it})$ and $\hat{g}_t$ is estimated as the coefficient β_n in the following regression:

$$\hat{m}_t^n(\Delta y_{it}) = \beta_n \hat{g}_t + \epsilon_t \tag{19}$$

The controlled coefficient β_{nx} is estimated in the following regression:

$$\hat{m}_t^n(\Delta y_{it}) = \beta_{nx} \hat{g}_t + \gamma_{nx} \hat{m}_t^n(\Delta x_{it}) + \epsilon_t^x \tag{20}$$

In case that the nth moment is correlated with GDP growth (that is, $\beta_n \neq 0$), we check whether controlling for employment time in equation (20) eliminates the correlation (that is, $\beta_{nx} = 0$). If it does, we interpret that as employment time accounting for the cyclicality of that moment.

We report the results for the mean, variance, and skewness of earnings growth for Italy in Table A.7. The leftmost table shows that the mean earnings growth is highly correlated with GDP growth (0.722, significant at 5%), but when controlling for employment time, the the correlation drops to 0.063 and becomes insignificant. The variance (center table) is negatively correlated with GDP growth (-0.322), but the estimated correlation is not statistically significant. When controlling for employment time the coefficients on GDP growth halves in

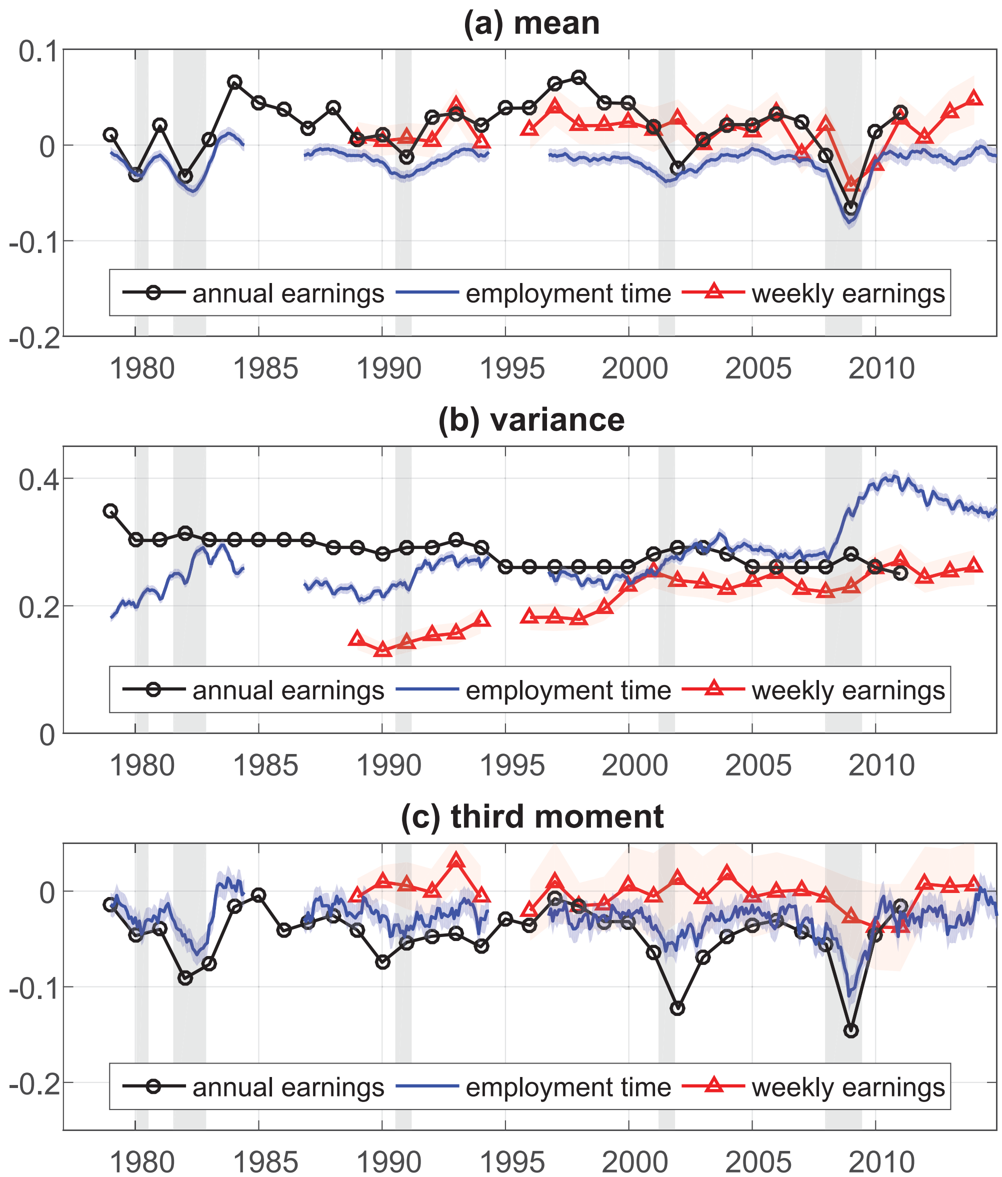

Figure A.3: Moment Decomposition of Annual Earnings Growth and its Components, US 1976-2013

Notes: Moments of annual earnings growth (black), moments of the implied distribution of changes in employment time (blue), and moments of weekly earnings growth (red). Construction of time series described in text. Panel (a) shows the mean of the distributions, panel (b) shows the variance of the distributions and panel (c) shows the third central moment of the distributions, defined as $\mathbb{E}_i[(z_{it} - \mathbb{E}(z_{it}))^3]$ for any variable z_{it} at every time t. Shaded area around moments show a 0.95 confidence intervals (computed using 500 bootstrap replications for employment time). *Sources:* Guvenen, Ozkan, and Song (2014) and IPUMS-CPS (Flood et al., 2015).

magnitude and stays non-significant. The skewness of annual earnings growth (obtained by normalizing the third central moment by the the third power of the standard deviation, rightmost table) is almost strongly procyclical (correlation 0f 0.629, significant at 5%), but the estimated correlation coefficient drops to an insignificant -0.091, confirming the results on the third central omment presented in the main text.

Table A.7: Accounting for Cyclicality of Various Moments of Annual Earnings Growth

Dependent variable	Mean of annual earnings growth		Variance of annual earnings growth		Skewness of annual earnings growth	
	(1)	(2)	(3)	(4)	(5)	(6)
GDP Growth	**0.722**	0.063	**-0.422**	**-0.257**	**0.629**	-0.091
	(0.110)	(0.120)	(0.176)	(0.096)	(0.160)	(0.071)
Mean of employment time growth		**0.833**				
		(0.150)				
Variance of employment time growth				**0.626**		
				(0.117)		
Skewness of employment time growth						**0.976**
						(0.081)
R-squared	0.52	0.78	0.18	0.54	0.40	0.83
Observations	27	27	27	27	27	27

Notes: The dependent variables are moments of earnings growth reported in the title of each panel. All time series are detrended with a linear trend and standardized. Standard errors robust to the presence of serial correlation are reported in parentheses (Newey-West with two lags). Coefficients in bold are significant at the 5 percent level. The control variables are GDP growth and moments of changes in earnings rate.

D Earnings Growth Over the Life Cycle

In this appendix we present some evidence on the earnings life cycle profile in Italy and present evidence that it does not affect the main results of the paper.

Figure A.4 presents the mean earnings growth, change in employment time and change in weekly earnings at every age. The growth rate of annual earnings declines over the life cycle, from 7.5 percent at age 26 to -20 percent at age 60. Employment time growth also declines over the life cycle. It is initially at 4 percent as workers join the labor force, then gradually decline to age 35 and stays near zero until about age 45. Then employment starts decreasing, reaching double digits mean decline at age 57 as workers retire.

Weekly earnings increase initially by a rate of 3 percent. The rate of growth decline gradually, flattens out and start increasing again at age 50. The increase in weekly earnings growth after 50 could be the result of composition effects: workers who experience a fall in weekly earnings retire and drop out of the sample while workers who experience gains stay.

We next remove a time-age fixed effect from all observations of annual earnings growth, employment time, and weekly earnings. This removes the age profile, and also removes any correlated movements across cohorts and age groups. We then use the residuals to recreate figures 1 and 5. Figures A.5 and A.6 present the results. There are no major changes in the results other than the mean of the distributions being mechanically set to zero.

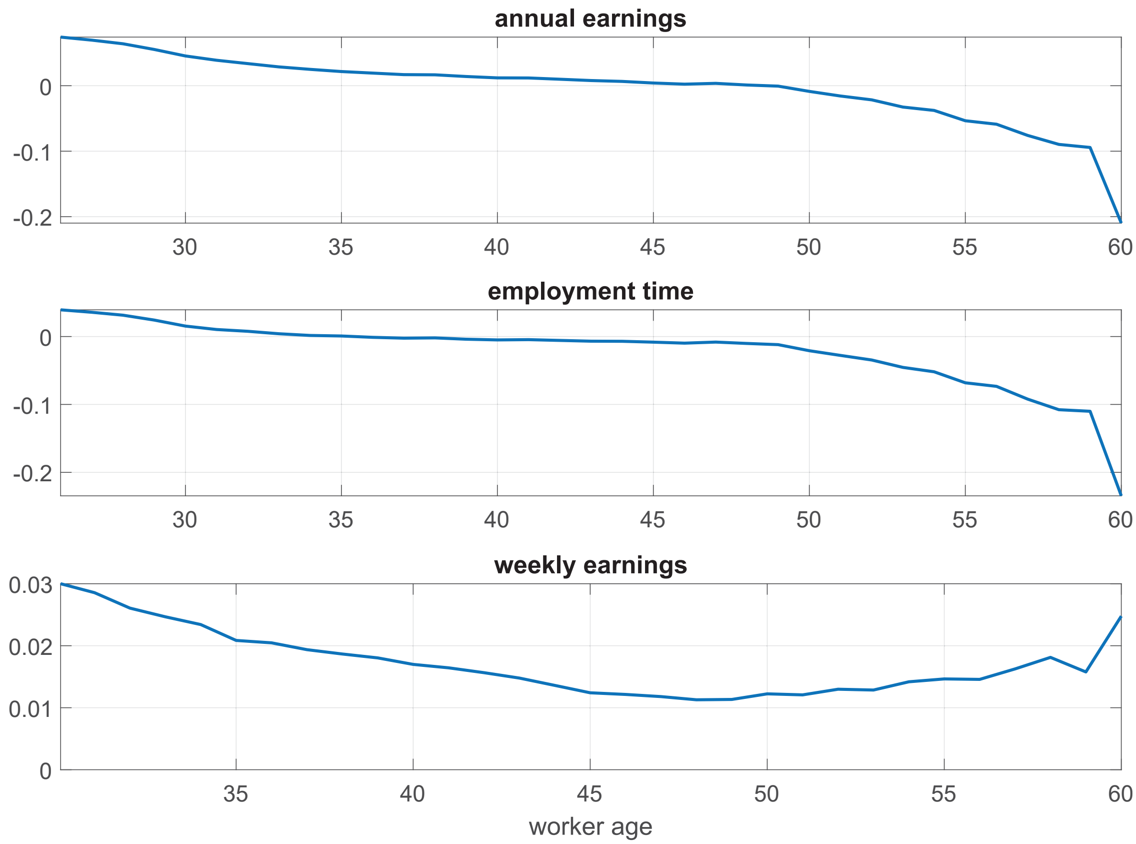

Figure A.4: Annual Earnings, Employment Time, and Weekly Earnings Growth Age Profiles

Notes: Mean one-year growth of annual earnings, employment time, and weekly earnings by age. Results are reported for males 26-60 years old. Means are pooled over all years in the sample (1986-2012). *Source:* INPS data provided by MLPS.

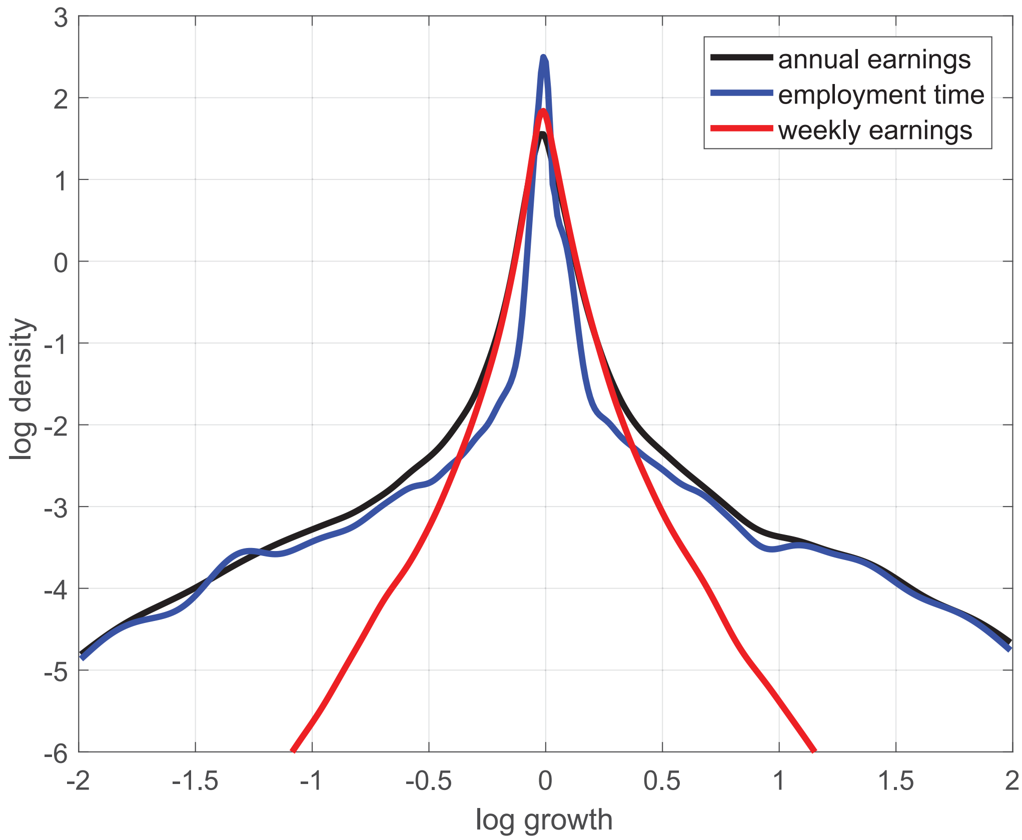

Figure A.5: Decomposition of Annual Earnings Growth Distribution – Age Profiles Removed

Notes: Log densities of one-year growth of annual earnings and its components **after removing age fixed effects**. Based on a representative sample of males 25-60 that includes 300,000 observations (approximately 6.5% of all male workers in the private sector in that age range), for the year 2002. Employment time is the number of weeks of work within a year. Weekly earnings is the annual earnings divided by employment time.

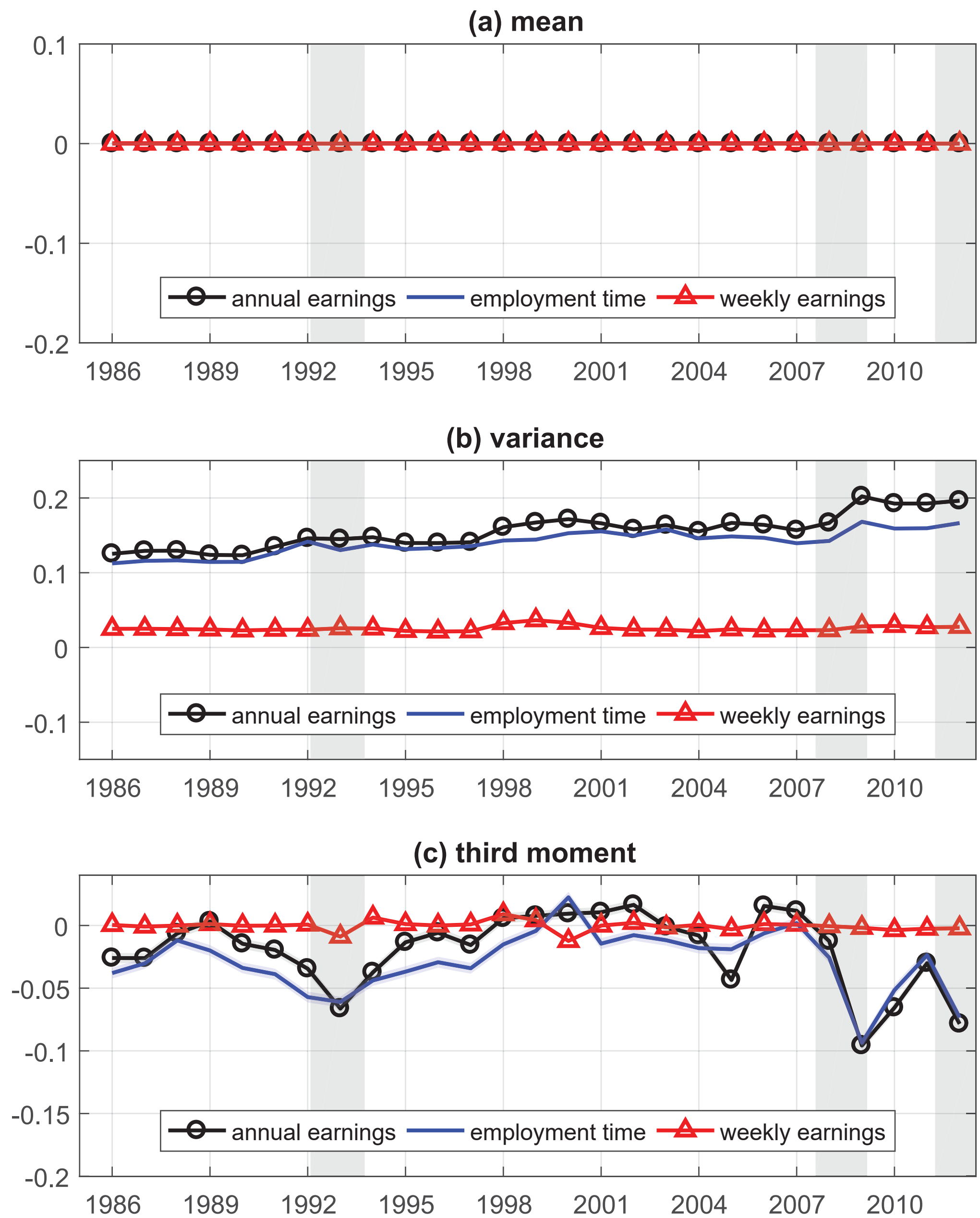

Figure A.6: Moment Decomposition of Annual Earnings, Employment Time, and Weekly Earnings Growth – Age Profiles Removed

Notes: Mean one-year growth of annual earnings, employment time, and weekly earnings by age. Results are reported for males 26-60 years old. Means are pooled over all years in the sample (1986-2012). *Source:* INPS data provided by MLPS.