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Income dynamics in dual labor markets

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Abstract

When measuring income dynamics, discrete labor market events have been traditionally ignored. However, income trajectory and labor market history are intricately linked. In this paper, I use the stochastic EM algorithm to estimate a tractable statistical framework that combines discrete events in a dual labor market with continuous variables characterizing income trajectory over time. The model takes into account potential endogenous selection, by allowing the same observable and latent characteristics of workers to explain both how their income evolves over time and their selection into labor market statuses. My empirical results highlight the existence of nonlinearities in the income process and the importance of considering a dual labor market framework, as the income dynamics of permanent and temporary workers differ dramatically. I further use my theoretical framework to document new relevant empirical facts about the functioning of dual labor markets. Among them, I provide evidence of compensating differentials in income levels between temporary and permanent workers, and I measure the lifetime impact of the entry labor market contract.

JEL Codes: C13, C15, E24, J31, J41, J42.

Keywords: Income process, EM algorithm, labor market duality, temporary jobs, labor income risk, latent variables.

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1 Introduction

A large strand of the literature has been interested in estimating models of income dynamics, as they represent a key ingredient to studying consumption and saving behavior. An income process provides a representation of the volatility in income that households face when deciding how much to save and how much to consume.[1] Models of income dynamics have been traditionally estimated using linear stochastic processes on a continuous support. The popular linear permanent-transitory representation assumes that income innovations over time are drawn from the same distribution and that the degree of persistence in income shocks is constant (Arellano, 2014).[2]

When measuring income dynamics, discrete labor market events such as losing a job or changing occupation have been traditionally ignored. However, income trajectory and labor market history are intricately linked. Depending on their labor market status, workers could be subject to income innovations of different magnitudes. In addition, there could be discrete events in the labor market that wipe out the memory of past income realizations. If this is the case, the persistence of income would vary over time, depending on *shocks* in the labor market. Some recent progress in this area has been made. Low et al. (2010) estimate a structural life-cycle model of consumption, labor supply and job mobility to distinguish between different sources of risk – shocks to productivity, job destruction and job arrival. Altonji et al. (2013) use indirect inference techniques to estimate a joint model of earnings, employment, job changes, wage rates and working hours over the career. They find that shocks associated with job changes and unemployment make a large contribution to the variance of career earnings. Arellano et al. (2017) estimate a flexible income process using a quantile-based framework. They find that the persistence of past income innovations varies depending on the size and the sign of current

[1] See, for example, Caballero (1990), Deaton et al. (1992), Deaton and Paxson (1994), Browning and Lusardi (1996), Huggett (1996), Carroll and Samwick (1997), Krusell and Smith (1998), Blundell (2014). Models of income dynamics have been used to study the cost of business cycles as well. Examples include Browning et al. (1999), Krusell and Smith Jr (1999), Storesletten et al. (2001).

[2] The popular representation of income dynamics is the Gaussian linear model with homogeneous parameters and the absence of heterogeneity across workers. However, there are recent departures. Geweke and Keane (2000), Bonhomme and Robin (2010) and Guvenen et al. (2021) relax the Gaussianity assumption. Browning et al. (2010) allow for heterogeneity in the structure of the income process, across different individuals. Carroll and Samwick (1997) consider parameters of the income process that could vary depending on the occupation, the educational level and the industry group. Karahan and Ozkan (2013) introduce a life-cycle dimension in a model of income dynamics. Lastly, a large strand of the literature considers heterogeneity in income levels and/or income growth. Among the others: Lillard and Weiss (1979), Guvenen (2009), Guvenen and Smith (2014).

shocks. These nonlinear features are at odds with standard linear models commonly used in the earnings dynamics literature, highlighting the importance of *unusual* shocks that could alter how income evolves over time.[3]

The set of discrete events in the labor market is potentially large. It includes, for example, job finding or separation transitions, changes in occupation or industry, job-to-job movements or changes in the type of contract. One of the key features of European labor markets is the co-existence of fixed-term jobs and open-ended contracts with large termination costs (Boeri et al., 2020). A duality structure traditionally describes this phenomenon (Cappellari et al., 2012; Garibaldi and Taddei, 2013; Bentolila et al., 2019).[4] The spread of fixed-term jobs is associated with workers experiencing high turnover rates (Blanchard and Landier, 2002). They are likely to move across different short-term jobs – potentially interspersed with non-employment spells – before landing on a stable occupation.

This duality structure of the labor markets, together with the relatively high incidence of unemployed individuals in European economies, makes it clear the importance of explicitly considering *shocks* in the labor market when measuring stochastic income changes.

The first contribution of this paper is to construct a tractable statistical framework that combines discrete events in a dual labor market with continuous variables characterizing income trajectory over time. Shocks in the labor market that could potentially alter the structural dynamics of income are specific to workers who find or lose a permanent or a temporary job, or to workers who change contract type across consecutive periods. Conditioning on the labor market status, income is modeled according to a standard linear permanent-transitory representation. The theoretical framework takes into account potential endogenous selection, by allowing the same characteristics of workers to explain both how their income evolves over time and their selection into labor market statuses. A latent ability effect complements the standard set of observable demographic characteristics.

To estimate the model, which contains several latent variables, I exploit the stochastic

[3]The nonlinear persistence in income is as well consistent with the empirical findings of Guvenen et al. (2014) and Guvenen et al. (2021).

[4]In most of the largest European economies, the fraction of temporary workers is well above 10 percent, with countries such as Spain, France or Italy where the same percentage is substantially higher. In Italy, every quarter about 14 percent of the employees working in the private sector are employed on a temporary job. The data refer to the period from 2005 to 2019, and to workers between the ages of 30 and 55. The measure includes contractor workers as well.

Expectation-Maximization (sEM) algorithm (Diebolt and Celeux, 1993), a simulated version of the original EM algorithm proposed by Dempster et al. (1977). In the first step, the algorithm simulates the posterior conditional distributions of the latent variables given observables, and computes draws. The simulation step of my estimating procedure relies on the Metropolis-Hastings (MH) algorithm (Metropolis et al., 1953; Hastings, 1970) – to estimate the unobserved worker-specific component – and on the Durbin-Koopman simulation algorithm (Durbin and Koopman, 2012) – to obtain the estimated time series of the stochastic income innovations, at the worker level. The second step of the algorithm updates the parameters, and the procedure is iterated until convergence. The model is estimated with a sample of Italian administrative panel data, tracking the careers of individuals employed in the private sector.

The empirical results highlight the existence of nonlinearities in the income process – which are driven by observable labor market events – and the importance of considering a dual labor market framework, as the income dynamics of permanent and temporary workers differ dramatically. On average, I find that workers who remain on a permanent occupation across consecutive periods receive small transitory shocks to their income, and face high income transmission over time. On the contrary, workers who remain employed with a temporary contract are subject to more volatile stochastic income trajectories, their labor market risk being relatively large. Earnings volatility is more than twice larger under temporary employment than under permanent occupations. Those who change status across consecutive periods – because they move from employment to non-employment, for instance – experience large income innovations, wiping out the memory of previous realizations.

Separate observations of labor market transitions and income changes give extra information to infer unobserved worker types. I find that the latent ability component is a key driver of income trajectories and labor market histories, with highly productive workers who earn more over their career *and* suffer less volatility in their income.

The second contribution of the paper is to document three new relevant empirical facts about the functioning of dual labor markets. First, I measure income gaps between temporary and permanent workers. It is well known that workers on permanent contracts earn more than workers on temporary jobs. However, one of the main limitations of the current literature is the difficulty of taking into account the endogenous selection of workers into contract types. The same observable and latent characteristics of individuals could indeed predict both their selection into labor market statuses *and* their income level. My results point to the existence of an important endogenous selection mechanism, which is a key driver of income differences across contract types. Once I take selection into account, I find evidence of compensating differentials in income levels. That is, temporary workers are paid slightly more, on average, compared to their colleagues employed on stable jobs. This result contrasts almost the entire existing literature.[5] Second, I use simulated data from the model to study the lifetime impact of entering the labor market with different contract types. In the literature, there is empirical evidence of how career outcomes are affected by the entry labor market condition. This evidence is restricted to the role of the business cycle and, more recently, to the role of the first employer.[6] My paper sheds light on a new channel that has long-lasting consequences: the entry labor market contract. I find that the entry status has persistent effects over the career, both on income volatility and labor market attainment. On average, workers who enter the labor market with a permanent contract spend on a stable occupation about 80 percent of their employment time. In comparison, the same fraction of time goes down to 40 percent for those who are on a temporary job during the entry period. This different labor market attainment has a direct impact on income dynamics, mainly during the first years of the career. Interestingly, the unobserved worker-specific component is a key driver of the heterogeneity in the lifetime effects of the entry status, with the importance of the initial labor market condition that increases with the latent productivity component. Lastly, based on simulated data, I measure average income losses when a non-employment shock hits workers, and I evaluate the subsequent income trajectory.[7] I describe the recovery phase, in terms of the probability of finding a new job. I do so by taking into account the labor market duality dimension, which is disregarded in the entire literature on the effects of job displacement events. I find that most productive workers – i.e. those with the highest latent ability – suffer larger income losses at job separating events. Although they

[5] A large strand of the literature studies income differentials among permanent and temporary workers, finding positive gaps in favor of permanent employees: Bentolila and Dolado (1994), Booth et al. (2002), Brown and Sessions (2005), Mertens et al. (2007), Bosio (2014), Kahn (2016), Bonhomme and Hospido (2016). Only some more recent empirical contributions highlight the existence of potential income premiums for temporary workers: Lass and Wooden (2019) and Albanese and Gallo (2020).

[6] Examples of the literature on the persistent effects of entering the labor market during downturns include: Kahn (2010), Oreopoulos et al. (2012), Brunner and Kuhn (2014), Altonji et al. (2016), Fernández-Kranz and Rodríguez-Planas (2018), Schwandt and Von Wachter (2019), Acabbi et al. (2022). On the role of workers' first employers: Arellano-Bover (2020) and Gregory (2020).

[7] A seminal contribution studying income losses for displaced workers is the one by Jacobson et al. (1993). Bertheau et al. (2022) provide systematic literature review.

need relatively more time to find a new job, in the long-run they have a larger probability of landing on a permanent occupation, compared to less productive workers. On average, after four years since the non-employment shock, highly productive workers have a probability of being on a permanent job which is already about 60 percent, and that quickly converges to 90 percent. Less productive workers are instead more likely to select into temporary jobs. Still, this relatively larger probability does not fully compensate for the lower chances they have of finding *and* retaining a permanent occupation.

The third contribution of the paper is to investigate whether the higher volatility that characterizes the income dynamics of temporary workers also reflects into a larger income risk – which denotes the fraction of income changes that agents cannot anticipate. The results are clear. The type of contract is a key driver of the heterogeneity in income risk observed in the population, with temporary workers suffering a notably higher degree of income uncertainty.

The rest of the paper is organized as follows. In Section 2 I characterize the Italian labor market and I review the literature about labor market duality. Section 3 lays out the labor market model and the nonlinear income process. Section 4 describes the panel data set and Section 5 the estimation strategy. Section 6 presents the empirical results. In Section 7 I exploit the estimates of the model to document a set of key empirical facts about the functioning of dual labor markets. Section 8 introduces an individual measure of income risk. Section 9 concludes.

2 A dual labor market

The Italian labor market is characterized by a persistent duality structure, with the majority of workers employed with permanent (open-ended) contracts and a small but not negligible fraction of the workforce employed with temporary (fixed-term) contracts.[8]

This existing segmentation is the result of labor market reforms that introduced a two-tier system, by liberalizing the use of temporary working arrangements while keeping largely unchanged the legislation applying to permanent contracts (Boeri and Garibaldi, 2007). With the main objective of stimulating job creation, these interventions – the most significant of them

[8]Every quarter about 14 percent of the employees working in the private sector are employed on a temporary job. The share is decreasing in age – see Figure 10, Panel (a) in Appendix C. In addition, every quarter about 65 percent of new hires from non-employment involve a temporary contract, with the share being slightly higher for older workers – see Table 8 in Appendix C. The data refer to the period from 2005 to 2019, and to workers between the ages of 30 and 55. The measure includes contractor workers as well.

being the *Treu reform* in 1997 and the *Biagi law* in 2003 – reshaped the Italian labor market from one of the most rigid to one of the most flexible, in Europe (Malacrino and Pistaferri, 2021). In most recent years, the large spread of temporary jobs led the Italian legislator to adopt several compensatory reforms, to promote stable employment – among these interventions: the *Fornero reform* in 2012, the *Jobs Act* in 2015 and the *Dignity decree* in 2018. Despite these reforms, the Italian economy remains characterized by a strong contract segmentation, which has broad consequences on labor market outcomes.

The consequences of labor market duality When studying the role of temporary contracts, the existing literature has extensively focused on a set of worker-level outcomes and, more in general, on how the spread of temporary jobs could affect the aggregate performance of the economy.

In particular, there is evidence of how temporary workers suffer relatively high turnover rates (Blanchard and Landier, 2002), leading to less stable careers and long-run earning losses (David and Houseman, 2010; García-Pérez et al., 2019). A large strand of the literature evaluates the so-called *stepping stone* hypothesis, according to which temporary jobs could be a port of entry into stable employment. Results remain controversial.[9] Other studies measure the effects of labor market duality on human capital accumulation (Garcia-Louzao et al., 2022) and, in this context, the willingness of firms to provide on-the-job training activities to temporary workers (Albert et al., 2005; Cabrales et al., 2017). In addition, the existing literature points to systematic income gaps between permanent and temporary employees, in most cases finding wage penalties associated with temporary jobs.[10]

Focusing on more aggregate outcomes, there is evidence of how a large spread of temporary jobs in the economy increases employment volatility over the business cycle (Bentolila and Saint-Paul, 1992; Boeri and Garibaldi, 2007; Costain et al., 2010) and how the high turnover rate associated with temporary contracts could have a negative impact on the average unem-

[9] Most of the literature finds negative or weak results: Magnac (2000) for France; Gagliarducci (2005) and Malacrino and Pistaferri (2021) for Italy; Güell and Petrongolo (2007) and García-Pérez et al. (2019) for Spain; de Graaf-Zijl et al. (2011) for the Netherlands. Other authors find a positive stepping stone mechanism. Among them: Booth et al. (2002) for the UK; Holmlund and Storrie (2002) for Sweden; Heinrich et al. (2005) for Austria. Bentolila et al. (2019) and Filomena and Picchio (2021) provide a systematic literature review.

[10] Bentolila and Dolado (1994), Booth et al. (2002), Brown and Sessions (2005), Mertens et al. (2007), Bosio (2014), Kahn (2016), Bonhomme and Hospido (2017). Only some more recent empirical contributions highlight the existence of potential income premiums for temporary workers: Lass and Wooden (2019) and Albanese and Gallo (2020).

ployment rate (Blanchard and Landier, 2002; Cahuc and Postel-Vinay, 2002). The literature also documents a negative association between average productivity and temporary jobs (Boeri and Garibaldi, 2007).

Labor market stability and income volatility Less attention has been devoted to quantifying how the labor market risk associated with temporary working arrangements reflects into life-cycle income volatility. On the one hand, the temporary employment appears as a relatively transient labor market condition, with large entry and exit probabilities.[11] On the other, even workers who remain employed with a temporary contract across consecutive periods could suffer a large labor market risk, resulting from experiencing transitions across multiple and consecutive short-spell jobs (Gagliarducci, 2005; Güell and Petrongolo, 2007; Sanz, 2011; Gorjón et al., 2021).[12] How does the employment risk in dual labor markets reflect into income volatility?

3 A model of labor market and income dynamics

This section lays out the theoretical framework I use to quantify the relationship between labor market statuses and income volatility. It aims at jointly explaining labor market histories – with workers that can transit across permanent employment, temporary employment and non-employment – and life-cycle income dynamics.

The model takes into account potential endogenous selection, with the same characteristics of workers that can explain both how their income evolves over time and their selection into labor market statuses. A latent ability effect complements the standard set of observable demographics. It measures all the extra heterogeneity, across workers, in addition to the quadratic effect of age and the linear effects of the gender indicator and of the geographical region of residence. The estimated worker-specific component is a key driver of labor market careers, pointing to the relative importance of unobserved heterogeneity when studying labor market allocation *and* income dynamics. Since this component enters the income equation with a

[11] Temporary workers have an estimated 15 percent quarterly probability of transiting to a permanent occupation or back into non-employment. The probability of leaving a permanent employment condition across consecutive quarters is instead below 2 percent. Figure 11 in Appendix C reports the average transitions probabilities in the Italian dual labor market.

[12] The majority of temporary contracts last between one and six months, and less than 10 percent of them last for more than a year. Figure 10, Panel (b), in Appendix C reports the share of temporary jobs by contract duration.

positive coefficient, I refer to it as a *latent ability* effect.

I next describe how workers select into different labor market statuses. Then, I present the nonlinear framework modeling income dynamics.

3.1 Labor market allocation

Consider an economy where every quarter an individual i can be employed with a permanent (P_{it}) or a temporary (T_{it}) contract, or can be non-employed (N_{it}). The probability of being in one of the three statuses at each point in time evolves according to a Markov process. It depends on the labor market status observed in the previous period (S_{it-1}), on a latent permanent ability component (α_i) and on a set of observable demographic characteristics (X_{it}).[13] The same set of workers' characteristics will enter the income equation as well.

Accordingly, the selection into labor market statuses is described by the following two equations:

$$P(S_{it}{=}s \mid S_{it-1}, X_{it}, \alpha_i) = F\left(\gamma(s, S_{it-1}) * X_{it},\ \delta(s, S_{it-1}) * \alpha_i\right) \tag{1}$$

$$s \in \{P, T\}, \quad S_{it-1} \in \{P, T, N\}$$

$$P(S_{it}{=}N \mid S_{it-1}, X_{it}, \alpha_i) = 1 - P(S_{it}{=}P \mid S_{it-1}, X_{it}, \alpha_i) - P(S_{it}{=}T \mid S_{it-1}, X_{it}, \alpha_i) \tag{2}$$

Where the F-function refers to the output of a Multinomial logistic regression model. The baseline status is the non-employment one. Every period, the model evaluates the probability of being in one of the two employment conditions, and it residually computes the probability of being non-employed. Each coefficient measures the role of the corresponding regressor in terms of the difference between the log-probability of being on a permanent (or a temporary) job and the log-probability of being non-employed, given the labor market status in the previous period.

3.2 Income dynamics

Let y_{it} denotes the pre-tax log-income of individual i a time t. I decompose y_{it} into three independent components: a function of the observables demographic characteristics, the un-

[13] The set of demographic characteristics includes a quadratic polynomial in age, the gender indicator and the macro-region of residence – which can be North-East, North-West, Centre and South, the baseline region. When estimating the probability of being in one of the two employment statuses, the set is expanded with a constant term.

observed time-invariant worker-specific effect and a time-varying latent stochastic component.[14]

$$y_{it} = g(X_{it}) + \alpha_i + \eta_{it} \tag{3}$$

$$\eta_{it} = z_{it} + \varepsilon_{it} \tag{4}$$

$$z_{it} = C^{S_{it,t-1}} + \rho^{S_{it,t-1}} z_{it-1} + v_{it} \tag{5}$$

$$v_{it} \overset{iid}{\sim} N\left(0, \left(\sigma_v^{S_{it,t-1}}\right)^2\right), \quad \varepsilon_{it} \overset{iid}{\sim} N\left(0, \left(\sigma_\varepsilon^{S_{it,t-1}}\right)^2\right), \quad \alpha_i \overset{iid}{\sim} N\left(\mu_\alpha, \sigma_\alpha^2\right)$$

$$S_{it,t-1} \in \{PP, PT, PN, TP, TT, TN, NP, NT, NN\}$$

The stochastic component η_{it} is the key driver of income volatility in the labor market. It describes income changes over the career that are not explained by workers' observable or latent characteristics.

I decompose the stochastic component into two additive and independent terms, having a continuous probability support. The first is the permanent component z_{it}, which is assumed to follow a first-order Markov process. Every period workers receive income innovations v_{it} that have long-lasting effects, depending on the persistence parameter ρ. These innovations are assumed to be Normally distributed with zero mean and to be independent over time. The constant term C – once normalized by the persistence parameter – is intended to capture the unconditional mean of the permanent income component. The second stochastic component is the transitory term ε_{it}, which captures income innovations that last for one period of time. It is assumed to be Normally distributed with zero mean and to be independent over time.[15] In this framework, the transitory innovation cannot be disentangled from the classical measurement error, so it is interpreted as a mixture of transitory shocks and measurement errors (Arellano et al., 2017). The latent ability component α_i is assumed to have continuous support, being Normally distributed in the sample population.[16]

[14] Based on the independence assumption, workers with different demographic characteristics or with a different latent ability effect draw their income innovations from the same conditional distributions. The model can handle some departures from this independence assumption. In particular, for each worker the first realization of the permanent stochastic component can be allowed to be correlated with the latent ability term – the two terms would be drawn from a Multivariate Normal distribution.

[15] The model can handle departures from the Normality assumptions. A tractable extension would consist in modeling each of the two income innovations with a Normal-Mixture made of two components.

[16] In my specification, the permanent ability component is the only latent characteristic. The model can be expanded to include an additional unobserved component entering the labor market transition probabilities, a *propensity to move* effect. Even if my theoretical framework is suitable to potentially identify both the two latent effects, in the interest of having a clear interpretation of the results I choose to measure latent heterogeneity by using a unidimensional component.

Nonlinear dynamics The model allows for nonlinear income dynamics. It does so by introducing a labor market dependence structure to an otherwise standard linear permanent-transitory income process – where all innovations that workers receive to their income are drawn from the same distribution and where the degree of income persistence remains constant over time.

My framework describes how income evolves over time by accounting for the labor market risk that workers face in dual labor market economies. In particular, while labor market risk has been traditionally modeled with stochastic processes on a continuous support, my model allows for the presence of *unusual* labor market events that could potentially alter how income evolves over time. Depending on their labor market status, workers receive income innovations that are drawn from distributions having different variance parameters, allowing for systematic heterogeneity in income volatility. The model also introduces heterogeneity in the persistence parameter, with specific labor market statuses potentially associated with higher or lower income transmission over time. In this framework, some of the events in the labor market are allowed to wipe out the memory of past income realizations. The constant parameter entering the permanent income component is assumed to be labor market status dependent as well, capturing systematic differences in the level of the stochastic income term.

Labor market statuses $S_{it,t-1}$ are identified by the interaction of the current and the previous labor market condition. In my economy, workers could remain employed with the same contract type across consecutive periods, could find a permanent or a temporary job, could change their contract type or could instead transit from a permanent or a temporary occupation to non-employment. Is the underline structure of the stochastic income trajectory different depending on these labor market statuses? Consider workers who remain on a permanent occupation across consecutive periods. They are expected to receive small transitory shocks to their income and to face high income transmission over time. On the contrary, workers who remain employed with a temporary contract could be subject to more volatile stochastic income trajectories, being their labor market risk relatively large. Those who instead change status across consecutive periods are expected to experience large income changes, potentially wiping out the memory of previous innovations.

4 Data

The data set I use for the analysis is an administrative longitudinal random sample compiled by the Italian National Social Security Agency (INPS), for the period from January 1985 to December 2019. It contains information on employee and contractor workers, employed in the private sector.[17] The Agency keeps track of labor market histories throughout periods of employment and registered unemployment – i.e. during periods covered by unemployment benefits.

For employee workers, the data set provides information about the exact activation and termination date of each registered contract, the type of contract – which can be permanent, temporary or seasonal – the part-time status, the qualification – which can be white-collar, blue-collar or apprentice – the amount of taxable wage and the identification number of the firm. Each piece of information is provided at a yearly frequency. For contractor workers, the data set provides a limited amount of information, consisting of the calendar months during which the worker has been employed, the corresponding taxable wage and the identification number of the firm. In this case, each piece of information is provided at a monthly frequency. The data set also reports periods covered by unemployment benefits and the corresponding income maintenance amounts. For all workers, the set of demographic information includes the gender indicator, the region of residence and the date of birth and death.

Income data The measure of income I construct for the analysis is the sum of labor earnings and unemployment benefits. Labor earnings refer to all regular and irregular pre-tax income that workers receive under registered contracts. Nominal values are deflated using the CPI to 2015 euros. Labor income data are top-coded. According to Malacrino and Pistaferri (2021), the cutoff always exceeds the 99.5th percentile of the income distribution. Since my analysis is not intended to track the income trajectories of top earners, I do not implement any correction to the upper tail of the distribution.

From administrative data to the working sample I restrict the sample from January 2005 to December 2019 and convert it to a quarterly frequency.[18] When workers have multiple

[17] The data set is the so-called *Longitudinal Sample INPS* (LoSaI). It includes workers born on 24 dates during the year, the first and the ninth day of each month. It covers about 6 percent of the Italian private workforce, including workers in publicly owned companies. Pure public sector jobs and self-employed workers are not reported.

[18] For years before 2005 the data set does not provide precise information about the activation and termination date of contracts.

overlapping or non-overlapping contracts during the same period, I sum the income amounts from the different sources and retain the contract-related information specific to the job relationship with the longest spell during the quarter or, when having the same spell, to the highest paying contract. When dealing with part-time working arrangements, I consider the full-time equivalent period.

Employment quarters are those covered by registered working relationships.[19] Unemployment is residually defined and corresponds to periods of employment gaps in the data set.[20] However, periods of absence from the data set could potentially refer to workers engaged in educational activities, retired or employed with other contractual forms not covered by INPS. I take care of these concerns by designing a procedure aimed at building an *extended* measure of unemployment that includes only individuals who maintain attachment to my specific labor market. This procedure aims at constructing a residual measure of unemployment – non-employment hereafter – that counts in those individuals who do not have a job but would like to have one – i.e. the standard stock of unemployed workers according to the official definition and the stock of marginally attached workers, among the inactive. I first restrict the sample data to individuals between the ages of 30 and 55, as to exclude most of those who are in education or retired. Secondly, I remove long periods of absence from the data set, so to restrict unemployment observations to those spells during which it is likely that workers remained attached to my specific labor market, even if they were neither employed in INPS nor receiving registered unemployment benefits. I detail in Appendix A the data adjustment procedure and the sample selection.

This procedure gives an average non-employment rate equal to 15.6 percent. By construction, since it includes marginally attached workers, it is higher than the official Labor Force Survey unemployment rate (7.6 percent). Notably, it is lower than the official non-employment rate – which is above 27 percent – as it likely does not include those inactive workers who are not attached to the labor market.

[19]A quarter is identified as a period of employment if it counts at least 14 days of registered employment – this period can refer to only one contract, or to multiple overlapping or non-overlapping contracts – and if the corresponding labor income is higher than a minimum threshold of €360. This amount corresponds to two weeks of employment – 40 hours per week – at half the average minimum wage across sectors.

[20]This procedure is due to data limitations. By only considering periods covered by some of the income maintenance benefits observed in the data set, I would obtain a sample unemployment rate of about 3.7 percent. During the same period, the official unemployment rate is above 7.6 percent (ISTAT).

Sample characteristics Table 9 in Appendix C reports the sample characteristics, with a focus on the labor market conditions. In addition, the table compares the administrative sample data (INPS) with the official Labor Force Survey data (ISTAT). My working sample counts approximately a million workers, with an average longitudinal dimension of 37 quarters. In the labor market, 84 percent of periods correspond to quarters of employment and 86 percent of them to periods of permanent occupation. The remaining quarters are those during which workers are not employed. Conditioning on non-employment periods, about 21 percent of the observations are covered by some income maintenance policy.

5 Estimation strategy

I devote this section to presenting the estimation strategy. It is based on the stochastic Expectation-Maximization (sEM) algorithm (Diebolt and Celeux, 1993), a simulated version of the original EM algorithm proposed by Dempster et al. (1977).

Starting from an initial guess of the parameters, the EM algorithm iterates between the E-step – which estimates the latent quantities by computing their conditional mean, given observable data – and the M-step – which solves the complete optimization problem and updates the parameters. In case the conditional expectation is not easy to compute, the latent quantities can be estimated by simulation. This is done by the stochastic EM algorithm, which replaces the standard E-step with a simulation procedure. In particular, it simulates the posterior conditional distributions of the latent variables given observables, and computes draws. The simulation step of my estimating procedure relies on the Metropolis-Hastings (MH) algorithm (Metropolis et al., 1953; Hastings, 1970) – to estimate the unobserved worker-specific component – and on the Durbin-Koopman simulation algorithm (Durbin and Koopman, 2012) – to obtain the estimated time series of the permanent and transitory income innovations, at the worker level.

E-step Starting from an initial guess of the parameters, the E-step of the algorithm estimates the latent variables by drawing from their posterior conditional distributions, given observables. In my framework, the latent variables are the worker-specific ability component and the two income innovations – persistent and transitory. I decompose the simulation step into two parts. First, I estimate the worker-specific latent effect. Second, I treat this quantity as observable and simulate the time series of the two stochastic income components, at the worker level.

Denote by D_i the matrix of observable data for worker i. It consists of the realizations of log-income $y_{i1:T_i}$ over the career, the labor market history $S_{i1:T_i}$ and the set of demographics X_i. Consider the following worker-specific log-likelihood decomposition:

$$\begin{aligned} log[P(\alpha_i \mid D_i)] &= log[P(\alpha_i, S_{i1:T_i}, y_{i1:T_i}, X_i)] - log[P(D_i)] \\ &= log[P(S_{i1:T_i}, y_{i1:T_i} \mid X_i, \alpha_i)] + log[P(X_i, \alpha_i)] - log[P(D_i)] \\ &= log[P(S_{i1:T_i} \mid X_i, \alpha_i)] + log[P(y_{i1:T_i} \mid X_i, \alpha_i)] + log[P(X_i, \alpha_i)] - log[P(D_i)] \\ &= log[P(S_{i1:T_i} \mid X_i, \alpha_i)] + log[P(y_{i1:T_i} \mid X_i, \alpha_i)] + log[P(\alpha_i)] + log[P(X_i)] - log[P(D_i)] \end{aligned}$$

where I exploit the fact that conditioning on worker' characteristics, income trajectory and labor market history are independent – this is a key feature of the model, used for identification. In the last row of the decomposition, I exploit the independence assumption between the observable characteristics and the latent ability component. The first term of the conditional log-likelihood is the Markov process resulting from the Multinomial logistic regression model, which I use to describe how workers select into different labor market statuses. The second entry refers to the conditional log-likelihood of the stochastic income realizations, which is recovered by using the Kalman filter and smoother algorithms.[21] The third term denotes the distribution of the latent ability component in the sample population, for which I assume Normality. The last two entries are constant, not depending on the latent ability effect.

This worker-specific conditional log-likelihood is expressed as a function of the latent ability component and it is used as the input of the Metropolis-Hastings (MH) algorithm. The outcome is a draw from it, representing the estimated value of the worker-specific unobserved effect.[22] Once the draws of the latent ability component are produced, I treat them as observables and subtract them from the income realizations – according to the income equation. I then apply the Durbin-Koopman simulation algorithm to this income residual, to estimate the time series of the two stochastic income components. The functioning of the algorithm is described in Appendix B, subsection B.3.

M-step The M-step updates the parameters, at every iteration of the algorithm. To update the

[21] See Appendix B, subsection B.1

[22] Appendix B, subsection B.2, describes the functioning of the MH algorithm.

coefficients of the demographic characteristics entering the income equation I subtract the latent ability effect from log-income data and regress this residual over the demographic indicators. The parameters characterizing the permanent stochastic income component are updated by regressing the current permanent components on previous realizations, conditioning on labor market statuses. This procedure updates the constant and the persistence parameters of the AR(1) process, and the standard deviation of the permanent income innovations. The standard deviation of the transitory component is updated by computing the sample standard deviation of the estimated transitory innovations in the sample population, conditioning on labor market statuses. The coefficients characterizing the transition probabilities in the labor market are updated with the Multinomial logistic regression model. At every iteration, the algorithm updates as well the sample mean and standard deviation of the latent ability effect.

Initial guess and iterations The first iteration of the algorithm requires an initial guess of the vector of parameters. For the sample distribution of the latent ability component, I assume an initial value of the cross-sectional standard deviation equal to 1 and an initial value of the sample mean equal to 3. The initial demographic coefficients entering the income equation and the labor market transition probabilities are assumed to be zero. I assume an initial value of 1 for the standard deviations of the two income innovations, a value equal to .9 for the persistence parameter and a value equal to zero for the constant term entering the equation of the permanent stochastic income component. The same initial values are used for all the labor market statuses.[23] The algorithm is iterated 50 times and the estimate of each worker-specific latent component is based on 15 MH draws.[24] The working sample used for the estimation is reduced to 101,511 randomly selected workers.

6 Empirical results

In this section, I present the empirical results. I start by describing how workers move across different labor market statuses. I then report the estimates of the parameters characterizing the nonlinear income process. Lastly, I comment on how the latent ability component relates to labor market performance.

[23] In a robustness check, I verify that different initial values of the parameters do not alter the final results.

[24] Figure 12 to Figure 14 in Appendix C report the convergence of the parameters characterizing the stochastic income component. Figure 15 in Appendix C reports the convergence of the labor market transition coefficients, by focusing on the latent ability effect. The convergence of the other coefficients is available upon request.

Table 1: Labor market transition probabilities

t-1 \ t	Permanent	Temporary	Non-employed
Permanent	.980 (.982)	.007 (.005)	.013 (.012)
Temporary	.076 (.055)	.849 (.876)	.075 (.069)
Non-employed	.047 (.033)	.082 (.079)	.872 (.888)

Note: the table reports the estimated conditional transition probabilities for male (female) workers. I consider 40-year-old workers, living in the Centre region, with an average latent ability component. Data are at a quarterly frequency. *Source*: own computation on Italian administrative data from 2005 to 2019, provided by the Social Security Agency (INPS).

6.1 Labor market allocation

The labor market transition probabilities I present in this section are the resulting estimates of the Multinomial logistic regression model described by Equation 1 and Equation 2. They provide reduced form evidence of how workers select into different labor market statuses, depending on their past employment history and on their characteristics.

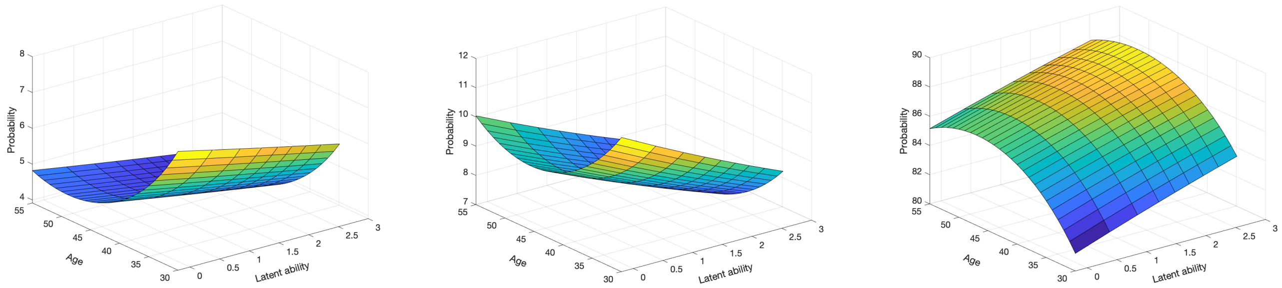
Table 1 reports the average quarterly conditional transition probabilities for male (female) workers. I consider a 40-year-old reference individual, living in the Centre region of the country, with an average latent ability component. I estimate an average conditional probability of finding a permanent job, being non-employed, of about 4.7 (3.3) percent and a probability of selecting instead into a temporary occupation of about 8.2 (7.9) percent. Workers employed with a permanent contract have a 1.3 (1.2) percent probability of losing their job and remaining non-employed for at least one quarter. In comparison, the average job separation probability into non-employment rises to 7.5 (6.9) percent for those employed with a temporary contract. The average conditional probability of transiting from a temporary to a permanent occupation is about 7.6 (5.5) percent.

These values describe the permanent employment condition as an absorbing labor market status, with workers having on average a 98 percent probability of retaining a permanent contract across consecutive periods. The temporary employment is instead a more transient condition, with an average contract retention probability that declines to 85 (88) percent. Temporary workers have indeed both a large probability of transiting into stable jobs and of transiting back into non-employment.

Life-cycle and latent ability Figure 1 to Figure 3 describe how the estimated transition probabilities vary over the life-cycle and by percentiles of the latent ability sample distribution.

Figure 1: Labor market transition probabilities - From non-employment

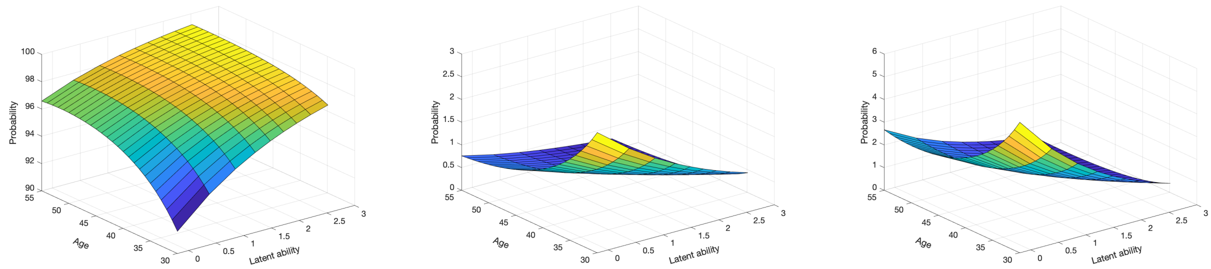
(a) To permanent (b) To temporary (c) To non-employment



Note: the plots report the conditional probabilities of transiting from non-employment to a permanent occupation – Panel (a) – and to a temporary occupation – Panel (b). Panel (c) reports the conditional probability of remaining non-employed. Probabilities are reported over age and over the latent ability dimension, for male workers living in the Centre region. Data are at a quarterly frequency. *Source*: own computation on Italian administrative data from 2005 to 2019, provided by the Social Security Agency (INPS).

Figure 2: Labor market transition probabilities - From permanent employment

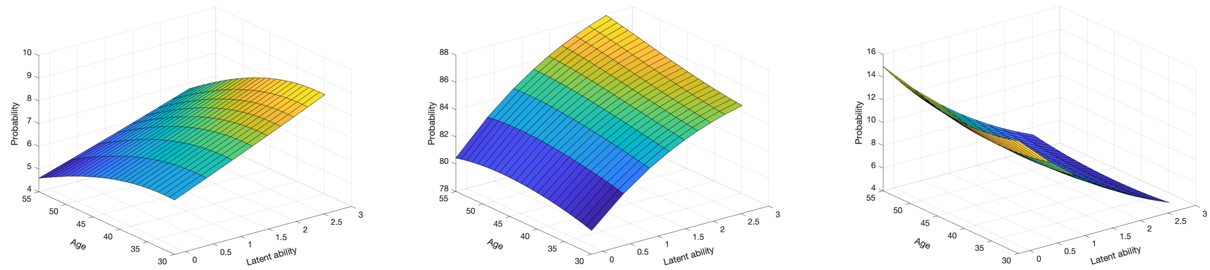
(a) To permanent (b) To temporary (c) To non-employment



Note: the plots report the conditional probability of remaining employed with a permanent contract – Panel (a) – and the conditional probabilities of transiting from a permanent occupation to a temporary job – Panel (b) – or to non-employment – Panel (c). Probabilities are reported over age and over the latent ability dimension, for male workers living in the Centre region. Data are at a quarterly frequency. *Source*: own computation on Italian administrative data from 2005 to 2019, provided by the Social Security Agency (INPS).

Figure 3: Labor market transition probabilities - From temporary employment

(a) To permanent (b) To temporary (c) To non-employment



Note: the plots report the conditional probabilities of transiting from a temporary occupation to a permanent job – Panel (a) – and the conditional probability of remaining employed with a temporary contract – Panel (b). Panel (c) reports the conditional probability of transiting from a temporary occupation to non-employment. Probabilities are reported over age and over the latent ability dimension, for male workers living in the Centre region. Data are at a quarterly frequency. *Source*: own computation on Italian administrative data from 2005 to 2019, provided by the Social Security Agency (INPS).

To report the probabilities, I consider male workers living in the Centre region of the country. Figure 1 reports the transition probabilities involving workers who are currently non-employed. Figure 2 and Figure 3 the transition probabilities involving workers who are currently employed on a permanent or on a temporary job, respectively.

I find that the probability of transiting from non-employment to a permanent occupation is decreasing in age, being higher for young workers – Figure 1, Panel (a). However, once on a stable job, young workers have a relatively lower job retention probability – Figure 2, Panel (a). This life-cycle dynamics is coherent both with firms being more willing to invest in young workers when offering a stable working arrangement and with young workers facing a more flexible labor market, in a process of searching for a suitable match. The probability of transiting from non-employment to a temporary job is convex in age – Figure 1, Panel (b) – with both young and older workers having a higher probability of selecting into temporary jobs. While for young workers temporary contracts could represent a stepping stone towards more stable occupations – Figure 3, Panel (a) reports a contract conversion probability which is higher for young workers and decreasing in age – for older individuals the selection into temporary jobs could be mostly due to firms being less willing to offer permanent contracts to workers who are about to retire. Once on a temporary job, older workers have a relatively larger probability of transiting back into non-employment – Figure 3, Panel (c).

Besides the life-cycle dimension, the estimated transition probabilities highlight a clear role of the latent ability component in driving labor market allocations. In particular, the job finding probabilities are decreasing in the worker-specific unobserved effect – Figure 1, Panel (a) and Panel (b) – denoting how individuals with a high latent ability component could be more selective when looking for a job, perhaps having better outside options.[25] However, once most productive workers find and accept a job, they have a large probability of retaining their occupation. It reaches 98 percent for older and productive workers employed with a permanent contract – Figure 2, Panel (a). Young and less productive workers have instead a relatively

[25]This view is corroborated by the fact that the job finding probability involving temporary contracts is relatively more decreasing in the latent ability component, compared to the job finding probability involving permanent jobs, which is instead almost flat over the latent ability dimension. Another possible explanation behind this dynamics is that workers having different latent ability components compete in potentially different labor markets. For instance, it could be relatively easier for less productive blue-collar workers to select into a job, compared to highly productive white-collar individuals looking for a job in more competitive sectors of the economy. In general, being reduced form estimates, the transition probabilities describe both firms' and workers' behavior behind the observed labor market events.

Table 2: Income process parameters - Persistence

t-1 \ t	Permanent	Temporary	Non-employed
Permanent	.986	.881	.830
	(.00023)	(.00245)	(.00395)
Temporary	.907	.911	.678
	(.00199)	(.00078)	(.00284)
Non-employed	.594	.657	.911
	(.00222)	(.00256)	(.00041)

Note: the table reports the estimated persistence parameter of the stochastic permanent component entering the income equation. Estimates and quantities in parenthesis refer to the average and the standard deviation of the last 30 percent iterations of the stochastic EM algorithm, respectively. Data are at a quarterly frequency. *Source*: own computation on Italian administrative data from 2005 to 2019, provided by the Social Security Agency (INPS).

larger probability of separating from their permanent occupations. Conditioning on being on a temporary job, most productive workers are less likely of going back into non-employment – Figure 3, Panel (c). They have both a high contract retention probability – Figure 3, Panel (b) – and, most importantly, a higher probability of transiting towards a stable occupation – Figure 3, Panel (a).

6.2 Income process estimates

Next, I report the empirical estimates of the nonlinear income process. In particular, I comment on the structural parameters characterizing the dynamics of the stochastic income component. Each parameter can take nine different values, one for each current *and* previous labor market status. Figure 17 in Appendix C reports the estimates of the demographic coefficients entering the income equation and the sample moments of the latent ability component.

Table 2 reports the persistence parameter, Table 3 and Table 4 the standard deviation of the permanent and transitory income innovations, respectively.

The empirical results highlight both the existence of nonlinearities in the income process – which are driven by observable labor market events – and the importance of considering a dual labor market framework, as the income trajectory of permanent and temporary workers differs dramatically. Workers who remain in the same labor market status across consecutive periods face high income transmission over time and suffer less uncertainty both in terms of permanent and transitory innovations. In particular, for workers who remain on a permanent occupation the persistence in income is close to one (.99). Over time they receive small innovations to their income, and for them the relative importance of permanent *versus* transitory shocks

Table 3: Income process parameters - Std of permanent shocks

t-1 \ t	Permanent	Temporary	Non-employed
Permanent	.159	.505	1.079
	(.00068)	(.00260)	(.00145)
Temporary	.391	.383	.942
	(.00202)	(.00104)	(.00358)
Non-employed	.838	.908	.386
	(.00195)	(.00276)	(.00106)

Note: the table reports the estimated standard deviation of the innovations to the stochastic permanent component entering the income equation. Estimates and quantities in parenthesis refer to the average and the standard deviation of the last 30 percent iterations of the stochastic EM algorithm, respectively. Data are at a quarterly frequency. *Source*: own computation on Italian administrative data from 2005 to 2019, provided by the Social Security Agency (INPS).

is larger, compared to workers who remain employed on a temporary job. On the contrary, income transmission appears to be relatively small and the magnitude of income innovations comparatively large both for workers who remain on a temporary occupation across consecutive periods and for workers who transit from a temporary to a permanent job.[26]

Discrete labor market events driven by transitions involving the non-employment status are associated both with low income persistence across periods and with large stochastic income changes. That is, transitions from and into non-employment wipe out the memory of past income realizations and are associated with large transitory and permanent stochastic income innovations, in their magnitude.

Figure 16 in Appendix C reports the asymptotic distribution of the stochastic income component, which depends on the current and on the previous labor market status.[27] The picture provides useful information on the average direction of the innovations – which can be positive or negative.

Workers who remain in the same labor market status across consecutive periods receive on average positive income innovations when remaining employed, and negative income realizations when remaining non-employed.[28] Workers who find a job or change contract type

[26]These results could be explained by workers who make transitions across different firms – even when remaining employed with a temporary contract. Another margin that could explain these results is related to the fact that, across consecutive quarters, temporary workers are likely to spend a different amount of time within the employment status, having less employment stability.

[27]The stochastic term, being the sum of two Normally distributed components – the permanent and the transitory term – has a Normal distribution. The mean coincides with the asymptotic mean of the permanent component and the variance is given by the sum of the variances of the permanent and the transitory income innovations. The asymptotic mean of the permanent component corresponds to the constant term divided by one minus the persistence parameter. The estimates of the constant term are reported in Table 10 in Appendix C.

[28]It is worth mentioning that since the permanent employment status is remarkably absorbing, the distribu-

Table 4: Income process parameters - Std of transitory shocks

t-1 \ t	Permanent	Temporary	Non-employed
Permanent	.044	.172	.317
	(.00209)	(.00460)	(.00213)
Temporary	.208	.100	.409
	(.00065)	(.00463)	(.00217)
Non-employed	.458	.466	.118
	(.00065)	(.00362)	(.00482)

Note: the table reports the estimated standard deviation of the stochastic transitory component entering the income equation. Estimates and quantities in parenthesis refer to the average and the standard deviation of the last 30 percent iterations of the stochastic EM algorithm, respectively. Data are at a quarterly frequency. *Source*: own computation on Italian administrative data from 2005 to 2019, provided by the Social Security Agency (INPS).

receive on average positive income innovations. Job separating events into non-employment are characterized by negative income changes, which are larger for those who were employed on permanent jobs. Workers on a stable occupation likely accumulated positive income realizations for a relatively long period of time, so that job losing events have a large impact on their income trajectory. Interestingly, once conditioning on the same observable and latent characteristics, the average income of those who enter a temporary occupation is higher compared to the average entry income of those who select into a permanent job.[29]

6.3 Lifetime income, labor market history and latent ability

Separate observations of labor market transitions and income changes give extra information to infer unobserved worker types. In this last chapter of the section, I measure the heterogeneity in lifetime career outcomes that is driven by the latent ability component. Table 5 reports the fraction of time spent within different labor market statuses, by groups of workers in different quartiles of the latent ability sample distribution. The table also reports descriptive statistics on lifetime income.

The latent ability component is a key driver of income trajectories and labor market his-

tion estimated when conditioning on workers who remain employed on a permanent job across *two* consecutive periods is a good representation of the stochastic income dynamics of permanent workers, in the sample. On average, they retain their contract type and they keep receiving small and positive income innovations over time. On the contrary, workers who remain employed with a temporary contract across *two* consecutive periods do receive positive income innovations, but on average they remain on a temporary occupation for a relatively short period of time. So that this estimated conditional distribution is less representative of the lifetime income dynamics of temporary workers.

[29] I investigate this result in Section 7, subsection 7.1, by providing evidence of compensating income differentials.

Table 5: Labor market history and income by quartiles of latent ability

	Q_1	Q_2	Q_3	Q_4
Average time within status (%)				
Permanent | Employment	58.8	76.6	84.4	88.5
Temporary | Employment	41.2	23.5	15.6	11.5
Non-employment	38.1	17.3	9.4	6.6
Lifetime log-income				
Mean	7.25	8.01	8.44	8.69
Standard deviation	.850	.535	.399	.357

Note: the first three rows of the table report the fraction of time spent within each labor market status over the career. Time spent under each contract type is conditional on the total employment period. Time spent as non-employed is conditional on all the periods during which the worker is observed. The last two rows report the average lifetime log-income and the average standard deviation of lifetime log-income, at the worker level. Columns refer to groups of workers defined by quartiles of the latent ability component. Data are at a quarterly frequency. *Source*: own computation on Italian administrative data from 2005 to 2019, provided by the Social Security Agency (INPS).

tories. The fraction of time spent in the non-employment status ranges from 38 percent for workers who are in the lowest quartile of the unobserved ability distribution, to 7 percent for those who are more productive. In addition, less productive workers spend about 60 percent of their total employment period on a permanent job, while the same fraction increases by almost 30 percentage points for those who are in the fourth quartile group.[30]

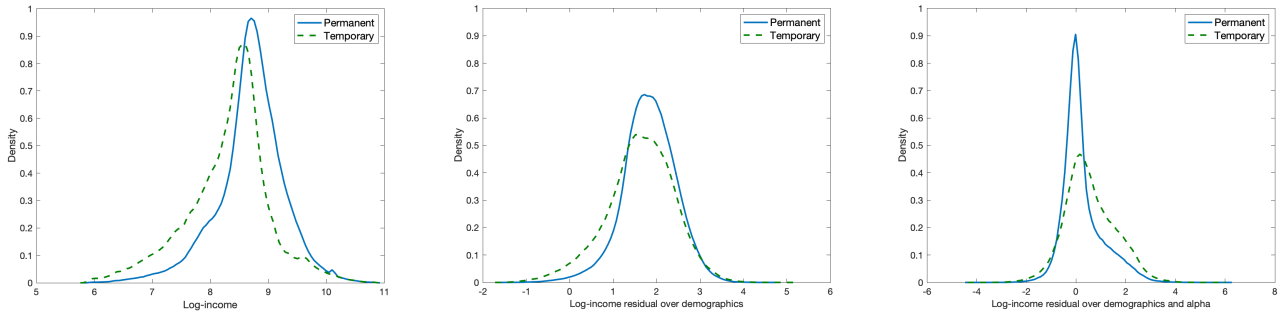
The latent effect clearly correlates with lifetime income as well. This result is driven by a direct productivity effect on income levels, and by an indirect effect through labor market attainment. In particular, the career of most productive workers is characterized by a higher average lifetime income *and* by a lower average lifetime income volatility. Most productive workers earn more than four times as much compared to their less productive colleagues, with one-third of the lifetime standard deviation. Figure 18 in Appendix C shows how the average lifetime income linearly increases with the latent ability component and how the average lifetime income volatility linearly moves in the opposite direction.

The unobserved worker-specific component satisfactorily tracks the labor market performance also when considering information or characteristics that are not explicitly taken into account in the estimation procedure. In particular, due to missing data, the qualifications and the economic sectors are not exploited when estimating the unobserved worker-specific effect. Nevertheless, Figure 20 in Appendix C shows a positive correlation between the latent ability

[30] Figure 19 in Appendix C confirms the positive relationship between the latent ability component and labor market attainment, by taking a career perspective.

Figure 4: Density of income by contract type

(a) Observed income (b) Demographics residual (c) Demo and alpha residual



Note: panel (a) reports the sample distribution of observed log-income. Panel (b) reports the distribution of the residual of log-income over the demographic characteristics. Panel (c) reports the distribution of the residual of log-income over the demographic characteristics and the latent ability effect. Data are at a quarterly frequency. *Source*: own computation on Italian administrative data from 2005 to 2019, provided by the Social Security Agency (INPS).

component and the level of qualification, and it reports an average latent effect that is larger for those working in high productive sectors.

7 The role of labor market duality

In this section, I exploit the estimates of my model to document three new relevant empirical facts about the functioning of dual labor markets. First, I show the existence of compensating income differentials between temporary and permanent workers. Next, I study the lifetime impact of the entry labor market status. Lastly, I measure income losses at job displacement events, and I document how workers recover over time.

7.1 Compensating income differentials

Labor market histories and income trajectories are closely related. The same observable and latent characteristics of workers could potentially affect both their probability of selecting into different labor market statuses and their average income over time. For instance, young workers often select into temporary jobs *and*, due to life-cycle dynamics, they are paid less on average, compared to older colleagues. Other types of selection could be driven by non-observable factors. When comparing income levels across workers in different labor market statuses it is then fundamental to take into account potential endogenous selection mechanisms. My model can successfully tackle the issue, evaluating income differentials across workers who have the same observable and latent characteristics.

Panel (a) of Figure 4 reports the unconditional distribution of log-income, by contract type. On average, workers employed with temporary contracts are paid less compared to their colleagues on stable jobs. This is a well-known result in the literature. Are these differences intrinsically due to the labor market condition or at least part of them can be explained by workers who have different characteristics and that according to them select into different employment contracts?

Panel (b) and (c) of Figure 4 report the income distribution once the effects of the demographic characteristics and, additionally, of the latent ability component are taken into account, respectively. After removing the role of the demographic characteristics, the conditional income distribution of workers employed on temporary jobs moves to the right, compared to the unconditional distribution, with the sample income averages of permanent and temporary workers that almost overlap. When I additionally remove the effect of the latent ability component, the income distribution of temporary workers further moves to the right, with a large probability mass on the right tail.

Two preliminary implications can be drawn from the figure. First, the sequence of the three plots points to the existence of important endogenous selection mechanisms in the labor market. Failing to take them into account could lead to misleading conclusions about income gaps. Second, I find evidence of compensating income differentials. Workers who are employed on temporary jobs are paid relatively more, on average.[31] This income premium is consistent with temporary workers being compensated for the larger income volatility and the higher labor market risk they face. Despite average income differences remain small in magnitude, the direction and the importance of the endogenous selection mechanism in the labor market clearly emerge from the analysis. Once I take selection into account, my results contrast most of the empirical literature, which points to large income penalties for workers on temporary jobs (Bentolila and Dolado, 1994; Booth et al., 2002; Brown and Sessions, 2005; Mertens et al., 2007; Bosio, 2014; Kahn, 2016; Bonhomme and Hospido, 2017). Only some more recent empirical evidence highlights the existing of potential income premiums for temporary workers (Lass and Wooden, 2019; Albanese and Gallo, 2020).

[31] Figure 21 in Appendix C goes beyond average results, by reporting the distribution of income residuals – after removing the effect of both the observable and the latent characteristics – for workers in the first and in the last quartiles of the income sample distribution. In this case, I do not find robust evidence of positive compensating differentials for temporary workers. If anything, the mechanism is more active at the bottom of the sample distribution. Importantly, my results still reject the hypothesis that temporary workers are relatively less paid.

7.2 The lifetime impact of the entry status

A large strand of the literature documents the long-run effects of the entry labor market condition. In most of the cases, it focuses on business cycle fluctuations, finding persistence effects on income losses and on occupational attainment for those who enter the labor market during economic downturns (Kahn, 2010; Oreopoulos et al., 2012; Brunner and Kuhn, 2014; Altonji et al., 2016; Fernández-Kranz and Rodríguez-Planas, 2018; Schwandt and Von Wachter, 2019; Acabbi et al., 2022). Another more recent strand of the literature documents the role of workers' first employers, finding that initial matches with larger firms – or, more in general, with high-growth firms – have positive and substantial effects on long-term outcomes (Arellano-Bover, 2020; Gregory, 2020).

Little is known about the lifetime impact of the entry contract type. In a dual framework, workers can enter the labor market employed on a permanent or a temporary job, or as non-employed. Does the entry contract – or, more in general, the entry status – have any persistent effect on labor market performance, over time?

In this section, I answer the question by establishing a direct causal relationship between the entry contract type and long-run career outcomes. In particular, I measure the effects on the average lifetime income and lifetime income volatility, and on the percentage of time spent within different labor market statuses over the career.

Relying on the estimates of my model, I simulate an economy where individuals have the same observable and latent characteristics, and I arbitrarily assign workers to labor market statutes during the entry period.[32] Since workers' characteristics are fixed, potential differences in income trajectories and in labor market histories are only driven by the entry status.

Table 6 presents the results. Columns report groups of workers based on their labor market condition when they first enter the labor market – permanent employment (P), temporary employment (T) and non-employment (N). The three sections of the table refer to economies with workers having a different latent ability component: the 10th, 50th and 90th percentiles of the sample distribution.

[32] I simulate the career of 10,000 male workers, living in the Centre region. They enter the labor market at age 30 and exit at age 55. I assume that in period zero they are non-employed. According to this assumption, during the first period the stochastic income component is characterized by the structural parameters specific to workers who were previously non-employed. I consider three different economies, depending on the value of the latent ability component – the first decile of the sample distribution, the median value and the last decile of the distribution.

Table 6: Labor market history and income by status during the entry period

	Alpha P_{10}			Alpha P_{50}			Alpha P_{90}		
	P	T	N	P	T	N	P	T	N
Time within status (%)									
Permanent	60.0	52.7	53.5	80.8	40.1	38.1	89.5	46.9	40.5
Temporary	15.7	21.3	18.1	8.4	40.9	21.7	5.0	40.2	20.5
Non-employment	24.3	26.0	28.5	10.8	19.0	40.1	5.5	12.9	39.0
Lifetime log-income									
Mean	6.80	6.81	6.68	8.16	8.14	7.50	9.56	9.58	8.85
Standard deviation	1.08	1.12	1.13	.52	.73	.79	.42	.63	.75

Note: the first three rows of the table report the fraction of time spent within each labor market status over the career. The last two rows report the average lifetime log-income and the average standard deviation of lifetime log-income, at the worker level. Columns refer to groups of workers based on their employment status (Permanent employment, Temporary employment or Non-employment) when they enter the labor market at age 30. The three groups of columns refer to economies with workers having a different latent ability component: the 10th, 50th and 90th percentiles of the distribution. *Source*: simulated quarterly data based on the estimates of the model. Data refer to male workers, living in the Centre region.

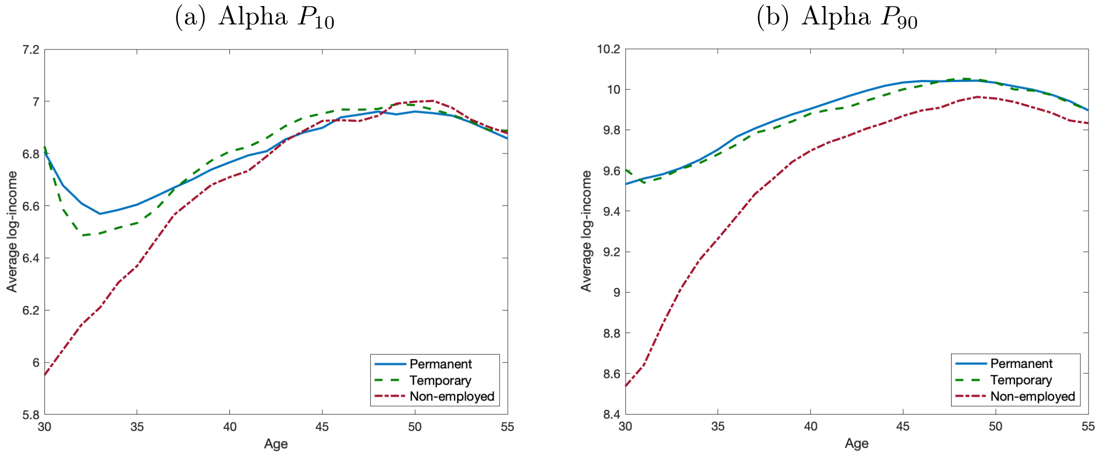
The entry status has persistent consequences on labor market attainment. Individuals that, by chance, start their working life on a temporary job spend on average more time employed with a temporary contract and without any occupation. Consider the economy populated by workers having a latent ability component equal to the median value of the sample distribution. Those who enter the labor force with a temporary contract spend about half the time on a permanent occupation, over their career, compared to their colleagues who enter the labor force on a stable occupation instead. In addition, over their working life, they spend about twice as long without any job.

Interestingly, the importance of the entry labor market status increases with the latent ability component. Less productive workers have both a smaller probability of retaining their permanent occupation and a higher probability of finding a job, when non-employed. Both these two margins reduce the importance, for them, of the initial labor market allocation.

I next focus on lifetime income. Conditioning on starting the career having a job, there is no evidence of significant heterogeneity in average lifetime income across workers who enter the labor market on a permanent or on a temporary contract.[33] On the contrary, lifetime income volatility is largely affected by the entry labor market status. Workers who enter the labor force with a permanent contract suffer on average about two-thirds the lifetime income volatility of those who enter the labor market on a temporary job. This gap is decreasing in the latent ability component.

[33] This result is in line with the compensating differential mechanism I presented in the previous section. The

Figure 5: Average income by entry status in the labor market



Note: the plots report the average log-income by entry labor market status. I compute the average income at the worker level over four quarters and I then evaluate the sample average, by age. The two graphs refer to economies with workers having a different latent ability component: the 10th and 90th percentiles of the distribution. *Source*: simulated quarterly data based on the estimates of the model. Data refer to male workers, living in the Centre region.

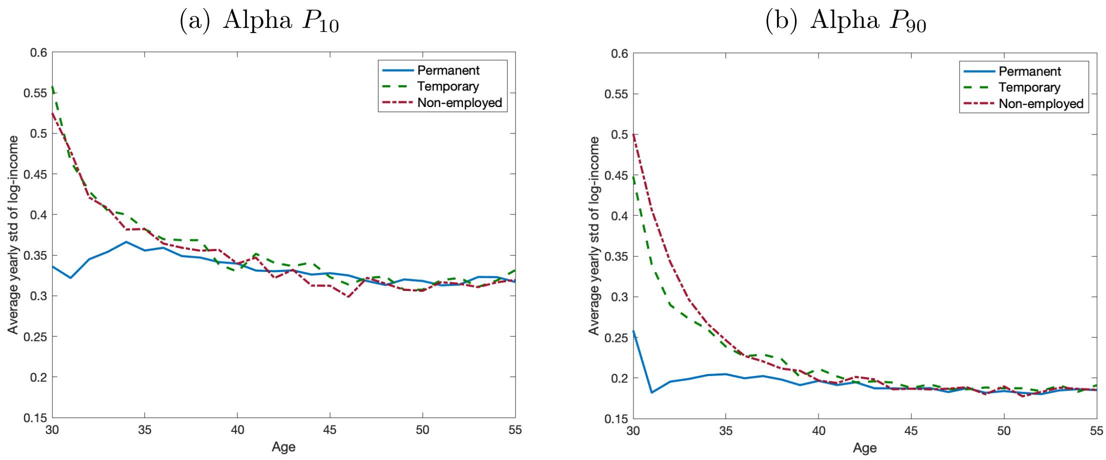
Figure 5 and Figure 6 go beyond average lifetime outcomes, reporting income trajectories over time. Figure 5 focuses on the yearly average income at the worker level, for different groups of individuals based on their entry status. It shows how the similar average lifetime income across workers who enter the labor market employed with different contract types is the result of almost overlapping income trajectories along the entire career. On the contrary, workers who enter the labor force without any job experience long-lasting income losses. In particular, less productive individuals need about ten years to close the negative income gap fully. High-productive workers face instead more persistent income losses, that barely disappear towards the end of their career.[34]

Figure 6 focuses on income volatility and reports the average yearly standard deviation of income at the worker level, for different groups of individuals based on their entry status. The figure documents clear convergence patterns, showing how the lifetime heterogeneity in income volatility is entirely driven by stochastic income realizations at the early stages of the career. Less productive workers who enter the labor market on a temporary occupation or without any job need about five years to close the gap they have in their yearly income volatility, compared to workers who enter the labor market on stable jobs. The length of the convergence period

average lifetime income is slightly higher for those who spend more time employed on temporary jobs.

[34]This finding is compatible with most productive workers who quickly start accumulating positive income innovations when they enter the labor market having a job. At the same time, they have a high probability of retaining their occupation, so that on average they do not suffer large and negative income shocks associated with job separating events. Both these two margins amplify the income gap.

Figure 6: Standard deviation of income by entry status in the labor market



Note: the plots report the average yearly standard deviation of log-income by entry labor market status. I compute the standard deviation of income at the worker level over four quarters and I then evaluate the sample average, by age. The two graphs refer to economies with workers having a different latent ability component: the 10th and 90th percentiles of the distribution. *Source*: simulated quarterly data based on the estimates of the model. Data refer to male workers, living in the Centre region.

increases to about ten years for most productive workers. Interestingly, when considering income volatility, the average trajectories of workers who start their career on a temporary occupation and those who enter the labor force without any job almost overlap.

7.3 Losing a job and recovering

Losing a job has long-lasting consequences on labor market outcomes.[35] The literature documents that the cost of losing a job substantially varies along the business cycle (Davis and Von Wachter, 2011; Acabbi et al., 2022; Schmieder et al., 2022) and that – at the intensive margin, for employed workers – income losses are mostly explained by firm-specific wage premiums (Karahan et al., 2019; Moore and Scott-Clayton, 2019; Lachowska et al., 2020; Fackler et al., 2021; Raposo et al., 2021; Pytka and Gulyas, 2021; Fackler et al., 2021; Bertheau et al., 2022). Over time, a large fraction of the persistent effect of losing a job is mostly driven by the probability of finding a new stable employment. In efficient labor markets, workers quickly reallocate, lowering earning losses after job displacement events (Farber, 2017; Bertheau et al., 2022). Bertheau et al. (2022) show how the unequal cost of losing a job across countries is mostly driven by the different probabilities workers have of finding a new occupation. Conditioning on workers who are back to an occupation, income losses are instead more uniform

[35]There is a large literature measuring income losses at job displacement events. A seminal contribution for the US is the one by Jacobson et al. (1993). Bertheau et al. (2022) provide systematic literature review.

across countries. The importance of the response on the extensive margin is then crucial when evaluating the effects of job displacement events. In this context, little attention has been devoted to investigating how workers recover in dual labor markets. On the one hand, the availability of temporary jobs can help displaced workers to regain quick access to an occupation. Besides reducing income losses in the short-run, this channel shortens the amount of time spent in unemployment, thus mitigating the negative effects of human capital depreciation on future income trajectories. On the other hand, since temporary jobs do not offer employment stability, in economies where it is more likely to obtain a temporary than a permanent contract, displaced workers could suffer persistent income losses and high income volatility over time.

In this section, I document the effects of losing a job in a dual labor market. In particular, I provide new evidence on two main aspects. First, I evaluate average income losses when workers are hit by a non-employment shock, and the subsequent income trajectory. Second, I describe the recovery phase, in terms of the probability of finding a new job, with a permanent or a temporary contract.

Based on the estimates of my model, I simulate the career of an individual who enters the labor market at age 30 and is hit by a non-employment shock at age 35, or at age 50.[36] One of the main advantages of using simulated data is that it is possible to move workers from employment to non-employment arbitrarily. The main drawback of using my theoretical framework in this context is that, besides the life-cycle dimension, income trajectories and labor market transitions do not depend on workers' tenure.[37]

Figure 7 plots the results by comparing average income differences between an economy where workers are hit by a non-employment shock – at age 35 or at age 50 – and a baseline simulated economy, without any exogenous shock. In particular, it reports the average percentage difference in income for three groups of workers, based on their latent ability. On average, I find that income losses are about 60 percent of the counterfactual income, during the first period after the job loss event.[38] Most productive workers suffer a relatively larger percentage drop in

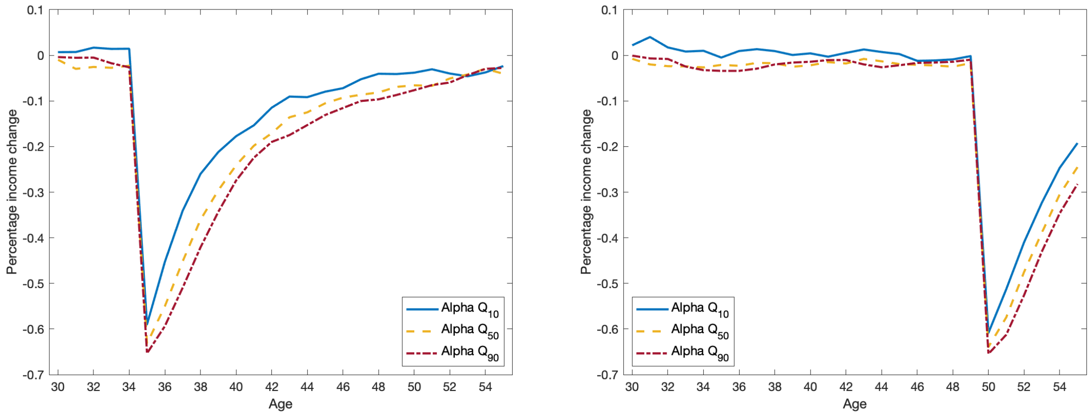
[36] I simulate the career of 15,000 male workers, living in the Centre region. I consider three different economies, depending on the value of the latent ability component – the first decile of the sample distribution, the median value and the last decile of the distribution. Workers enter the labor market at age 30 as non-employed. For the analysis, I condition on workers who are employed during the period before the exogenous non-employment shock.

[37] This limitation is due to missing information in the data, where I cannot observe the full employment history of workers.

[38] Note that, by construction, in my simulated economy workers remain without a job for at least the entire

Figure 7: Average percentage income drop at job losing events

(a) Losing a job at age 35 (b) Losing a job at age 50



Note: the plots report the percentage difference between the average income in an economy hit by a non-employment shock and the average income in an economy without any exogenous shock, by age. I consider only workers who are employed the period before losing their job. Income changes are computed in economies with workers having a different latent ability component: the 10th, 50th and 90th percentiles of the distribution. *Source*: simulated quarterly data based on the estimates of the model. Data refer to male workers, living in the Centre region.

their income and need more time to recover. Percentage income changes for workers who lose their job at age 35 or at age 50 are similar, meaning that the absolute income gap is larger for older displaced workers.

The cost of losing a job is clearly persistent. After five years since the non-employment shock, the average income is below counterfactual earnings by a percentage that ranges from 20 to 30 percent, depending on the latent ability component.[39]

I next focus on the probability of transiting back into an occupation. Figure 8 reports the average probability of being employed over time, after the job displacement event. The figure measures the probability by contract type and distinguishes across groups of workers based on their latent ability component.

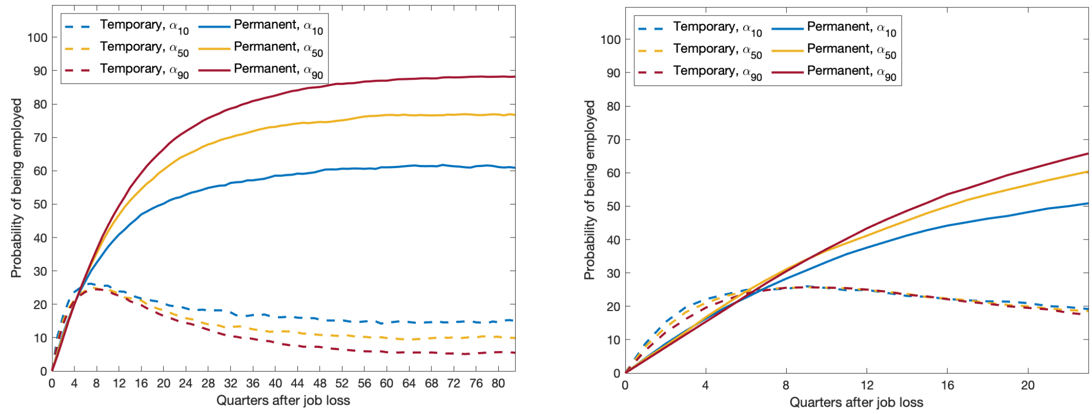
After five years since the non-employment shock, the average probability of being employed is about 80 percent, similar to what Bertheau et al. (2022) find for Southern European countries. This result is driven by a 20 percent probability of being employed on a temporary job and by a 60 percent probability, on average, of being employed on a permanent occupation. The unobserved worker-specific effect is a key driver of the recovery phase. In the long-run, most productive workers have a relatively larger probability of selecting into permanent jobs. On average, after four years since the non-employment shock, the probability of being on a

quarter after the non-employment shock.

[39] This result is in line with the empirical evidence we have from the literature (Bertheau et al., 2022).

Figure 8: Probability of being employed by contract type

(a) Losing a job at age 35 (b) Losing a job at age 50



Note: the plots report the average probability of being employed, by contract type. Period zero is when the shock hits and workers move to non-employment. Probabilities are computed in economies with workers having a different latent ability component: 10th, 50th and 90th percentiles of the distribution. *Source*: simulated quarterly data based on the estimates of the model. Data refer to male workers, living in the Centre region.

permanent job for them is already about 60 percent, and it quickly converges to 90 percent. On the contrary, less productive workers are more likely to select into temporary jobs. Still, this higher probability does not fully compensate for the lower chances they have of finding *and* retaining a permanent occupation.

Figure 22 in Appendix C focuses on the first two years after the non-employment shock, highlighting the role of temporary jobs. For the entire post-displacement year, conditioning on being employed, workers have a larger probability of being on temporary jobs. In particular, less productive workers quickly select into temporary jobs, so that in the very short-run they have a relatively larger probability of being employed. Already after one year since the non-employment shock, most productive workers are more likely to be employed on a permanent than on a temporary job. Less productive workers need about two additional quarters to achieve the same result.

The overall pattern is similar for workers who lose their job at age 35 or later over the career, at age 50. If anything, temporary jobs play a more relevant role in the recovery phase of older workers.

8 Income volatility *vs* income risk

A key motivation of the literature on income dynamics is to measure the amount of uncertainty that workers face in their income growth. Generally speaking, this measurement exercise estimates the conditional moments of the stochastic income distribution and proxies the amount of income uncertainty with the variance of income innovations. However, income volatility could be largely predicted by individuals, so that it does not translate into income risk – which denotes the fraction of income changes that agents cannot anticipate.

The estimates of my model show that the temporary employment condition is associated with large volatility in income trajectories. Does this volatility reflect into income risk? The answer to this question is key to understanding the transmission of income volatility to consumption and saving choices. At the extreme, if permanent and temporary workers suffer a different amount of volatility in their income but they have the same ability to predict future income dynamics, then the heterogeneity in income volatility should have limited consequences on consumption behavior.

In this last section of the paper, I build on Arellano et al. (2021) to construct an individual measure of income uncertainty, and I further investigate whether this indicator of income risk varies depending on the labor market status.

When measuring income uncertainty, we aim at reproducing the prediction problem of agents who want to anticipate income changes over consecutive periods. The availability of high-frequency administrative data makes this problem feasible for economists, who can indeed rely on precise information about income realizations and on a large set of information about workers' characteristics and their labor market history.

Denote by X_{it-1} the information set of worker i at time *t-1*, exploited to predict her income realization at time t, denoted by Y_{it}.[40] The measure of income risk used for the analysis is the following coefficient of variation, which captures the part of income growth that the agent cannot predict.

$$CV_{it}(X_{it-1}) = \frac{\mathbb{E}(\mid Y_{it} - \mathbb{E}(Y_{it}|X_{it-1}) \mid |X_{it-1})}{\mathbb{E}(Y_{it}|X_{it-1})}$$

The numerator reports the conditional absolute prediction error and the denominator a

[40]The information set includes six groups of covariates. (i) A cubic polynomial in log-income. (ii) The standard set of demographics: a quadratic polynomial in age, the gender indicator and the region of residence. (iii) The source of income: indicators for labor income earners and unemployment benefit recipients. (iv) A measure of job stability: the number of working weeks and indicators for having spent the previous four quarters employed and for having spent the previous four quarters in the same firm. (v) The labor market status: indicators for permanent and temporary employment. (vi) A set of business cycle indicators: GDP quarterly growth rate and demographic-specific quarterly unemployment rate. Both measures are considered up to lags of four quarters.

Table 7: Average income risk by labor market status

Average	Permanent	Temporary	Non-employed
.120	.038	.354	.351

Note: the table reports the average CV measure in the sample population and by labor market status. The sample is split after having estimated the CV indicator. Data are at a quarterly frequency. *Source*: own computation on Italian administrative data from 2005 to 2019, provided by the Social Security Agency (INPS).

measure of location – i.e. the conditional income mean. The indicator is estimated by using two linear regressions.[41] To interpret the magnitude of the income risk coefficient, Arellano et al. (2021) propose a simple welfare interpretation. It provides a bridge between the CV indicator and the percentage reduction in consumption that individuals would have to suffer to eliminate income risk fully. Accordingly, an estimated CV lower than 0.1 would reflect relatively low individual income uncertainty, whereas values of 0.3 or higher would correspond to a substantial amount of income risk, across consecutive periods.

Table 11 in Appendix C reports a set of summary statistics describing the estimated measure of income risk. On average, I measure a CV indicator of about .12 in the population, denoting how across consecutive quarters individuals face a small amount of uncertainty when predicting their future income growth. Table 7 goes beyond average results, reporting the measure of income risk across groups of workers based on their labor market status.[42] The results show how temporary workers suffer a substantially larger amount of income risk, about ten times more compared to their colleagues on stable jobs.

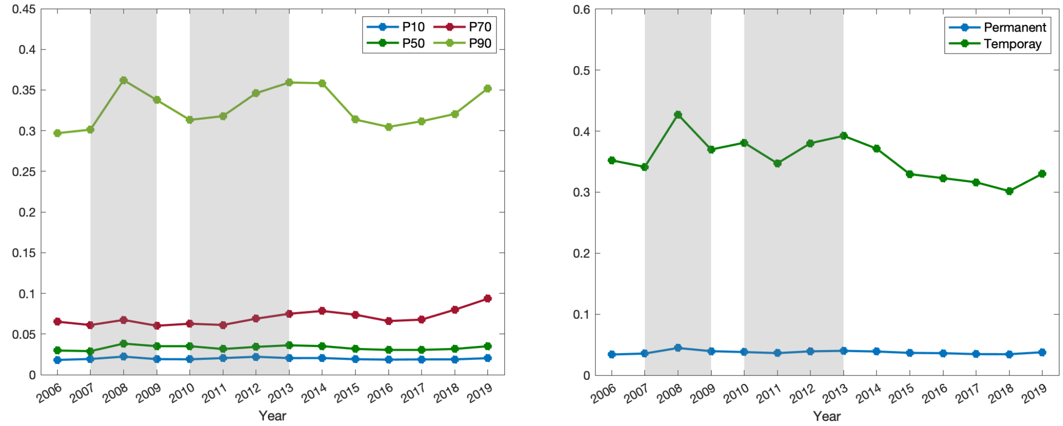
Figure 9 reports the CV measure over time. Panel (a) reports the evolution of different percentiles of the income risk indicator, showing how more than half of the Italian economy suffers little income uncertainty. Panel (b) focuses on employed individuals and reports the income risk measure for permanent and temporary workers, separately. It emerges how permanent workers do not suffer income uncertainty across consecutive quarters, with a small average income risk that stays constant over the business cycle. In comparison, those on temporary jobs are less able to predict their future income growth, and face a more volatile income uncertainty over

[41] First, I regress income data on the set of covariates, to compute the estimated conditional income mean. Next, I construct the absolute prediction error and regress this residual on the same set of covariates. This second regression estimates the conditional expected absolute prediction error, the numerator of the CV indicator.

[42] Table 12 and Table 13 in Appendix C estimate the CV indicator by including the average lifetime income, as a proxy for the unobserved worker-specific effect, in the set of covariates. It is included in the form of quartile groups. Results are essentially unchanged.

Figure 9: Average income risk

(a) By percentiles (b) By contract type



Note: panel (a) reports the average CV measure over calendar years and by percentiles of the CV sample distribution. Panel (b) reports the average CV measure over calendar years by contract type. The sample is split after having estimated the CV measure. Data are at a quarterly frequency and then averaged over calendar years. *Source*: own computation on Italian administrative data from 2005 to 2019, provided by the Social Security Agency (INPS).

the business cycle.[43]

Overall, this measure of individual income risk complements the evidence on income volatility presented in the previous sections of the paper. The high volatility that characterizes the income dynamics of temporary workers is mostly not anticipated, so that it could have large consequences on consumption and saving choices.

9 Conclusions

This paper studies the dynamics of income in dual labor markets. I construct a model that combines continuous structural parameters characterizing the income process with discrete labor market events. The theoretical framework takes into account potential endogenous selection, by allowing the same characteristics of workers to explain both how their income evolves over time and their selection into labor market statuses. A latent ability effect complements the standard set of observable demographic characteristics. The events that could potentially alter the structural dynamics of income are specific to workers who find or lose a permanent or a temporary job, or to workers who change contract type across consecutive periods.

The empirical results highlight both the existence of nonlinearities in the income process – which are driven by observable discrete events in the labor market – and the importance of

[43] Figure 23 in Appendix C provides additional evidence on how the CV measure of income risk varies across workers employed with different contract types.

considering a dual labor market framework, as the income trajectory of permanent and temporary workers differs dramatically. Separate observations of labor market transitions and income changes give extra information to infer unobserved worker types. I find that the estimated latent ability component is a key driver of income trajectories and labor market histories, with productive workers who earn more over their career *and* suffer less volatility in their income.

The paper also contributes to the literature about the causal effects of temporary jobs on career outcomes. First, I provide evidence of endogenous selection mechanisms in the labor market. Once this selection is taken into account, I find the existence of compensating income differentials. That is, temporary workers are paid slightly more, on average, compared to their colleagues employed with permanent contracts. Second, the paper sheds light on a new channel that has long-lasting consequences on labor market performance: the entry labor market contract. I find that the entry status has persistent effects over the career, in terms of income volatility and labor market attainment. Lastly, I measure average income losses when a non-employment shock hits workers, and I evaluate the subsequent income trajectory. I also describe the recovery phase in terms of the probability of finding a new job in a dual labor market. On average, after four years since the non-employment shock, highly productive workers have a probability of being on a permanent job which is already about 60 percent, and that quickly converges to 90 percent. Less productive workers are instead relatively more likely to select into temporary jobs. Still, this larger probability does not fully compensate for the lower chances they have of finding *and* retaining a permanent occupation.

Another contribution of the paper is to investigate whether the higher income volatility associated with the temporary employment condition also reflects into larger income risk – which denotes the fraction of income changes that agents cannot anticipate. I find that the type of contract is a key driver of the heterogeneity in income risk observed in the overall population, with temporary workers suffering a notably higher degree of income uncertainty.

The next step of this research agenda is to bring the individual measure of income risk introduced in the last section of the paper to consumption data. In addition, there are several extensions to the model that would be worth exploring. One of the most ambitious is to construct a model of income dynamics that explicitly incorporates choices that individuals make in the labor market. In this case, transition probabilities would be the combined result of a predetermined individual policy function and of shocks that workers receive in the labor market.

A second natural next step is to use the estimates of my income process to calibrate a life-cycle model of consumption and saving decisions. This would allow describing how the presence of temporary jobs in the economy impacts the lifetime welfare of workers.

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Appendix

A The administrative working sample

This section details the sample selection and the data adjustment procedure I implement to construct the working data set.

The data set I use for the analysis is an administrative longitudinal random sample compiled by the Italian National Social Security Agency (INPS), for the period from January 1985 to December 2019. It contains information on employee and contractor workers, employed in the private sector.[44] The Agency keeps track of labor market histories throughout periods of employment and registered unemployment – i.e. during periods covered by unemployment benefits.

The sample is restricted to the period from January 2005 to December 2019 and converted to a quarterly frequency.[45]

Defining the non-employment status Employment quarters are those covered by registered working relationships.[46] Unemployment is residually defined and it corresponds to periods of employment absence from the data set.[47] In particular, the data set is expanded so to cover, for each worker with at least one registered employment spell, the entire period from the first quarter of 2005 to the last quarter of 2019. However, periods of absence from the data set could potentially refer to workers engaged in educational activities, retired or employed with other contractual forms not covered by INPS. This would be the case if over her working life the worker has been both employed as a private employee within INPS and, for example, as a public employee, as a self-employed paying social contributions to a private fund or employed abroad.

[44] The data set is the so-called *Longitudinal Sample INPS* (LoSaI). It includes workers born on 24 dates during the year, the first and the ninth day of each month. It covers about 6 percent of the Italian private workforce, including workers in publicly owned companies. Pure public sector jobs and self-employed workers are not reported.

[45] For years before 2005 the data set does not provide precise information about the activation and termination date of contracts.

[46] A quarter is identified as a period of employment if it counts at least 14 days of registered employment – this period can refer to only one contract, or to multiple overlapping or non-overlapping contracts – and if the corresponding labor income is higher than a minimum threshold of €360. This amount corresponds to two weeks of employment – 40 hours per week – at half the average minimum wage across sectors.

[47] This procedure is due to data limitations. By only considering periods covered by some of the income maintenance benefits observed in the data set, I would obtain a sample unemployment rate of about 3.7 percent. During the same period of time, the official unemployment rate is above 7.6 percent (ISTAT).

I take care of these concerns by designing a procedure aimed at building an *extended* measure of unemployment that includes only individuals who maintain attachment to my specific labor market. This procedure aims at constructing a residual measure of unemployment – non-employment hereafter – that counts in those individuals who do not have a job but would like to have one – i.e. the standard stock of unemployed workers according to the official definition and the stock of marginally attached workers, among the inactive. First, I restrict the sample to workers between the ages of 30 and 55, where the fraction of individuals engaged in education or retired is fairly small. Workers who do not have any employment relationship appearing in the data set during this age range, between January 2005 and December 2019, are not considered for the analysis. Second, I remove from the working sample long periods of absence from the data set, denoting low attachment to my specific labor market. These gaps in the data set could refer to spells between periods of registered employment – or unemployment, when covered by income maintenance benefits – or could appear when workers first enter – or exit for the last time – the data set. Periods of absence appearing between two registered employment spells on average refer to short non-employment periods, with about 82 percent of them being shorter than a two-year spell and 67 percent of them even shorter than one year. Only 10 percent of *internal* gaps last for more than three years. In addition, according to official LFS data, the probability of leaving the private employee employment only for a short period of time – because of moving to a public job or to self-employment – is relatively small. I count all the internal employment gaps as non-employment spells, assuming that workers remain attached to my specific labor market, even if they are neither working nor receiving income maintenance benefits. Gaps in the data set appearing when workers first enter – or exit for the last time – the data set are more problematic, as in these instances it is more difficult to evaluate labor market attachment. Consider a worker who first appears in the data set at age 40, in 2010. Without any restriction, my residual procedure would assign to this worker five years of non-employment, back until 2005. When these spells refer to long periods of absence, they likely denote workers who were engaged in other activities before entering the data set, or workers who leave the private employment, because they are moving to early retirement or to other employment forms. To address this issue, I first exploit information about retirement periods. When a worker exits the data set and starts receiving a retirement pension, I do not count the subsequent period as a non-employment spell. Second, I remove initial and ending gaps in the data set that are longer than a three-year period. When removing these observations, I do not count the corresponding transitions.

This procedure gives an average non-employment rate equal to 15.6 percent. By construction, since it includes marginally attached workers, it is higher than the official Labor Force Survey unemployment rate (7.6 percent). Notably, it is lower than the official non-employment rate – which is above 27 percent – as it likely does not include inactive workers who are not attached to the labor market.

Measuring income The measure of income I construct for the analysis is the sum of labor earnings and unemployment benefits. Labor earnings refer to all regular and irregular pre-tax income that workers receive under registered contracts. Nominal values are deflated using the CPI to 2015 euros. By construction, the residual procedure I adopt to define the non-employment status produces zero-income observations. During these periods, I assign workers a minimum income amount, according to the following formulation:[48]

$$Y_{it} = Y_{\min} + 0.1(3Y_{it} + 1000U_{[0,1]})$$

This equation moves low – or zero – income levels above a minimum amount, by introducing some noise, according to a Uniform distribution. The specification is intended both to preserve the ranking of income earners below the threshold and to never assign to non-employed workers an amount of income higher than the requirement used to identify employment quarters in the data set. This minimum income amount corresponds to €200. It is the quarterly equivalent of a universal social assistance measure available in Italy for workers above age 65 – the so-called *Carta acquisti ordinaria*. In my context, this amount can be interpreted as the outcome of informal transfers.

Additional data adjustments I implement a set of further data adjustments. (i) I remove workers in the agriculture sector, to increase comparability across individuals in the sample. (ii) I drop seasonal employees, as they move in and out of employment for contractual reasons that are orthogonal to the typical reasons and mechanisms by which workers lose and regain jobs.[49] (iii) I drop workers observed as professionals during at least one calendar year.[50] (iv) Contrac-

[48]See the working paper version of Guvenen et al. (2021).

[49]Specifically, I drop workers who have been seasonal for at least one period during their working life, between the ages of 30 and 55.

[50]A small number of professionals who do not have a dedicated private fund are included in the data set. However, as I am only provided with yearly information on these workers, I drop them from the working sample.

tor and apprentice workers are considered temporary employees. (v) I restrict the sample to individuals who remain in the data set for at least two cumulative years – counting both periods of employment and of non-employment. (vi) Lastly, I do not consider for the analysis workers who have at least one outlier observation in income level or in income percentage change across consecutive quarters. In both cases, I adopt a conservative approach, by identifying as outliers only those observations that are above the 99.9th percentile of the income distribution – in levels or in percentage changes.

B The estimation strategy

This section provides the details of the estimation algorithm. First, I describe the Kalman filter and smoother algorithms. Next, I introduce the Metropolis-Hastings algorithm, which is used to estimate the unobserved worker-specific effect. Lastly, I describe the functioning of the Durbin-Koopman simulation algorithm, which I use to obtain the realizations of the two stochastic income components.

This section relies on the following state-space representation of the income process. Equation 6 is known as the *observation equation*, Equation 7 as the *state equation*.

$$\eta_{it} = y_{it} \mid (X_{it}, \alpha_i) = y_{it} - g(X_{it}) - \alpha_i = \underbrace{\begin{bmatrix} 1 & 1 \end{bmatrix}}_{H} \underbrace{\begin{bmatrix} z_{it} \\ \varepsilon_{it} \end{bmatrix}}_{h_{it}} \tag{6}$$

$$\underbrace{\begin{bmatrix} z_{it+1} \\ \varepsilon_{it+1} \end{bmatrix}}_{h_{it+1}} = \underbrace{\begin{bmatrix} C^{S_{it+1,t}} \\ 0 \end{bmatrix}}_{C_{it+1}} + \underbrace{\begin{bmatrix} \rho^{S_{it+1,t}} & 0 \\ 0 & 0 \end{bmatrix}}_{F_{it+1}} \underbrace{\begin{bmatrix} z_{it} \\ \varepsilon_{it} \end{bmatrix}}_{h_{it}} + \underbrace{\begin{bmatrix} \sigma_v^{S_{it+1,t}} & 0 \\ 0 & \sigma_\varepsilon^{S_{it+1,t}} \end{bmatrix}}_{G_{it+1}} \underbrace{\begin{bmatrix} \tilde{v}_{it+1} \\ \tilde{\varepsilon}_{it+1} \end{bmatrix}}_{\tilde{e}_{it+1}} \tag{7}$$

$$\tilde{e}_{it+1} \overset{iid}{\sim} N(0_2, I_2), \quad h_{i0} \sim N(\mu_0, \Sigma_0)$$

As for the initial conditions, I assume that the first realization of the state vector h_{i0} is drawn from a Normal distribution with zero mean μ_0 and with a covariance diagonal matrix Σ_0 specific to workers who remain in the same labor market status across consecutive periods. Based on the observed entry labor market status, during the first period the variances of the stochastic income innovations are specific to workers who remain in the same entry status across two consecutive quarters.

B.1 The Kalman filter and smoother algorithms

This section introduces the Kalman filter and smoother algorithms (Kalman, 1960). Define the following quantities:

$$\mu_{it_1|t_0} = E[h_{it_1} \mid \eta_{i1:t_0}], \quad \Sigma_{it_1|t_0} = Var(h_{it_1} \mid \eta_{i1:t_0}), \quad \eta_{it_1|t_0} = E[\eta_{it_1} \mid \eta_{i1:t_0}], \quad P_{it_1|t_0} = Var(\eta_{it_1} \mid \eta_{i1:t_0})$$

Set $\mu_{i0|0} = \mu_0$ and $\Sigma_{i0|0} = \Sigma_0$. Following the notation of the state-space representation, for t=0,...,$T_i - 1$ the Kalman filter algorithm produces:

$$\mu_{it+1|t} = C_{it} + F_{it}\mu_{it|t}$$

$$\Sigma_{it+1|t} = F_{it}\Sigma_{it|t}F'_{it} + G_{it}G'_{it}$$

$$\eta_{it+1|t} = H\mu_{it+1|t}$$

$$P_{it+1|t} = H\Sigma_{it+1|t}H'$$

$$\mu_{it+1|t+1} = \mu_{it+1|t} + \left[\Sigma_{it+1|t}H'P^{-1}_{it+1|t}\right]\left(\eta_{it+1} - \eta_{it+1|t}\right)$$

$$\Sigma_{it+1|t+1} = \Sigma_{it+1|t} - \Sigma_{it+1|t}H'P^{-1}_{it+1|t}H\Sigma_{it+1|t}$$

The Kalman smoother algorithm, in turn, produces:

$$\left\{\left(\mu_{it|T_i}, \Sigma_{it|T_i}\right)\right\}_{t=0}^{T_i-1}$$

In particular, given $\left(\mu_{iT_i|T_i}, \Sigma_{iT_i|T_i}\right)$, for t=$T_i - 1$, ..., 0 the Kalman smoother algorithm recursively computes:

$$\mu_{it|T_i} = \mu_{it|t} + \Sigma_{it|t}F'_{it}\Sigma^{-1}_{it+1|t}\left(\mu_{it+1|T_i} - \mu_{it+1|t}\right)$$

$$\Sigma_{it|T_i} = \Sigma_{it|t} - \Sigma_{it|t}F'_{it}\Sigma^{-1}_{it+1|t}\left(\Sigma_{it+1|t} - \Sigma_{it+1|T_i}\right)\Sigma^{-1}_{it+1|t}F_{it}\Sigma_{it|t}$$

With the Normality assumption, in every period the distribution of the stochastic income component reads as follows:

$$y_{it|t-1} \mid (X_i, \alpha_i) = \eta_{it|t-1} \sim N\left(H\mu_{it|t-1}, H\Sigma_{it|t-1}H'\right)$$

B.2 The Metropolis-Hastings algorithm

To estimate the worker-specific latent component, I exploit the Metropolis-Hastings (MH) algorithm (Metropolis et al., 1953; Hastings, 1970). For each worker, it produces a draw of the latent ability component from the worker-specific posterior conditional distribution, given observable data. Denote by D_i the matrix of observable data for worker i. It consists of the realizations of log-income $y_{1:T_i}$ over the career, the labor market history $S_{1:T_i}$ and the set of demographics X_i. Consider the following worker-specific log-likelihood decomposition:

$$
\begin{aligned}
log[P(\alpha_i \mid D_i)] &= log[P(\alpha_i, S_{i1:T_i}, y_{i1:T_i}, X_i)] - log[P(D_i)] \\
&= log[P(S_{i1:T_i}, y_{i1:T_i} \mid X_i, \alpha_i)] + log[P(X_i, \alpha_i)] - log[P(D_i)] \\
&= log[P(S_{i1:T_i} \mid X_i, \alpha_i)] + log[P(y_{i1:T_i} \mid X_i, \alpha_i)] + log[P(X_i, \alpha_i)] - log[P(D_i)] \\
&= log[P(S_{i1:T_i} \mid X_i, \alpha_i)] + log[P(y_{i1:T_i} \mid X_i, \alpha_i)] + log[P(\alpha_i)] + log[P(X_i)] - log[P(D_i)]
\end{aligned}
$$

where I exploit the fact that conditioning on workers' characteristics, income trajectory and labor market history are independent – this is a key feature of the model, used for identification. In the last row of the decomposition, I exploit the independence assumption between the observable characteristics and the latent ability component. The first term of the conditional log-likelihood is the Markov process resulting from the Multinomial logistic regression model, which I use to describe how workers select into different labor market statuses. The second term refers to the conditional log-likelihood of the stochastic income realizations, which is recovered by using the Kalman filter and smoother algorithms. The third term of the decomposition is the distribution of the latent ability component in the sample population, for which I assume Normality. The last two terms are constant, not depending on the latent ability effect.

For each worker, consider an initial guess of the latent ability. It is drawn from a Normal distribution with zero mean and a variance corresponding to the variance of the latent ability effect in the population. Given this initial value, I call the algorithm. First, it draws a candidate from a Normal distribution with a mean equal to the initial guess and a standard deviation equal to the one used above, divided by two. Second, it computes the log-Hastings ratio, as the difference between the conditional log-likelihood of α evaluated at this new candidate and the same conditional log-likelihood evaluated at the initial guess. If the ratio is larger than the log of a draw from a Uniform distribution, the algorithm accepts the candidate, otherwise it keeps the entry value. I iterate the algorithm 15 times.

B.3 The Durbin-Koopman simulation smoother

This section describes the procedure used to decompose the income residual over workers' characteristics $\eta_{i1:T_i}$ into a permanent and a transitory stochastic component. It is based on the Durbin-Koopman simulation smoother (Durbin and Koopman, 2012), which estimates the two components by producing draws from their simulated conditional distributions.

The Durbin-Koopman simulation smoother works as follow. For each worker, it simulates the $\hat{h}_{i0:T_i}$ vector – i.e. it draws the first realization of the state vector h_{i0}, the series $\tilde{e}_{i1:T_i}$ and uses Equation 7 to construct the entire time series. Next, it constructs the series of simulation errors $\hat{\eta}_{i1:T_i}$. Every period the error is computed as:

$$\hat{\eta}_{it} = \eta_{it} - H\hat{h}_{it}$$

Starting from these values, the algorithm uses the Kalman recursions to compute a new estimate of the state vector. In particular, it computes:

$$h^{+}_{i0:T_i} = E[h_{i0:T_i} \mid \hat{\eta}_{i1:T_i}]$$

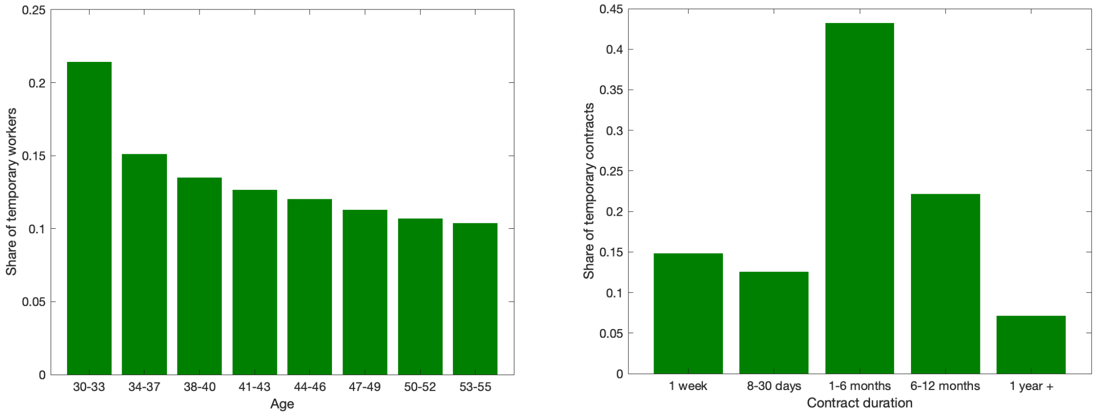
Lastly, with these new quantities, the algorithm forms the estimated time series of the two stochastic income components, at the worker level. By construction, the resulting vector is a draw from the simulated conditional distribution of the state vector, given the income realizations:

$$h^{*}_{i0:T_i} = \hat{h}_{i0:T_i} + h^{+}_{i0:T_i} \sim \mathrm{P}\left(h_{i0:T_i} \mid \eta_{1:T_i}\right)$$

C Additional figures and tables

Figure 10: Spread and duration of temporary contracts

(a) Share of temporary workers by age (b) Share of temporary contracts by duration



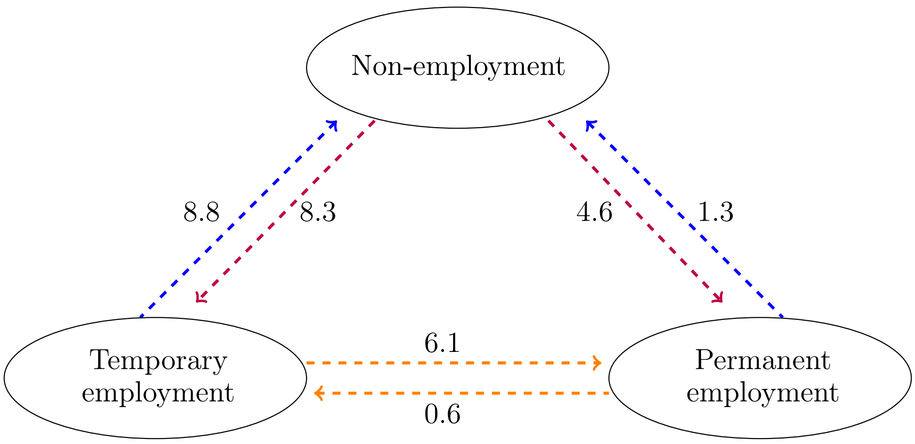
Note: panel (a) reports the share of temporary workers over total employment, by age. Data are at a quarterly frequency. Panel (b) reports the share of temporary contracts by duration, over the total number of observed temporary contracts during the sample period. *Source*: own computation on Italian administrative data from 2005 to 2019, provided by the Social Security Agency (INPS) and by the Ministry of Labour (CICO).

Table 8: Share of *ins* and *outs* of temporary employment

	30-33	37-40	44-47	51-55
Job finding	.637	.639	.655	.688
Job separation	.551	.499	.507	.507

Note: the table reports the share of job finding transitions from non-employment and job separation transitions into non-employment involving temporary contracts, over the total number of transitions. Shares are computed for different age groups at a quarterly frequency and then averaged over the sample period. *Source*: own computation on Italian administrative data from 2005 to 2019, provided by the Social Security Agency (INPS).

Figure 11: Labor market transition probabilities



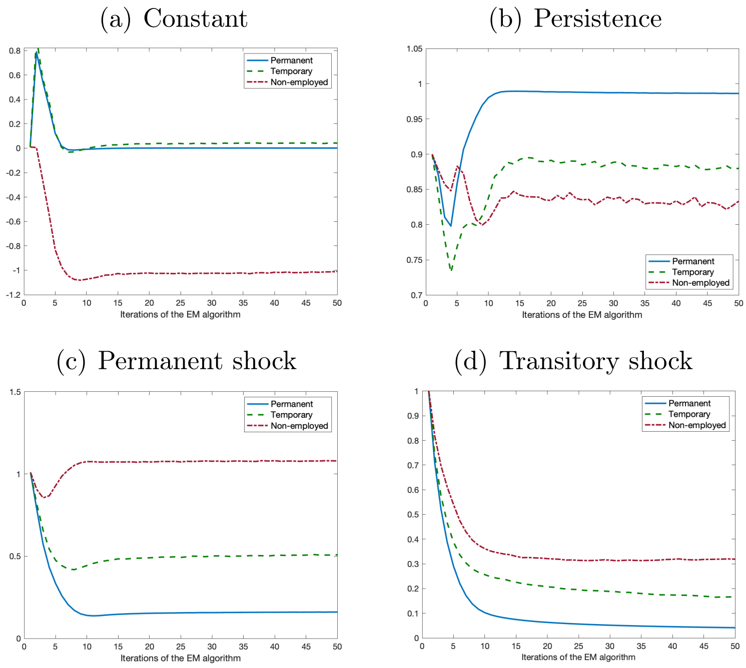
Note: the plot reports the unconditional transition probabilities. Measures are computed at a quarterly frequency and then averaged over the sample period. *Source*: own computation on Italian administrative data from 2005 to 2019, provided by the Social Security Agency (INPS).

Table 9: Sample characteristics and the labor market

	INPS	ISTAT
Number of workers	1,015,560	
Quarterly observations	60,933,600	8,244,264
Average panel dimension (quarters)	36.9	1
Employment (%)		
Employees and contractors	100	77.1
Permanent employment	86.2	87.8
Temporary employment	13.8	12.2
Non-employment (%)		
Non-employment rate	15.6	27.5
Non-employment benefits coverage	20.8	

Note: the table reports the number of workers and observations in the sample, the average panel dimension and the share of workers by labor market condition. The table further compares the characteristics of the administrative working sample provided by INPS with cross-sectional Labor Force Survey data provided by ISTAT. The shares are computed at a quarterly frequency and then averaged over the sample period. *Source*: own computation on Italian administrative data from 2005 to 2019, provided by the Social Security Agency (INPS), and on LFS data from 2005 to 2019, provided by ISTAT.

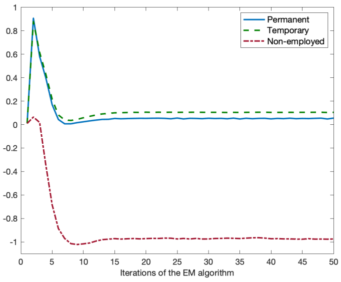
Figure 12: Convergence of income process parameters
From permanent employment



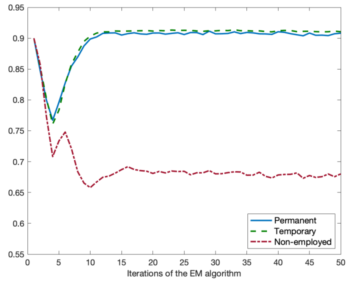
Note: the plots report the values of the income process parameters over the iterations of the stochastic EM algorithm. Parameters refer to the stochastic income component of workers who are currently on a permanent job. Data are at a quarterly frequency. *Source*: own computation on Italian administrative data from 2005 to 2019, provided by the Social Security Agency (INPS).

Figure 13: Convergence of income process parameters
From temporary employment

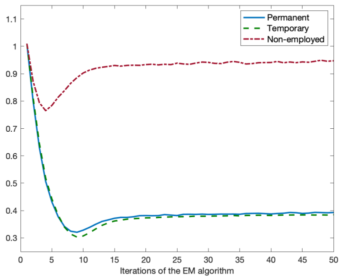
(a) Constant



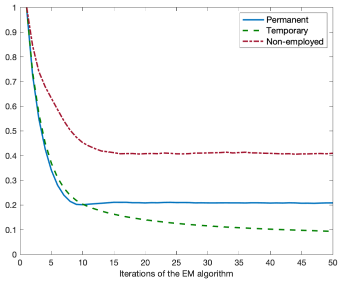
(b) Persistence



(c) Permanent shock



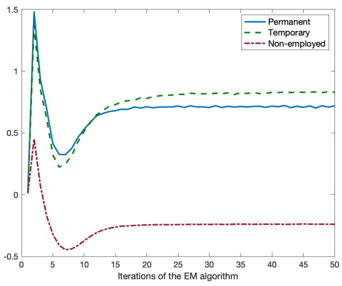
(d) Transitory shock



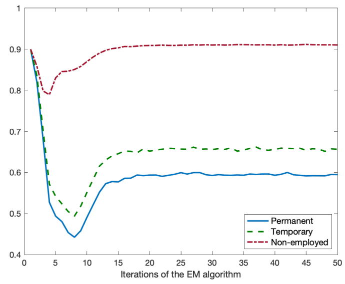
Note: the plots report the values of the income process parameters over the iterations of the stochastic EM algorithm. Parameters refer to the stochastic income component of workers who are currently on a temporary job. Data are at a quarterly frequency. *Source*: own computation on Italian administrative data from 2005 to 2019, provided by the Social Security Agency (INPS).

Figure 14: Convergence of income process parameters
From non-employment

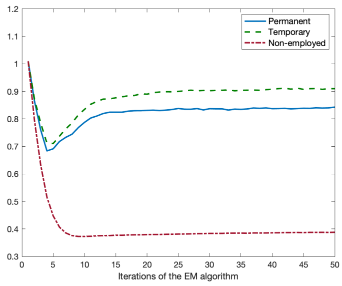
(a) Constant



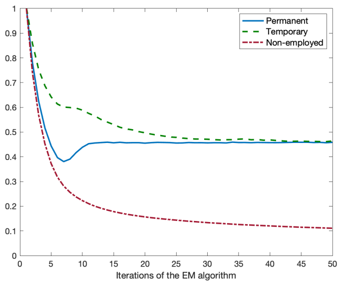
(b) Persistence



(c) Permanent shock

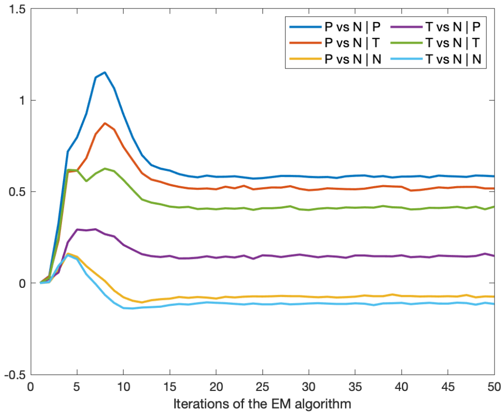


(d) Transitory shock



Note: the plots report the values of the income process parameters over the iterations of the stochastic EM algorithm. Parameters refer to the stochastic income component of workers who are currently non-employed. Data are at a quarterly frequency. *Source*: own computation on Italian administrative data from 2005 to 2019, provided by the Social Security Agency (INPS).

Figure 15: Convergence of labor market transition coefficients
Latent ability



Note: the plots report the values of the coefficients entering the labor market transition probabilities over the iterations of the stochastic EM algorithm. The plot focuses on the coefficients associated with the latent ability component. Data are at a quarterly frequency. *Source*: own computation on Italian administrative data from 2005 to 2019, provided by the Social Security Agency (INPS).

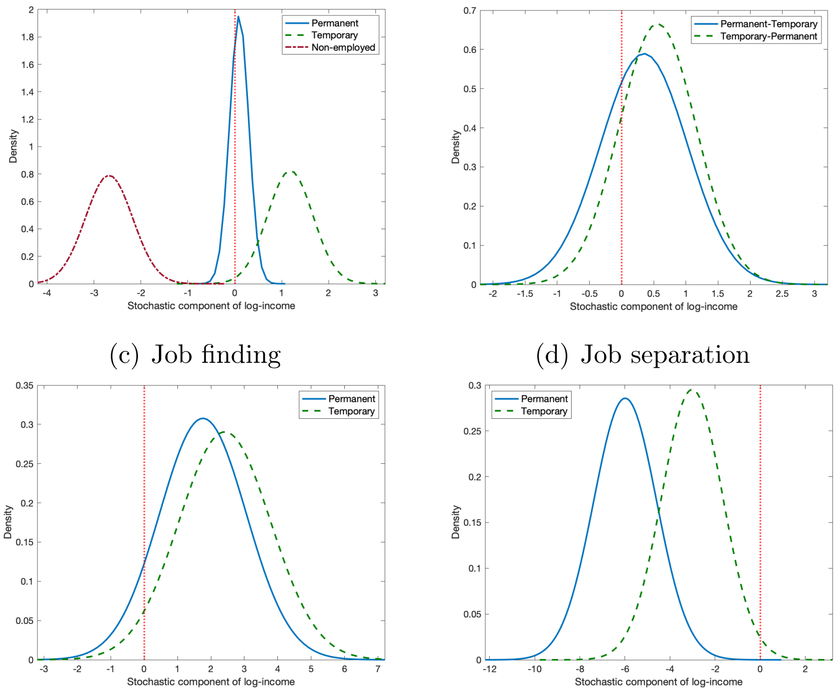
Table 10: Income process parameters - Constant

t-1 \ t	Permanent	Temporary	Non-employed
Permanent	.001	.041	-1.018
	(.00014)	(.00208)	(.00599)
Temporary	.052	.105	-.972
	(.00228)	(.00081)	(.00985)
Non-employed	.714	.828	-.239
	(.00304)	(.00672)	(.00155)

Note: the table reports the estimated constant parameter of the stochastic permanent component entering the income equation. Estimates and quantities in parenthesis refer to the average and the standard deviation of the last 30 percent iterations of the stochastic EM algorithm, respectively. Data are at a quarterly frequency. *Source*: own computation on Italian administrative data from 2005 to 2019, provided by the Social Security Agency (INPS).

Figure 16: Asymptotic conditional distribution of the stochastic income component

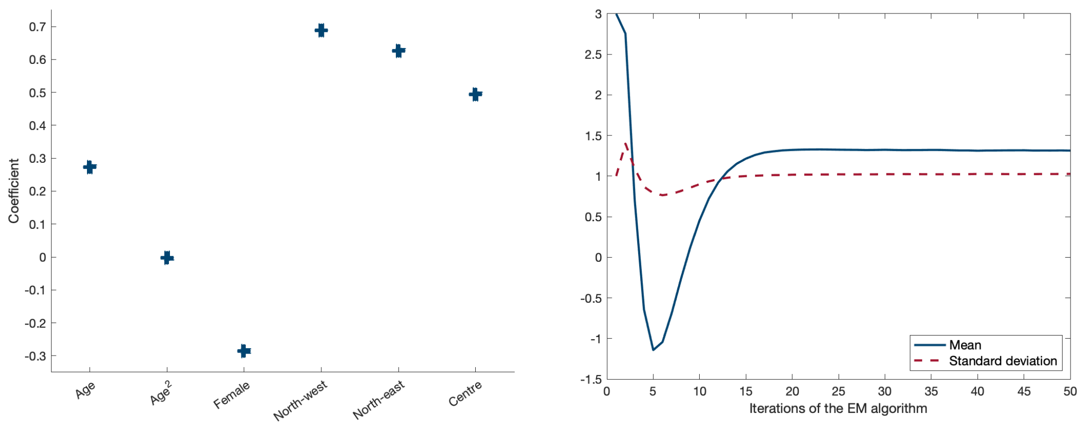
(a) Stayers (b) Contract changing (c) Job finding (d) Job separation



Note: the plots report the conditional asymptotic distribution of the stochastic component entering the income equation – i.e. the sum of the persistent and the transitory components. Panel (a) reports the distributions focusing on workers who remain in the same labor market status across consecutive periods. Panel (b) reports the distribution computed using the parameters that characterize the contract-changing transitions. Panel (c) reports the distribution computed using the parameters that characterize the job finding transitions. Panel (d) reports the distribution computed using the parameters that characterize the job separating transitions. Data are at a quarterly frequency. *Source*: own computation on Italian administrative data from 2005 to 2019, provided by the Social Security Agency (INPS).

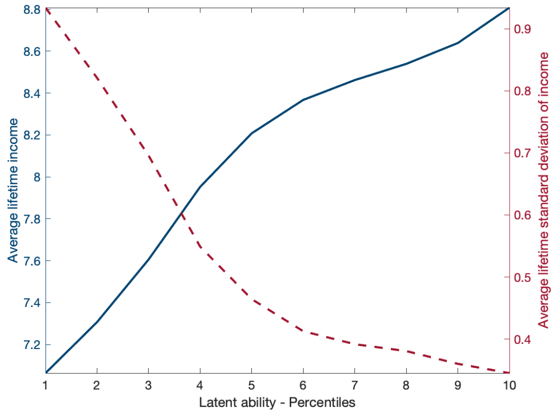
Figure 17: Demographics and latent ability in the income equation

(a) Coefficients on demographics (b) Sample moments of latent ability



Note: panel (a) reports the coefficients of the g-function entering the income equation. Panel (b) reports the mean and the standard deviation of the distribution of the latent ability component in the sample population. It reports all the iterations of the stochastic EM algorithm. Data are at a quarterly frequency. *Source*: own computation on Italian administrative data from 2005 to 2019, provided by the Social Security Agency (INPS).

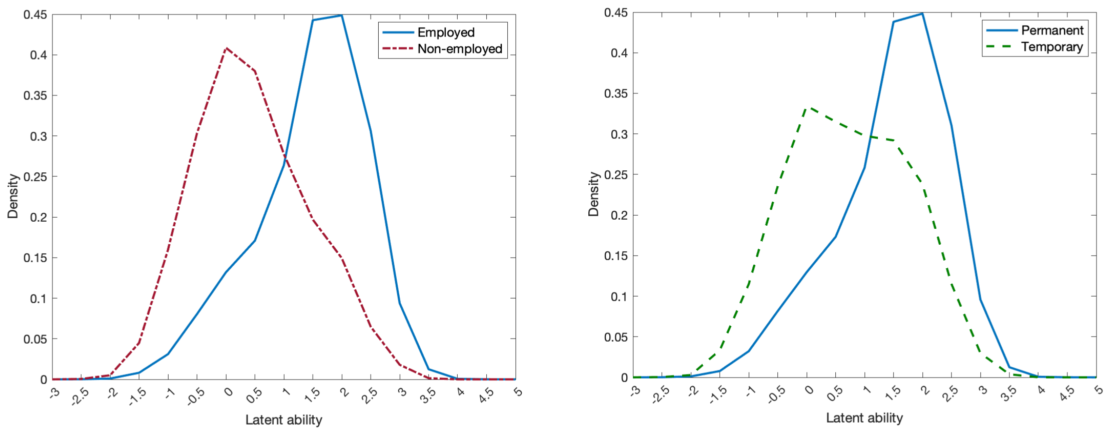
Figure 18: Average lifetime income and latent ability



Note: the figure reports the average lifetime log-income and the average standard deviation of lifetime log-income at the worker level, by percentiles of the latent ability component. Each measure is computed at the worker level and then averaged within percentiles of the latent ability effect. Data are at a quarterly frequency. *Source*: own computation on Italian administrative data from 2005 to 2019, provided by the Social Security Agency (INPS).

Figure 19: Density of latent ability by labor market status over the career

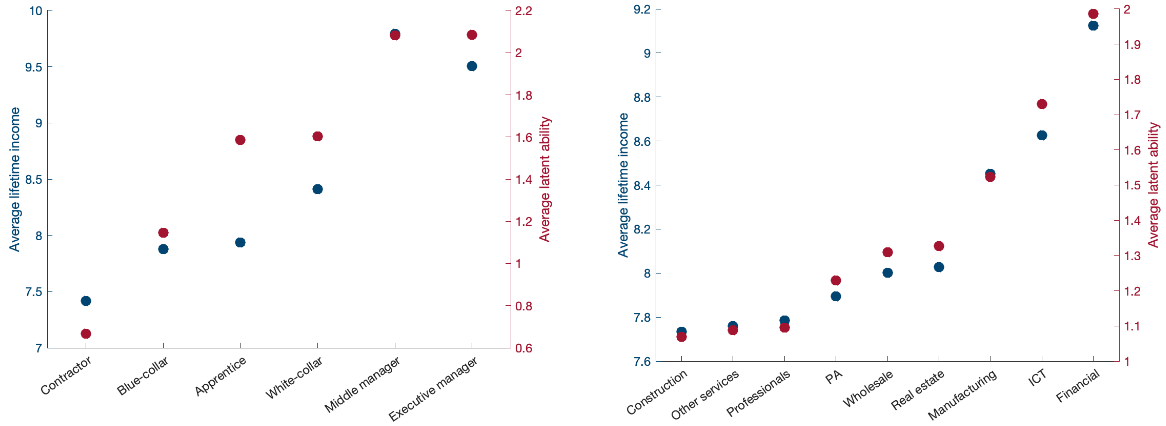
(a) Employment *vs* non-employment (b) Permanent *vs* temporary



Note: panel (a) reports the density of the latent ability component for workers who during the observed career spend at least half of the time employed and for workers who spend instead more than half of the time without any job. Panel (b) repeats the same exercises conditioning on the fraction of time spent on a permanent or on a temporary job – above or below 50 percent – over the total employment period. Data are at a quarterly frequency. *Source*: own computation on Italian administrative data from 2005 to 2019, provided by the Social Security Agency (INPS).

Figure 20: Average lifetime income and latent ability

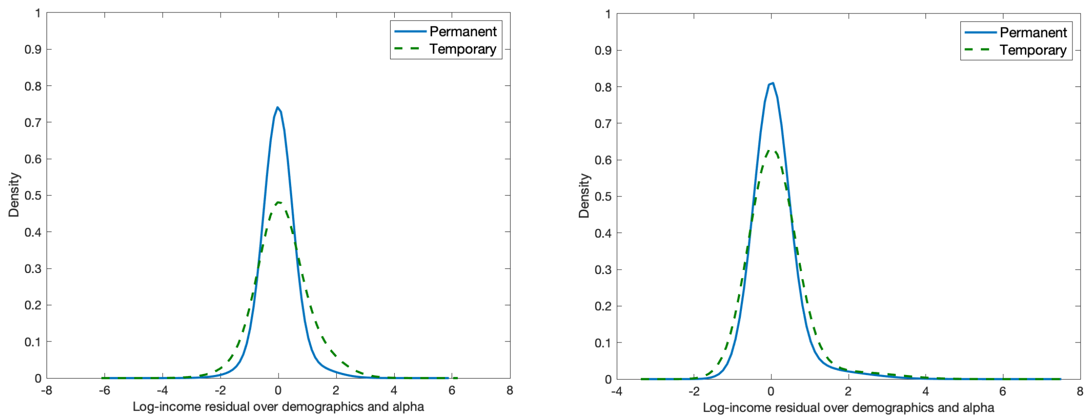
(a) By qualification (b) By sector



Note: panel (a) reports the average lifetime income at the worker level and the average latent ability component by qualifications. I consider the qualification under which the worker spends most of the time during the observed career. Panel (b) reports the average lifetime income and the average latent ability component by sectors. I consider the sector where the worker spends most of the time during the observed career. Data are at a quarterly frequency. *Source*: own computation on Italian administrative data from 2005 to 2019, provided by the Social Security Agency (INPS).

Figure 21: Density of income by contract type

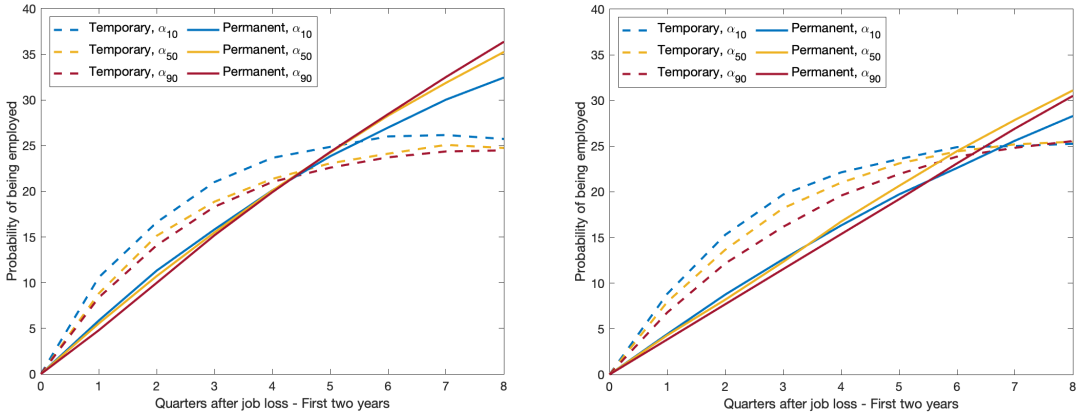
(a) First quartile (b) Fourth quartile



Note: the figures report the sample distribution of the log-income residual over the demographic characteristics and the latent ability component, by contract type. Panel (a) and (b) report the income residual computed within the first and the fourth quartiles of the income sample distribution, respectively. Data are at a quarterly frequency. *Source*: own computation on Italian administrative data from 2005 to 2019, provided by the Social Security Agency (INPS).

Figure 22: Probability of being employed by contract type - First two years after the shock

(a) Losing a job at age 35 (b) Losing a job at age 50



Note: the plots report the average probability of being employed, by contract type. Period zero is when the shock hits and workers move to non-employment. Probabilities are computed in economies with workers having a different latent ability component: the 10th, 50th and 90th percentiles of the distribution. *Source*: simulated quarterly data based on the estimates of the model. Data refer to male workers, living in the Centre region.

Table 11: Income risk: summary statistics

Average	Std	Median	P_{10}	P_{90}
.120	.370	.033	.020	.328

Note: the table reports a set of descriptive statistics of the CV measure estimated using all predictors, for the entire working sample. Data are at a quarterly frequency. *Source*: own computation on Italian administrative data from 2005 to 2019, provided by the Social Security Agency (INPS).

Table 12: Income risk: summary statistics

Average	Std	Median	P_{10}	P_{90}
.116	.198	.047	.025	.311

Note: the table reports a set of descriptive statistics of the CV measure estimated using all predictors, for the entire working sample. The set of predictors also includes the average lifetime income, as a proxy for the unobserved worker-specific effect. It is included in the form of quartile groups. Data are at a quarterly frequency. *Source*: own computation on Italian administrative data from 2005 to 2019, provided by the Social Security Agency (INPS).

Table 13: Average income risk by labor market status

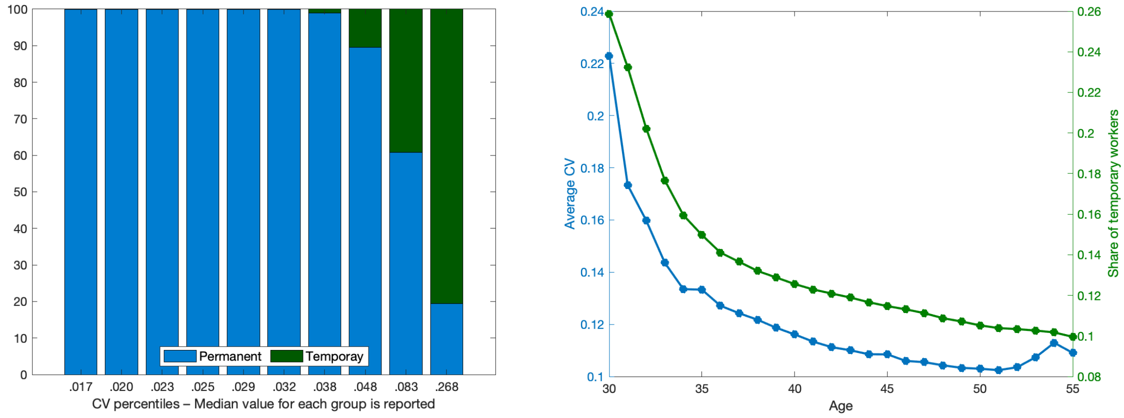
Average	Permanent	Temporary	Non-employed
.116	.048	.283	.327

Note: the table reports the average CV measure in the sample population and by labor market status. The sample is split after having estimated the CV indicator. The set of predictors used to estimate the CV measure also includes the average lifetime income, as a proxy for the unobserved worker-specific effect. It is included in the form of quartile groups. Data are at a quarterly frequency. *Source*: own computation on Italian administrative data from 2005 to 2019, provided by the Social Security Agency (INPS).

Figure 23: Income risk and the labor market

(a) Share of contract type by CV percentiles

(b) Income risk and temporary share by age



Note: panel (a) reports the share of workers employed with permanent and temporary contracts within ten percentiles of the CV sample distribution. I compute percentiles conditioning on periods of employment. Panel (b) reports the average CV measure by age (sx) and the average share of temporary contracts by age (dx). The sample is split after having estimated the CV measure. Data are at a quarterly frequency. *Source*: own computation on Italian administrative data from 2005 to 2019, provided by the Social Security Agency (INPS).