Income Dynamics in Dual Labor Markets*

Ivan Lagrosa[†]
CEMFI

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Abstract

In dual labor markets, stable jobs coexist with short, fixed-duration contracts. While some workers hold permanent positions, others experience employment instability, transitioning through multiple short-term jobs before securing a stable contract. This paper examines how employment instability arises from contract types versus worker characteristics and how duality impacts individual income volatility. I propose a statistical framework where observable and latent individual characteristics jointly influence labor market trajectories and income dynamics. The model decomposes the portion of income not attributable to individual factors into persistent and transitory components. The persistence and the magnitude of these components are allowed to vary with labor market status and transitions, giving rise to nonlinear and non-normal income dynamics. The estimates reveal that latent characteristics are key drivers of heterogeneity in employment instability and that labor market status and transitions significantly affect income volatility. The analysis further uncovers substantial welfare costs of employment instability driven by heightened precautionary savings.

JEL Classification: C13, C15, E21, E24, J31, J41, J42

Keywords: income process, labor market duality, fixed-term jobs, latent heterogeneity, EM algorithm, consumption, wealth accumulation

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[†]E-mail: ivan.lagrosa@cemfi.edu.es. Personal website: ivanlagrosa.com.

1 Introduction

Many labor markets – including those in Spain, France, and Italy, for instance – exhibit a dual structure where stable long-term employment jobs coexist with short-term, fixed-duration contracts. In these markets, some workers enjoy stable lifetime employment. Others encounter instead employment instability, transitioning through multiple short-term jobs before eventually securing a stable contract, and often experiencing periods of non-employment between jobs. This raises three main questions. To what extent is employment instability related to contract types or to individual characteristics? How does contract duality influence individual income volatility? And what are the implications of dual labor markets for consumption and wealth accumulation?

These questions stem from two simple considerations. First, workers on fixed-term contracts encounter more employment instability. They are more likely to change their employment status from one quarter to the next, and face a higher risk of non-employment. In Italy, approximately 17 percent of fixed-term workers change their labor status each quarter, either by moving into open-ended jobs (8 percent) or by becoming non-employed (9 percent). By contrast, the share of workers on open-ended jobs who change contract type or transition into non-employment is less than 2 percent, on a quarterly basis. Additionally, the short-term nature of fixed-term contracts often leads to workers staying employed under consecutive fixed-term contracts but in different firms (Gagliarducci, 2005; Güell and Petrongolo, 2007; Sanz, 2011; Gorjón et al., 2021).[1] In Italy, around 3 percent of fixed-term workers change employers each quarter, potentially experiencing brief periods of non-employment in between. This pattern further creates greater employment instability compared to workers on open-ended contracts, who switch employers much less frequently.

The degree of employment instability observed in dual labor markets can vary depending on individual worker characteristics. While the data reveal greater instability among fixed-term workers, *a priori* this may not be entirely attributable to the contract type itself. Instead, it could reflect individual characteristics, with those experiencing higher levels of instability – regardless of contract type – more frequently ending up in fixed-term positions. For instance, young workers are more likely to hold fixed-term contracts and, regardless of their contract type, change employers more often and face a higher risk of non-employment. Some of this variation may also stem from factors not captured by the available data, such as latent productivity or abilities. The key empirical challenge is determining whether the differing degree of employment instability associated with each contract type is driven by the contract itself or by the distinct characteristics of workers who select into each contract type.

The second consideration is that workers on fixed-term contracts face significantly higher income volatility. On average, the volatility of income growth over one year is twice as large for

[1] In Italy, the majority of fixed-term contracts last between one and six months, and less than 10 percent of them last for more than a year.

fixed-term as for open-ended workers.[2] This poses a direct link between employment instability and income volatility, emphasizing how trajectories in the labor market might be associated with varying magnitude and persistence of income fluctuations. For instance, consider a worker employed under a stable contract. She benefits from a high job retention probability, resulting in small and relatively stable income fluctuations over time. Conversely, a worker on a fixed-term contract may experience more pronounced income fluctuations. This worker might change contract type or employer from one period to the next, securing a stable job or another fixed-term position before the current contract expires. Both scenarios are likely associated with relatively large income innovations. Alternatively, there's a risk of experiencing significant income drops during periods of non-employment following contract terminations.

To quantify the relationship between labor market conditions and income volatility, this paper develops a tractable statistical framework that comprehensively accounts for discrete labor market statuses and continuous income dynamics. Individuals can be employed in open-ended or fixed-term jobs or be non-employed. The model tracks transitions across these statuses from one calendar quarter to the next. Depending on their labor market status or the transition they experience, workers are potentially subject to systematically different income volatility. The framework integrates both observable and latent individual characteristics, which jointly influence labor market transitions and the level of income realizations over time.

To track income dynamics, the model decomposes income observations into two components. The first component is predictable, based on observable individual demographic characteristics and a latent individual term measuring worker's ability or productivity. The second term is stochastic, encompassing both a persistent and a transitory component, according to a standard permanent-transitory representation of income dynamics. This stochastic term is the main driver of income changes over the career that cannot be attributed to individual characteristics.

The framework accounts for nonlinear, non-Gaussian income dynamics, allowing both the persistence and magnitude of the two stochastic income components to vary with labor market status and age, on a quarterly basis. Specifically, the model introduces systematic heterogeneity in income evolution based on both current and previous labor market statuses. This approach departs from conventional linear-Gaussian models – where all income innovations are drawn from the same distribution regardless of the worker's labor market condition, and are associate to the same persistence – by recognizing that individuals in different labor statuses may experience systematically different income dynamics. By allowing the income parameters to vary based not only on the current labor market status but also on the previous one, the framework further acknowledges that *changes* in labor market conditions typically involve large positive or negative income innovations, that can potentially wipe out the memory of past income realizations. This additional layer of flexibility in the model accommodates the presence of *unusual*

[2]This result refers to the standard deviation of log-income growth over one year, which in Italy is equal to 0.23 for open-ended workers and to 0.44 for fixed-term workers. The standard deviation is first computed at the individual level and then averaged in the sample. At this stage, it does not account for individual characteristics.

labor market events that can substantially influence income trajectories over time.

To track labor market transitions, the model estimates a Markovian process providing a reduced-form representation of how workers move across different labor statuses over the career. The transition probabilities are modeled as functions of the observable demographic characteristics and latent individual component, which are the same individual-specific factors influencing income levels at any given point in time.

By integrating data on individuals' labor market histories and income trajectories, the model enhances the identification of latent worker types, providing a comprehensive understanding of both individual and aggregate labor market dynamics. My method classifies workers along a continuum of types by simulating the individual-specific posterior distribution of the latent component, based on observed labor market transitions and income patterns over the career, while also accounting for demographic characteristics. Although the theoretical framework assumes a positive influence of the latent component on income realizations, it does not impose any predefined relationship between latent types and employment stability. Because in the model latent heterogeneity affects income volatility only through labor market trajectories, systematic differences in individual income volatility across latent types are also empirically determined.

To estimate the statistical model, I exploit the stochastic Expectation-Maximization (sEM) algorithm (Diebolt and Celeux, 1993), a simulated version of the original EM algorithm (Dempster et al., 1977). In the first step, the algorithm estimates the latent quantities through simulation, by drawing from their conditional posterior distribution, given the observable data and current parameter estimates. The simulation step of the estimation 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 persistent and transitory stochastic income components, which are not directly observed in the data. The second step of the algorithm updates the parameters and the procedure is iterated until convergence.

The analysis is based on an administrative longitudinal random sample compiled by the Italian National Social Security Institute (INPS), covering the period from January 1985 to December 2019. This dataset tracks labor market careers over time, capturing both periods of employment and periods covered by unemployment benefits. In addition to high-frequency income and contract details, the dataset includes demographic characteristics such as gender, region of residence and date of birth.

Three key findings emerge. First, certain groups of workers, based on their individual characteristics, are more likely to experience employment instability, regardless of their current contract type. For instance, while older, more productive workers have a 99 percent chance of retaining their open-ended job from one quarter to the next, this probability decreases to 92 percent for younger, less productive individuals, who face a higher likelihood of transitioning from stable contracts to non-employment or fixed-term positions.[3] Similarly, among workers in fixed-term positions, the risk of employment instability varies systematically across individuals. Less productive workers are more likely to transition back to non-employment, while more productive individuals in fixed-term positions have a better chance of smoothly securing stable contracts. Specifically, on average over the life cycle, male workers in the first decile of the latent component distribution have an 8.8 percent probability of moving from a fixed-term to a stable contract, and a 13 percent probability of separating from a fixed-term contract into non-employment. For those in the last decile of the distribution, these probabilities are 9.9 percent and 5.9 percent, respectively.

After accounting for individual characteristics, fixed-term employment remains more transient and carries a higher risk of non-employment, whereas open-ended employment is a highly absorbing status. Workers on open-ended contracts have a high probability of maintaining their contract type across consecutive calendar quarters. In contrast, fixed-term workers are more likely to return to non-employment or to change their contract type – transitioning into stable jobs. These contract-specific patterns hold true across workers with varying characteristics, though to different degrees.

Second, labor market status and transitions play a significant role in shaping the size and persistence of income innovations. Specifically, changes in labor status often coincide with large income shocks that disrupt previous income patterns, making past innovations less persistent. For example, the degree of income persistence drops from 0.97 for workers who retain open-ended jobs across consecutive periods to 0.03 for those transitioning from non-employment to an open-ended job. Additionally, systematic differences in income dynamics are observed even among workers who remain employed over consecutive periods – without changing their labor status – but under different contract types. Workers with open-ended contracts experience greater income persistence and smaller fluctuations over time compared to those with fixed-term contracts, leading to more predictable income paths. The standard deviation of the persistent stochastic log-income component is about 40 percent larger for fixed-term workers compared to open-ended workers, while the difference in the standard deviation of the transitory component between these two groups increases to 70 percent.

Third, the estimated latent individual component is a key driver of heterogeneity in the labor market. More productive workers in the last quintile of the latent component distribution rarely experience non-employment and spend about 93 percent of their career in open-ended jobs – the same figure being about 25 percentage points lower for less productive workers in the first quintile of the distribution. As a consequence, productive workers contribute minimally to the average non-employment rate. Fewer than 5 percent of the non-employed individuals belong to the top 20 percent of the latent component distribution. Similarly, only 8 percent of labor

[3] These values refer to male workers aged 25 and 59, in the first and last deciles of the latent component distribution.

market transitions involve these highly productive workers, who experience greater labor market stability and seldom change their labor market status. In terms of income performance, more productive workers not only earn higher lifetime average quarterly incomes but also experience less income volatility throughout their careers. In the aggregate, this heterogeneity in latent types accounts for about 45 percent of the cross-sectional income inequality observed in the population.

After accounting for both observable and latent selection into the labor market, income differences between contract types decrease substantially. In the data, workers in open-ended jobs earn, on average, about 40 percent more per quarter. However, when comparing individuals with similar observable demographic characteristics and latent component, this gap shrinks to 10 percent. This finding highlights that the income disparity between contract types that we observe in the data is largely driven by the fact that lower-earning individuals are more likely to select into fixed-term positions.

What are the economic consequences of employment instability and income volatility? Among the numerous potential applications of the estimated joint model of income and labor market dynamics, this paper focuses on its implications for individual precautionary savings, consumption volatility and welfare. Workers exposed to higher income uncertainty typically save more as a precautionary measure to smooth consumption over time. In this context, the labor market dimension introduces a new source of systematic heterogeneity in exposure to income volatility, which varies across workers and over time depending on individual characteristics. Consider, for example, a worker in a fixed-term position. When deciding how much to consume or save, this worker evaluates her specific probability of transitioning into a stable job next period, which would reduce future income uncertainty and diminish the need for precautionary savings. On the other hand, a higher probability of becoming non-employed would heighten the need for saving. Similarly, workers in open-ended jobs, depending on their individual characteristics, face varying degrees of employment instability, which in turn influences their wealth accumulation strategies.

To study how labor market trajectories systematically relate to consumption choices, the paper integrates a dual labor market setting into an otherwise standard life-cycle consumption model (Huggett, 1996; Kaplan and Violante, 2010). The framework incorporates the labor market dynamics detailed in the first part of the paper. Workers in the model are heterogeneous. Specifically, they differ by age, gender and by their latent type. These characteristics influence both the probabilities of transitioning between labor market statuses and income realizations at any given point in time.

I find that workers in fixed-term jobs accumulate more financial wealth to smooth consumption. At age 25, workers with fixed-term contracts save about 12 percent of their available resources from one period to the next, compared to 7 percent for those in stable jobs. This result holds for workers with varying latent components, though the magnitude of the difference varies slightly. Additionally, irrespective of contract type, saving rates tend to be lower for more productive workers and higher for those with a lower latent component, as they face higher employment instability – even when employed on open-ended contracts. These results are consistent with data from the Italian Survey of Household Income and Wealth, where households with the main earner in a fixed-term position report relatively higher saving rates.

Employment instability also shapes the consumption choices of workers in stable jobs, as they remain exposed to the risk of transitioning to fixed-term contracts or non-employment, depending on their individual characteristics. In an economy without fixed-term jobs and the associated non-employment risk, the saving rate of 25-year-old workers would drop, leading young workers to even consume part of their initial financial wealth. This counterfactual scenario is akin to the experience of public-sector employees, who hold open-ended jobs and do not encounter the risk of transitioning to fixed-term positions or non-employment.

Within this consumption framework, it is possible to further assess the welfare costs of employment instability and income volatility. To measure this, I compute the fraction of consumption that workers would be willing to forgo each period, to live in an economy without employment instability – specifically, one devoid of fixed-term jobs and the associated non-employment risk. On average, workers would be willing to give up 12 percent of their lifetime consumption to eliminate employment instability, living in an economy where only open-ended jobs exist and where they face income volatility specific to this contract type. The welfare cost rises to 18 percent of lifetime consumption for less productive workers who begin their careers with fixed-term jobs, while it falls to 2 percent for more productive workers who start with open-ended jobs. This reflects very large inequalities in employment instability and income volatility. Finally, to fully smooth income fluctuations in this counterfactual economy, where only open-ended jobs exist, workers would be willing to accept an additional 8 percent reduction in lifetime consumption.

Literature review This paper connects with three main strands of literature. First, it contributes to research on labor income dynamics, particularly studies that extend beyond the traditional linear-Gaussian framework. Geweke and Keane (2000) and Bonhomme and Robin (2010) challenge the typical normality assumption in income shock distributions, suggesting instead a normal mixture representation that better fits the data. More recently, Arellano et al. (2021) find that income innovations display both departures from normality and nonlinear persistence. Using U.S. administrative data, Guvenen et al. (2021) support these findings. With Norwegian data, Halvorsen et al. (2024) show that nonlinear mean reversion in income stems from hours worked, while hourly wage dynamics are close to linear. Non-normalities are instead influenced by both hours and earnings per unit of time.[4]

[4] Hoffmann and Malacrino (2019), using Italian data, and De Nardi et al. (2021), using data from the Netherlands, perform a similar decomposition between employment time and wages per unit of time. They focus on deviations from normality, finding that the negative skewness in earnings changes is mostly driven by changes in hours rather than changes in wages per unit of time. These studies do not examine the asymmetric mean reversion in earnings.

Other studies provide further insights into nonlinearities in income process and deviations from normality, through multivariate models incorporating wages, employment, and job mobility. Low et al. (2010) develop a life-cycle model that distinguishes two types of income risk: one stemming from labor market events like job loss and random job offers, and another from standard productivity shocks. Altonji et al. (2013) estimate a joint model of employment, job changes, wages, hours, and earnings, capturing the impact of shocks such as unemployment and job mobility on income dynamics. Similarly, Bagger et al. (2014) use a job search framework to explore the roles of human capital, labor market frictions, and firm-worker heterogeneity in shaping income trajectories.

This paper advances this literature by examining how contract duality and non-employment jointly influence income dynamics. Using a multivariate model of income volatility and labor market transitions, it offers a novel empirical explanation for the observed nonlinearities and non-normalities in income dynamics, linking them to labor market status and transitions within a dual contractual framework.[5]

Second, this paper connects to the literature estimating workers' latent types from observed labor market transitions. Hall and Kudlyak (2019) develop a model that classifies workers into five distinct types based on their labor market trajectories. Similarly, Gregory et al. (2021) assess worker heterogeneity in terms of labor market patterns, by identifying three latent types of individuals. More recently, Ahn et al. (2023) have expanded on this by segmenting individuals into three latent states using reported labor market history, revealing a dual labor market structure, in the US, complemented by a third segment related to home production. All these contributions share the common approach of using observed labor market careers to uncover latent worker types and consistently find similar results. Specifically, these papers reveal that individuals in the labor market are heterogeneous regarding employment stability. Some workers are almost always employed, while others cycle through jobs, search periods, and non-employment activities.

My paper contributes to this literature in three ways. First, it identifies latent types by incorporating both labor market transitions and income realizations throughout individuals' careers. Second, it extends the focus to a European context, using Italy as a case study, thereby broadening the geographical scope of the research. Third, my model differentiates between two sources of labor market instability: one associated with contract types, reflecting the dual labor market regulation that is typical in many European countries, and another one that is worker-specific, based on observable and latent characteristics. By examining the interaction between

[5]This study also contributes to research on heterogeneity in income levels and volatility. For example, Carroll and Samwick (1997) allow income process parameters to vary by occupation, education, and industry, while Browning et al. (2010) incorporate individual-level income structure heterogeneity. Life-cycle dimensions are added by Karahan and Ozkan (2013), and Guvenen (2009) and Guvenen and Smith (2014) explore heterogeneity in income levels and growth. This paper introduces life-cycle components and labor market-specific parameters, and assesses the impact of latent heterogeneity's on income dynamics. Altonji et al. (2023) provides a comprehensive review of this literature.

these two sources of heterogeneity, the paper offers a more nuanced understanding of labor market dynamics.

The third area of literature to which this paper contributes examines the impact of fixed-term contracts on individual outcomes. This study first expands on this literature by analyzing how labor market duality affects individual income volatility. Second, it clarifies the extent to which employment instability is driven by contract type versus individual characteristics. Third, it considers the implications of contractual duality for wealth accumulation. Section 2 offers a thorough review of this strand of the literature.

The paper is organized as follows. Section 2 provides an overview of the Italian labor market. Section 3 presents the model describing the income process and the theoretical framework to track labor market trajectories. Section 4 details the estimation strategy, followed by Section 5, which outlines the data used for analysis. In Section 6, I discuss the main empirical findings. Section 7 examines the impact of latent heterogeneity on labor market dynamics. Section 8 introduces the consumption model, exploring how employment instability and income volatility affect wealth accumulation choices. Section 9 offers concluding remarks.

2 The Italian dual labor market

The Italian labor market is characterized by a persistent contractual segmentation, with the coexistence of a majoritarian component of open-ended contracts, as well as a substantial share of fixed-term employment. Every calendar quarter, about 7 percent of the Italian employees working in the private sector are employed on a fixed-term job, with the share being above 15 percent among young workers. In addition, every quarter about 50 percent of new hires from non-employment involve a fixed-term contract.[6]

Fixed-term contracts refer to dependent employment relationships with an expiration date from the start. This generally allows employers to unilaterally discontinue the contractual agreement at expiration without incurring any costs (Bentolila et al., 2020; Boeri and Garibaldi, 2024).[7] On the opposite, open-ended contracts do not have a predetermined expiration date and are subject to severance payments in case the employer wants to dismiss the worker.

In countries with high costs associated with dismissing open-ended workers, fixed-term contracts serve as a flexible tool for firms to adjust employment levels. This contractual dualism results from reforms that have expanded the scope of fixed-term contracts for new hires by liberalizing their use while keeping largely unchanged the legislation applying to open-ended contracts (Boeri and Garibaldi, 2007; Boeri and Garibaldi, 2024). With the main objective

[6]The data refer to the period from 2008 to 2016, and to workers between the ages of 25 and 59. See Section 5 for more details about the data and the sample.

[7]Only in few countries – not including Italy – the employers not renewing a fixed-term contract at expiration have to pay severance costs. These remain lower than those associated to open-ended contracts.

of stimulating job creation, these interventions – the most significant of them 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 (Hoffmann et al., 2022). In recent years, the large spread of fixed-term 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 efforts, the Italian economy continues to exhibit significant contractual segmentation, which has broad implications for labor market outcomes.

The consequences of labor market duality When studying the role of fixed-term contracts, existing literature has extensively focused on a set of worker-level outcomes and, more broadly, on how the spread of fixed-term jobs affects the aggregate performance of the economy. In particular, fixed-term jobs tend to increase employment volatility over the business cycle (Bentolila and Saint-Paul, 1992; Boeri and Garibaldi, 2007; Costain et al., 2010), with the high turnover rate associated with these contracts potentially negatively impacting the average unemployment rate (Blanchard and Landier, 2002; Cahuc and Postel-Vinay, 2002). The literature also documents a negative association between average productivity and fixed-term jobs (Boeri and Garibaldi, 2007). While limiting the use of fixed-term contracts can increase aggregate productivity, it may also reduce total employment, leading to an overall decline in total output and welfare (Pijoan-Mas and Roldan-Blanco, 2024).

Focusing on individual-level outcomes, fixed-term 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). In terms of employment stability, a large strand of the literature evaluates the so-called *stepping stone* hypothesis, according to which fixed-term contracts could be a port of entry into stable open-ended jobs. Results remain controversial.[8] In terms of earnings performance, the existing literature points instead to systematic income gaps between open-ended and fixed-term employees, in most cases finding wage penalties associated to fixed-term jobs.[9]

These wage penalties align with systematic differences in human capital accumulation between open-ended and fixed-term workers. For instance, having a fixed-term contract is associated with lower levels of on-the-job training (Cabrales et al., 2017). Workers on fixed-term contracts are not only less likely to be employed by firms that provide training, but also, when they are in such firms, they have a lower probability of being selected to participate in firm-

[8] Most of the literature finds negative or weak results: Magnac (2000) for France; Gagliarducci (2005) and Hoffmann et al. (2022) 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.

[9] 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 fixed-term workers: Lass and Wooden (2019) and Albanese and Gallo (2020).

provided training activities (Albert et al., 2005). Furthermore, regardless of participation in job-training activities, Garcia-Louzao et al. (2022) document that young workers in fixed-term contracts experience lower returns to accumulated experience compared to their counterparts in open-ended contracts.

Lastly, fixed-term employment also influences wealth accumulation decisions, as workers in such contracts tend to save more for precautionary reasons (Barceló and Villanueva, 2016; Clark et al., 2022). This increased saving rate among fixed-term workers is primarily linked to the higher non-employment risk associated with these contract types.[10] In a broader context, Kuhn and Ploj (2020) abstract from contractual heterogeneity and show that job stability influences consumption and saving decisions, finding that individuals in stable jobs tend to be wealthier and save less for precautionary reasons, although this finding is model-dependent.[11]

This paper contributes to the literature on the impact of fixed-term contracts on individual-level outcomes by examining how labor market duality influences individual income volatility and, consequently, wealth accumulation choices. Furthermore, it clarifies the extent to which employment instability is attributable to different contract types as opposed to individual characteristics.

3 Modeling labor market and income dynamics

This section presents the theoretical framework for examining the relationship between labor market statuses and income volatility. The model incorporates systematic variation in income volatility by estimating an income process with parameters tailored to distinct labor market conditions. Additionally, it analyzes how workers transition across labor statuses over their careers, based on individual characteristics.

Integrating a labor market model into the estimation of the income process primarily serves to assess latent individual characteristics that may influence both workers' transitions across different labor statuses and their income levels, while accounting for observable factors. This is crucial because the same individual characteristics that shape income trajectories are also likely to affect labor market transitions. For example, younger workers are often employed in

[10]The literature provides evidence that saving behavior is influenced by non-employment risk. Lise (2013) examines savings behavior and earnings dynamics within a model incorporating on-the-job search and unemployment risk, demonstrating that saving behavior depends on the job destruction rate. Similarly, Michelacci and Ruffo (2015) analyze a life-cycle consumption-savings model that includes human capital investment and job loss events, finding that unemployment insurance is particularly valuable for young workers who have limited means to smooth consumption during unemployment spells. Furthermore, Larkin (2019) develop a life-cycle model that considers heterogeneity in job risk, highlighting a positive correlation between job risk and the liquidity of household portfolios.

[11]My paper adopts a distinct estimation approach that measures income volatility before examining its impact on consumption. It also differentiates between *stable* and *unstable* jobs using objective contractual characteristics, whereas Kuhn and Ploj (2020) rely on proxies like employer tenure or the number of employers over a worker's career.

fixed-term jobs *and* tend to earn lower incomes, reflecting a typical life-cycle pattern. The same selection issue may extend to latent characteristics that are not observable in the data. More productive workers might have greater success in securing stable contracts *and* higher incomes regardless of whether they hold fixed-term or open-ended contracts.

If these characteristics are unevenly distributed across labor statuses, failing to account for them could exaggerate the measured income volatility within certain labor market conditions – especially those with greater variability in individual characteristics – capturing cross-sectional heterogeneity rather than individual income volatility. To address this issue, the model incorporates both observable and latent characteristics that influence workers' selection into labor market statuses and their income dynamics. The theoretical framework includes standard observable demographic factors, supplemented by a latent individual component.

This latent term captures additional heterogeneity among workers beyond age, gender, and region of residence, influencing both income levels and the likelihood of transitioning between labor market statuses. The framework assumes that individuals with a higher unobserved component tend to earn greater average incomes, although the contribution of this component to income inequality remains an empirical question. Meanwhile, the influence of latent types on labor market transitions is estimated without constraints on the relevant coefficients, allowing the model to capture how workers' careers diverge based on these unobserved characteristics. Because latent heterogeneity affects income volatility only through labor market trajectories, differences in lifetime individual income volatility across types are also empirically determined.

In the model, latent types are estimated by jointly analyzing income realizations *and* labor market trajectories. This combined approach provides a measure of latent heterogeneity that captures pure individual-specific effects on income, independent of the performance in the labor market – such as time spent in non-employment. Distinguishing these effects is crucial for accurately assessing income volatility tied to different labor market conditions, after isolating pure workers' specific effects. Within this framework, the latent component can be interpreted as a measure of latent ability, or productivity.

3.1 The income process

This section introduces the income process, examining income volatility in relation to varying labor market conditions.

The model Let y_{it} denote the pre-tax log-income of individual i at time t, measured at a quarterly frequency. This income is modeled as a linear additive function of three components, assumed to be independent – except for the age effect, which also influences the distribution of the stochastic term, as will be discussed later. These components include a function (g) of observable demographic characteristics (x_{it}), the unobserved time-invariant worker-specific effect (α_i), and a time-varying stochastic element (η_{it}).

$$y_{it} = g(x_{it}) + \alpha_i + \eta_{it} \tag{1}$$

$$\eta_{it} = z_{it} + \varepsilon_{it} \tag{2}$$

$$z_{it} = c + \rho z_{it-1} + \sigma_v \tilde{v}_{it}, \quad \varepsilon_{it} = \sigma_\varepsilon \tilde{\varepsilon}_{it} \tag{3}$$

$$\tilde{v}_{it}, \tilde{\varepsilon}_{it} \sim F\,(0, 1)$$

The function of demographic characteristics comprises a cubic function of age and indicators for gender and macro-regions of residence.[12] Together with the latent individual effect, these characteristics represent the predictable fraction of income. In contrast, the stochastic term captures the unaccounted-for portion of income, serving as the main driver of income volatility over the career. This term is further divided into two elements, each governed by continuous probability distributions: a persistent factor (z_{it}) and a transitory term (ε_{it}), both of which are assumed to be mutually independent.

The persistent component z_{it} follows a first-order Markov process (Equation 3), capturing income innovations ($\tilde{v}_{it}$) that have lasting effects in subsequent calendar quarters. In contrast, the transitory component reflects short-term income fluctuations ($\tilde{\varepsilon}_{it}$) that dissipate after one period and are assumed to be independent over time. In this framework, the transitory component accounts for both genuine short-term income shocks and measurement errors. These persistent and transitory innovations are drawn from distributions (F) with zero mean and unit variance.

Nonlinear, non-Gaussian dynamics The model incorporates nonlinear, non-Gaussian dynamics, enabling the parameters governing the stochastic income term to vary according to workers' labor market conditions. Furthermore, it introduces systematic heterogeneity throughout the life-cycle. Accordingly, the two stochastic components are expressed as:

$$z_{it} = f_c(s_{it}, s_{it-1}) + f_\rho(s_{it}, s_{it-1}, age_{it}) z_{it-1} + f_{\sigma_v}(s_{it}, s_{it-1}, age_{it}) \tilde{v}_{it} \tag{4}$$

$$\varepsilon_{it} = f_{\sigma_\varepsilon}(s_{it}, s_{it-1}, age_{it}) \tilde{\varepsilon}_{it} \tag{5}$$

$$s_{it}, s_{it-1} \in \{OE, FT, N\}, \quad \tilde{v}_{it}, \tilde{\varepsilon}_{it} \sim F\,(0, 1)$$

Where f_{σ_v} and f_{σ_ε} are functions that influence the size – specifically, the variance – of the stochastic persistent and transitory innovations, respectively. These functions are defined in terms of current (s_{it}) and previous (s_{it-1}) labor market statuses – which can be open-ended (OE) or fixed-term (FT) employment, and non-employment (N) – as well as age. Similarly, the persistence parameter (f_ρ) and the constant term (f_c) of the first-order Markov process depend

[12] Specifically, North-East, North-West, Centre, and South, with South serving as the baseline region.

on the same factors.[13] The interaction of the current and previous labor status results in nine distinct possible labor market conditions. For instance, workers can remain employed under an open-ended contract across consecutive periods, change contract types, or transition in and out of non-employment.

In the model, nonlinearities arise from allowing the persistence of past income innovations to vary with workers' labor market conditions across periods. Non-normality results from each labor market condition having a unique constant term and persistence for the Markovian component. Within any given status or transition, income innovations follow a Gaussian distribution. Consequently, the overall distribution of the stochastic component is a mixture of nine normals – one for each labor market condition – with weighting probabilities determined by the share of workers in each category.

First, this approach recognizes that different labor market statuses can be systematically associated with varying degrees of income volatility, even for workers who maintain the same contract type or employment status between consecutive quarters. For instance, open-ended workers benefit from a high probability of contract retention, which likely guarantees relative income stability over time. In contrast, fixed-term workers often experience frequent job changes from one fixed-term occupation to another, which may include brief periods of non-employment during the quarter. Even with continued fixed-term employment, these transitions can contribute to increased income volatility.

Second, by allowing income parameters to vary based not only on the current labor market status but also on the previous one, the framework acknowledges that *unusual* labor market events, such as changes in employment conditions, can result in significant income shifts that may erase the memory of past income realizations and effectively *refresh* the income process. For example, the magnitude of income innovations experienced by a current open-ended worker may depend on whether the worker held an open-ended position in the previous period or was non-employed instead. In the latter case, the worker might experience substantial income gains from one period to the next, with the shift in labor status also contributing to lower income persistence – making past income realizations less relevant for predicting future dynamics.

Beyond capturing labor market dependencies, the framework also integrates systematic variations in income dynamics over the life cycle. This implies that, regardless of their labor market status, individuals at different career stages may experience distinct income innovations in terms of both magnitude and persistence. The life-cycle component itself could be of particular interest, revealing significant patterns in income dynamics throughout an individual's career. Furthermore, neglecting to consider this aspect may lead to the incorrect attribution of income volatility observed in specific age groups to particular labor statuses.[14]

[13]Since the stochastic term is computed after accounting for the age-level effect, the constant term of the persistent component is fixed throughout the life cycle, to simplify interpretation. It captures labor market-specific differences in the location of the distribution of the stochastic term.

[14]In a robustness exercise, I also include the latent component in the functional forms of the income process

Functional forms The model parametrizes the functional forms associated with the variances of the two stochastic components and the persistence term as quadratic functions of age. However, it does not impose any specific functional form related to the labor market, allowing for a flexible, non-parametric specification of the parameters and coefficients associated to different labor market conditions.

$$f_j(s_{it}, s_{it-1}, age_{it}) = \beta_{j0}(s_{it}, s_{it-1}) + \beta_{j1}(s_{it}, s_{it-1})age_{it} + \beta_{j2}(s_{it}, s_{it-1})age_{it}^2 \tag{6}$$

$$j \in \{\rho, \sigma_v, \sigma_\varepsilon\}, \quad s_{it}, s_{it-1} \in \{OE, FT, N\} \tag{7}$$

The model assumes that both income innovations and the cross-sectional distribution of latent types follow a normal distribution. Because income innovations are normally distributed within each labor market condition, the aggregate stochastic component – encompassing all labor market conditions – follows a Normal Mixture distribution, with weights corresponding to the proportion of individuals in each labor market situation.[15] To initialize the process, income innovations in the first period apply specifically to workers who remained in the same labor status as in the prior period.

$$\tilde{v}_{it} \overset{iid}{\sim} N(0,1), \quad \tilde{\varepsilon}_{it} \overset{iid}{\sim} N(0,1), \quad \alpha_i \overset{iid}{\sim} N\left(\mu_\alpha, \sigma_\alpha^2\right) \tag{8}$$

$$[z_{i1} \ \varepsilon_{i1}]' \sim N\left(\mu_1, \Sigma_{i1}\right) \tag{9}$$

3.2 Framework for labor market transitions

I next present the theoretical framework for modeling labor market trajectories. In the setup, each quarter t an individual i can be employed with an open-ended contract, a fixed-term contract, or be non-employed. The probability of each of these statuses at any given time evolves according to a Markov process, conditional on the previous period's labor market status (s_{it-1}) the latent individual permanent component (α_i), and the observable demographic characteristics (x_{it}). These individual-specific characteristics are the same influencing income realizations. Formally, these transition probabilities can be expressed as:

$$P(s_{it} \mid s_{it-1}, \alpha_i, x_{it}) = F\left(\phi(s_{it}, s_{it-1}),\ \delta(s_{it}, s_{it-1})\alpha_i,\ \gamma(s_{it}, s_{it-1})x_{it}\right) \tag{10}$$

where P denotes the probability measure, and F specifies this measure following a multinomial logistic regression model. Here, coefficients γ and δ capture the influence of the latent and observable characteristics on the log-odds of currently being in open-ended or fixed-term employment (s_{it}), relative to non-employment – which serves as the baseline status – conditional on the labor market status in the previous period (s_{it-1}). Within this framework, the

parameters. The results remain essentially unchanged, indicating that the primary effect of latent heterogeneity on income dynamics is mediated through its influence on labor market trajectories.

[15] As discussed in Appendix B, Normality is a convenient but not essential assumption for identification.

conditional probabilities of being in one of the three statuses are given by:

$$P(OE \mid s_{it-1}, \alpha_i, x_{it}) = \frac{\exp(\phi(OE, s_{it-1}) + \delta(OE, s_{it-1})\alpha_i + \gamma(OE, s_{it-1})x_{it})}{1 + \Sigma_{k \in \{OE,FT\}} \exp\left(\phi(k, s_{it-1}) + \delta(k, s_{it-1})\alpha_i + \gamma(k, s_{it-1})x_{it}\right)} \tag{11}$$

$$P(FT \mid s_{it-1}, \alpha_i, x_{it}) = \frac{\exp(\phi(FT, s_{it-1}) + \delta(FT, s_{it-1})\alpha_i + \gamma(FT, s_{it-1})x_{it})}{1 + \Sigma_{k \in \{OE,FT\}} \exp\left(\phi(k, s_{it-1}) + \delta(k, s_{it-1})\alpha_i + \gamma(k, s_{it-1})x_{it}\right)} \tag{12}$$

$$P(N \mid s_{it-1}, \alpha_i, x_{it}) = 1 - \Sigma_{k \in \{OE,FT\}} P(k \mid s_{it-1}, \alpha_i, x_{it}) \tag{13}$$

$$s_{it-1} \in \{OE, FT, N\}$$

In this formulation, the model evaluates the probabilities of each employment status – open-ended or fixed-term – with the remaining probability reflecting the likelihood of being non-employed. This setup ensures that the transition probabilities across all next-period labor statuses sum to one.

4 Estimation strategy

This section presents the estimation strategy, which relies on the Expectation-Maximization (EM) algorithm proposed by Dempster et al. (1977). This algorithm is a powerful empirical tool for obtaining maximum-likelihood estimates of parameters in models with latent variables. Starting with an initial guess for the parameters, it iterates between two main steps: the E-step and the M-step.

The E-step (Expectation) computes the conditional mean of the complete-data log-likelihood, as a function of latent variables and conditional on the observed data and current parameter estimates. This step effectively *fills in* missing latent information based on the observable data. The M-step (Maximization) solves the optimization problem and updates the parameters. Specifically, it addresses the optimization problem by maximizing the conditional expectation computed in the E-step, over the set of parameters. The updated parameter values are then used as initial estimates for the next E-step, and the algorithm continues iterating until convergence.

Since the conditional expectation in the E-step is analytically infeasible in my model, I use a simulated version of the algorithm. Specifically, I rely on the stochastic Expectation-Maximization (sEM) algorithm proposed by Diebolt and Celeux (1993), which replaces the standard E-step with a simulation procedure (sE-step). In this case, the latent quantities are estimated through simulation, by drawing from their posterior distribution, given the observable data and current parameter values. As in the standard version, the M-step updates the parameters, treating the simulation draws as if they were the observable values of the latent quantities.

Let Υ represent the set of observable data, including quarterly income realizations ($\mathbf{y}$), quarterly labor market status, and demographic characteristics (x). Define Ω as the set of latent variables, which comprises the individual-specific latent component (α) and two stochastic terms governing income dynamics (z and ε). Let $\mathbb{P}_{\Omega|\Upsilon}(\Omega \mid \Upsilon, \Theta)$ denote the posterior distribution of the latent variables, conditioned on the observable data and model parameters – where Θ represents the parameters of the income process and the labor market transition coefficients.

The algorithm starts with an initial guess $\hat{\Theta}^0$ for the parameters, and at each iteration i it alternates between the following two steps, until convergence:[16]

1. Stochastic E-step: draw Ω^i from $\mathbb{P}_{\Omega|\Upsilon}(\Omega \mid \Upsilon, \hat{\Theta}^{i-1})$
2. M-step: set $\hat{\Theta}^i = \arg\max_{\Theta} f\left(\Upsilon, \Omega^i \mid \Theta\right)$

where f is a generic estimation objective function. Specifically, in the M-step I use a linear regression model to update the demographic coefficients in the income equations, Maximum Likelihood Estimation (MLE) for updating the income process parameters, and a Multinomial Logit model for updating the labor market transition coefficients.

In the stochastic sE-step, I employ a two-stage estimation strategy. First, using the assumption of independence among the latent variables, I estimate the latent individual component. This is done using with the Metropolis-Hastings (MH) algorithm (Metropolis et al., 1953; Hastings, 1970). The algorithm draws from the posterior distribution of the latent individual component, conditional on observable data and model parameters. In the second stage, treating the estimated latent individual effect as given, I estimate the two stochastic income terms. This is done using the Durbin-Koopman simulation algorithm (Durbin and Koopman, 2012), which decomposes the stochastic income component into persistent and transitory parts, by sampling from their posterior distribution given the observable data, latent individual component, and model parameters. Details of the estimation strategy are provided in Appendix B, where I also discuss the identifying assumptions.

Convergence and model fit to the data The results are based on 50 iterations of the sEM algorithm, with 15 Metropolis-Hastings draws per individual in each iteration. Final parameter estimates are computed by averaging over the last I iterations of the algorithm, where $I = 15$. This averaging process yields stable estimates that approximate the Maximum Likelihood Estimator (MLE) as the algorithm converges.

Figure 20 and Figure 19 and Appendix G illustrate the convergence of the income process parameters and labor market transition coefficients, respectively. Appendix C discusses the model's performance in replicating aggregate moments in the data.

[16] In the sEM algorithm, convergence refers to reaching a stationary distribution for the parameters: as iterations progress, the parameter estimates stabilize, approaching a distribution that no longer exhibits significant changes with further iterations.

5 Data

The analysis is based on an administrative longitudinal random sample compiled by the Italian National Social Security Agency (INPS), covering the period from January 1985 to December 2019.[17] This dataset tracks labor market careers over time, capturing both employment periods and registered unemployment – specifically, periods in which individuals receive unemployment benefits.

Drawn from the universe of private-sector employees, the dataset provides extensive information on workers' characteristics and occupational details. It includes the activation and termination dates for each registered employment spell, contract type (open-ended, fixed-term, seasonal), part-time status, and job qualifications (white-collar, blue-collar, or apprentice). Additionally, it records total taxable labor earnings within the calendar year, firm identification numbers, and details on unemployment benefits and related income maintenance amounts from certain public policies. Demographic information, including gender, region of residence, and dates of birth and death, is available for all workers.

From administrative data to the working sample I restrict the sample to the period from January 2008 to December 2016 and convert it to a quarterly frequency.[18] When workers have multiple employment spells within the same quarter, I aggregate labor income from all sources and retain the contract-related information specific to the highest-paying contract or, in cases of equal income, the job with the longest duration during the quarter. This approach results in a quarterly panel dataset comprising only employment observations.

Unemployment is defined residually as periods of employment gaps in the dataset.[19] However, gaps in the dataset may also reflect workers engaged in education, retirement, or other contractual forms not covered by INPS, such as self-employment. To address these issues, I develop a procedure to construct a measure of non-employment that captures only those periods when individuals are likely to remain attached to the specific labor market being studied. This measure includes both the standard stock of unemployed individuals and marginally attached workers among the inactive.

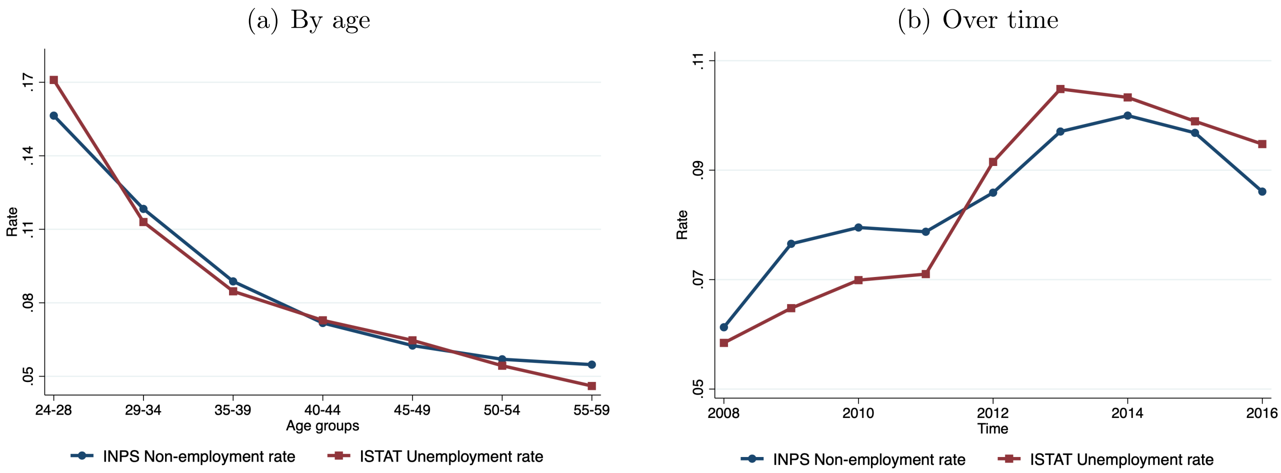
Specifically, I first restrict the sample to individuals aged 25 to 59, excluding those primarily involved in education or retirement. Next, I remove workers with long absences from the dataset to ensure that the remaining non-employment observations pertain to periods when individuals likely remained attached to the labor market. Details of this data adjustment procedure and

[17] The dataset is known as the *Longitudinal Sample INPS* (LoSaI). It includes approximately 6 percent of the Italian private workforce, encompassing workers in publicly owned companies but excluding pure public sector jobs and self-employed individuals.

[18] Data prior to 2005 lack precise contract activation and termination dates. Data from 2005 to 2007 and from 2017 to 2019 are used in the data adjustment procedure but are not included in the estimation sample (see Appendix A).

[19] This residual procedure arises from data limitations, as the sample includes information solely on income benefit recipients rather than actual (un)employment status. Benefits are limited in duration and depend on prior employment history, resulting in uneven distribution across the population.

Figure 1: Non-employment rate: INPS vs. ISTAT survey data



Note: The figure compares the non-employment measure derived from the administrative sample used in the analysis (INPS) with the official unemployment rate from Labor Force Survey data (ISTAT). Panel (a) presents the measures by age, while Panel (b) illustrates the trends over time.

sample selection are provided in Appendix A.

Income data The income measure utilized in the analysis corresponds to the sum of labor earnings and unemployment benefits on a quarterly basis. Labor earnings encompass all pre-tax income, both regular and irregular, received under registered contracts.

In the dataset, income is reported annually. This reporting structure implies that variations in income within the year not related to a change in contract – such as shifts in part-time status, job qualification, or contract type – are not tracked. Observed income fluctuations across different quarters of the same year may arise from variations in the number of working days, if some registered contracts do not span the entire calendar year. For non-employment periods associated with zero income, I assume these are covered by universal social assistance. To account for this, I implement a mechanism to establish a minimum income floor, with the underlying assumptions and detailed procedure provided in Appendix A.

Labor income observations are top-coded, with the cutoff set above the 99.5th percentile of the income distribution, as detailed by Hoffmann et al. (2022). Since the analysis does not focus on the income trajectories of top earners, no adjustments are made for the upper tail of the distribution. To adjust for inflation, nominal values are converted to 2015 euros using the Consumer Price Index (CPI).

Sample characteristics The adjustment procedure to construct the working sample yields an average non-employment rate of 8.4 percent, which closely aligns with the official unemployment rate from the Labor Force Survey (ISTAT), recorded at 8.1 percent for the same calendar period. Not only does the non-employment rate derived from administrative data match the official average, but it also closely corresponds across different age groups and over time (Figure 1).

Table 8 in Appendix G provides additional characteristics of the resulting working sample.

Table 1: Average labor market transition probabilities

t-1 \ t	Open-ended	Fixed-term	Non-employed
Open-ended	.986 (.987)	.003 (.003)	.010 (.011)
Fixed-term	.096 (.066)	.816 (.865)	.088 (.069)
Non-employed	.089 (.093)	.113 (.099)	.798 (.808)

Note: The table reports the estimated transition probabilities for male (female) workers. It considers 40 years old individuals residing in the Centre region, with a median latent ability component. Data are at a quarterly frequency.

Regarding labor market conditions, approximately 90 percent of employment quarters consist of open-ended contracts. This finding is generally consistent with data from the official Labor Force Survey, which indicates that about 11 percent of dependent employees aged 25 to 59 are employed in fixed-term positions on a quarterly basis.

6 Empirical results

This section presents the main empirical findings. It begins by describing worker's transition probabilities across various labor market statuses, followed by a discussion of the estimated parameters that characterize income volatility.

6.1 Labor market transitions

The labor market transition probabilities provide reduced-form evidence on how workers move between various labor market statuses based on their prior employment history and individual characteristics. These probabilities are derived from the estimation of the Markovian process described by Equation 11 to Equation 13. Two significant findings emerge.

Employment instability and contract types First, fixed-term employment is more transient and carries a greater risk of non-employment. This remains the case after accounting for individual factors. Among comparable workers, those with fixed-term contracts are more likely to change their labor market status from one quarter to the next, either by returning to non-employment or transitioning into more stable occupations. By contrast, open-ended contracts tend to provide greater job stability, with workers in such jobs showing a high likelihood of maintaining their employment status over consecutive quarters, regardless of their individual characteristics.

Table 1 presents quarterly transition probabilities for male and female workers (female probabilities in parentheses), highlighting the varying levels of employment stability associated with different contract types. The values reflect similar individuals in terms of gender, age (40 years old), latent component (median), and location (central region). On average, only 1 out of every 100 open-ended workers changes employment status from one quarter to the next, compared to approximately 20 out of 100 among those in fixed-term contracts. Specifically, the probability of retaining a fixed-term position over consecutive quarters ranges from 82 to 87 percent. This figure reflects both a higher likelihood of transitioning to stable employment (6.6 to 9.6 percent) and a comparable probability of changing contract type, moving from fixed-term jobs to non-employment. These estimated probabilities indicate that non-employment risk is 6 to 9 times higher for fixed-term workers than for similar individuals in open-ended occupations.

Employment instability and individual characteristics Second, employment instability is not evenly distributed across the population. Depending on individual characteristics, some workers experience little to no exposure to fixed-term contracts and non-employment, enjoying high job finding and retention rates in stable positions. On the contrary, others face employment instability even when employed with open-ended contracts. Figure 2 to Figure 4 depict this varying exposure to employment instability by showing estimated transition probabilities over the life cycle, broken down by percentiles of the latent component distribution. The figures focus specifically on male workers residing in the central region of the country.

The life-cycle significantly influences employment instability, as younger workers tend to change their labor status more frequently. They have a slightly higher likelihood of moving from non-employment into jobs but also experience lower retention rates, resulting in more frequent returns to non-employment – whether from fixed-term or open-ended contracts. For male workers with an average latent component, the probability of retaining an open-ended (fixed-term) job from one quarter to the next is 96.9 percent (77.9 percent) for 25-year-old individuals, compared to 99.5 percent (85.4 percent) for older workers, aged 55. Moreover, younger workers are more likely to transition from fixed-term to open-ended contracts than their similar older counterparts (11.3 percent versus 7.7 percent).

In addition to life-cycle factors, individual latent characteristics also shape employment instability. Workers with higher latent component tend to secure stable occupations faster and are more likely to retain their job, facing lower non-employment risk regardless of their contract type. They also have more chances of obtaining fixed-term jobs from non-employment, which for them often provide a smooth path to open-ended contracts. Specifically, the probability of transitioning from non-employment to an open-ended (fixed-term) job rises from 8.4 percent (8.3 percent) in the first decile of the latent ability cross-sectional distribution to 9.2 percent (15.2 percent) in the top decile. Once in fixed-term jobs, those with higher latent component are 9.9 percent likely to move to an open-ended job, compared to 8.8 percent for lower-ability workers. Additionally, separation into non-employment from an open-ended (fixed-term) job drops from 3.0 percent (12.6 percent) for lower-ability workers to 0.4 percent (6.0 percent) for those in the highest decile.[20]

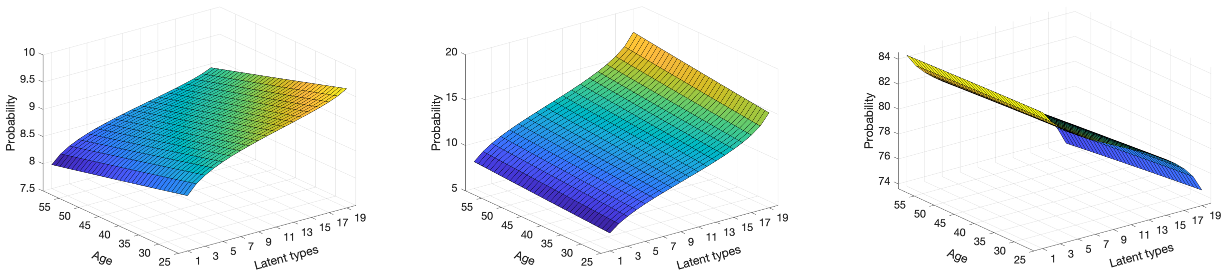
The figures also illustrate how the latent component interacts with the life-cycle dimension, exacerbating employment instability for younger workers. These individuals are more likely

[20]These transition probabilities refer to male workers in the central region of the country, and are weighted averages over the life-cycle. Figure 2 to Figure 4 report the values for the same workers, but over the life-cycle.

to be employed in fixed-term contracts and face a greater risk of non-employment, regardless of their contract type. This combination results in a challenging early-career phase characterized by lower retention rates and an increased likelihood of fixed-term employment, rendering younger, less-experienced workers particularly vulnerable to fluctuations in the labor market.

Figure 2: Labor market transition probabilities - From non-employment

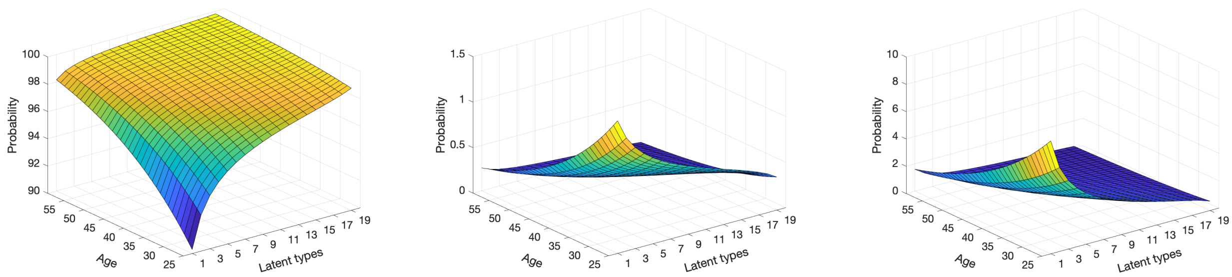
(a) To open-ended (b) To fixed-term (c) To non-employment



Note: The plots display the conditional probabilities of transitioning from non-employment to an open-ended occupation in Panel (a) and to a fixed-term occupation in Panel (b). Panel (c) shows the probability of remaining non-employed. Probabilities are reported across age and the latent component dimension (quintiles) for male workers residing in the Centre region. Data are at a quarterly frequency.

Figure 3: Labor market transition probabilities - From open-ended employment

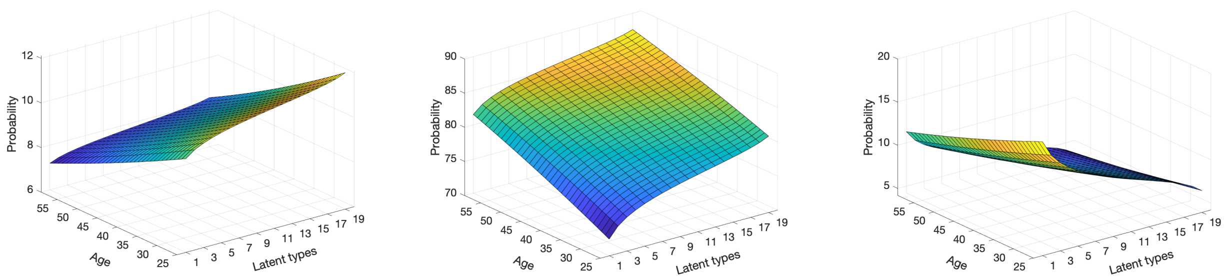
(a) To open-ended (b) To fixed-term (c) To non-employment



Note: The plots present the conditional probability of remaining employed with an open-ended contract in Panel (a), along with the probabilities of transitioning from a open-ended occupation to a fixed-term job in Panel (b), and to non-employment in Panel (c). Probabilities are reported across age and the latent component dimension (quintiles) for male workers residing in the Centre region. Data are at a quarterly frequency.

Figure 4: Labor market transition probabilities - From fixed-term employment

(a) To open-ended (b) To fixed-term (c) To non-employment



Note: The plots present the conditional probabilities of transitioning from a fixed-term occupation to an open-ended job in Panel (a) and the probability of remaining employed with a fixed-term, contract in Panel (b). Panel (c) illustrates the probability of transitioning from a fixed-term occupation to non-employment. Probabilities are reported across age and the latent component dimension (quintiles) for male workers residing in the Centre region. Data are at a quarterly frequency.

6.2 Income process estimates

I next discuss the empirical estimates of the income process, as outlined in Equation 1 to Equation 5.[21] The results emphasize the significant role that labor market statuses and transitions play in shaping the dispersion and persistence of income innovations. Changes in labor market status are associated to large income innovations, disrupting the continuity of past income patterns. In contrast, workers who remain in the same status across periods experience more stable income dynamics. For these individuals, income transmission over time is stronger, and both persistent and transitory income innovations are smaller in magnitude, being more concentrated around zero. Table 2 to Table 4 report the parameters by labor market conditions, averaged over age.

Contract type heterogeneity Consider at first workers who remain in the same labor status across consecutive periods. Depending on their contract type, they experience varying levels of income volatility. Specifically, workers who remain employed on open-ended contracts enjoy near-perfect income transmission over time, while those on fixed-term contracts face larger and less persistent income innovations. Income persistence decreases from 0.968 for open-ended workers to 0.951 for fixed-term workers. In a hypothetical scenario where workers never change their employment status, this difference implies that it would take approximately 18 years for the impact of a persistent shock to decline to 10 percent of its initial magnitude for open-ended workers, compared to about 12 years for fixed-term workers.

Additionally, workers who remain employed on fixed-term contracts experience larger income innovations. A one-standard-deviation persistent shock results in an immediate 9.6 percent change in the stochastic income component for open-ended workers, while for fixed-term workers it leads to a 16.9 percent change on impact. The difference in the average magnitude of transitory shocks is even more pronounced: a one-standard-deviation transitory innovation leads to a 3.4 percent change in the stochastic income for open-ended workers, compared to an 11.4 percent change for fixed-term workers.[22]

Both margins – the reduced income transmission and the higher dispersion of income innovations – diminish the ability of fixed-term workers to predict their future income dynamics, increasing the uncertainty they face. This heightened volatility may be attributed to their frequent transitions between different firms, often securing another fixed-term job before or shortly after their previous one ends. Additionally, fixed-term workers are more likely to spend some period of time in non-employment within a given quarter, as securing new fixed-term jobs can take time.

Individuals who do not change their labor status over consecutive quarters due to remaining non-employed face relatively greater income uncertainty. The persistence of the stochastic

[21] I focus in particular on the stochastic component. The coefficients associated with the demographic variables and the cross-sectional distribution of the latent component are reported in Figure 21 in Appendix G.

[22] These changes represent deviations from the expected value of the stochastic component, which depends on both the constant and the current value of the persistent term.

Table 2: Income process parameters: Persistence (ρ)

t-1 \ t	Open-ended	Fixed-term	Non-employed
Open-ended	.968	.493	.301
Fixed-term	.754	.951	.654
Non-employed	.029	.114	.723

Note: The table shows the persistence of persistent income innovations. Estimates are derived from the average of the final 30 percent of iterations in the stochastic EM algorithm. Values represent weighted averages by age. Data are at a quarterly frequency.

component drops to 0.723, while the standard deviation of persistent innovations increases to 0.530. In contrast, the standard deviation of the transitory component is more similar to that of workers who remain in fixed-term contracts over time, equaling 0.096.

Changes in labor market status Next, consider individuals who change their labor status over consecutive quarters. These labor market transitions drive significant income changes that disrupt the continuity of past income histories. When workers change labor market status, their income evolves non-linearly, resulting in substantial and *unusual* fluctuations that standard linear income models may struggle to capture. First, these transitions are associated with low income persistence, effectively *refreshing* the process and making new income realizations relatively independent of past history. When a non-employed individual finds a job, income persistence from one period to the other drops to values close to zero, ranging from 0.029 to 0.114. Such low values indicate that future realizations are largely disconnected from previous income history. Consider a non-employed worker who secures for instance an open-ended position: from that moment onward, her income evolution diverges significantly from the prior trajectory.

Second, changes in labor market status are associated to large income innovations in their size, reflecting both substantial income drops and gains. For instance, a one-standard-deviation persistent income shock resulting from job separations into non-employment typically leads to a 90 to 100 percent change in the stochastic income component upon impact, relative to the predictable value.

Overall, the estimated parameters of the income process indicate that income volatility rises and predictability declines when workers transition between labor statuses. As mentioned, this trend is also observable, albeit to a lesser extent, among workers who remain in fixed-term jobs or non-employment across consecutive periods. Combined with the labor market transition probabilities discussed in the previous section, these findings suggest that individuals with greater exposure to employment instability and fixed-term contracts – due to both observable and latent characteristics – experience increased income uncertainty. The next section integrates these two aspects – labor market trajectories and income dynamics – to quantify the overall income dispersion faced by workers with varying contract types and individual charac-

Table 3: Income process parameters: Std of persistent shocks (v)

t-1 \ t	Open-ended	Fixed-term	Non-employed
Open-ended	.096	.311	1.022
Fixed-term	.235	.169	.898
Non-employed	.462	.467	.530

Note: The table shows the standard deviation of persistent income innovations. Estimates are derived from the average of the final 30 percent of iterations in the stochastic EM algorithm. Values represent weighted averages by age. Data are at a quarterly frequency.

teristics.

The overall density In addition to dispersion and persistence, the sign of income innovations varies systematically with labor market conditions, influencing the density's location. The density's probability mass shifting towards positive or negative values impacts the likelihood of realized income exceeding or falling short of the predictable component based on individual characteristics.[23] Specifically, a negative stochastic component indicates that the realized income is below the typical level for workers with a certain set of characteristics, whereas a positive component indicates the opposite.

To illustrate these differences across labor market conditions, Figure 25 in Appendix G presents the long-run asymptotic density of the stochastic component – which is independent of the accumulated persistent innovations – specific to each labor condition.[24] These density functions indicate that workers who remain employed across consecutive periods – whether in open-ended or fixed-term jobs – generally face a stochastic income component centered around zero. This suggests that their actual income closely aligns with the expected value based on their demographic characteristics and latent ability – the deterministic component. A similar pattern is observed for workers transitioning from non-employment to employment. In contrast, individuals who remain non-employed tend to experience income realizations below the expected level derived from their individual characteristics, resulting in a negative stochastic component. Likewise, job separations leading to non-employment are associated with a negative stochastic income term.

Lastly, Figure 26 in Appendix G shows the unconditional density of the stochastic component, aggregated across labor market conditions. This overall distribution is a mixture of Normals, with weights based on the proportions of workers in each labor category. The figure demonstrates how the labor market dimension contributes to non-Gaussian income dynamics, producing a left-skewed density.

[23] In this context, income refers to the combined impact of predictable and stochastic components.

[24] The stochastic components, being the sum of two normally distributed terms – the persistent and the transitory – follow a normal distribution. The mean coincides with the asymptotic mean of the persistent component, while the variance is the sum of the asymptotic variance of the persistent component and the variance of the transitory income innovations. The estimates of the constant term used for the computation are reported in Table 9 in Appendix G.

Table 4: Income process parameters: Std of transitory shocks (ε)

t-1 \ t	Open-ended	Fixed-term	Non-employed
Open-ended	.034	.218	.893
Fixed-term	.136	.114	.932
Non-employed	.307	.381	.096

Note: The table shows the standard deviation of transitory income innovations. Estimates are derived from the average of the final 30 percent of iterations in the stochastic EM algorithm. Values represent weighted averages by age. Data are at a quarterly frequency.

Life-cycle dynamics How do income volatility vary over the life cycle? The model allows for potential heterogeneity in the income process parameters by imposing a quadratic structure in age, within each labor market condition. Below, I present the age-varying estimation results, focusing on workers who maintain employment with either open-ended or fixed-term contracts across consecutive periods (Figure 5). Detailed age-specific parameters for the other labor market conditions are provided in Figure 22 to Figure 24 in Appendix G.

In the early stages of a career, income innovations exhibit moderate persistence. At age 25, income transmission across consecutive periods is approximately 0.94, increasing to 0.99 by age 59. This significant life-cycle difference suggests that a persistent income shock would take around 9 years to reduce to 10 percent of its initial magnitude for younger workers. In contrast, for individuals in the later stages of their careers, this duration hypothetically extends to about 57 years.

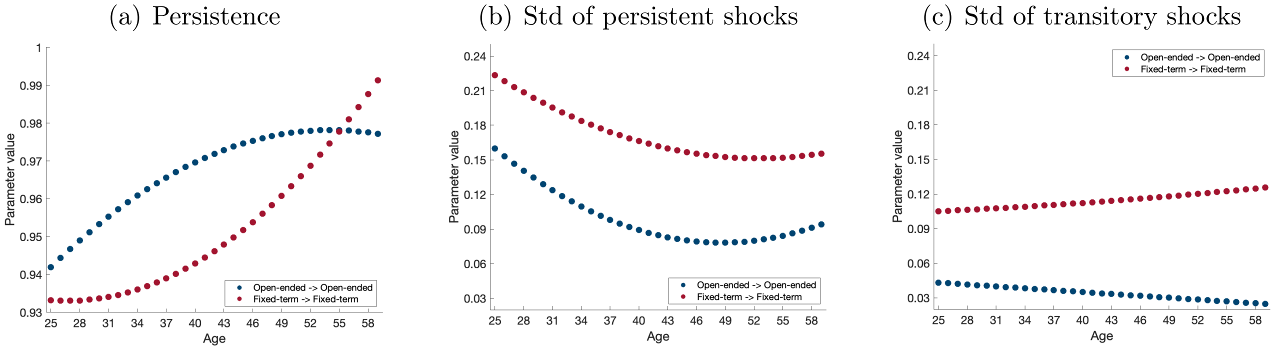
Younger workers also receive larger persistent income innovations in size. A one-standard-deviation persistent shock results in a 16 to 22 percent change on impact in the stochastic income component, relative to the predictable value. As individuals progress in their careers, these changes decrease to 10 to 16 percent, depending on their contract type. In contrast, the standard deviation of transitory shocks remains relatively stable over the life cycle, slightly increasing for those in open-ended occupations and slightly decreasing for those in fixed-term contracts.

Overall, the combination of low persistence and more dispersed innovations indicates that younger workers experience a higher degree of income volatility compared to their older counterparts. This outcome applies to both individuals in open-ended and fixed-term occupations and is likely due to the higher frequency of job changes among younger workers.

6.3 Integrating labor market and income dynamics

The previous two sections outlined how workers encounter different levels of employment instability and non-employment risk, as well as income volatility associated with various employment conditions. Based on their observable and latent characteristics, some workers quickly attain stable, long-term jobs, while others move between short-term occupations, often with periods of

Figure 5: Income process parameters over the life-cycle



Note: The figure presents estimates of the income process parameters over the life cycle, focusing on workers who remain employed in either open-ended or fixed-term jobs across consecutive quarters. Panel (a) shows the persistence, Panel (b) the standard deviation of the stochastic persistent component, and Panel (c) depicts the standard deviation of the transitory stochastic component. Data are at a quarterly frequency.

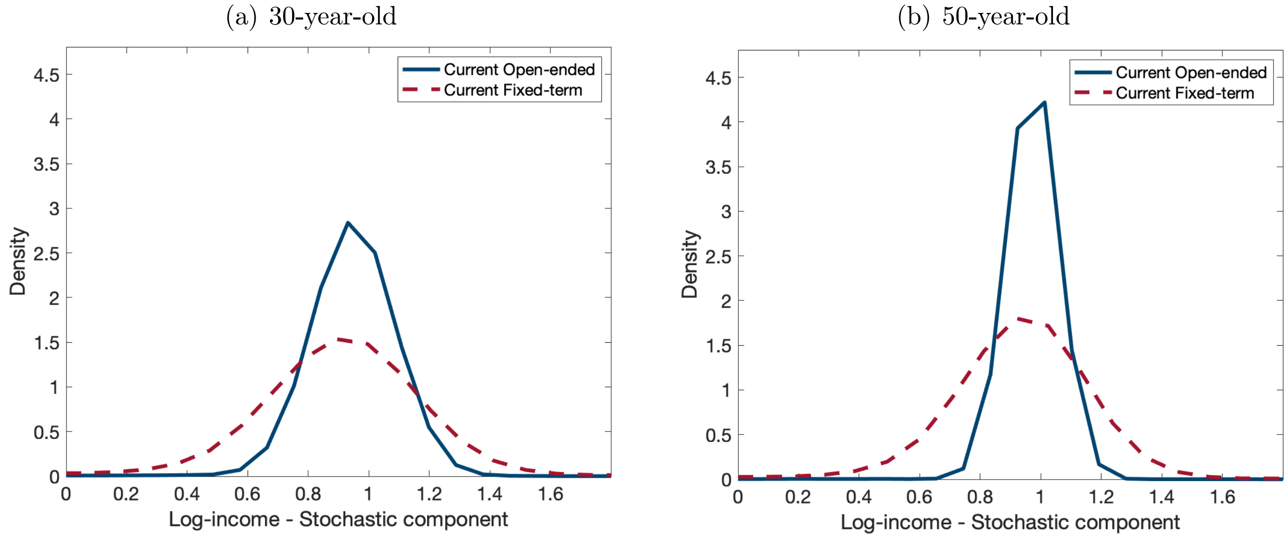
non-employment in between. Employment instability influences both the size and persistence of income innovations, with income process parameters varying across employment statuses and transitions. Specifically, income volatility is larger and predictability lower when workers transition between labor statuses, or when they remain in fixed-term jobs or non-employment across consecutive periods. This section combines these elements to offer a comprehensive view of the varying degrees of income predictability that different workers face over the course of their labor market careers.

Consider a worker seeking to forecast her income for the next period. Given her individual characteristics, she faces a probability distribution for transitioning between different labor market statuses in the upcoming calendar quarter. This labor market outcome will influence her income. For example, income may decline if she moves into non-employment, or it could stay relatively stable if she maintains her current job, with stability depending on whether she maintains an open-ended or fixed-term contract. According to Equation 1, part of the next-period income is predictable based on individual characteristics, so that the focus of the prediction exercise is on the stochastic component (η_{t_1}), defined as the sum of the persistent and transitory elements. Specifically, the distribution of the next-period stochastic income term follows this representation:

$$\mathbb{P}[\eta_{t_1}|s_{t_0}, z_{t_0}, \mathrm{a}_{t_0}, \alpha] = \sum_{s_{t_1} \in \{OE,FT,N\}} \Gamma(s_{t_1}|s_{t_0}, \mathrm{a}_{t_1}, \alpha) \left[z_{t_1}\mathbb{P}(z_{t_1}|z_{t_0}, s_{t_1}, s_{t_0}, \mathrm{a}_{t_1}) + \varepsilon_{t_1}\mathbb{P}(\varepsilon_{t_1}|s_{t_1}, s_{t_0}, \mathrm{a}_{t_1}) \right]$$

Where according to Equation 4 and Equation 5 the realizations of the persistent (z_{t_1}) and stochastic (ε_{t_1}) terms are drawn from distributions that depend on the worker's current and upcoming labor market status (s_{t_0}, s_{t_1}), next-period age (a_{t_1}) and, for the persistent term, the current value of the component (z_{t_0}). Each realization is weighted by the probability Γ that the worker will be in a particular labor market status during the next period, conditional on her

Figure 6: Density of next-period stochastic income by current contract type



Note: The figure presents the density of the next-period stochastic log-income component, assuming a current value of the persistent term equal to one. It is shown separately by current contract type. Panel (a) focuses on 30-year-old workers, while Panel (b) examines 50-year-old workers. The distributions are specific to male workers with an average latent ability and residing in the central region of the country. Results are based on simulated data at a quarterly frequency.

current status, next-period age, and latent ability (α).[25] This structure demonstrates how labor market instability shapes the predictability of future income. First, a higher probability of a status change increases uncertainty regarding the distribution from which the next stochastic components are drawn. Second, when status changes occur, evidence from the income process estimates suggests that the corresponding income realizations are drawn from distributions yielding larger innovations in size, with weaker correlations to prior income – which increases the degree of uncertainty.

I simulate this density of next period's stochastic income realizations for workers currently employed in either open-ended or fixed-term contracts. The simulation focuses on male workers residing in the central region of the country, assuming an average latent ability component and standardizing the current persistent stochastic component value to one – the current transitory component is kept to zero. The analysis is conducted separately for workers aged 30 and 50, and the resulting density functions are shown in Figure 6.

Similar workers experience greater income uncertainty when fixed-term than in open-ended employment, as evidenced by a more dispersed density of the next-period stochastic component. For workers aged 30, the standard deviation of next-period log-income realizations is 1.9 times higher for those currently in fixed-term contract – increasing to 2.6 times higher by age 50. Specifically, 30-year-old fixed-term workers have a 50 percent probability of experiencing at least a 10 percent reduction in their next period's stochastic income, along with a 5 percent chance of their income falling below 10 percent of its current value. In contrast, these probabilities for open-ended workers drop to 37 percent and 1 percent, respectively. Fixed-term workers also

[25] For simplicity, this framework does not include additional demographic factors like gender or geography, which are held constant.

have a relatively higher likelihood of experiencing income improvements, often resulting from transitions to stable occupations or from securing another but longer-lasting fixed-term job in the subsequent calendar quarter.[26]

Besides the role of contract types, individual characteristics also play a significant role. The simulated data reveal that older workers experience less uncertainty in their income, with future realizations more closely clustered around the current value. This increased income stability – primarily observed among older workers in open-ended jobs – is attributed to both a higher likelihood of contract retention and a decrease in income volatility within labor statuses over the life cycle.

While these findings relate to workers with an average latent ability, Figure 27 and Figure 28 in Appendix G further differentiate between low and high latent types. The figures reveal that income uncertainty is slightly higher for less productive workers, who are more exposed to employment instability.[27]

In summary, the joint distribution of labor market and income dynamics illustrates varying degrees of income predictability based on labor market conditions and individual worker characteristics. Fixed-term workers, along with those more exposed to employment instability – such as younger and less productive individuals – experience greater income volatility due to higher transition probabilities across different statuses and fluctuating income levels. Assessing these varying degrees of uncertainty is essential for understanding economic choices of different workers and households, across various employment statuses.

7 Latent heterogeneity

This chapter provides a comprehensive analysis of how latent heterogeneity influences individual lifetime career trajectories as well as overall labor market outcomes.

The model assumes a positive relationship between latent types and income levels, with the corresponding income equation's coefficient normalized to one. This setup implies that individuals with a larger unobserved component tend to earn higher average incomes, though the contribution of this component to overall income inequality remains an empirical question. Essentially, the model estimates the dispersion of latent types within the sample freely, without constraints. Conversely, the influence of latent types on labor market transitions is estimated without restrictions on the corresponding coefficients, allowing the model to empirically capture how worker careers diverge based on latent characteristics. Since the impact of latent types on

[26]Even after one year, the difference in income dispersion between currently fixed-term and open-ended workers remains substantial. For workers aged 30, the standard deviation of log-income realizations one year later is 1.7 times higher for those currently in fixed-term employment (2.3 times higher by age 50).

[27]Unlike the age factor, the impact of latent types on individual income volatility is purely indirect, mediated through their labor market trajectories.

Table 5: Average time within labor status over lifetime career (%)

Labor status \ Latent types	Q_1	Q_2	Q_3	Q_4	Q_5
Non-employment	22.2	12.4	8.4	5.5	2.8
Open-ended employment	68.1	79.6	84.9	88.9	93.3
Fixed-term employment	9.6	7.9	6.7	5.5	3.9

Note: The table reports the fraction of time – at a quarterly frequency – spent within each labor market status over a 35-year career. Fractions are computed at the individual level and then averaged within quintiles of the latent ability distribution. Results are based on simulated data.

income volatility occurs only through labor market trajectories, differences in lifetime income volatility across latent types are likewise determined empirically by the data.

The analysis begins by examining heterogeneity in career paths, followed by a detailed investigation of income inequality. This assessment is based on a simulated economy of 300,000 individuals, with entry conditions replicating the observed distribution in the data, tailored to individual characteristics. Initial stochastic income realizations are drawn from distributions specific to individuals maintaining the same labor status across consecutive periods. Workers enter the labor market at age 25 and retire at age 60, offering 35 years of observed career histories.

7.1 Latent types and career trajectories

The latent individual component is a key predictor of labor market career trajectories. The transition probabilities presented in Section 6 indicate that more productive workers have a higher likelihood of securing and retaining stable jobs from one quarter to the next. In contrast, less productive workers face increased exposure to labor market duality and non-employment risk. How do these differences in transition probabilities shape lifetime careers?

To address this question, I compute the average fraction of time that individuals of various latent types spend in each of the three labor market statuses over their careers, measured at a quarterly frequency. For ease of interpretation, workers are grouped into quintiles based on the latent ability sample distribution. Table 5 presents the results.

The fraction of time spent in non-employment across an entire career varies significantly, ranging from about 3 percent for the most productive workers (top quintile of the latent ability distribution) to 22 percent for the least productive workers (bottom quintile). Over a 35-year career, this equates to approximately one year in non-employment for more productive workers, compared to over seven years for less productive individuals. Regarding employment, more productive workers spend over 90 percent of their time in open-ended jobs, while this share decreases by roughly 25 percentage points for less productive individuals. Similarly, the time spent in fixed-term jobs decreases from 10 percent for less productive workers to 4 percent for those with a higher latent component.

Contribution to labor market aggregates This latent heterogeneity in individual career trajectories directly impacts aggregate labor market outcomes. More productive workers contribute minimally to the overall non-employment rate. On average, only 5 percent of the non-employed at any given time are from the top 20 percent of the latent productivity distribution. In contrast, individuals in the lowest productivity quintile are over-represented, making up over 40 percent of the non-employed stock. Low-productivity workers are also disproportionately represented in fixed-term jobs, with nearly half of all fixed-term employees at any given time coming from the bottom 40 percent of the latent productivity distribution.

Different segments of the population also contribute asymmetrically to aggregate labor market flows. Approximately 35 percent of quarterly flows across various labor market statuses are attributed to workers in the lowest quintile of the latent ability component. By contrast, less than 8 percent of observed labor market transitions are associated with the most productive individuals, who tend to experience greater labor market stability and seldom change employment status. Low-productivity workers account for a relatively large proportion of all transition types, including both job separations and job-finding events, reflecting their higher exposure to labor market instability as they frequently cycle in and out of non-employment.

Figure 30 in Appendix G illustrates these aggregate outcomes, displaying the share of workers across different quintiles of the latent ability distribution, segmented by labor market statuses and various transition types.

7.2 Latent types and income outcomes

The latent component not only affects employment stability but also serves as a key predictor of income performance. It has a direct and positive influence on income levels through a permanent individual income factor, while indirectly impacting income volatility (and levels) by shaping labor market trajectories.

By design, individuals with a larger unobserved component, ceteris paribus, achieve higher average incomes. However, the extent to which this unobserved characteristic contributes to income inequality is determined empirically. Results show that the average quarterly income is approximately five times higher for more productive workers than that for those at the bottom of the latent ability distribution (Panel (a) of Figure 7). Workers in the first decile earn around €1,300 per quarter on average, while those in the top decile earn up to €9,200 per period. This significant disparity arises from both the direct effect of latent productivity on income and the greater employment stability of highly productive individuals, who, for instance, spend less time in non-employment.

In terms of individual income volatility, the influence of latent types is determined entirely through the empirical analysis. Findings indicate that more productive workers experience less income volatility throughout their careers. Specifically, the lifetime standard deviation of log-income is 2.2 times lower for highly productive individuals compared to their less productive counterparts (Panel (b) of Figure 7). Given that income growth over the life cycle is assumed to be consistent across latent types, differences in income volatility stem from short-term fluctuations around the income growth trend, rather than from varying life-cycle income growth rates. These deviations arise from labor market trajectories, with lower-productivity individuals who face more employment instability and spend more time in labor statuses associated with higher income volatility, such as fixed-term employment.

Cross-sectional inequality Individual heterogeneity in income dynamics contributes to cross-sectional inequality. To assess this effect, I simulate a counterfactual economy devoid of heterogeneity in latent characteristics and compare the age-specific cross-sectional log-income variance to that of the baseline economy. Furthermore, to evaluate the impact of latent types on income inequality relative to the other potential drivers of income dispersion, I conduct the same counterfactual analysis across various economies, each with a distinct source of heterogeneity deactivated – these sources include stochastic income innovations, observable demographic characteristics, and employment instability.

Panel (b) of Figure 7 shows the results. Each section of the bars illustrates the contribution of the examined mechanism as the percentage reductions in cross-sectional income variance relative to the baseline economy. Since the model is not linear, these contributions do not sum to one. The results indicate that transitory shocks are a minor source of income inequality. Without them, income dispersion would decrease by approximately 0.5 percent. In contrast, persistent income innovations have a substantial impact. In an economy without persistent shocks, the cross-sectional variance declines by nearly 70 percent, with this reduction being more pronounced in the early stages of a career. This significant contribution also reflects the indirect effect of heterogeneity in labor market stability – and thus the indirect effect of latent types on income – since, in the model, employment instability influences income realizations through its effect on the stochastic component.

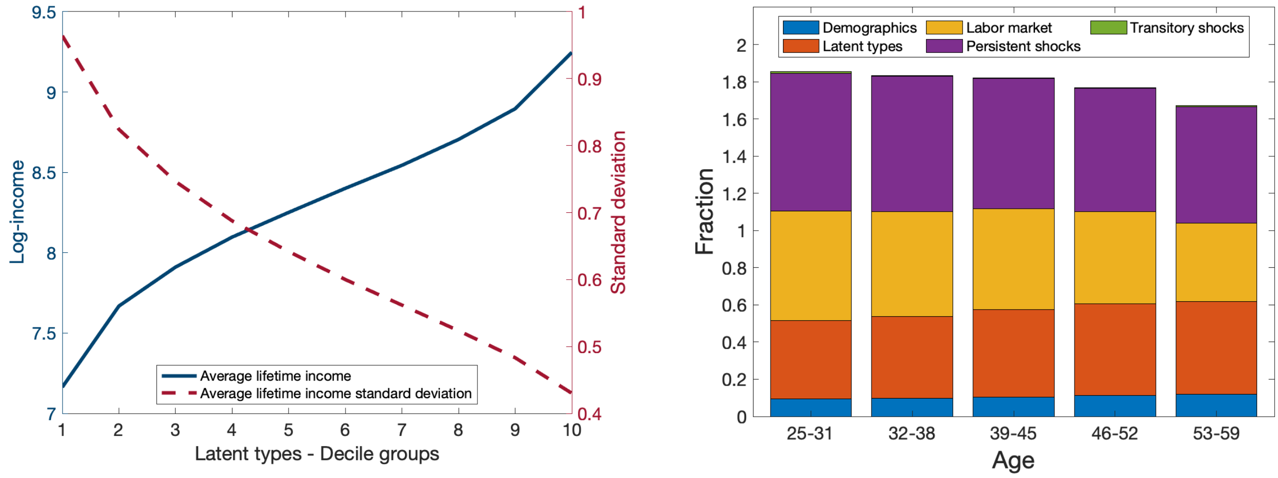
Individual characteristics also play a substantial role in income inequality. Both demographic and latent factors influence inequality directly by affecting income levels and indirectly by guiding selection into various labor market statuses, each associated with different magnitudes of income fluctuations. In an economy without dispersion in observable demographic characteristics, income inequality would decline by approximately 8.5 percent. In contrast, in a counterfactual economy devoid of heterogeneity in latent characteristics, cross-sectional income variance would be 46 percent lower. These numbers highlight the significant impact of latent types on income inequality, which is about five times larger compared to the effects of observable individual characteristics.[28]

Finally, I examine the impact of employment instability – and, more broadly, the existence of varied labor statuses – on income inequality by comparing the baseline economy with one

[28] To evaluate the impact of individual characteristics, I simulate different economies in which only male workers in the Centre region are present or where the latent ability component is held at its average value.

Figure 7: Individual income dynamics and cross-sectional inequality

(a) Individual income average and volatility (b) Relative contributions to income variance



Note: Panel (a) of the figure shows the average lifetime log-income and the lifetime standard deviation of individual log-income by deciles of the latent ability distribution. Both measures are calculated at the individual level and then averaged within latent types. Panel (b) displays the relative contribution of each examined mechanism to cross-sectional income inequality, expressed as percentage reductions in cross-sectional variance compared to the baseline economy. Results are based on simulated data at a quarterly frequency.

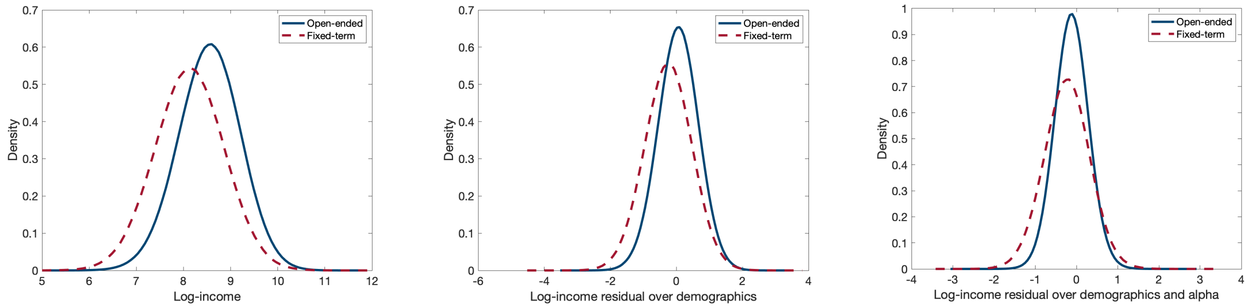
in which all workers hold open-ended jobs over the career. In this scenario, labor market heterogeneity is eliminated, leading all workers to experience the same distribution of income innovations. Consequently, the effect of individual characteristics is diminished, as they no longer drive heterogeneity in labor market trajectories, although their direct impact on income remains active. I find that without labor market heterogeneity, cross-sectional variance declines by nearly 52 percent, with this reduction being more pronounced in the early stages of careers.

Difference in income levels In the context of understanding cross-sectional income inequality, a key question in the empirical literature on fixed-term contracts is whether workers on these short-term agreements are systematically paid more or less than their counterparts on open-ended contracts. On one hand, fixed-term workers often have less bargaining power, which can lead to lower incomes (Bentolila and Dolado, 1994). In this context, most empirical studies indicate that fixed-term workers earn less (Bentolila and Dolado, 1994; Booth et al., 2002; Brown and Sessions, 2005; Mertens et al., 2007; Bosio, 2014; Kahn, 2016; Bonhomme and Hospido, 2017). On the other hand, in a frictionless environment, fixed-term workers should be compensated for the reduced employment stability associated with this contract type. In this context, recent empirical evidence indeed suggests the existence of potential income premiums for fixed-term workers (Lass and Wooden, 2019; Albanese and Gallo, 2020). This sequence of results highlights that approximately 75 percent of the observed log-income differences between open-ended and fixed-term workers can be attributed to the selection of lower-paid workers into fixed-term occupations.

The main empirical challenge in understanding income differences across contract types is that different workers may systematically select into different contracts. As highlighted in

Figure 8: Density of quarterly income by contract type

(a) Actual data (b) Demographics residual (c) Demog. and latent residual



Note: The figure illustrates the density of quarterly log-income. Panel (a) presents the density of raw log-income. Panel (b) shows the density of the residual log-income after accounting for demographic characteristics. Panel (c) displays the density of the residual log-income after accounting for both demographic characteristics and the latent ability effect. All results are based on simulated data.

previous sections of this paper, young and less productive workers, for instance, have a higher probability of being employed in fixed-term jobs and, simultaneously, earn less, regardless of the contract type. My theoretical framework addresses the endogeneity issue and offers new insights into income differentials.

Figure 8 presents the cross-sectional distribution of quarterly log-income by contract type, based on simulated data. Panel (a) illustrates actual income, revealing that workers in open-ended jobs earn, on average, about 40 percent more than their fixed-term counterparts. Panel (b) incorporates the margin of endogenous selection driven by observable demographic characteristics, showing the distribution of income residuals. Here, the average income difference between the two contract types declines to 30 percent. Finally, Panel (c) accounts for income portions attributable to workers' latent characteristics rather than the contract type itself, resulting in an average income difference that drops to 11 percent.

8 Wealth accumulation and welfare implications

What are the economic consequences of employment instability and income volatility on consumption and wealth accumulation? Workers facing greater income uncertainty often save more as a precaution to stabilize consumption. This chapter examines wealth accumulation choices within a dual labor market, where workers can hold different contract types and vary in their exposure to employment instability.

Depending on their current labor status and individual characteristics, workers experience varying levels of employment instability, which closely links to income volatility. For instance, consider workers on fixed-term contracts: they adjust their savings based on their likelihood of securing stable employment or facing non-employment in the next period. A higher probability of obtaining a stable job reduces future income uncertainty, diminishing the need for precautionary savings, whereas a higher probability of becoming non-employed increases the incentive to save. Moreover, employment instability – and consequently income volatility – can differ significantly among workers regardless of their labor status. A highly productive worker on a fixed-term contract may have a strong likelihood of moving into stable employment, whereas a younger, less productive worker in an open-ended job faces a relatively higher chance of transitioning to non-employment or to a fixed-term contract.

This chapter is structured as follows: the first section presents empirical evidence on consumption and saving choices from survey data, the second introduces a theoretical quantitative life-cycle model, and the final sections explore the model's implications for wealth accumulation and welfare.

8.1 Data and empirical evidence

The labor market administrative data used to estimate the income process and labor market transition probabilities lack information on consumption and wealth. To gain empirical insights into wealth accumulation decisions across different labor market participants, I instead rely on survey data – specifically, the Italian Survey of Household Income and Wealth (SHIW), a representative sample of the Italian population constructed by the Bank of Italy.

The data The dataset is biennial and provides detailed insights into demographic variables, income, consumption, wealth, and the labor status of each household member. Consumption and wealth data are aggregated at the household level. The survey features a panel component, with about 50 percent of the sample consisting of households interviewed in previous waves and the remaining 50 percent representing new interviews each year. Each wave includes approximately 8,000 households, and I utilize data spanning six waves from 2004 to 2020.

To construct the working sample, I classify each household based on the labor status of its main earner. I limit the sample to households where the main earner is either an open-ended or a fixed-term employee or unemployed. Additionally, I exclude households with non-positive financial wealth or debts.[29] Finally, I remove the top 95 percent of households in terms of financial wealth and the top 1 percent in total income, as the observed income distribution is less skewed compared to that of financial wealth.

Preliminary empirical evidence Before exploring the consumption model, I first examine the wealth accumulation behavior reflected in empirical data, using this working sample. Due to data limitations, this analysis serves primarily as a benchmark for assessing and validating the model's outcomes and predictions.[30]

[29]Most of the households with zero financial wealth do not have bank accounts, making it impossible to determine their wealth status from the data.

[30]The main limitations are as follows: first, wealth information is household-specific, while labor market status is individual-specific. Second, individuals typically leave their family home and establish new households only when they have a certain degree of employment and income stability, resulting in relatively few households in the sample where the primary income earner is a fixed-term worker, particularly among the youngest. Third,

Specifically, I measure systematic differences in wealth accumulation based on the labor market status of the primary household earner. I employ a linear regression model where the dependent variable is the saving rate, defined as the ratio of the change in financial wealth between two periods to the total available financial resources at the current time. Financial wealth in the data is computed at the end of each period, meaning that the saving rate reflects the resources households intend to carry into the next period relative to their current total resources – which include the financial wealth at the beginning of the year and the realized labor income during the period. The regression includes explanatory variables such as a dummy indicator for the labor status (stable jobs versus fixed-term employment or non-employment), a quadratic function of age, indicators for education groups, gender, and indicators for total wealth quintiles.[31]

I find that households in fixed-term positions tend to increase their financial wealth relatively more compared to households in stable jobs. Specifically, the saving rate is about 11.5 percentage points higher for households in fixed-term positions compared to those in stable jobs.[32]

This result is compatible with recent empirical findings in the literature. Clark et al. (2022) focus on the Italian case and evaluate differences in saving rates using the 2012 *Fornero reform* as a natural experiment, in a difference-in-differences framework. They find that greater job insecurity reduces consumption and increases savings. Similarly, Barceló and Villanueva (2016) find that older workers covered by fixed-term contracts in Spain accumulate more financial wealth.

8.2 The model

I next introduce the quantitative life-cycle framework. Specifically, to examine how labor market trajectories shape consumption choices, this section incorporates a dual labor market structure into an otherwise standard life-cycle consumption model (Huggett, 1996). The framework draws on labor market and income dynamics estimates introduced earlier in the paper. Workers in this model are heterogeneous, differing in age, gender, and latent types. These characteristics influence both income realizations at each point in time and the probabilities of transitioning across labor market statuses.

Model's framework The model is a partial-equilibrium, life-cycle, incomplete-markets framework operating without aggregate uncertainty. Individuals enter the labor market as active

sample selection significantly restricts the sample size. Combined with the second point, this limitation renders life-cycle analysis less meaningful due to the scarcity of observations.

[31] Including total wealth indicators allows for a comparison of financial wealth behavior among workers with similar overall asset holdings, primarily accounting for home ownership. However, omitting these wealth indicators does not significantly alter the results.

[32] The confidence interval ranges from -0.07 to 23.08. Omitting the total wealth indicator leads to a 10.1 percentage difference, with confidence in interval ranging from -.50 to 20.79.

workers – including the possibility of non-employment – and retire at age J^{ret}. By age J, they die with certainty. An individual of age j faces a probability of death $(1 - \phi_j)$ by the end of each period, where ϕ_j is the age-specific survival probability. Each period, a new cohort of agents is born, and the population grows at a constant rate n.

During their active working years, individuals can be employed in an open-ended or fixed-term position, or remain non-employed. The transition from one labor status today (s) to another status next period (s') follows a Markovian process with transition probabilities Γ, which depend on individual characteristics. Workers in the model differ by age (j), gender (g), and latent individual component (α).

Income during the working phase evolves exogenously through a deterministic component linked to individual characteristics, and a stochastic component that includes both persistent (z) and transitory (ε) shocks. The distribution of these stochastic elements varies by age and labor market condition, specifically by the current and previous labor status. Upon retirement, individuals receive a fixed pension from the government, determined based on their individual characteristics.

Agents are risk-averse, maximizing expected lifetime utility. Preferences are time-separable with a constant discount factor (β), and intra-period utility follows a Constant Relative Risk Aversion representation. Asset markets are incomplete: individuals can potentially borrow up to an exogenous limit $(\underline{a})$ and invest solely in a risk-free asset offering a fixed rate of return r.

There is no market to insure against mortality risk. As a result, each period sees a positive flow of accidental bequests, representing wealth accumulated by individuals who pass away. This wealth does not transfer to other individuals or to the government and is effectively removed from the economy.

The household's problem At the start of each period, agents observe their available resources in terms of cash-on-hand (χ), which comprises accumulated assets plus any earned interest, along with realized labor income. They are also aware of their current labor status, the realized persistent stochastic component of income, age, gender, and latent type. Based on this information from the state vector, they decide how to allocate their resources between consumption (c) and savings – risk-free asset holdings for the next period (a'). Consumption directly influences the agent's immediate utility, while savings contribute to the resources available in future periods.

The current state vector influences the agent's decisions by shaping the expected outcomes related to future utility. Specifically, each agent encounters a probability distribution over the next-period labor market status that varies according to individual characteristics and current employment condition. These labor market outcomes, combined with the age component, subsequently affect the distribution of next-period stochastic income realizations.

Accordingly, the optimal decision rule for consumption and savings is derived from solving the dynamic programming problem outlined below – where for clarity, I will use subscripts to denote individual characteristics. During their working years ($j < J^{\text{ret}}$), agents face the following recursive problem:

$$V^W_{j,g,\alpha}(\chi, z, s) = \max_{a'} \left\{ u(c) + \phi_j \beta \Sigma_{s'} \Gamma_{j,g,\alpha}(s'|s) \int V^W_{j',g,\alpha}(\chi', z', s') \; \mathbb{P}_{j'}(z'|z, s, s') \; \mathbb{P}_{j'}(\varepsilon'|s, s') dz' d\varepsilon' \right\}$$

$$\begin{aligned} \text{s.t.} \;\; & c + a' = \chi, \quad a' \geq 0 \\ & \chi' = a'R + (1 - \tau)y' \\ & y' = G(j', g) + \alpha + z' + \varepsilon' \end{aligned}$$

From the retirement age J^{ret} onward, the recursive problem reads as:

$$\begin{aligned} V^R_{j,g,\alpha}(\chi) &= \max_{a'} \left\{ u(c) + \phi_j \beta V^R_{j,g,\alpha}(\chi') \right\} \\ \text{s.t.} \;\; c + a' &= \chi, \quad a' \geq 0 \\ \chi' &= a'R + p \end{aligned}$$

Where p denotes the fixed pension amount. It is not included in the state vector because it is modeled as a deterministic function of individual characteristics, which explicitly influence the optimization problem.

Calibration In the model, individuals begin their working life at age 25 and retire at age 60, after which they are certain to die by age 80. Age-specific survival probabilities are derived from OECD yearly data, and each period in the model corresponds to a calendar quarter.

The coefficient of relative risk aversion is set to 2, consistent with standard risk aversion in economic models. The risk-free quarterly interest rate is 1.2 percent, while the discount factor is calibrated to achieve a financial wealth-to-income ratio of 0.85 – reflecting the observed value in survey wealth data – resulting in a value of 0.9825. Additionally, the exogenous borrowing limit is established at zero, indicating that individuals cannot borrow against future income.

Labor market transition probabilities and the parameters describing the income process are informed by the estimates from the statistical framework outlined in Section 3. The income process is discretized through simulation, utilizing 15 grid points for both the persistent and transitory stochastic components, with grid values specific to each labor status. Details and performance of the discretization algorithm are presented in Appendix E. Latent types are categorized into five groups based on the quintiles of the estimated cross-sectional distribution.

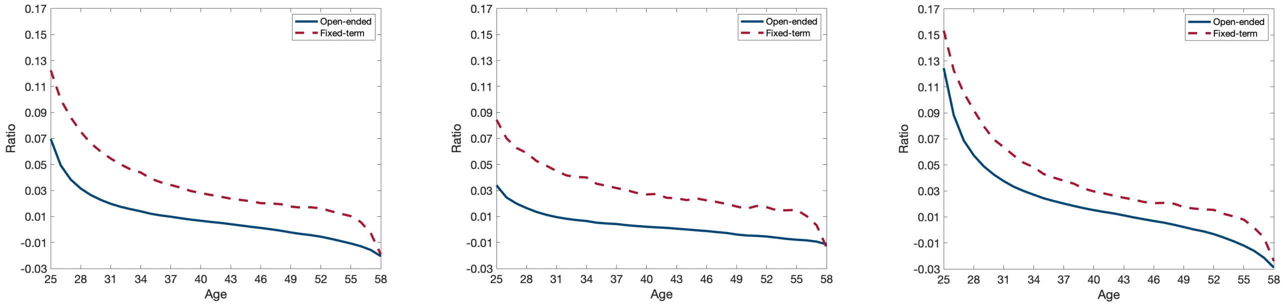
The pension amount is modeled as a function of individual characteristics and is calculated as a fraction (ω) of the predictable income during the last working period (l):

$$p = \omega * (G(j_l, g) + \alpha)$$

The gross replacement ratio (ω) is calibrated from OECD data and set uniformly at 0.78, as it does not exhibit significant variation across income groups. To finance the pension system,

Figure 9: Saving rate by contract type over the life-cycle

(a) All individuals (b) High types (Q_{80}) (c) Low types (Q_{20})



Note: The figure displays the saving rate as a percentage of total available resources over the life cycle, segmented by contract type. Panel (a) covers the entire sample, while Panels (b) and (c) highlight high- and low-productivity individuals in the top and bottom quintiles of the latent component distribution, respectively. Results are derived from model simulations.

individuals in the model pay a flat social security tax, calibrated to ensure that the government budget constraint is balanced on average. With the specified replacement ratio, the calibrated tax rate is set at 0.132.

Simulation To simulate the economy and generate counterfactual scenarios, the model requires two additional assumptions. The initial distribution of workers across various labor market statuses mirrors the conditional distribution observed in labor market administrative data at the entry age, differentiating by individual characteristics. Furthermore, the initial level of assets is set to match the deterministic income component at entry age. This mirrors the empirical observation in survey data that young workers typically have financial wealth levels approximately equal to their average quarterly labor income. This ratio remains consistent across open-ended (1.19) and fixed-term (1.14) contract households, ensuring that the initial financial wealth level in the model is uniform regardless of contract type.

8.3 Wealth accumulation

In the model, two potentially countervailing forces influence wealth accumulation decisions. The first is a life-cycle motive. When individuals are relatively young, they anticipate income growth over their working life, diminishing the need to accumulate wealth for future periods. In an economy without income uncertainty and with access to borrowing, young workers would leverage future income to maintain a stable consumption profile over the life-cycle. The second force is a precautionary motive, which drives individuals to accumulate wealth as a buffer against income fluctuations. Evidence presented earlier in this paper indicates that workers with specific individual characteristics and those in fixed-term jobs face heightened employment instability and income volatility. For these individuals, the balance between the precautionary and life-cycle motives becomes particularly relevant, and the precautionary margin may override the life-cycle mechanism.

Saving rate by contract type To assess the relative importance of these two motives, I examine the model's predictions regarding life-cycle saving rates for workers in different employment contracts and with varying latent ability levels. This approach provides insight into how employment instability influences wealth accumulation decisions. The metric used to quantify savings is the proportion of financial wealth that workers choose to carry forward to the next period, expressed as a share of their total currently available resources.

Figure 9 reports the results. Panel (a) shows that, on average, 25-year-old workers in fixed-term contracts save around 12 percent of their resources each period, compared to about 7 percent for those in stable employment. This disparity in savings rates by contract type persists over the life-cycle, though the gap narrows slightly with age. This model result reflects the increased income uncertainty faced by fixed-term workers, arising from both the higher likelihood of non-employment associated with such contracts and the relatively large income fluctuations they experience even when they remain in fixed-term employment over time.

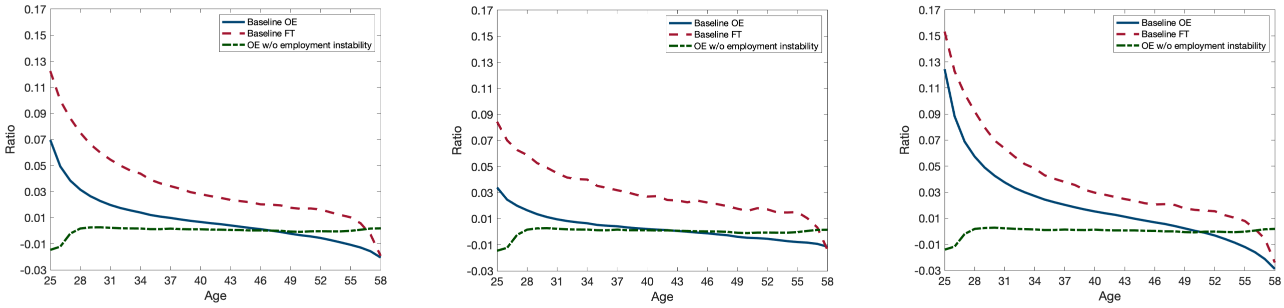
The strength of the precautionary saving motive also varies across individuals, regardless of their contract type, with those experiencing greater employment instability and income volatility generally saving more. For instance, young workers accumulate more precautionary wealth due to the overall higher income volatility they experience early in their careers. Over time, this volatility decreases as employment instability lessens with age, and as income fluctuations tied to specific labor statuses become less pronounced.

Latent characteristics further contribute to this variation. Panels (b) and (c) of Figure 9 show saving rates for workers in the bottom and top quintiles of the latent component distribution, respectively. Less productive workers tend to save more, even when in stable jobs, as they face higher risks of job separation into non-employment or transitions to fixed-term roles, thus reinforcing their need for precautionary savings. Conversely, highly productive workers save relatively less compared to the sample average, even when in fixed-term contracts. Specifically, low-productive young workers save around 15 percent of their resources in fixed-term jobs and about 13 percent when in open-ended occupations, whereas these rates decline to 9 percent and 3 percent, respectively, for young workers at the upper end of the latent component distribution.

Fully insured employment instability To further examine the impact of employment instability on saving behavior, I conduct a counterfactual analysis that eliminates this instability from the economy. Specifically, this scenario assumes the absence of both fixed-term positions and non-employment spells – two closely related phenomena. In this hypothetical setting, all workers are employed on open-ended contracts throughout their careers, facing income fluctuations specific of this stable employment type. This economy resembles the experience of public-sector employees, who generally maintain stable positions without risk of job separation. Since the latent component influences income volatility solely through its effect on employment stability, saving behavior in this counterfactual economy is uniform across types.

Figure 10: Saving rate by contract type w/ and w/o employment instability (Only OE)

(a) All individuals (b) High types (Q_{80}) (c) Low types (Q_{20})



Note: *Note*: The figure displays the saving rate as a percentage of total available resources over the life cycle, segmented by contract type and for workers who are in open-ended jobs and who are not subject to employment instability. Panel (a) covers the entire sample, while Panels (b) and (c) highlight high- and low-productivity individuals in the top and bottom quintiles of the latent component distribution, respectively. Results are derived from model simulations.

The findings show that in an economy fully insured against employment instability, wealth accumulation remains minimal (Figure 10). Young workers, motivated primarily by life-cycle considerations, consume a portion of their initial wealth, holding only modest precautionary savings to smooth minor income variations. In this scenario, each €100 of initial wealth allows young workers to consume around €1 of these resources – while in the baseline economy young workers in open-ended contracts save approximately €7 out of their initial resources. This contrast in saving behaviors is even more pronounced for low-productivity workers, who gain particular value from protections against employment instability.

The difference in saving patterns of open-ended workers between the baseline and this counterfactual economy serves as a measure of the precautionary saving response to the portion of income volatility driven by employment instability. The findings highlight that employment instability is the primary source of income volatility – and consequently of precautionary savings – rather than fluctuations inherent to specific labor statuses.[33]

8.4 Welfare

The counterfactual exercise presented in the previous section highlights the extent at which wealth accumulation choices are shaped by employment instability. Workers on fixed-term contracts or those more susceptible to employment fluctuations tend to build up more precautionary savings, primarily to buffer against uncertain income. However, this accumulation reduces their utility, as resources are diverted from consumption to wealth stock, which does not directly affect current utility levels. This leads to an essential question: how do these

[33] This statement holds true even when comparing fixed-term workers in the baseline economy to a scenario where fixed-term contracts are fully insured, meaning workers are not subject to employment instability and always remain employed with this contract type. In this scenario, saving rates are slightly higher than in the counterfactual economy with only open-ended jobs but lower than those for fixed-term workers in the baseline economy, particularly for low-productive workers who are more exposed to employment instability. The results for this additional counterfactual economy are presented in Figure 29 in Appendix G.

Table 6: Welfare cost of employment instability (% of lifetime consumption)

	First labor status in baseline economy		
Latent types	Open-ended	Fixed-term	Non-employed
Q_1	15.4	18.0	25.2
Q_2	8.4	12.7	18.9
Q_3	5.7	10.1	16.0
Q_4	3.8	8.5	13.6
Q_5	1.7	6.3	10.6

Note: The table reports the fraction of consumption that individuals would be willing to forgo each period to live in an economy without the risk of fixed-term or non-employment states. Columns represent different individuals based on their entry labor status in the baseline economy, while rows correspond to different latent types (quintiles). Results are derived from model simulations.

varying saving behaviors translate into welfare outcomes? To explore this, I evaluate welfare as the constant fraction of consumption that individuals would be willing to forgo each period to experience a lower level of income volatility.

First, I measure the welfare cost associated with the portion of income volatility driven by employment instability. Specifically, I calculate the share of consumption individuals would be willing to forego to live in an economy free from the risk of fixed-term or non-employment statuses. In this scenario, workers would enter the labor market with open-ended contracts and remain in stable occupations throughout their careers, experiencing only the limited income volatility typical of secure employment and avoiding substantial income shifts caused by labor market transitions.

Since employment instability systematically varies across individuals and contract types, a single aggregate measure of welfare cost may lack meaningful insights. Some individuals face minimal instability, while others are highly exposed. To capture this heterogeneity, I compute welfare costs by quintiles of the latent ability distribution and by initial labor market status, which in the simulation exercises reflects individual characteristics in probabilistic terms. Consider, for instance, a highly productive worker who enters the labor market with an open-ended contract. With a strong job retention probability, this worker would have relatively low willingness to pay to eliminate employment instability. In contrast, a lower-productivity worker who enters as non-employed or with a fixed-term contract might encounter more instability over their career, leading to a higher willingness to pay to avoid it and instead live in an economy with only open-ended jobs. Beyond these two extremes, the interaction between latent types and initial labor market statuses creates varied exposures to employment instability, and consequently, to the associated welfare costs.

The results are presented in Table 6. The welfare cost of employment instability varies widely, from 1.7 of lifetime consumption for highly productive workers starting in stable jobs to 25.2 percent for low-productivity workers who begin their careers as non-employed. Generally, welfare costs decrease with higher latent component and increase as initial labor market status becomes more precarious. Interestingly, the gap in welfare cost between workers who begin in open-ended versus fixed-term jobs narrows as latent ability decreases. For less productive workers, exposure to employment instability remains high regardless of contract type, leading to a consistently high willingness to pay to avoid such instability – similar to that of workers entering instead the labor market with fixed-term jobs.

Second, I evaluate the welfare cost of pure income volatility. Even in a counterfactual economy where workers remain in open-ended jobs throughout their careers, they are still exposed to income fluctuations associated with this stable employment status – which are relatively small and persistent. I find that workers in this hypothetical setting would be willing to forgo an additional 7.8 percent of their lifetime consumption to completely eliminate income volatility. This value remains constant across workers with different latent types, as productivity does not directly influence income volatility – and the counterfactual economy lacks variation in labor market statuses since all workers are assumed to hold open-ended contracts.

9 Conclusions

In this paper, I study individual income volatility in a dual labor market, where stable jobs coexist with short-term, fixed-duration contracts. Specifically, I first investigate the extent to which employment instability arises from contract types versus worker characteristics. Second, I measure how different labor market statuses are associated with varying degrees of income volatility, after accounting for individual characteristics.

To address these issues, I propose a statistical framework where observable and latent individual characteristics shape both labor market and income trajectories. The model introduces systematic heterogeneity in income evolution based on labor market status and transitions. Specifically, it decomposes the portion of income not attributable to individual characteristics into two components: a Markovian persistent term and a transitory innovation. The persistence and the magnitude of these components are allowed to vary with labor market status and transitions, introducing nonlinearities and non-normalities in income dynamics. To track labor market trajectories, the model estimates a Markovian process, representing how workers transition across different labor statuses throughout their careers.

The model accounts for nonlinearities and non-normalities in income dynamics. Nonlinearities arise from allowing the persistence of past income innovations to vary with workers' labor market conditions across periods. Non-normality results from each labor market condition having a unique constant term and persistence for the Markovian component. Within any given status or transition, income innovations follow a Gaussian distribution. Consequently, the overall distribution of the stochastic component is a mixture of nine normals – one for each labor market condition – with weighting probabilities determined by the share of workers in each category.

The findings highlight that latent characteristics are key drivers of heterogeneity in employment instability. Certain groups of workers, based on their individual characteristics, are more likely to experience employment instability, regardless of their current contract type. This instability directly affects income dynamics, as changes in labor status often coincide with significant income shocks that disrupt previous income patterns, reducing the persistence of past innovations. Systematic differences in income dynamics are also observed among workers who remain employed across consecutive periods – without changing their labor status – but under different contract types. Workers in fixed-term jobs, in particular, face more income uncertainty. Overall, the results demonstrate how labor market status and transitions within dual labor markets serve as an empirical source of nonlinearities and non-normalities in income dynamics.

The paper further explores the impact of employment instability on wealth accumulation, revealing substantial welfare costs driven by increased precautionary savings. These welfare costs represent 18 percent of lifetime consumption for less productive workers who begin their careers in fixed-term jobs, while they fall to 2 percent for more productive workers who start with open-ended jobs.

While providing a cost-benefit analysis of fixed-term contracts is beyond the scope of this paper – since it would require considering the demand side of the economy as well – the results underscore important implications for labor market policy. Specifically, this paper demonstrates that fixed-term contracts are associated with higher employment instability and income volatility – even after accounting for individual-specific effects – and that these consequences result in welfare costs. These broader costs associated with the use of fixed-term contracts should be taken into account when designing labor market interventions. Additionally, the paper emphasizes the relevance of pre-labor market factors – such as education, soft skills, and production technology – that influence workers' productivity and employment stability throughout their careers.

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Appendix

A The working sample construction

This section presents the sample selection and outlines the data adjustment procedure used to construct the working dataset.

The analysis is based on a longitudinal administrative random sample compiled by the Italian National Social Security Agency (INPS), covering the period from January 1985 to December 2019. This dataset, known as the *Longitudinal Sample INPS* (LoSaI), is drawn from the universe of private-sector employees, covering approximately six percent of the Italian private workforce, including employees in publicly owned companies.[34] INPS tracks labor market careers over time, covering periods of employment and registered unemployment – i.e., times during which individuals receive unemployment benefits. For the analysis, the sample is restricted to the period from January 2008 to December 2016 and converted to a quarterly frequency.[35]

Defining non-employment Employment quarters are defined as periods covered by registered contracts that meet minimum duration and income requirements. Specifically, a quarter qualifies as an employment period if it includes at least 30 days of registered employment – either from one or multiple contracts – and if the total labor income exceed the threshold amount for 30 days of work, calculated at two-thirds of the average daily wage, adjusted by age and contract type. Unemployment is defined residually, representing periods where no employment is registered in the dataset.[36]

The dataset is structured to cover the entire period from a worker's first to last recorded employment spell. However, periods of absence in the dataset may represent other situations, such as engagement in educational activities, retirement, or employment in contracts not covered by INPS. For instance, a worker could be absent if she holds a public-sector position, she is a self-employed with private contributions, or works abroad. To address these ambiguities and ensure the measure of unemployment focuses on individuals attached to this specific labor market, I restrict the sample to workers aged 25 to 59, where engagement in education or retirement is less likely. Workers with no employment recorded in INPS during this age range are excluded from the analysis. Additionally, workers with any gaps exceeding five years between employment spells are removed, indicating a low attachment to this labor market – given that

[34] The sample consists of individuals born on 24 specific dates throughout the year, specifically the first and ninth day of each month. Pure public sector jobs and self-employed workers are not included.

[35] For years prior to 2005, the dataset lacks precise information about contract activation and termination dates. Data from 2005 to 2007 and from 2017 to 2019 are used in the data adjustment procedure but are excluded from the estimation sample.

[36] This residual definition of unemployment is due to data limitations, as the dataset only includes information on income benefit recipients rather than actual employment status. Benefits are limited in duration and depend on prior employment history, so they do not cover the population uniformly.

most employment gaps are shorter than two years.

Income data The income measure used in the analysis is defined as the quarterly sum of labor earnings and unemployment benefits. Labor earnings include all pre-tax income – both regular and irregular – received under registered contracts, while unemployment benefits refer to income maintenance policies. For non-employment periods reporting zero income, I assume coverage by universal social assistance, assigning a minimum income amount as specified below:[37]

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

This equation raises low or zero income levels above a minimum threshold by adding noise, modeled by a uniform distribution. This approach aims to preserve the ranking of income earners below the threshold while ensuring non-employed workers do not receive income levels that exceed the minimum required to qualify as an employment quarter. The minimum income level, set at €200 per quarter, reflects the quarterly equivalent of a universal social assistance measure available in Italy for individuals over age 65, known as the *Carta acquisti ordinaria*. In this context, this amount can be understood as reflecting informal transfers or charity.

It's also important to note that income in the dataset is recorded annually. As a result, intra-year income variations that are not tied to contract changes – such as shifts in part-time status, job qualification, or contract type – are not captured. Observed income variations across quarters within the same year are attributed primarily to differences in working days, when a contract does not cover the full calendar year.

Additional data adjustments I apply additional data adjustments to refine the sample. (i) I exclude workers in the agriculture sector to improve comparability across individuals. (ii) I drop seasonal employees and contractors.[38] (iii) I remove individuals who appear as professionals for at least one calendar year.[39] (iv) Finally, I restrict the sample to individuals who remain in the dataset for at least four cumulative quarters, including both employment and non-employment periods.

B The estimation strategy

This section provides the details of the estimation strategy, focusing in particular on the algorithms used in the sE-step of the sEM algorithm.

At each iteration of the algorithm, I begin by removing the effects of observable demographic characteristics from the observed income realizations. In the first stage of the sE-step, I use the

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

[38]Specifically, I exclude workers who held a seasonal or contractor job for at least one period.

[39]A small number of professionals without a dedicated private fund are included in the dataset. However, as I have only annual information on these workers, they are excluded from the sample.

Metropolis-Hastings (MH) algorithm to estimate latent types. Once these values are obtained, I subtract them from the income residual (after adjusting for demographics) and decompose this remaining portion of income into persistent and transitory stochastic components, using the Durbin-Koopman simulation algorithm. In the M-step, I treat all latent quantities as observable data and update the full set of parameters. These updated parameter values then serve as the new initial guess for the next iteration, and the process repeats until convergence. The steps of the algorithm are as follows:

1. Guess vector of parameters and compute income residual
   - Guess the full vector of income process parameters and labor market transition coefficients
   - Use the demographic coefficients in the income equation to compute income residual over observable demographics
2. sE-step - Simulate latent variables
   - *Stage 1.* Using this residual, estimate the latent individual-specific component (Metropolis-Hastings)
   - *Stage 2.* Treating the estimated latent individual effect as given, estimate persistent and transitory stochastic components (Durbin-Koopman)
3. M-step - Update parameters
   - Demographics: linear regression of observed income over demographics
   - Income process parameters: Maximum Likelihood Estimation
   - Labor market transition probabilities: Multinomial logistic regression
4. Iterate until convergence

Next, I describe the Metropolis-Hastings algorithm. Following this, I outline the Durbin-Koopman simulation algorithm.

B.1 The Metropolis-Hastings algorithm

To estimate the worker-specific latent component (α_i), I use the Metropolis-Hastings (MH) algorithm (Metropolis et al., 1953; Hastings, 1970), a Markov Chain Monte Carlo method for sampling from a target probability distribution. The primary identifying assumption for estimating this latent individual component is that it remains constant throughout the worker's career. Te algorithm generates samples from the individual-specific posterior distribution of the latent component, conditional on observable data and model parameters. For each individual i, the observable data consist of log-income realizations $y_{1:T_i}$ over the entire career, labor market history $s_{1:T_i}$, and demographic characteristics x_i. This information are observed at quarterly frequency in the data. In this setup, the posterior log-likelihood function can be decomposed as follows, omitting dependence on model parameters for simplicity:

$$\begin{aligned}
\mathbb{P}(\alpha_i|s_{i1:T_i}, y_{i1:T_i}, x_{it}) &= \mathbb{P}(\alpha_i, s_{i1:T_i}, y_{i1:T_i}, x_{it}) - \mathbb{P}(s_{i1:T_i}, y_{i1:T_i}, x_{it}) \\
&= \mathbb{P}(y_{i1:T_i}|s_{i1:T_i}, \alpha_i, x_{it}) + \mathbb{P}(s_{i1:T_i}, \alpha_i, x_{it}) - \mathbb{P}(s_{i1:T_i}, y_{i1:T_i}, x_{it}) \\
&= \mathbb{P}(y_{i1:T_i}|s_{i1:T_i}, \alpha_i, x_{it}) + \mathbb{P}(s_{i1:T_i}|x_{it}, \alpha_i) + \mathbb{P}(\alpha_i, x_{it}) - \mathbb{P}(s_{i1:T_i}, y_{i1:T_i}, x_{it}) \\
&= \mathbb{P}(y_{i1:T_i}|s_{i1:T_i}, \alpha_i, x_{it}) + \mathbb{P}(s_{i1:T_i}|x_{it}, \alpha_i) + \mathbb{P}(\alpha_i) + \mathbb{P}(x_{it}) - \mathbb{P}(s_{i1:T_i}, y_{i1:T_i}, x_{it})
\end{aligned}$$

The first term represents the conditional log-likelihood of stochastic income, which I recover using the Kalman filter and smoother algorithms (see the next Section). Specifically, this term captures the conditional distribution of log-income residual over individual characteristics – I included also the dependence on the labor market history to highlight the dependence of this stochastic term on the labor market conditions. The second term describes the Markov chain governing labor market trajectories. Since the model assumes that transitions in the labor market are conditionally exogenous – meaning that they do not depend on income realizations – this term fully characterized by the Multinomial Logit model described in Section 3.

The third and the fourth term follow from the assumption that individual observable demographic characteristics are independent form the latent component, so that the joint density of observable and latent individual characteristics can expressed as the sum of the two marginal distributions. For the marginal distribution of the latent component in the cross-sectional I assume Normality. The marginal density of the latent characteristics – as well as the last term of the decomposition – does not enter the estimation algorithm since it does not depend on the latent component.

The MH algorithm samples from this posterior distribution through the following steps:

1. *Initialization.* For each individual, an initial guess for α_i is drawn from a Normal distribution with mean zero and a variance matching the cross-sectional variance of the latent component distribution. This value is iteratively updated in the following steps.
2. *Proposal step.* A new candidate value for α_i is drawn from a Normal distribution centered on the current value, with standard deviation equal to half of the initial draw's standard deviation.
3. *Acceptance step.* The algorithm computes the log-Hastings ratio, the difference in the posterior log-likelihood between the candidate and current value. If this ratio exceeds the log of a uniform random draw (between 0 and 1), the candidate is accepted as the new value for α_i. Otherwise, the current value is retained.

After 15 iterations, the final estimate for each worker is taken from the last iteration, based on the assumption of convergence to the stationary distribution – meaning that the sampled draws stabilize around values that align with the posterior conditional distribution.

This approach provides an estimate of the latent component for each worker that closely aligns with the Maximum Likelihood Estimate (MLE), as the sampled values converge. Although averaging over the last few iterations can improve stability by reducing variability due to residual sampling noise, I rely on the last realization for computational efficiency, under the assumption that convergence has been achieved.

B.2 The Durbin-Koopman simulation smoother

This section describes the procedure used to decompose the income residuals over workers' individual characteristics $\eta_{i1:T_i}$ into persistent and transitory stochastic components, which are a priori non-observable in the data. This separation relies on the panel structure of the dataset, enabling the assessment of income persistence over time, with the residual portion of income treated as transitory innovations. The decomposition is based on the Durbin-Koopman simulation smoother (Durbin and Koopman, 2012), which estimates these two components by generating draws from their simulated conditional distributions, given the observable data, the latent individual component and the values of model parameters. Since the algorithm uses the Kalman filter and smoother algorithms, I first introduce them.

Sate-space representation This section relies on the following state-space representation of the income process described in Section 3, where Equation 14 is known as the *observation equation*, Equation 15 as the *state equation*. In this context, the state vector refers to the two unobserved stochastic income components.

$$\eta_{it} = y_{it} \mid (x_{it}, \alpha_i) = y_{it} - g(x_{it}) - \alpha_i = \underbrace{\begin{bmatrix} 1 & 1 \end{bmatrix}}_{H} \underbrace{\begin{bmatrix} z_{it} \\ \varepsilon_{it} \end{bmatrix}}_{h_{it}} \tag{14}$$

$$\underbrace{\begin{bmatrix} z_{it+1} \\ \varepsilon_{it+1} \end{bmatrix}}_{h_{it+1}} = \underbrace{\begin{bmatrix} c_{it+1} \\ 0 \end{bmatrix}}_{C_{it+1}} + \underbrace{\begin{bmatrix} \rho_{it+1} & 0 \\ 0 & 0 \end{bmatrix}}_{F_{it+1}} \underbrace{\begin{bmatrix} z_{it} \\ \varepsilon_{it} \end{bmatrix}}_{h_{it}} + \underbrace{\begin{bmatrix} \sigma^v_{it+1} & 0 \\ 0 & \sigma^\varepsilon_{it+1} \end{bmatrix}}_{G_{it+1}} \underbrace{\begin{bmatrix} \tilde{v}_{it+1} \\ \tilde{\varepsilon}_{it+1} \end{bmatrix}}_{\tilde{e}_{it+1}} \tag{15}$$

$$\tilde{e}_{it+1} \overset{iid}{\sim} N(0_2, I_2), \quad h_{i1} \sim N\left(\mu_1, \Sigma_{i1}\right)$$

Where the parameters are time-varying because they depend on the current and previous labor market status of the workers – to simplify the notation and focus on the algorithm, here in this section I omit the explicit dependence of the parameters on the labor market. As for the initial conditions, I assume that the first realization of the state vector h_{i1} is drawn from a Normal distribution with zero mean (μ_1) and with a covariance diagonal matrix (Σ_{i1}) specific to workers who remain in the same labor market status across consecutive periods. Based on the observed entry labor market status in the data, 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. The first realization of the persistent term is only made of the innovation component, which is drawn from this initial distribution.

Kalman filter and smoother algorithms The Durbin-Koopman simulation smoother relies on the Kalman filter and smoother algorithms (Kalman, 1960), which are essential tools for estimating the latent components of income processes over time. The Kalman filter is specifically designed for the sequential estimation of latent states in a linear state-space model, updating estimates as new data becomes available. It produces the optimal linear estimate of the unobserved state at each time step, integrating past observations with current data to minimize estimation error.

Define the following quantities, representing the conditional expectations and variances of the latent state vector (h_{it}) and of the observable income residual in the data (η_{it}):

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

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

As mentioned, I initialize the filter with starting values for the mean and variance of the latent state vector:

$$\mu_{i1|1} = \mu_1, \quad \Sigma_{i1|1} = \Sigma_{i1}$$

For each individual and each period $t = 1, \ldots, T_i$, the Kalman filter algorithm performs two main steps – prediction and updating – producing sequential estimates based on the state-space representation of the model. The prediction step generates estimates of the latent state vector for the next period, based on current information up to the period t. These predicted values provide expectations about the state vector before the next observation is incorporated:

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

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

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

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

In the update step, the algorithm refines these predictions by incorporating the new observed data, resulting in adjusted estimates for the mean and variance of the latent state. This step reduces uncertainty based on the new information and is calculated as follows:

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

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

The output of the Kalman filter algorithm is a series of updated estimates of the latent income components, over time. The Kalman filter generates these estimates of the latent state vector based solely on the information available up to the current time. In contrast, the Kalman smoother refines these estimates by incorporating all available observations, both past and future. This post-processing step enhances the accuracy of the latent state estimates across the entire time series, by working backward through the sequence. It "smooths" the estimates by adjusting them in light of later observations, resulting in estimates that have reduced uncertainty and greater precision. Given the final estimates from the Kalman filter $\left(\mu_{iT_i|T_i}, \Sigma_{iT_i|T_i}\right)$, the smoother recursively calculates:

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

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

The Kalman filter and smoother algorithms generate forecasts of the data and provide estimates of the latent states that are optimal within the class of estimators that are linear functions of the observable data. Under the assumption of normality for the distribution of income innovations, these estimators are optimal among all functions of the data. Moreover, with this normality assumption the covariance matrix of the state vector captures the full uncertainty associated with the process, and the conditional distribution of the data at each step is fully characterized by the mean and covariance estimates:

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

Durbin-Koopman simulation smoother The Durbin-Koopman simulation smoother decomposes income residuals into the persistent and transitory components (the state vector) by generating draws from their conditional distribution given individual characteristics and the parameters of the model. The procedure is outlined as follows.

For each individual in the sample, the algorithm first simulates the state vector trajectory, denoted $\hat{h}_{i1:T_i}$, starting with an initial draw (h_{i1}). It then generates a sequence of stochastic innovations $(\tilde{e}_{i2:T_i})$ and uses the state-space model to sequentially construct the entire time series of the state vector.

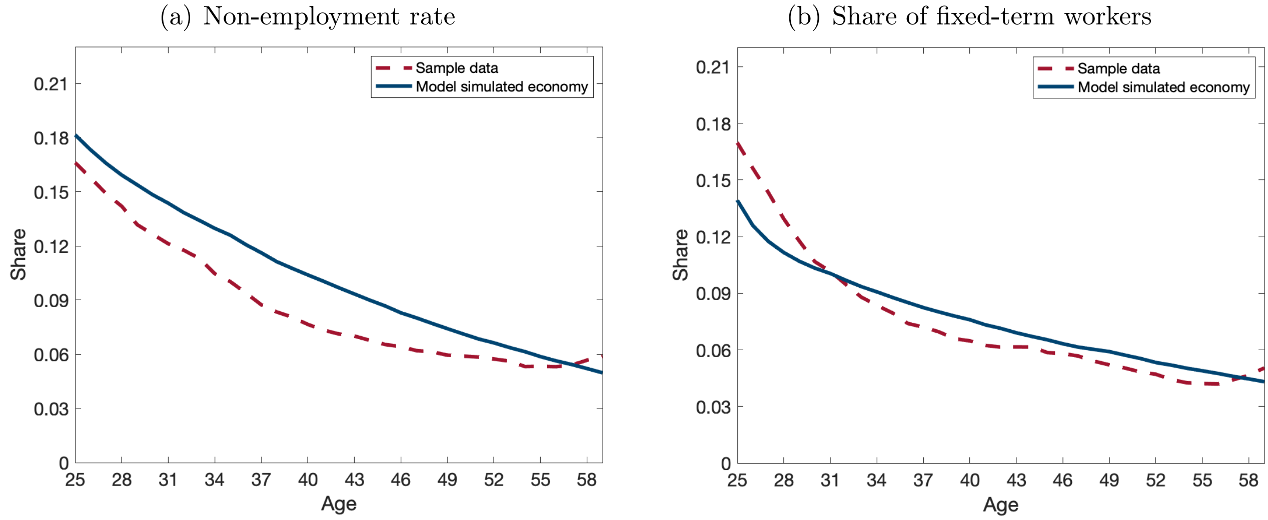
At each period, the algorithm then computes the sequence of simulation errors $(\hat{\eta}_{i1:T_i})$, defined as:

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

These residuals capture the difference between observed income residual and the simulated state estimates, allowing for an iterative refinement of the state vector. Using $\hat{\eta}_{i1:T_i}$, the algorithm applies the Kalman filtering recursions to calculate the updated conditional expectation of the state vector:

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

Figure 11: Aggregate labor market shares in the model and in the data



Note: Panel (a) of the figure reports the non-employment rate. Panel (b) the share of fixed-term workers over total employment. It compares the measures derived from the actual sample data with those from the simulated model economy.

The resulting vector represents the series of refined estimates of the state variables, taking into account the observed residuals. Finally, the algorithm constructs the estimated time series of the two stochastic income components, at the individual level. By construction, this resulting quantities represent draws from the conditional distribution of the state vector given the observed income residuals:

$$h_{i1:T_i}^* = \hat{h}_{i1:T_i} + h_{i1:T_i}^+ \sim \mathrm{P}\left(h_{i1:T_i} \mid \eta_{i1:T_i}\right)$$

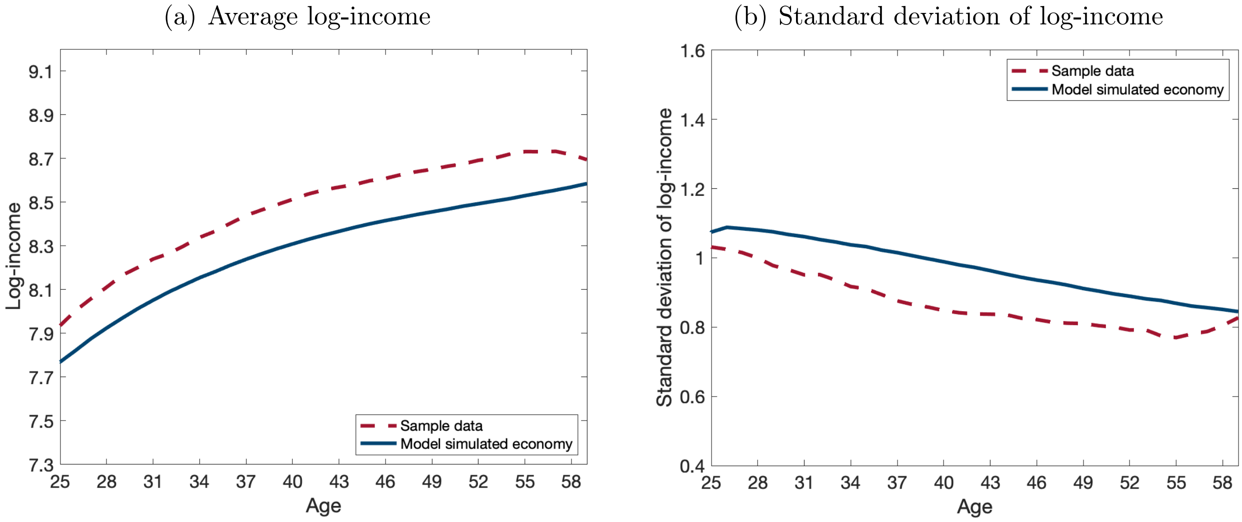
This approach provides draws from the simulated posterior distribution for the latent state vector, conditioned on the observed income data, offering a probabilistic characterization of the two income components.

C Model fit

In this section, I demonstrate the model's ability to account for average life-cycle income profiles and aggregate labor market shares. Specifically, I simulate the careers of 300,000 individuals, tracking their labor market trajectories and income realizations. In the simulated economy, the entry conditions in the labor market replicate the distribution observed in the data, based on workers' demographic characteristics and the estimated individual latent component. At the entry period, the stochastic income components are drawn from distributions specific to workers who do not change their labor status over consecutive quarters.

On the labor market side, the model performs well in tracking the aggregate dynamics over the life-cycle. Figure 11 reports the non-employment rate and the share of fixed-term workers

Figure 12: Life-cycle income profiles in the model and in the data



Note: Panel (a) of the figure reports the cross-sectional log-income mean. Panel (b) the cross-sectional log-income standard deviation. It compares the moments derived from the actual sample data with those from the simulated model economy.

over age, as they result from the simulated economy compared to the actual sample data. The non-employment rate decreases from approximately 16-18 percent early in life to about 6 percent among older individuals. Similarly, the share of fixed-term workers drops from about 14-16 percent for workers at the early stages of their careers to less than 6 percent for workers above age 50.

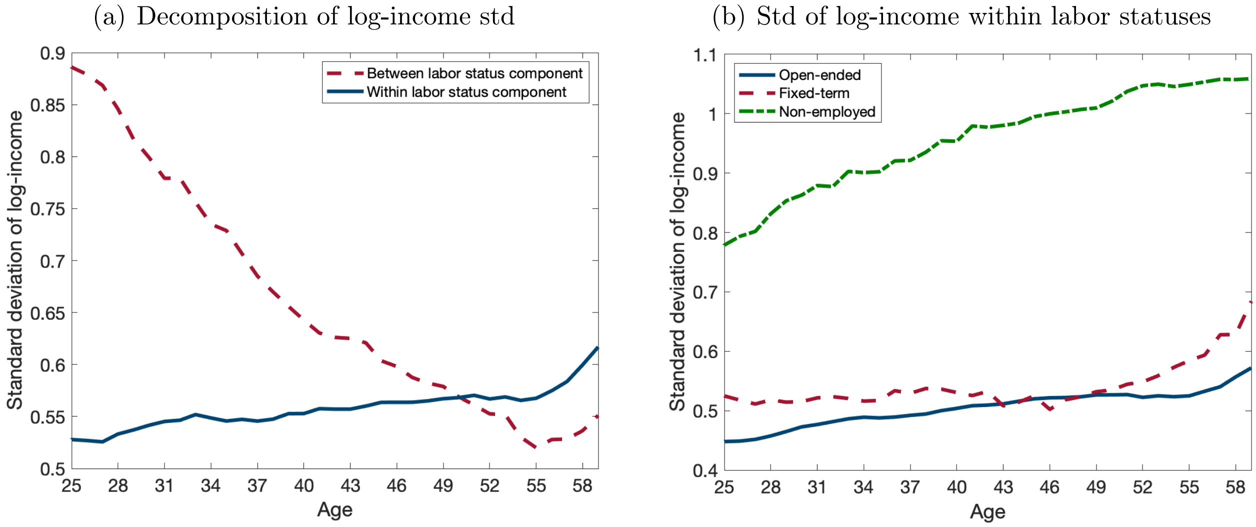
The model successfully replicates also life-cycle income patterns, capturing both the rising average income and the declining cross-sectional log-income standard deviation (Figure 12). Over the life cycle, log-income increases from approximately 7.8 log points (a quarterly income of around €2,440) to 8.6 log points (about €5,430 per quarter). In contrast, cross-sectional income inequality steadily decreases with age, and the model closely mirrors this linear decline. Notably, this result challenges the common empirical finding that income inequality increases over the life cycle. The next section (Appendix D) illustrates that this decline is primarily driven by a decreasing proportion of non-employed individuals and fixed-term workers as people age, leading to a more homogeneous sample of workers.

D The life-cycle decline in income inequality

Figure 12 shows that the cross-sectional income inequality steadily decreases with age, challenging the conventional view that income inequality increases over the life cycle. This section illustrates that this decline is primarily driven by a decreasing proportion of non-employed individuals and fixed-term workers as people age, leading to a more homogeneous sample of workers.

Specifically, I decompose the cross-sectional log-income variance into two components: the

Figure 13: Life-cycle profile of crss-sectional income inequality



Note: Panel (a) of the figure reports the between- and within- labor market status components of the cross-sectional income standard deviations. Panel (b) focuses on the within-component and presents it by labor market status. The values are based on actual sample data.

portion due to differences in income between labor statuses (σ_B^2) and the portion due to differences in income across workers within each of the three labor statuses (σ_W^2). This decomposition is performed for each age j:

$$\sigma_B^2(j) = \sum_{s\in\{OE,FT,N\}} \omega_{js} \left[\mathbb{E}(y \mid j, s) - \mathbb{E}(y \mid j)\right]^2$$

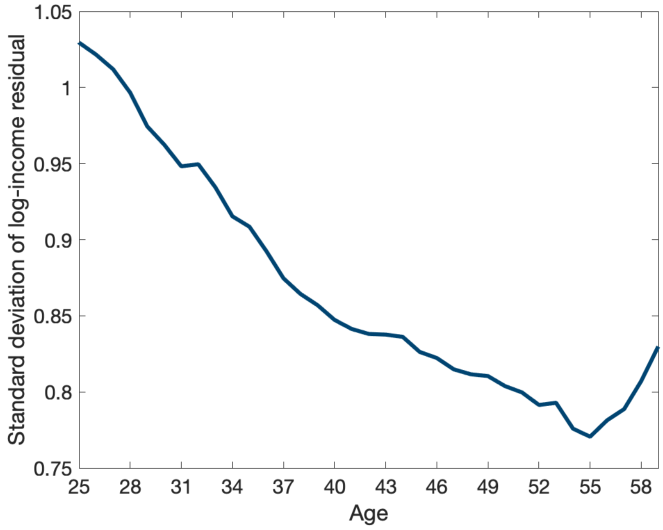
$$\sigma_W^2(j) = \sum_{s\in\{OE,FT,N\}} \omega_{js} \left(\frac{1}{N(s,j)} \sum_{i\in\text{group}(j,s)} \left[y_i - \mathbb{E}(y \mid j, s)\right]^2 \right)$$

Where ω_{js} denotes the share of individuals in labor market status s, by age j, and $N(s,j)$ represents the corresponding stock of individuals in that group. The between-group variance $\sigma_B^2(j)$ measures how much of the total cross-sectional income inequality for age group j is explained by differences in average income across workers in different labor statuses. In contrast, the within-group variance $\sigma_W^2(j)$ captures the contribution to overall inequality from the variation in income among individuals within the same labor status.

Panel (a) of Figure 13 presents the results of the decomposition in terms of standard deviations. Values are computed on actual sample data The declining life-cycle profile of income inequality is almost entirely driven by the reduction in inequality between different labor statuses. Specifically, as the shares of non-employed and fixed-term workers decrease with age, the sample population becomes more homogeneous, leading to a lower overall level of inequality. In contrast, Panel (b) shows that income inequality within each labor market status slightly increases over the life cycle.

Aside from changes in sample composition over the life cycle by labor status, another poten-

Figure 14: Std of log-income residual after removing cohort-effects



Note: The figure reports the standard deviation of the log-income residual by age, after linearly removing cohort effects.

tial source of the declining cross-sectional income inequality with age could be cohort composition. Specifically, due to the limited time span of the sample, younger workers in the dataset predominantly represent more recent generations, which may exhibit higher income inequality compared to older cohorts. However, I demonstrate that the observed decline in income inequality is not attributable to a cohort effect. To do this, I first compute log-income residuals by linearly removing cohort-specific effects, through a fixed effects linear regression. Next, I calculate the standard deviation of these residuals by age. The results, presented in Figure 14, confirm that cross-sectional income inequality continues to decline over the life cycle, even after accounting for cohort effects.

E Discretization of the income process

To integrate the estimated income process into the life-cycle consumption framework, I convert it into a discretized version. Given the non-linear nature of the income process, this conversion is achieved through simulation. Specifically, I first simulate the labor market careers and income histories of 300,000 individuals and store the realizations of the persistent and transitory stochastic income components. In a second step, I group these two components into a finite set of bins and describe how individuals move from one bin to the other over time.[40]

The AR(1) persistent component (z)) is discretized using an age- and labor status-dependent Markov chain. This discretized process is fully characterized by a state-space vector of size K_z,

[40]In the simulated environment, the initial labor market status is assigned based on the observed distribution in the data, conditional on worker's demographic characteristics and latent type. The distributions of the stochastic components for the initial period reflect those of workers who maintain the same labor market status across consecutive quarters.

which contains the persistent stochastic values, along with a corresponding transition matrix. I define one state-space vector for each combination of age and labor market status, allowing the transition matrix to be age-specific as well. Let $\mathbf{z} \in \mathbb{R}^{K_z \times S \times A}$ represent the discretized state-space, and $\Gamma_z \in \mathbb{R}^{K_z \times K_z \times S \times S \times A}$ denote the corresponding transition matrix, where S refers to the set of possible labor market statuses (open-ended employment, fixed-term employment, and non-employment) and A denotes the number of age groups. The state-space for the persistent stochastic component is specific to the current labor status and does not depend on prior labor market conditions.[41]

I determine the state-space points and the transition matrices using the following procedure:

1. For each age a and current labor status s, I allocate each realization of the persistent stochastic term into groups defined by the percentiles of this component distribution. The percentiles are calculated using a scaled sine function, which ensures finer grouping at both the lower and upper tails of the income distribution, where variability tends to be greater. This approach helps capture the dynamics of extreme income values more accurately.

2. Once the income realizations are grouped into bins, the points of the state-space vector are selected based on the median value within each bin:

$$\mathbf{z}(k, s, a) = \text{median}(z \mid s, a, z \in \text{bin } k)$$

3. I then compute the transition probability matrices Γ_z, which capture the likelihood of moving across income bins from one period to the next. Specifically, let $\Gamma_z(k_{-1}, l, s, s_{-1}, a, t)$ denote the probability of transitioning from income bin k_{-1} to income bin l across consecutive periods, at calendar time t and at the corresponding age a, and for a given combination of consecutive labor market statuses. While the state-space vector is age-specific, I allow the transition matrix to be defined at the quarterly level:

$$\Gamma_z(k_{-1}, l, s, s_{-1}, a, t) = \frac{\int_\Theta \mathbb{1}\{\mathbf{z}(k_{-1}, s_{-1}, a_{-1} \mid t_{-1}) \to \mathbf{z}(l, s, a \mid t)\}}{\sum_{l'} \int_\Theta \mathbb{1}\{\mathbf{z}(k_{-1}, s_{-1}, a_{-1} \mid t_{-1}) \to \mathbf{z}(l', s, a \mid t)\}}$$

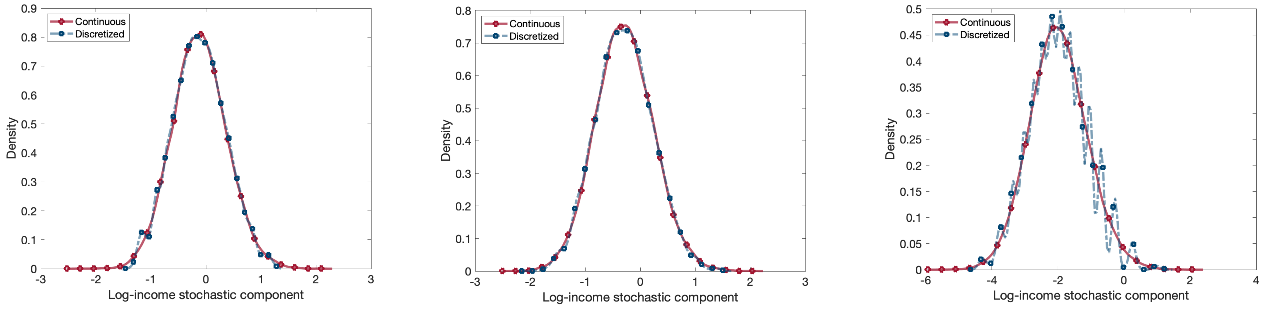
   Where Θ in this context denotes all individuals in the relevant state space, defined by age and labor market statuses. Time t represents time since labor market entry. Given the quarterly frequency, individuals may share the same age across these periods.

4. Lastly, I convert the quarterly transition probability matrices to yearly frequency through simple averaging. This approach establishes a one-to-one correspondence between calendar time and age. The resulting transition matrix between group income bins k_{-1} and l for a specific combination of age and labor market statuses is expressed as: $\Gamma_z(k_{-1}, l, s, s_{-1}, a)$.

[41] In cases where the state-space grid involves multiple periods, calculating the transition probabilities would indeed require considering more than just two consecutive quarters.

Figure 15: Conditional density of stochastic component - From non-employment

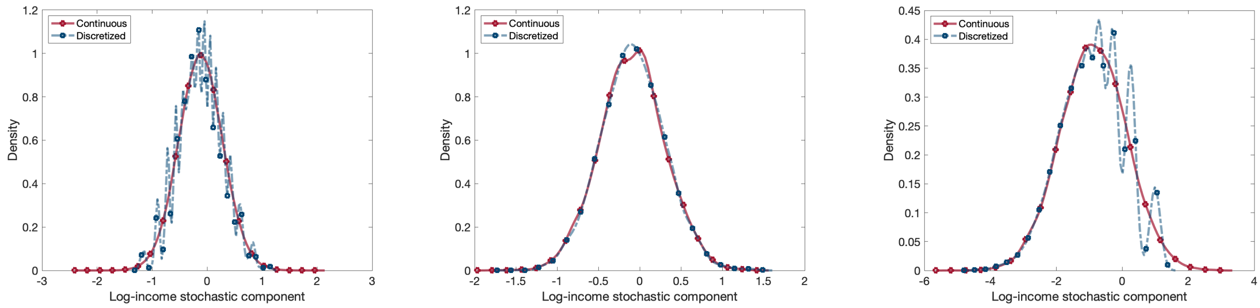
(a) To open-ended (b) To fixed-term (c) To non-employment



Note: The figures illustrate the asymptotic density of the stochastic income component, as it results from two different simulated economies: one where income evolves according to the continuous process and one where it evolves according to the discretized counterpart. Each plot is specific to workers transitioning from non-employment to each labor market status. Results are based on simulated data at a quarterly frequency.

Figure 16: Conditional density of stochastic component - From open-ended employment

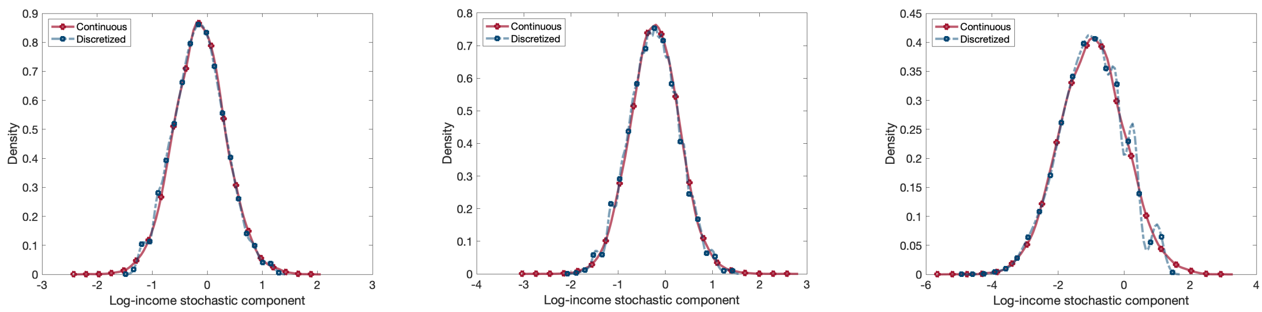
(a) To open-ended (b) To fixed-term (c) To non-employment



Note: The figures illustrate the asymptotic density of the stochastic income component, as it results from two different simulated economies: one where income evolves according to the continuous process and one where it evolves according to the discretized counterpart. Each plot is specific to workers transitioning from open-ended employment to each labor market status. Results are based on simulated data at a quarterly frequency.

Figure 17: Conditional density of stochastic component - From fixed-term employment

(a) To open-ended (b) To fixed-term (c) To non-employment



Note: The figures illustrate the asymptotic density of the stochastic income component, as it results from two different simulated economies: one where income evolves according to the continuous process and one where it evolves according to the discretized counterpart. Each plot is specific to workers transitioning from fixed-term employment to each labor market status. Results are based on simulated data at a quarterly frequency.

The transitory stochastic income component (ε) is discretized into a grid of size K_ε for each combination of age and the interaction of labor statuses across consecutive periods. Let $\boldsymbol{\varepsilon} \in \mathbb{R}^{K_\varepsilon \times S \times S \times A}$ represent the discretized state-space vector, with bins computed using the same methodology applied to the persistent component. The probability Γ_ε of being in each income bin k is uniformly distributed, corresponding to $1 \backslash K_\varepsilon$.

To evaluate the performance of the discretization algorithm, I compare the density of the stochastic income component – the sum of the persistent and transitory terms – as it results from two different simulated economies: one where income evolves according to the continuous process and one where it evolves according to this discretized counterpart. Figures 15 to 17 illustrate these density functions, specific to each current labor market status and its interaction with the previous status. The two densities align across all labor market scenarios.

F Income volatility versus income risk

The empirical results presented in the paper demonstrate that workers in different labor statuses experience varying levels of income volatility. Specifically, fixed-term workers face larger and less persistent income innovations compared to their open-ended counterparts. However, this volatility may be largely predictable by individuals, meaning it does not necessarily translate into income risk – defined as the portion of income changes that agents cannot anticipate.

Predictability is crucial for understanding how income volatility affects economic decisions, such as consumption and wealth accumulation. In the extreme case, if open-ended and fixed-term workers experience different income volatility but have similar abilities to predict future income dynamics, the impact of this volatility on their economic behavior would be marginal.

The distinction between income volatility and actual income risk arises from the fact that individuals may use a broader set of information to predict income changes than the econometrician typically relies on. In this context, measuring actual income risk requires to replicate the agents' income prediction process. The availability of high-frequency administrative data makes this task feasible, as economists can leverage detailed income records alongside rich information on workers' characteristics and labor market histories.

In this section, I build on Arellano et al. (2022) to construct an individual measure of income risk, and I further investigate whether this indicator varies depending across labor market statuses. 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}.[42] The measure of income risk used for

[42]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 estimated latent individual component. (iv) The source of income: indicators for labor income earners and unemployment benefit recipients. (v) Measures 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. (vi) The labor market status: indicators for open-ended and fixed-term employment. (vii) The

Table 7: Average income risk by labor market status

Average	Open-ended	Fixed-term
.060	.050	.213

Note: The table reports the average CV measure in the all sample and by labor market status. The sample is split after having estimated the CV indicator. Data are at a quarterly frequency.

the analysis is the following coefficient of variation (CV), which captures the fraction of income changes from one period to the other that the agent cannot predict:

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

The numerator represents the conditional absolute prediction error, while the denominator serves as a measure of location. The indicator is estimated using two Poisson regressions, focusing only on periods of employment, due to the limited information set available in the data for non-employment quarters – the subsequent period's income may still correspond to non-employment periods. To interpret the magnitude of the income risk coefficient, Arellano et al. (2022) propose a simple welfare framework. This connects the coefficient of variation to the percentage reduction in consumption that individuals would need to endure to fully eliminate income risk. An estimated CV below 0.1 indicates relatively low income uncertainty, whereas values of 0.3 or higher suggest a significant degree of income risk across periods.

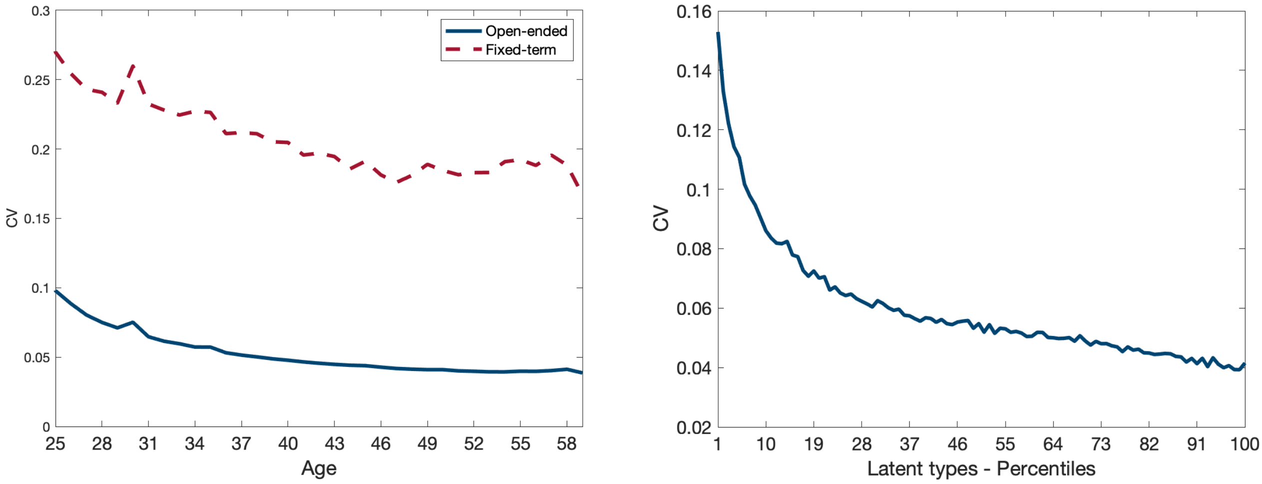
On average, I measure a CV of approximately 0.06 for the population, indicating that individuals experience a low level of uncertainty when predicting income growth across consecutive quarters (Table 7). When broken down by labor market status, the results show that workers in fixed-term jobs face substantially higher income risk – around four times greater than those in stable jobs. Furthermore, income risk tends to decline over the life cycle and is more pronounced among workers with relatively lower latent individual components, who are more subject to labor market instability. Figure 18 illustrates the CV indicator along these two dimensions.

Overall, this measure of individual income risk complements the evidence on income volatility discussed in the paper. The high volatility observed in the income dynamics of fixed-term workers is largely unanticipated, which could have significant implications for economic behavior.

qualification and the employment sector. (viii) An indicator denoting weather the worker was employed in multiple jobs during each calendar quarter. (ix) A set of business cycle indicators: year dummies, GDP quarterly growth rate and demographic-specific quarterly unemployment rate. Both measures are considered up to lags of four quarters.

Figure 18: Income risk (CV)

(a) By age and contract type (b) By latent types



Note: Panel (a) reports the CV values by contract type and over the life-cycle. Panel (b) reports the average CV by percentiles of the latent individual component distribution. Data are at a quarterly frequency.

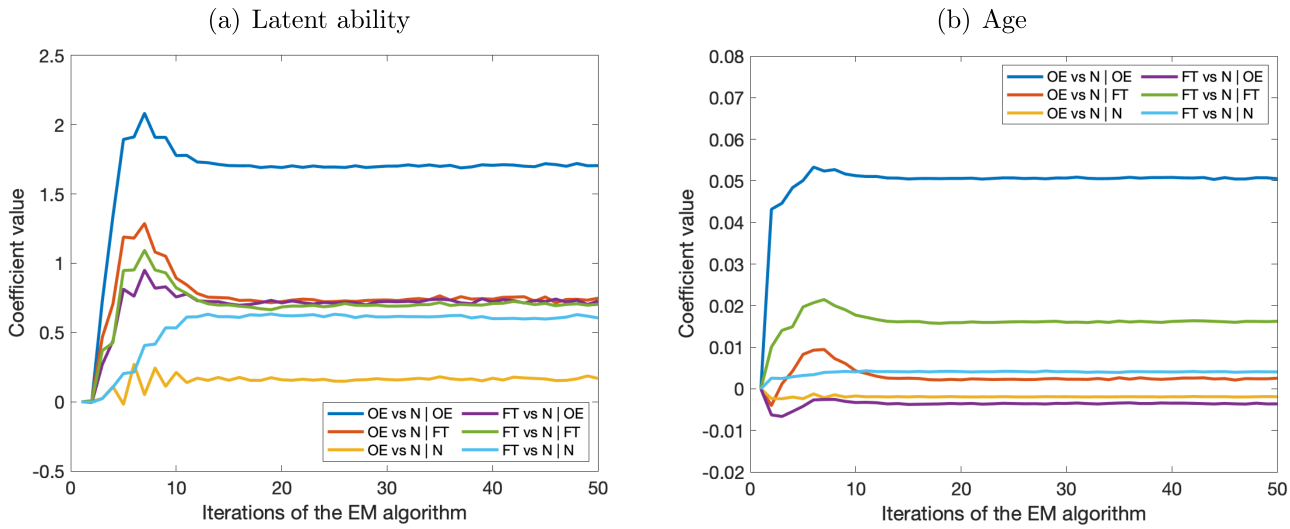
G Additional figures and tables

Table 8: Sample characteristics and the labor market

Number of workers	208,073
Quarterly observations	7,490,628
Average panel dimension (quarters)	26.3
Employment (%)	
Permanent employment	92.7
Temporary employment	7.3
Non-employment (%)	
Non-employment rate	8.4
Non-employment benefits coverage	26.0
Demographics	
Females (%)	38.4
Average age	41.6
North-west region (%)	33.7
North-east region (%)	23.2
Center region (%)	19.5
South region (%)	23.6

Note: the table reports the number of workers and observations in the sample, the average panel dimension, the share of workers by labor market condition and by demographic characteristics.

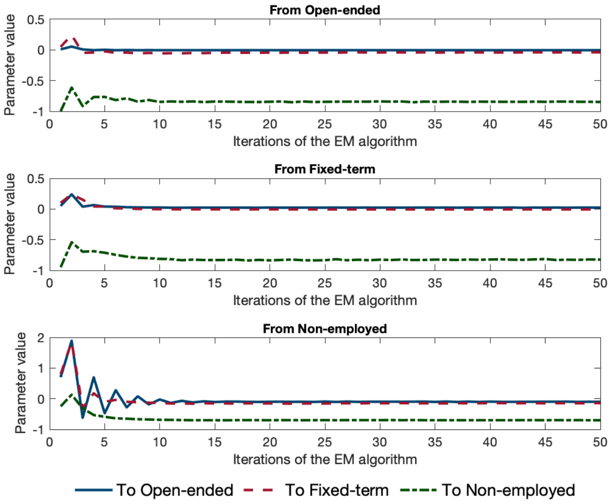
Figure 19: Convergence of labor market transition coefficients



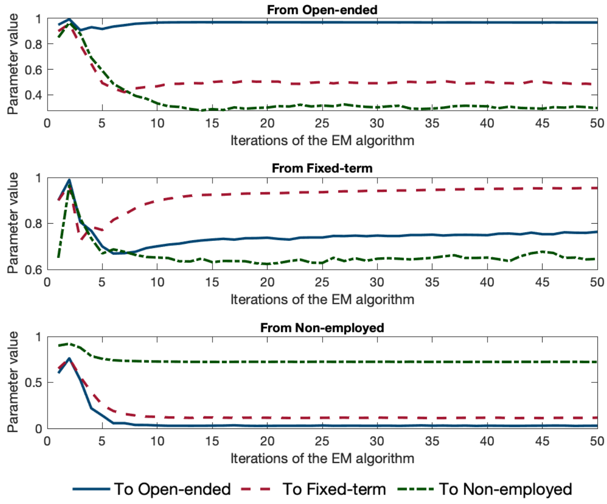
Note: The plots display the values of the coefficients related to labor market transition probabilities over iterations of the stochastic EM algorithm. Panel (a) focuses on coefficients associated with the latent ability component, while Panel (b) shows those linked to the age component.

Figure 20: Convergence of income process parameters

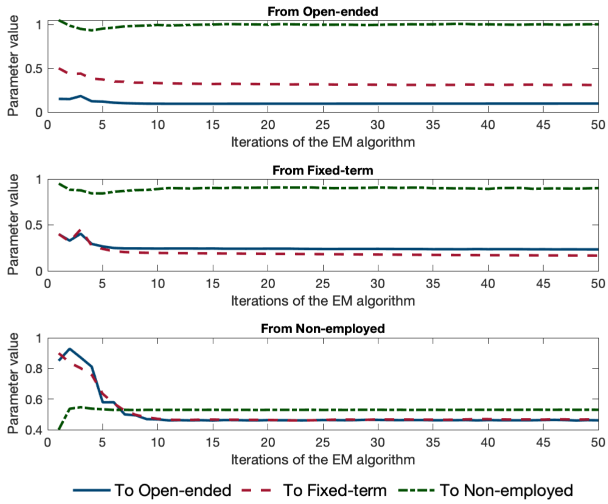
(a) Constant



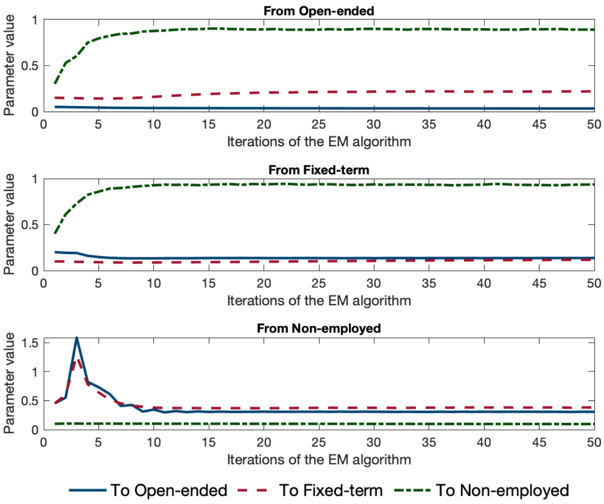
(b) Persistence



(c) Std of persistent shocks



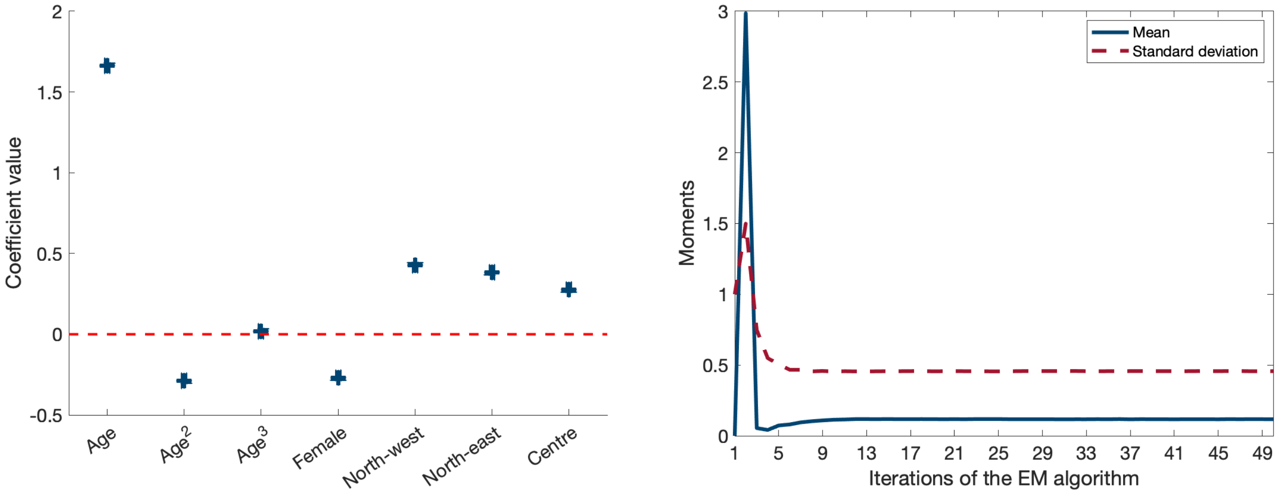
(d) Std of transitory shocks



Note: The plots display the values of the income process parameters across iterations of the stochastic EM algorithm. At each iteration, the parameters represent weighted averages over age-specific coefficients.

Figure 21: Demographics in the income equation and latent ability

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



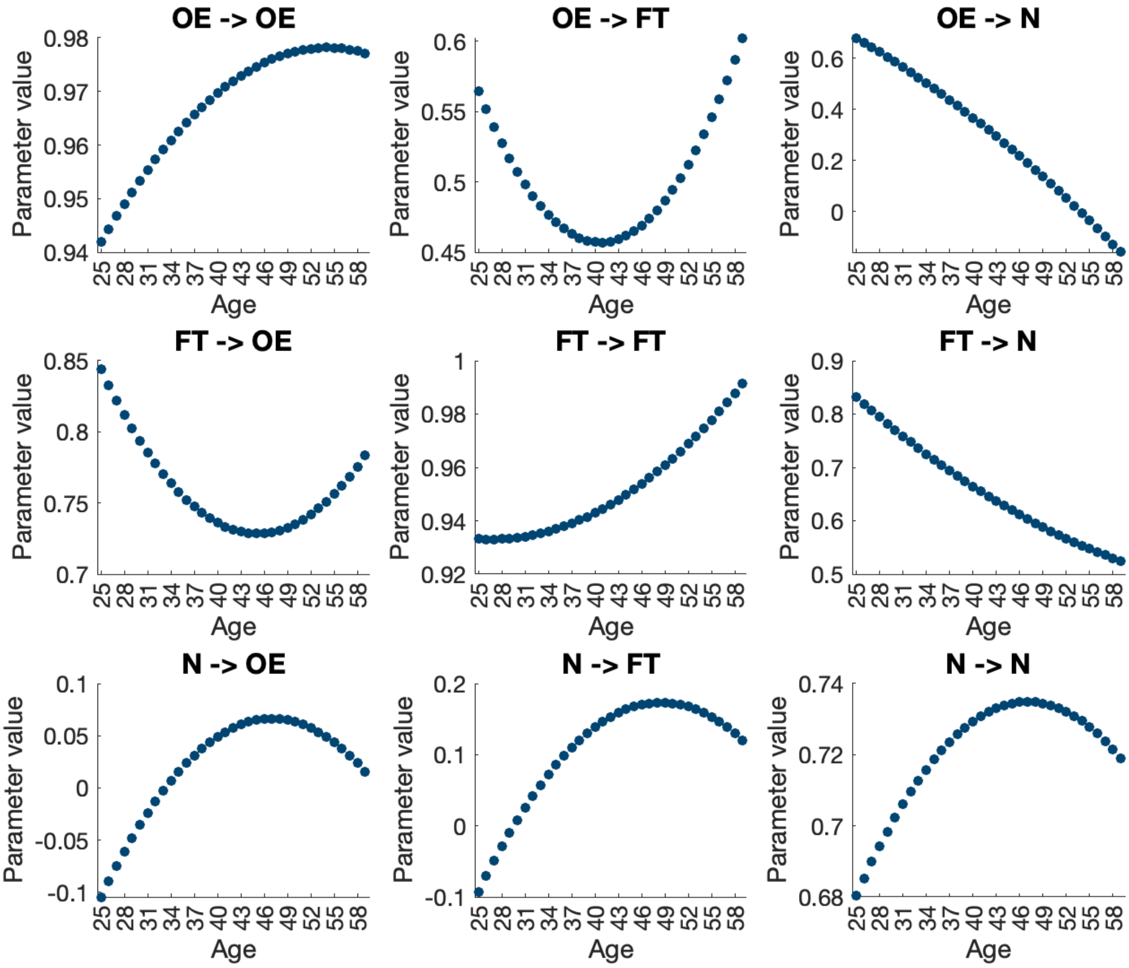
Note: Panel (a) presents the coefficients of the demographics included in the income equation. Panel (b) shows the mean and standard deviation of the latent ability component's distribution within the sample population, incorporating all iterations of the stochastic EM algorithm. Data are at a quarterly frequency.

Table 9: Income process parameters: Constant (c)

t-1 \ t	Open-ended	Fixed-term	Non-employed
Open-ended	-.004	-.040	-.844
Fixed-term	.023	-.007	-.826
Non-employed	-.100	-.148	-.700

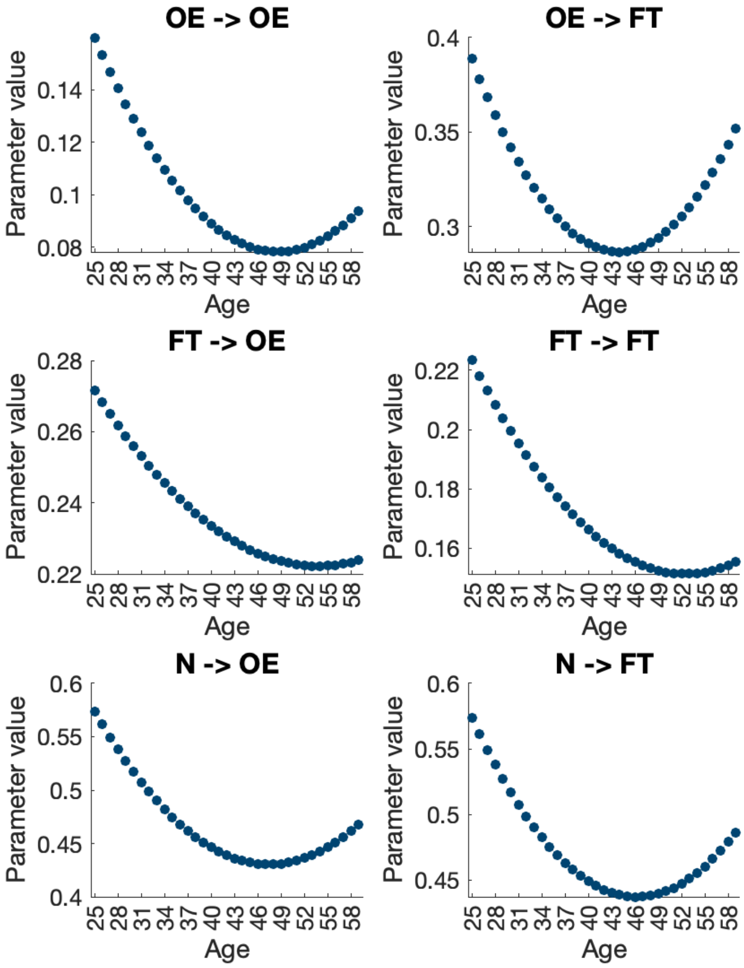
Note: The table shows the constant of the persistent income component. Estimates are derived from the average of the final 30 percent of iterations in the stochastic EM algorithm. Weighted average over age. Values represent weighted averages by age. Data are at a quarterly frequency.

Figure 22: Income process parameters over life-cycle: Persistence (ρ)



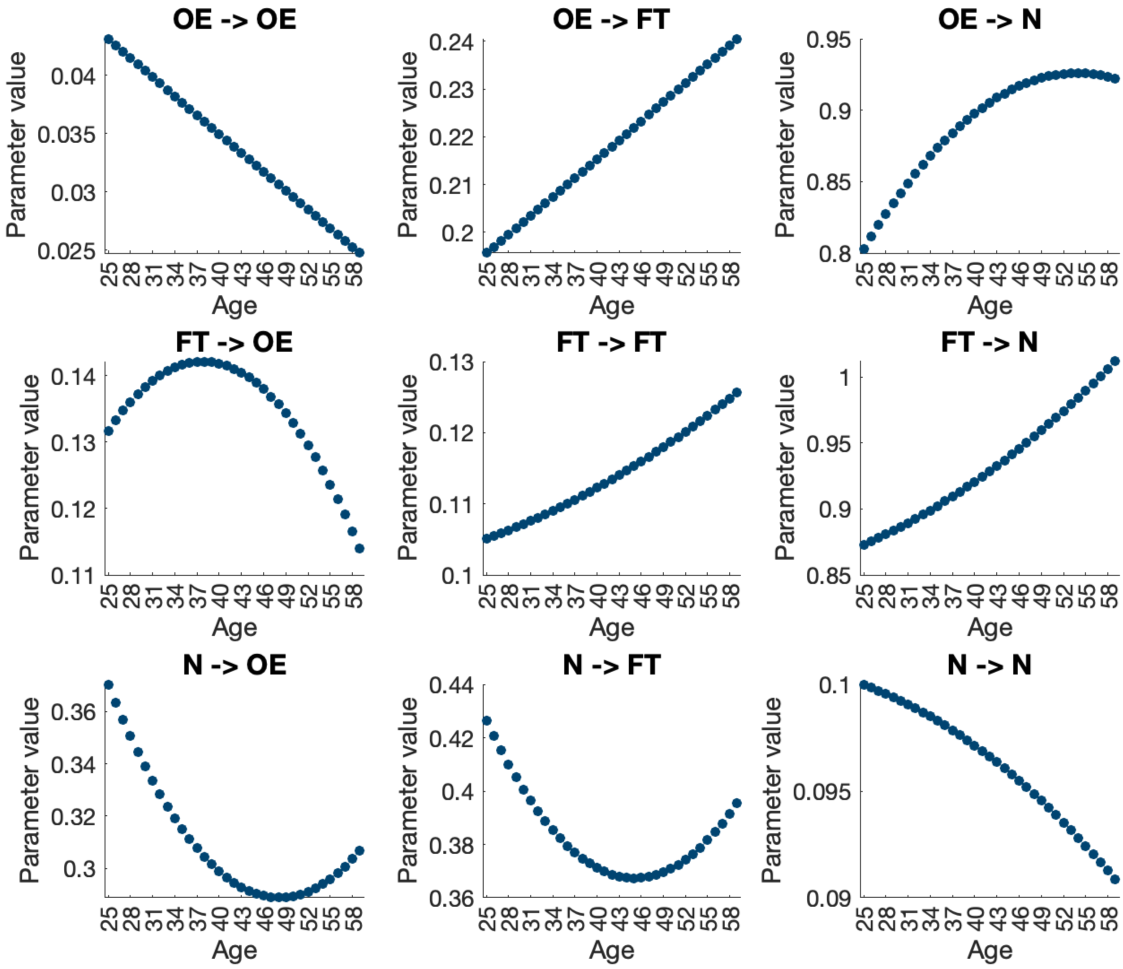
Note: The figure presents the persistence parameter of the persistent stochastic income component, categorized by labor market condition and over the life cycle. The estimates reflect the average of the last 30 percent of iterations from the stochastic EM algorithm. Data are at a quarterly frequency.

Figure 23: Income process parameters over life-cycle: Std of persistent shocks (v)



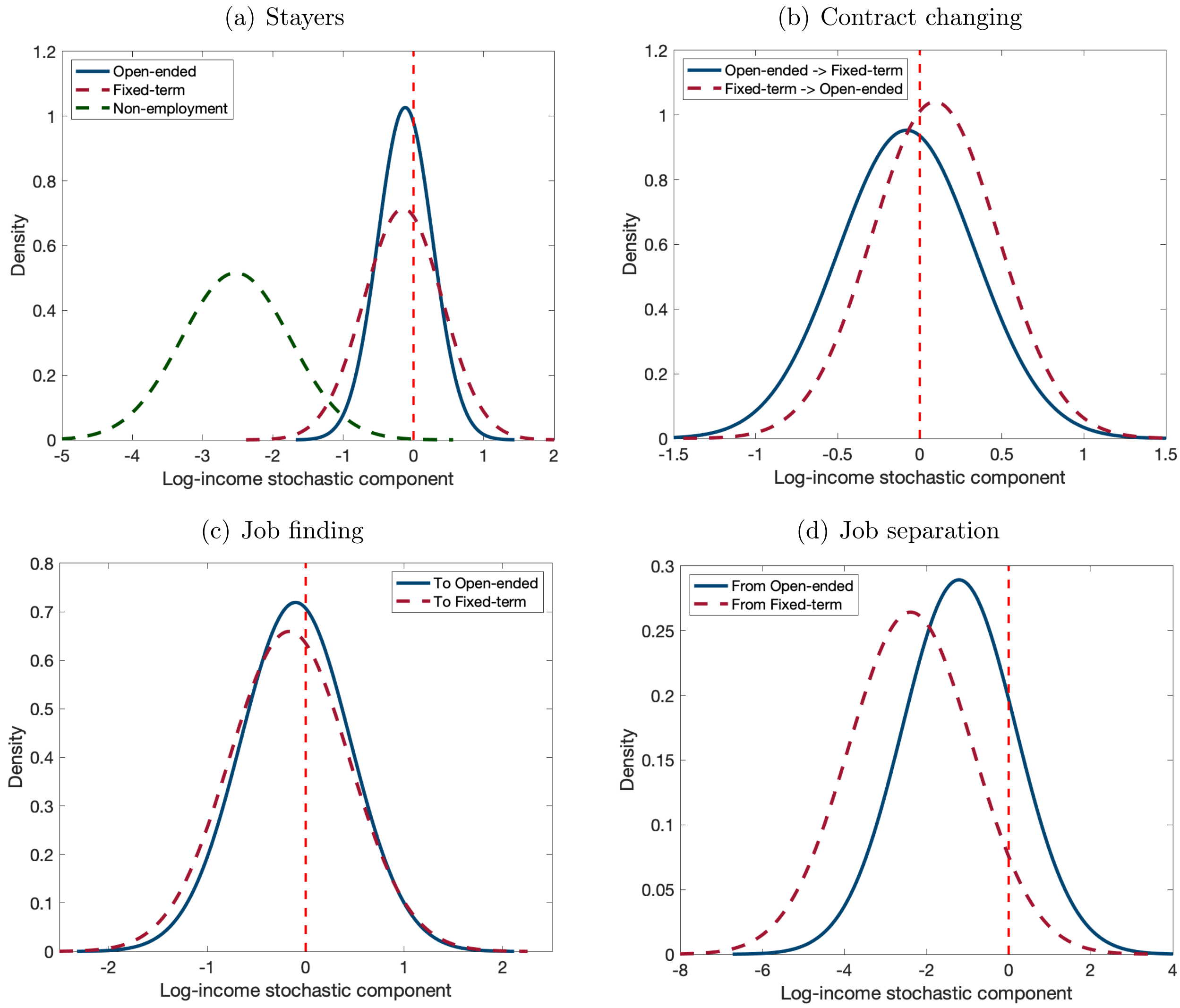
Note: The figure displays the standard deviation of persistent income innovations, categorized by labor market condition and over the life cycle. The estimates represent the average of the last 30 percent of iterations from the stochastic EM algorithm. Data are at a quarterly frequency.

Figure 24: : Income process parameters over life-cycle: Std of transitory shocks (ε)



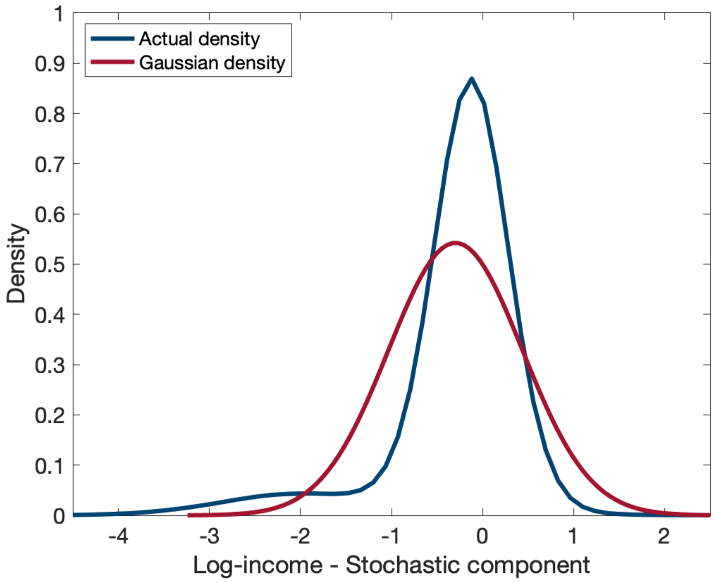
Note: The figure presents the standard deviation of transitory income innovations, categorized by labor market condition and over the life cycle. The estimates reflect the average of the last 30 percent of iterations from the stochastic EM algorithm. Data are at a quarterly frequency.

Figure 25: Asymptotic density of the stochastic income component



Note: The figures illustrate the asymptotic density of the stochastic income component, which is the sum of the persistent and transitory terms. Panel (a) displays the distributions for workers who maintain the same labor market status across consecutive periods. Panel (b) the density based on parameters characterizing contract-changing transitions. Panel (c) the one derived from parameters related to job-finding transitions, while Panel (d) depicts the density based on parameters specific to job-separating transitions. Data are at a quarterly frequency.

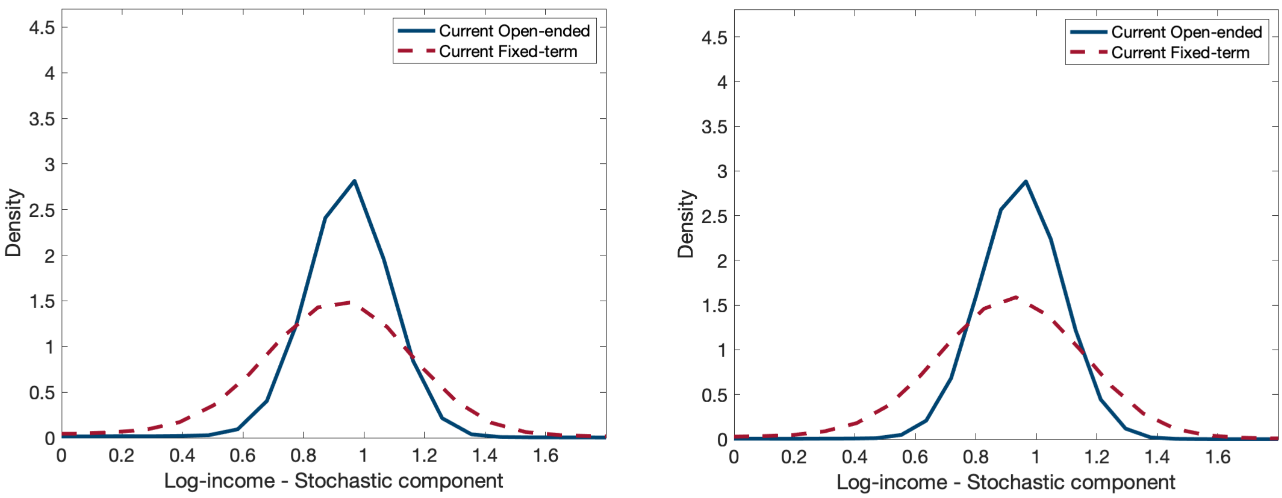
Figure 26: Unconditional density of the stochastic income component



Note: The figure illustrates the unconditional density of the stochastic income component, aggregated across labor market conditions, and compare it with a Gaussian distribution having the same mean and standard deviation. Results are based on simulated data at a quarterly frequency.

Figure 27: Next-period stochastic income density by current contract type - 30 year old

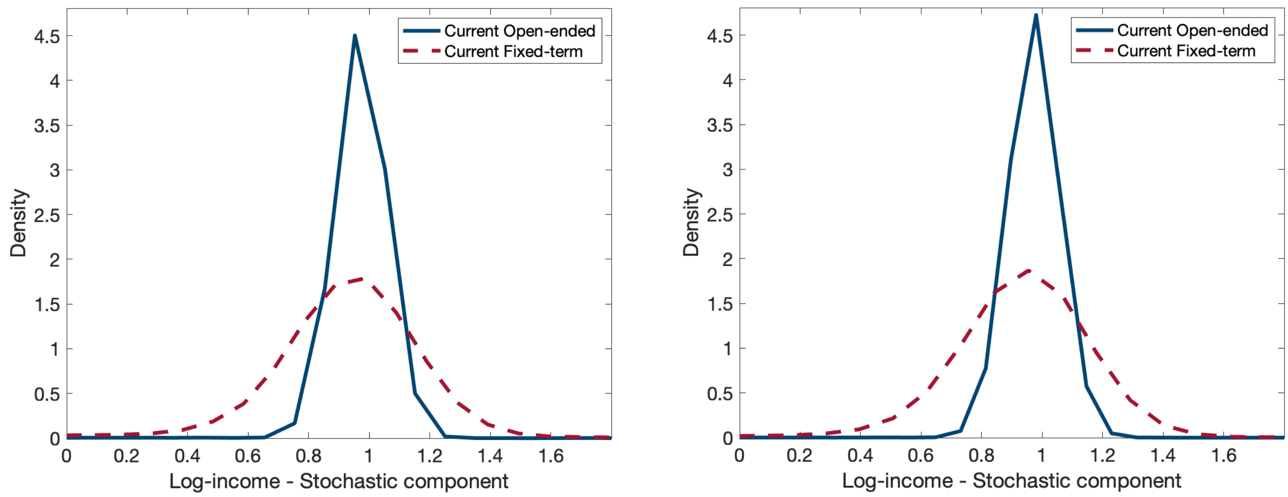
(a) Low types (Q_{20}) (b) High types (Q_{80})



Note: The figure presents the distribution of the next-period stochastic log-income component, assuming a current value of the persistent term equal to one. It is shown separately by current contract type. Panel (a) focuses on low ability types, while Panel (b) examines high ability types. The distributions are specific to 30 year old male workers residing in the central region of the country. Results are based on simulated data at a quarterly frequency.

Figure 28: Next-period stochastic income density by current contract type - 50 year old

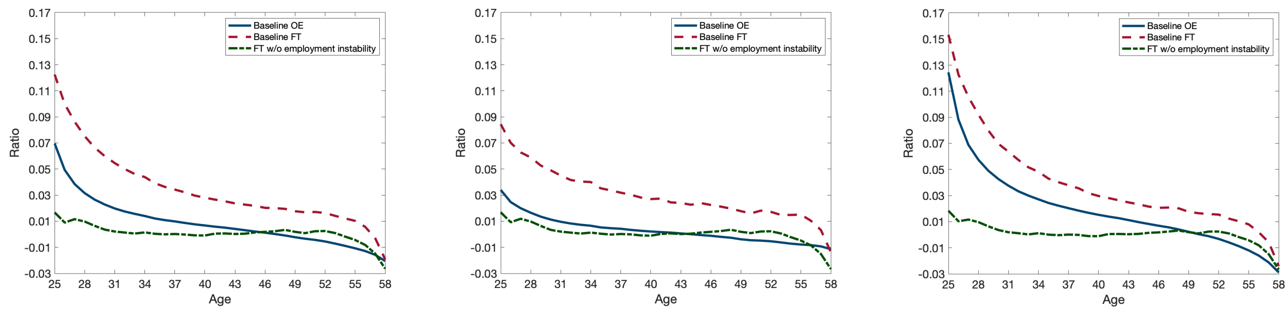
(a) Low types (Q_{20}) (b) High types (Q_{80})



Note: The figure presents the distribution of the next-period stochastic log-income component, assuming a current value of the persistent term equal to one. It is shown separately by current contract type. Panel (a) focuses on low ability types, while Panel (b) examines high ability types. The distributions are specific to 50 year old male workers residing in the central region of the country. Results are based on simulated data at a quarterly frequency.

Figure 29: Saving rate by contract type w/ and w/o employment instability (Only FT)

(a) All individuals (b) High types (Q_{80}) (c) Low types (Q_{20})



Note: *Note*: The figure displays the saving rate as a percentage of total available resources over the life cycle, segmented by contract type and for workers who are in fixed-term jobs and who are not subject to employment instability. Panel (a) covers the entire sample, while Panels (b) and (c) highlight high- and low-productivity individuals in the top and bottom quintiles of the latent component distribution, respectively. Results are derived from model simulations.

Figure 30: Share of workers of different latent types by labor market conditions

Note: Panel (a) of the figure reports share of workers in different quintiles of the latent ability distribution by labor market status. Panel (b) replicate the same exercise but considers specific labor transitions instead than statuses. Results are based on simulated data at a quarterly frequency.