A macroeconomic analysis of heterogeneous labor market risk

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Abstract

A recent literature has documented population heterogeneity in labor market risk. It has identifed that a small fraction of the population belongs to an unstable labor market type, which accounts for a disproportionate share of aggregate unemployment and faces greater labor market risk. This paper documents additional new facts on labor market type heterogeneity and measures its welfare implications. We document that labor market type heterogeneity is related to but distinct from heterogeneity in individual productivity or wages. Unstable types have longer non-employment spells and shorter job spells, as well as lower and flatter wage trajectories. They also hold substantially less wealth. We use a general equilibrium heterogeneous-agent life cycle model with incomplete markets and realistic institutions to measure the distribution of the welfare cost of employment fluctuations. We find that labor market risk imposes a welfare cost on unstable types that is almost an order of magnitude greater than that for stable types. Precautionary saving allows individuals of the unstable type to mitigate this cost. Their wealth is nevertheless low as it is drained by repeated episodes of job loss. A greater unemployment insurance replacement rate helps little to mitigate the welfare cost of employment fluctuations, but expanding the coverage of unemployment insurance can yield welfare gains.

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1. Introduction

Job loss is one of the major risks individuals face in their lives. A large quantitative literature has measured this risk and the extent of private and public insurance against it. Over the last few years, evidence has emerged that clearly shows that the risk of job loss and persistent non-employment is very unequally distributed in the population, and only imperfectly correlated with other dimensions of heterogeneity, like skill. This work suggests the existence of distinct "labor market types". This paper extends this mostly empirical literature in three ways. First, we document new facts on differences between labor market types, notably wage trajectories and wealth. Second, we use a general equilibrium heterogeneous-agent life cycle model with incomplete markets to measure the distribution of the cost of non-employment risk across labor market types, taking into account both the unemployment insurance (UI) system and self-insurance. Third, we quantitatively evaluate a broad set of policies designed to mitigate this risk.

The recent literature on labor market types started with the observation that lifetime unemployment varies strongly in the population (Morchio 2020).[1] Subsequent work showed that the population can be partitioned into a set of types – dubbed "labor market types" – who differ strongly in their job finding and separation rates and, as a result, in their non-employment propensity and the duration of the employment and non-employment spells (Shibata 2019; Gregory, Menzio, and Wiczer ????; Hall and Kudlyak 2022; Ahn, Hobijn, and Sahin 2023). Castro, Lange, and Poschke (2025) review this work and show that, across data sources and emprical methods, similar descriptions of labor market types emerge. All methods suggest the existence of an "unstable" labor market type with higher job loss rates, lower job finding rates, and more frequent, longer non-employment spells. Members of this type generally account for a small part of the population, but make up a large fraction of the non-employed.[2]

In this paper, we document further differences across labor market types, using data from the National Longitudinal Survey of Youth (NLSY) 1979. The NLSY, with its long panel covering one cohort's entire labor market history, is highly suitable for measuring labor market types, and provides a wealth of further information.[3] We use and build on the recent estimates of labor market types by Castro et al. (2025) for these data. There, unstable types amount to about 10% of the population of highly attached individuals we

[1]Early references noting this include Hall (1970) and Clark and Summers (1979). Advances in data accessibility and increases in the length of both administrative and survey data have now allowed more complete analyses.

[2]Different types of data sources require different methods, and on occasion deliver more or less heterogeneity in finding versus separation rates. Yet all agree in identifying an unstable type that accounts for a small part of the population, but a large fraction of non-employment.

[3]The downside is that it only covers a single cohort. The advantage is that this cohort by now has completed its labor market history, which can be observed in detail and in its entirety. See below and Bick, Blandin, and Rogerson (2025a) for a detailed analysis of the NLSY's representativeness.

focus on.

We begin by establishing a set of additional new facts on labor market types. First, we find that heterogeneity in labor market type is correlated with but clearly distinct from that in wages. While almost all “unstable types” have relatively low wages, only one sixth of workers with low lifetime wages are unstable types. Even in the bottom decile of lifetime wages, only a third of individuals belong to the unstable type. Going forward, we thus distinguish three types of workers: unstable types, stable low-wage types, and stable high-wage types. Second, unstable types have lower entry wages and flatter log wage-age profiles than stable low-wage types. Finally, their wealth on average amounts to less than half that of stable low-wage types, and only a seventh of high-wage types.

Clearly, unstable types go through challenging labor market histories. Everything points to them being less well off than other individuals. A natural question is to what extent this is due to labor market flows versus wage profiles, and whether any policies can help. To answer these questions, we build a detailed general equilibrium heterogeneous-agent life cycle model with incomplete markets. Relative to a rich literature using such models, the novelty in our approach is to explicitly allow for heterogeneity in labor market types.

Individuals in our model enter the labor market at age 22. They differ in labor market and wage type. Throughout their lives, they experience wage growth that differs by type, are subject to wage shocks, and to the possibility of job separations. Wage growth and job flows differ by type. They face a realistic tax, retirement and UI benefit system. An important realistic feature is that not all the unemployed receive benefits. Every period, they decide on work and savings. The effects of job loss are cushioned by UI benefits and private saving. We calibrate the model to closely match the features of labor market types we documented in the data.

The model closely replicates the rich heterogeneity in the US economy. Importantly for our analysis, it closely matches the distributions of earnings, income and wealth, including at the bottom. It also closely replicates empirical estimates of the consumption response to job loss, suggesting that the model realistically replicates the degree of insurance present in the data. Indeed, we find that unstable types in the model economy actively engage in precautionary savings, which they build at the cost of much lower consumption when employed, compared to stable low-wage types. These savings are regularly run down as they cushion the consumption drops occuring with job loss.

As a result, the welfare cost of employment fluctuations for unstable types is very large, equivalent to more than a third of their consumption. Three quarters of this come from the direct consumption loss due to lost income. The remainder reflects the cost of consumption fluctuations as well as the cost of engaging in precautionary saving. For stable types, the cost of employment fluctuations ranges from 3.5% (high-wage) to 7.7%

(low-wage). Welfare of unstable types is about a third lower than that of stable low-wage types, mostly due to differences in job flow rates.

In the model economy, the average cost of employment fluctuations amounts to 8.7%. For comparison, we also measure the cost of employment fluctuations in a model economy with a single labor market type – the typical specification in the literature. This amounts to 10.7%. This “common-flows” model thus overstates the cost of employment fluctuations for 90% of the population, while severely understating it for unstable types. We also observe that the common-flows model overstates the aggregate cost of employment fluctuations because it confounds risk and heterogeneity.

Finally, we analyze a broad set of policies that appear to be good candidates for improving welfare. These include both modifications of the UI system and tax and transfer policies. Perhaps counterintuitively, we find that raising the UI replacement rate generates hardly any welfare gains. This reflects the fact that the greatest risk in case of job loss is to be non-employed and uninsured. Hence, expansions in UI coverage provide greater gains, most of which do not rely on redistributive motives.

Related literature.. Our work relates most closely to the literature on labor market risk and to that on heterogeneity and optimal redistribution. Most of the literature on labor market risk cited above is empirical and contains little to no theoretical, welfare or policy analysis. An exception is Gregory, Menzio, and Wiczer (????). These authors use a search-theoretic model of the labor market to better understand differences in dynamics by type, but do not consider saving or analyze potential policy reforms. Castro et al. (2025) provide a detailed analysis of labor market type heterogeneity. They find that unstable types have worse health, and that adverse health events and labor market outcomes early in life strongly predict later unstable labor market trajectories. Their analysis considers neither wages nor wealth.

Most of the work on heterogeneity and redistribution has focussed on heterogeneity in earnings, often abstracting from employment risk. Exceptions are Low, Meghir, and Pistaferri (2010) and Krusell, Mukoyama, and Sahin (2010), who contrast the importance of productivity and employment risk, but do not capture heterogeneity in employment risk.[4] More recent work does consider some amount of heterogeneity in employment risk, mostly across income groups. For example, Krusell et al. (2017) and Guvenen et al. (2021) have shown that non-employment risk is higher for low-wage workers. Birinci and See (2024) document the relationship between income and wealth and unemployment risk. Ozkan, Song, and Karahan (2023) provide a detailed analysis of job flows by lifetime earnings, with a focus on their impact on wage paths. We instead show that labor market types are only weakly correlated with wages, and focus on differences in labor market

[4] Krusell, Mukoyama, and Sahin (2010) and Nakajima (2012) also analyze the impact of employment risk and insurance on fluctuations in equilibrium unemployment over the business cycle.

flow rates across labor market types, which dwarf the differences in non-employment risk across income groups that the literature has taken into acocunt.

The remainder of this paper is structured as follows. Section 2 provides new evidence on labor market types. Section 3 describes the model we use, and 4 its calibration and important features of the benchmark economy. Section 5 presents our analysis of the welfare effects of employment fluctuations. Section 6 contains the policy analysis, and Section 7 concludes the paper.

2. Labor market types

In this section, we describe how we classify individuals as being of stable or unstable labor market type, how these types differ in labor market histories, wages, and wealth, and how their differences compare to differences across wage groups.

2.1. Data source

Our analysis requires a dataset that follows individuals for a long time, records high-frequency information on their labor market histories, contains information on earnings and hours worked, and ideally also on wealth. These are stringent requirements that few data sources fulfill.

One dataset that fulfills our requirements completely is the US National Longitudinal Survey of Youth 1979 (NLSY). It follows a cohort of individuals aged 14 to 22 in 1979 over their entirely working lives, from labor market entry in the early 1980s to 2022, when they approach retirement age. This gives a full overview of their working lives.[5]

As a result, the NLSY contains all the information we require. It contains labor market histories at a weekly frequency, which we use to estimate labor market types. We combine it with information on annual earnings and hours worked to compute average wages per year. To evaluate model fit, we also make use of the wealth information in the NLSY.

Compared to administrative data sources like the LEHD, the survey has the advantage of the high frequency of labor market histories, and the availability of demographic and wealth information. The high frequency of observation in labor market histories is also an advantage compared to the PSID. Finally, the CPS and the SIPP do not follow individuals for long enough to precisely estimate an individual's type.[6] As the NLSY has recently completed coverage of a cohort's entire working life, we expect it to be used broadly for macroeconomic analysis. For example, Bick, Blandin, and Rogerson (2025b) use the NLSY

[5] The survey was conducted annually from 1979 through 1994, and then every two years from 1996 to 2022.

[6] They can be used to estimate the distribution and characteristics of types in the population; see Hall and Kudlyak (2022) or Ahn, Hobijn, and Sahin (2023).

to study heterogeneity in lifetime earnings and hours worked.[7]

2.2. Sample description and selection

In 1979, the NLSY began surveying 12,686 individuals born between 1957 and 1964. This sample was followed first annually, and after 1994 biannually. We use data from when an individual first turned 22 (this occurred between 1979 and 1986) up to the year 2022. We use NLSY sample weights.

To be able to estimate labor market types, we also require individuals to be in the sample between the prime age working years of 30 to 50. More precisely, we exclude anyone who is not interviewed in five or more consecutive years between the ages of 30 and 50.[8] Following Low, Meghir, and Pistaferri (2010), our analysis focusses on men. This leaves us with 73,410 observations on 2,447 respondents.

In the weekly employment histories, the employment status can take the values employed, unemployed or out of the labor force. Around three quarters of prime age employed histories are complete, and only around five percent have gaps longer than two years. They are thus reasonably complete for a very large part of the sample.

We follow Bick, Blandin, and Rogerson (2025b) in the treatment of wage outliers. At the bottom, we set any wage below half of the federal minimum wage to half of the federal minimum wage. At the top, we assume that the top 0.1% of wages result from misreported hours, and accordingly set hours, wages and earnings in the affected observations to missing. We also set hours observations below 200 hours a year to missing. We compute real wages using the CPI, and express them in 2022 dollars.

2.3. Labor market types and wage types

2.3.1. Stable and unstable types

We use CKLLP's estimates of labor market types in the NLSY. Following GMW and CLP, CKLLP estimate each individual's labor market type using k-means clustering on data from their prime age years, ages 30 to 50. For each individual, they measure and cluster based on the following five moments: the average durations of employment and non-employment, the fraction of weeks spent out of the labor force (OLF) or unemployed, and the number of jobs relative to the number of quarters employed in each individual's history. These moments distinguish individuals based not only on the time they spent

[7] Bick, Blandin, and Rogerson (2025a) conduct a detailed investigation of the representativeness of the NLSY79 over time. They conclude that "the remaining NLSY79 sample continues to be broadly representative of their national cohorts regarding key labor market outcomes. For NLSY79 age cohorts, life-cycle profiles of employment, hours worked, and earnings are comparable to those in the Current Population Survey."

[8] This restriction automatically excludes the oversamples of military and economically disadvantaged white youth, which were discontinued.

non-employed, but also on the duration of employment and non-employment spells, which are informative on the stability of labor market histories. The separate inclusion of information on unemployment and OLF status help distinguish types most often OLF from those more frequently unemployed.[9]

CKLLP show that four types are best suited to describe the heterogeneity in labor market histories in the NLSY. In addition, there are two groups of individuals who cannot be clustered because they either work the entire period from age 30 to age 50 (so no moments related to non-employment can be computed) or almost never work. Out of these six types, two consist of individuals who spent most of their prime age years out of the labor force, and who spent less than ten percent of their non-employed time searching for jobs. Since our analysis focusses on individuals who are attached to the labor market, we exclude individuals belonging to these two types. Among the remaining four types of attached individuals, one type spends around 40% of the time non-employed, and has short employment spells with an average duration barely exceeding a year. We consider this type to be unstable. We consider the other three types to be stable. They have average durations of employment spells ranging from over three years to the entire sample.[10,11]

2.3.2. Lifetime wage types

Like most quantitative analyses of incomplete markets models, which typically distinguish permanent wage types as part of the calibration, we also divide the population in two permanent wage types.[12] We consider an individual "high-wage" if their average wage between the ages 22 and 55 exceeds the sample mean.[13]

2.3.3. Two distinct types

Table 1 shows the distribution of the two types in the population. Around 10% of attached individuals are of the unstable labor market type. This number is smaller than that found by GMW in the LEHD or by CLP in Canadian administrative data. This is not entirely surprising, given different ways of treating less attached individuals. As labor market statistics below will show, our unstable types thus are even less stable than those analyzed

[9]The absolute value of pairwise correlations among these moments is mostly around 0.2 to 0.3.

[10]The unstable type corresponds to that labelled 4.3 by CKLLP. GMW detect a similar type, labelled γ, and similarly exclude less attached individuals from their analysis.

[11]CKLLP investigate in detail which individual characteristics are associated with different types. They find that demographics, health and early labor market outcomes help predict types. Industry and occupation provide very little additional information.

[12]Alternatively, the literature often considers two education types, as e.g. Low, Meghir, and Pistaferri (2010) do. Ozkan, Song, and Karahan (2023) directly document differences in earnings growth and labor market experiences of lifetime *earnings* types, since the administrative data they use do not allow measuring wages. Compared to them, we distinguish both wage and labor market types, and show that these dimensions are related but distinct.

[13]The characteristics of the two wage groups are similar when using different age cutoffs.

by GMW. We will explore robustness of our results to different definitions of the unstable type later on.

TABLE 1. Population distribution of labor market and wage types

	Wage type		
	low	high	Total
Labor market type			
unstable	9.6	1.0	10.5
stable	51.4	38.1	89.5
Total	61.0	39.0	100.0

The high-wage type makes up just under 40% of the sample. This reflects the definition based on the mean, combined with the typical skewed distribution of wages.

Considering wage and labor market types jointly, the most populous type is the stable, low-wage type, followed by the stable, high-wage type. Again, slightly fewer than half the stable individuals belong to the high-wage type.

More than 90% of unstable individuals belong to the low-wage type. Hardly anyone (just 1%) belongs to the unstable, high-wage type. We will thus abstract from this type in our analysis. In a nutshell, the population thus consists of three groups: a stable, low-wage type (around half of the population), a stable high-wage type (around 40%), and an unstable low-wage type (around 10%).[14]

The fact that the low-wage stable type makes up the largest share of the population indicates that wage and labor market type are distinct. We investigate this further in Figure 1, which shows the share of individuals of the unstable type by lifetime wage decile. The figure shows that even in the bottom wage decile, only about a third of individuals have unstable labor market histories. In the next fifty percent of the wage distribution, the share of unstable individuals is close to its population share. In the top forty percent, it becomes negligible, as also seen in Table 1. Hence, while correlated, the two type dimensions are clearly distinct.[15]

[14]The imperfect correlation between labor market and wage type is not due to the specific threshold used for the wage type. For example, when choosing the threshold so that the low-wage group has a similar size as the unstable group, it is still the case that the share of unstable individuals of the low-wage type far exceeds the population low-wage share, indicating some correlation between types. At the same time, it also remains the case that most low-wage individuals are of the stable type, indicating that labor market types and wage types, while correlated, are distinct.

[15]This conclusion is also supported by the pairwise correlations between the log mean lifetime wage and the labor market history moments used in clustering, which are around 0.3 in absolute value.

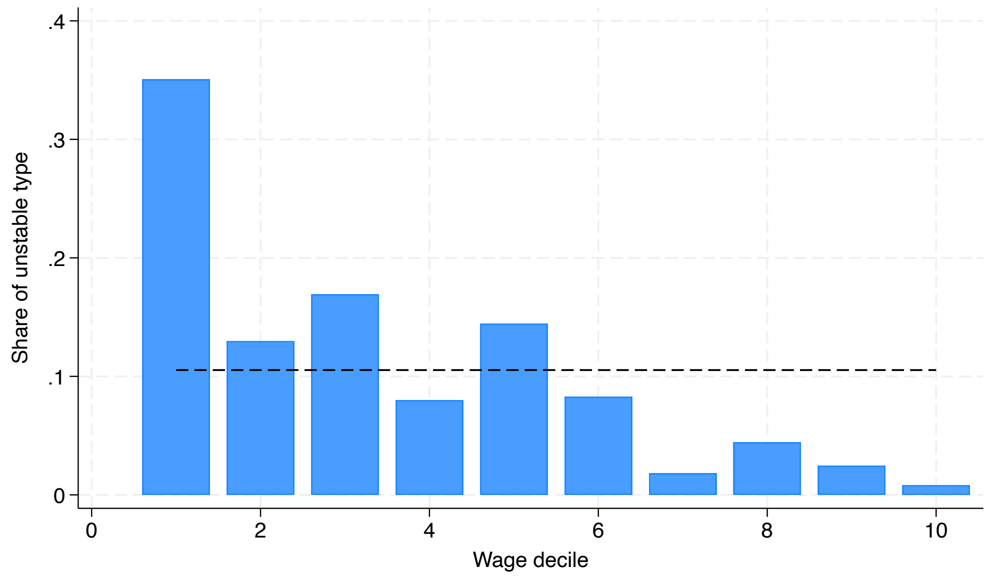


FIGURE 1. Share of unstable type by wage decile and overall (horizontal line)

2.4. Labor market experiences by type

Tables 2 and 3 summarize labor market experiences of the different types. It is evident that the types differ very strongly in their labor market experiences. Unstable types spend 31% of their time non-employed, and stable types only 5%.[16] As a result, unstable types account for almost half of the non-employed, although they only account for one tenth of the attached population.

Wage types also differ in the time they spend non-employed. This accounts for 11% of the time of the low-wage group, but only 3% for the high-wage. However, this difference is much smaller than that across labor market types.

Table 3 shows that on average in this attached population, job spells last 284 weeks, or five to six years, and non-employment spells about a third of a year. The stable type experiences even longer job spells, of more than 300 weeks on average, and slightly shorter non-employment spells. Unstable types have a completely different experience of the labor market, with average job spells lasting less than a year, and the average non-employment spell lasting almost as long as the average job.

Again, wage types also differ in spell length, with high-wage types experiencing signif-

[16]Of this time, unstable types spend a third in unemployment and the remainder out the labor force. Stable types spend only 2% of their time unemployed. Unstable types also frequently transition between unemployment and out of the labor force, as already observed by Kudlyak and Lange (2014) and Elsby, Hobijn, and Şahin (2015). For this reason, we consider the empirical counterpart of “unemployment” in the theoretical analysis to be non-employment, and use the two terms interchangeably in the following. Note that the unstable types we focus on in our analysis are again very distinct from individuals who are not attached to the labor market, and who spend the majority of their time out of the labor force.

TABLE 2. Share of time non-employed by wage and labor market type

	Wage type		
	low	high	Total
Labor market type			
unstable			
non-employment	0.32	0.20	0.31
unemployment	0.11	0.11	0.11
stable			
non-employment	0.06	0.03	0.05
unemployment	0.03	0.01	0.02
Total			
non-employment	0.11	0.03	0.08
unemployment	0.04	0.01	0.03

icantly longer job spells and shorter non-employment spells. Yet again, the differences between these two types are much smaller than those between labor market types.

Naturally, job finding and separation rates also differ across the two types. The mean spell durations shown in Table 3 imply that for the stable types, the separation rate is about 0.3% per week or 1.4% per month, whereas it is much higher, at 9.7% per month, for unstable types. Conversely, the job finding rate from non-employment is 25.3% per month for stable types, but only 10.5% for unstable types.[17]

Overall, it is clear that labor market types differ very strongly in their labor market experiences, and that the experience by unstable types is very far from the average. While wage types also differ in their labor market experiences, this differences are eclipsed by those between labor market types. While types are correlated, the correlation is far from perfect, with the largest group in the population low-wage but stable. Earning a relatively low wage and thus is a very different attribute from having an unstable labor market experience. This is why we separately labor market and wage types.

2.5. Wages and wealth by labor market and wage types

Figure 2 shows age-wage profiles for the different groups.[18] By construction, the group with higher lifetime wages earns higher wages overall. However, stable low-wage individuals also earn significantly higher wages than their unstable counterparts.

Compared to high-wage types, starting wages at age 22 are 29% lower for stable low-

[17]This job finding rate from *non-employment* is somewhat lower than that from *unemployment* documented by Shimer (2005) or Elsby, Hobijn, and Şahin (2013).

[18]A quadratic fits these profiles remarkably well. We use estimates of this quadratic fit in the model calibration below.

TABLE 3. Mean spell length (weeks) by wage and labor market type

	Wage type		
	low	high	Total
Labor market type			
unstable			
Job spells	42.66	44.56	42.83
Non-employment spells	40.89	21.50	39.14
stable			
Job spells	260.28	382.78	312.39
Non-employment spells	18.47	10.96	15.28
Total			
Job spells	226.09	374.52	283.99
Non-employment spells	21.99	11.22	17.79

wage types, and 34% lower for unstable types. These gaps grow over the life cycle. Grom age 25 to 55, wages of high-wage types grow by 87 log points (or about 140%), those of stable low-wage types by 35 log points (or about 42%), and those of unstable types by only 29 log points (or about 34%). The gap between stable and unstable types is particularly large around age 40.

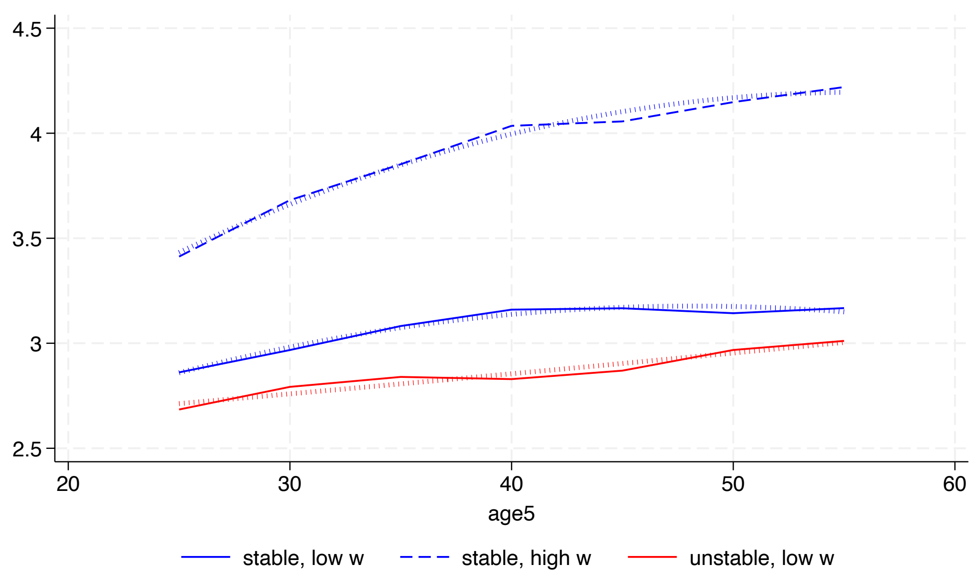


FIGURE 2. Age-wage profiles by labor market and wage type

Table 4 shows corresponding wealth differences. The table shows mean wealth across ages 22 to 65 by type. The gaps across wage and labor market types are very large. High-wage individuals are on average more than three times as wealthy as low-wage individuals. Yet what is particularly striking is that in turn, stable low-wage individuals are on average more than twice as wealthy as their unstable counterparts.

TABLE 4. Mean wealth (thousands of 2022$) by wage and labor market type

	Wage type		
	low	high	Total
Labor market type			
unstable	76.92	264.45	94.30
stable	165.39	587.54	349.07
Total	151.05	579.46	321.68

Figure 3 shows wealth by age for each group. The left panel shows the mean and the right the median wealth for each labor market, wage and age group, in thousands of 2022 dollars. It is clear that while there are already small wealth differences at labor market entry, the differences in means shown in Table 4 are the consequence of different growth rates of wealth over the life cycle. High-wage types accumulate wealth from early on. Low-wage types accumulate wealth at a lower rate, but nevertheless end up with median wealth of close to 240 thousand dollars at age 60. Unstable types, in contrast, accumulate hardly any wealth. At age 60, their median wealth barely exceeds 30 thousand dollars. Median wealth of unstable individuals of ages 22 to 60 combined is only 6 thousand dollars. These wealth gaps are much larger than the wage gaps observed above.

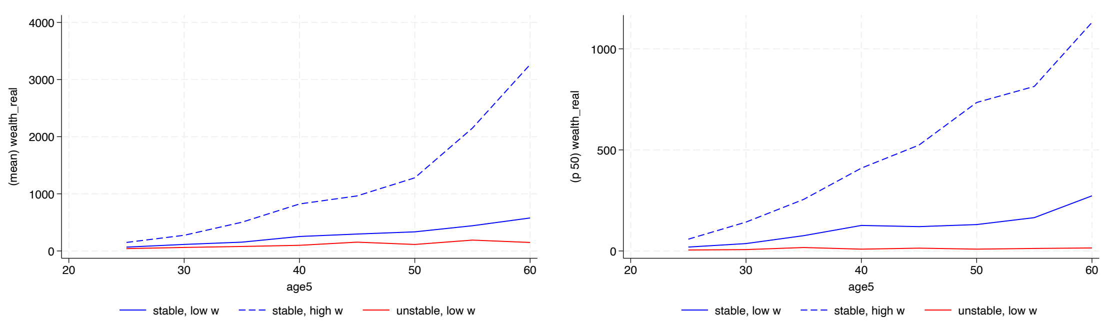


FIGURE 3. Age-wealth profiles by labor market and wage type (left: mean, right: median)

Summary. This section has provided evidence on labor market histories, wages and wealth of different population groups. By construction, labor market types differ strongly in their labor market histories, and wage types in their wage trajectories. The two type dimensions are distinct, as most low-wage individuals have stable labor market histories, even at the bottom of the wage distribution.

The extent of heterogeneity in labor market trajectories is large. Unstable types experience many more and longer non-employment spells, and much shorter employment spells. They also earn somewhat lower wages, and hold very little wealth.

As a result, average unemployment rates and flow rates clearly do not describe the labor market experiences of individuals of the unstable type well. In our analysis, we will take into account this strong heterogeneity, and explicitly model the two labor market and wage types as distinct.

3. Model

Our objective is to measure the distribution of labor market risk in the population, and to explore the effect of policies, in particular unemployment insurance. To do so, we build a model with a few key features: (i) Agents differ in potential wages and in labor market type. (ii) Apart from unemployment insurance, there are no instruments for insuring against wage and unemployment shocks. (iii) Realistic institutional features, including time-limited, partial coverage by unemployment insurance (financed by a payroll tax), progressive taxes, some flat transfers, and social security. (iv) A life cycle, which implies age-varying ability to self-insure. Compared to the literature, this implies incorporating realistic UI institutions and labor market type heterogeneity into an incomplete-market, heterogeneous-agent life-cycle model.

The model economy is populated by a measure one of households, a representative firm, and a government. We discuss each in turn.

3.1. Households

Households enter the economy with age 1, and live for J periods. They work for J_r periods, and then retire. So at any point in time, the economy is populated by households ranging in age from 1 to J. After age J, households die. Each period, new age-1 households enter the economy, so that total population and the age distribution are constant.

At any point in time, households differ in age j, a permanent skill level denoted by η, a transitory skill component denoted by ϵ, labor market type χ, employment status ξ, and net worth (assets) a. Differences in the permanent skill component η and labor market type χ are permanent, i.e. these attributes are fixed for an individual's entire life. The transitory skill component ϵ follows a discrete first-order Markov process with transition matrix Π. Denote productivity, which depends on the permanent and the transitory component as well as on an age-dependent component, by z. Over time, it evolves both deterministically, with aging, and stochastically, with the transitory component.

Denote a state bundle as $(a, \eta, \epsilon, \xi, \chi, j) = s \in \mathcal{S}$.[19] Let the population distribution of s

[19] For compactness of notation, we sometimes use s_{-x} to refer to a state bundle excluding the state variable

be $\Gamma(s)$.

Households maximize the expected discounted lifetime value of flow utility. We assume that utility is time-separable, and that period utility is given by the separable utility function

$$u(c,h) = \frac{c^{1-\sigma}}{1-\sigma} - \theta \frac{h^{1-\phi}}{1-\phi}, \tag{1}$$

which increases in consumption c and decreases in hours worked h.

Work, income, and taxes. Households obtain income from their savings, from transfers, and, if they are employed, from working. Given a wage rate per efficiency unit of labor w and hours worked h, an employed household of productivity z has labor earnings $e \equiv wzh$. These are taxed at a progressive rate. We denote after-tax earnings by $y^d(e)$. In addition, earnings up to the UI payroll tax cap $\bar{E}^{PR}$ are subject to a payroll tax at rate τ^{PR}.

Households can save by investing in an asset that pays a risk-free return r. Investment income is subject to a tax at rate τ^a.[20] Households initially enter the economy without assets, and cannot borrow.

There are three types of transfers in this economy. All households receive a flat transfer ι. The unemployed receive UI benefits b. Retirees receive social security benefits ss. Both depend on household characteristics.

Labor market dynamics. At each point in time, working-age individuals can be employed ($\xi = W$) or non-employed. The non-employed differ in whether they receive UI benefits ($\xi = B$) or not ($\xi = NB$). For retirees, $\xi = R$.

Individuals change employment status stochastically. To focus on risk and insurance, we assume that transition probabilities are exogenous, but differ by labor market type.[21] Every period, the employed face a probability γ^χ of job loss. In case of job loss, they receive UI benefits with probability $p^{UI} \in [0,1]$. We allow for this probability to be less than one to reflect transitions into non-employment as well as the fact that some job losers are not eligible for UI benefits.

The non-employed find a job with probability ζ^χ. Those who receive benefits lose benefits with probability p^{los}. This is a parsimonious way of capturing the finite duration of benefits in the data. Overall, labor market dynamics can be summarized as a transition

x. The excluded variable appears either as a superscript of the value function or as a separate state variable.

[20]The assumption that earnings and investment income are taxed differently follows Conesa, Kitao, and Krueger (2009). It also reflects recent evidence measuring effective tax rates in the US.

[21]Endogenizing them constitutes an important extension, which we are exploring. It is beyond the scope of this draft.

matrix Λ^X,

$$\Lambda^X = \begin{bmatrix} 1-\gamma^X & \gamma^X * p^{UI} & \gamma^X * (1-p^{UI}) \\ \zeta^X & (1-\zeta^X)(1-p^{los}) & (1-\zeta^X)p^{los} \\ \zeta^X & 0 & 1-\zeta^X. \end{bmatrix} \tag{2}$$

with the first row referring to employment, the second row to non-employment with UI benefits, and the final row to non-employment without benefits. Element i, i' of the matrix gives the probability of transition from the state in row i (today) to the state in column i' (next period). We assume that the transitory component of productivity, ϵ, does not change upon job loss or during non-employment.

The household's problem. In this setting, the recursive form of the employed household's problem is

$$\begin{aligned} V^W(s_{-\epsilon,\xi}, \epsilon) = &\max_{c,a',h} \frac{c^{1-\sigma}}{1-\sigma} - \theta\frac{h^{1-\phi}}{1-\phi} \\ &+ \beta E[(1-\gamma^X)V^W(s'_{-\epsilon,\xi}, \epsilon') + \gamma^X(p^{UI}V^B(s'_{-\epsilon,\xi}, \epsilon) + (1-p^{UI})V^{NB}(s'_{-\epsilon,\xi}, \epsilon))|\epsilon] \\ \text{s.t.}\quad & c + a' \leq y^d(e) - \tau^{PR}\min\{e, \bar{E}^{PR}\} + (1 + r(1-\tau^a))a + \iota \\ & e = wzh \\ & a' \geq 0;\quad c > 0;\quad h \in [0,1] \end{aligned} \tag{3}$$

where $V^W(s)$ denotes the value of state bundle s for an employed agent. The expectation is taken over ϵ' conditional on ϵ. The formulation incorporates the labor market type-specific probability γ^X of job loss, and the probability p^{UI} of benefit receipt in case of job loss.

Our analysis focusses on stationary equilibria. To simplify notation, we thus already suppress time-dependence of all model objects.

The problem of an insured non-employed household is

$$\begin{aligned} V^B(s_{-\xi}) = &\max_{c,a'} \frac{c^{1-\sigma}}{1-\sigma} \\ &+ \beta\left[\zeta^X V^W(s'_{-\xi}) + (1-\zeta^X)\left((1-p^{los})V^B(s'_{-\xi}) + p^{los}V^{NB}(s'_{-\xi})\right)\right] \\ \text{s.t.}\quad & c + a' \leq (1 + r(1-\tau^a))a + y^d(b(s)) + \iota \\ & a' \geq 0;\quad c > 0. \end{aligned}$$

This differs from the employed in that the non-employed do not work, and receive unemployment benefits b, which depend on their productivity z in a way outlined below. The non-employed are subject to income taxes on UI benefits received and to capital income taxes, but not to the payroll tax. In addition, they face a type-specific probability ζ^{χ} of job finding as well as a probability p^{los} of benefit expiry each period.

The problem of an uninsured non-employed household is

$$\begin{aligned} V^{NB}(s_{-\xi}) = \max_{c,a'} & \frac{c^{1-\sigma}}{1-\sigma} \\ & + \beta\left[\zeta^{\chi}V^{W}(s'_{-\xi}) + (1-\zeta^{\chi})V^{NB}(s'_{-\xi})\right] \\ \text{s.t.} \quad & c + a' \leq (1 + r(1-\tau^{a}))a + \iota \\ & a' \geq 0; \quad c > 0. \end{aligned}$$

Compared to the insured non-employed, the uninsured do not receive (and thus cannot lose) UI benefits.

Finally, the problem of a retired household is

$$\begin{aligned} V^{R}(s) = \max_{c,a'} & \frac{c^{1-\sigma}}{1-\sigma} + \beta V^{R}(s') \\ \text{s.t.} \quad & c + a' \leq (1 + r(1-\tau^{a}))a + y^{d}(ss(s)) + \iota \\ & a' \geq 0; \quad c > 0. \end{aligned}$$

As productivity remains constant after retirement, this is a deterministic problem. At the final age J, households consume all their resources.

3.2. Government

The government spends on goods and transfers, and raises taxes on earnings, income, and some types of transfers.

First, the government levies a progressive income tax on labor income as well as benefits from UI and social security. Following Benabou and HSV, we assume that disposable income is a long-linear function of taxable income: $y^{d} = \lambda y(s)^{1-\tau}$ for some income y. As shown by these earlier authors, this tax function provides a good fit to effective taxes paid. τ parameterizes the progressivity of the tax system. For $\tau = 0$, taxes are linear. For $\tau > 0$, they are progressive, and the average tax rate increases in taxable income. The parameter λ then controls the average tax rate. Total revenue from this tax is

$$T^{E}(\lambda,\tau) = \int_{s}\left[y(s) - y^{d}(s)\right]d\Gamma(s) = \int_{s}\left[y(s) - \lambda y(s)^{1-\tau}\right]d\Gamma(s) \tag{4}$$

$$\text{where } y(s) \quad = \quad \begin{cases} e(s) & if\ j < J_r \ \&\ \xi = W \\ b(s) & if\ j < J_r \ \&\ \xi = B \\ ss(s) & if\ j \geq Jr. \end{cases}$$

In addition, capital income is taxed at a constant rate τ^a. Total revenue is

$$T^a = \int_S \tau^a ra(s)d\Gamma(s) = \tau_a rK. \tag{5}$$

Finally, the government levies a linear payroll tax on workers at a rate τ^{PR}, up to a cap $\bar{E}^{PR}$. Revenue from this tax thus is

$$T^{PR}(\tau^{PR}) = \int_S \tau^{PR} \min\{e, \bar{E}^{PR}\}d\Gamma(s) \tag{6}$$

In our exploration of optimal UI benefits below, changes in benefits are financed by changes in the payroll tax rate, τ^{PR}.

Turning to the spending side, we assume that unemployment benefits b are a function of an individual's productivity z. We compute potential benefits as a *UI replacement rate* b^{UI} times expected earnings $\bar{e} \equiv wz\bar{h}$, where $\bar{h}$ are average hours of employed agents of the same productivity level. Benefits are capped at a level $\bar{E}^{UI}$, so that $b(z) = b^{UI} \min\{wz\bar{h}, \bar{E}^{UI}\}$. Let total UI benefits paid be B^{UI}.

Retirees receive social security benefits. We assume a constant replacement rate b^{SS} on expected earnings $\hat{e}$. These are computed using transitory productivity in the final working period, the average of the highest 35 years of life-cycle efficiency, and average hours of employed agents of that productivity level and labor market type. The result differs by skill group and labor market type. Benefits are capped at a maximum benefit level $\bar{B}^{SS}$, so that overall benefits are $ss(s) = \min\{b^{SS}\hat{e}, \bar{B}^{SS}\}$. Let total social security benefits paid be B^{SS}.

Finally, the government pays a lump-sum transfer ι to all households, and incurs fixed expenditure G.

In equilibrium, we impose government budget balance, which implies

$$G + B^{SS} + B^{UI} + \iota = T^E + T^a + T^{PR}(\tau^{PR}).$$

When studying counterfactual UI benefit policies, we assume that the payroll tax rate τ^{PR} adjusts to ensure budget balance.

3.3. Technology

A representative firm produces the single good in this economy with a Cobb-Douglas production function $Y = K^\alpha N^{1-\alpha}$ with capital elasticity α, taking factor prices (w, r) as given. K denotes aggregate capital, and N aggregate labor input in efficiency units. In equilibrium, marginal products equal factor prices.

3.4. Market clearing

In equilibrium, factor markets and the output market clear:

$$\begin{aligned} N &= \int_s z(s)h(s)d\Gamma(s) \\ K &= \int_s a d\Gamma(s) \\ Y &= \int_s c(s)d\Gamma(s) + G + \delta K, \end{aligned}$$

where N is the aggregate labor input in efficiency units, K is aggregate capital, Y is aggregate output, and δ is the depreciation rate of capital.

3.5. Equilibrium

A stationary equilibrium consists of value functions $V^{\xi}(s_{-\xi})$, policy functions $c(s)$ and $h(s)$, a distribution $\Gamma(s)$, pricing functions $w(s)$ and $r(s)$ as well as a payroll tax rate τ^{PR} such that

a. given the pricing functions, the value functions and associated policy functions solve the household problems;
b. the pricing functions satisfy

$$\begin{aligned} w &= (1-\alpha)\left(\frac{K}{N}\right)^{\alpha} \\ r &= \alpha\left(\frac{K}{N}\right)^{\alpha-1} - \delta; \end{aligned}$$

c. the government budget is balanced;
d. factor markets clear; and
e. the aggregate distribution Γ is stationary, i.e. $\Gamma' = \Gamma$.[22]

4. Calibration and the benchmark economy

To be able to use the model for quantitative analysis, we parameterize and calibrate it. In fact, we calibrate two version of the model – one with heterogeneity in labor market types and one without – to enable us to assess the importance of labor market type heterogeneity. We refer to the former as setting as "heterogeneous flows" and the latter as "common flows".

[22] The law of motion of Γ follows from aging, productivity and unemployment shocks, and household choices in the usual way. See Appendix ?? for details.

4.1. Calibration strategy and data sources

In both cases, our calibration strategy is to set some parameters to values common in the literature, some to values we measure in the NLSY, and the remaining ones so that the model matches key data moments. Many model parameters are standard in incomplete markets models. Our analysis differs in modeling labor market flows, and in letting several parameters vary by type. As we go along, we discuss which parameters are common and which are type-specific, and what motivates our choices.

TABLE 5. Exogenous Parameters

Parameter	Description	Value
Demographic and Preference		
J_r, J	Retirement age, lifespan (years)	65, 85
σ	Inverse of IES	1.5
ϕ	Inverse of Frisch elasticity	1.2
Production		
α	Capital income share	0.35
δ	Depreciation rate (annual)	0.076
ρ, σ_e^2	AR(1) productivity persistence, variance	0.9, 0.05
η_L, η_H	Permanent component in labor efficiency	0.843, 1.186
ψ_j	Age-dependent labor efficiency	Data
λ_0	Initial distribution of idiosyncratic component [a]	0.9
p_0^W, p_0^B, p_0^{NB}	Initial distribution of employment status	0.75, 0, 0.25
p^X	Share of types	Table 2
Fiscal Policy		
b^{SS}	Social security replacement rate	0.4
b^{UI}	Unemployment insurance replacement rate	0.5
p^{UI}	UI receipt probability	0.135
τ	Tax progressivity parameter	0.137
τ_a	Capital income tax rate	0.25

Notes: The exogenous parameters are the same in both versions of the model.
[a] For a given type, the initial distribution of the five ordinary states are expressed as a vector of λ_0: $\left[\frac{1-\lambda_0}{6}, \frac{1-\lambda_0}{3}, \lambda_0, \frac{1-\lambda_0}{3}, \frac{1-\lambda_0}{6}\right]$

Table 5 shows the parameters we calibrate externally. These are the same in both versions of the model. Table 6 shows the values of internally calibrated parameters, as well as model and data moments.

Demographics and technology. Agents enter the model at age 22, retire at age 65, and die at age 85. A model period is a quarter, so agents work for 176 model periods, spend 80 model periods retired, and live for 256 model periods in total. The specification of production is standard, with a Cobb-Douglas production function with a capital elasticity α of 0.35 and a depreciation rate of 0.076.

Preferences. We assume that the coefficient of relative risk aversion and the Frisch elasticity are common across types. We set the coefficient of relative risk aversion to 1.5, a value commonly used in the literature following arguments in e.g. Carroll and De Nardi and Yang (2016). We set the Frisch elasticity of labor supply $1/\phi$ to 1/1.2, consistent with the average estimate in the survey by Keane (2011) and slightly above the recent one by Blundell, Pistaferri, and Saporta-Eksten (2016).

In contrast, we allow the discount factor and the disutility of labor supply to vary across types, to match the substantial differences in hours worked and wealth across the types shown in Section 2. In the common-flow version, we set the discount factor β to generate a capital-output ratio of 3. With type heterogeneity, we additionally target the relative wealth levels of the three types. Recall that average wealth of the low stable type is only 28% of that of the high-stable type, as shown in Table 4. This ratio is 13% for the unstable type. Similarly, we set the disutility of labor supply for each labor market and wage type to match average hours by type shown above.

Labor market flow heterogeneity. In the heterogeneous-flow model, we impose the type distribution from the data shown in Table 1 above. In addition, we assume that upon entry into the model, three quarters of each group are employed, and one quarter is unemployed and not insured.

We calibrate transition probabilities across employment states internally. We set the job finding and loss probabilities for each labor market type and wage type, ζ^χ and γ^χ, to match average time spent non-employed during ages 30 to 50 (a type's "unemployment rate") and the average length of employment spells for each type. We set the probability of benefit loss, p^{los}, to match the observed average benefit duration among benefit recipients of 16 weeks.[23] With common flows, we set these parameters to match the corresponding population moments.

Productivity process. Productivity z consists of three components:

$$\ln z_{ij} = \ln \eta_i + \ln \psi_j + \ln \epsilon_{ij},$$

[23]This requires different values of p_{los} for each type.

where j denotes age. It consists of a fixed individual-specific component η_i, the age-efficiency profile ψ_j and the transitory component ϵ_{ij}. We set the first two to match their counterparts in our NLSY sample. We set the values of η to match the high- and low wage types described in Section 2. We estimate the age-efficiency profile separately for each combination of labor market and wage type.

We allow the transitory component to take on six values; five "regular" ones and one very high "awesome" state, which allows the model to replicate the highly skewed empirical distributions of earnings and wealth.[24] We set the values and transition probabilities across the five regular states to match an AR(1) process with persistence 0.9 and variance 0.05. We set this parameter and the initial distribution of newborns over transitory states so that the model matches the empirical variance of wages as well as their rate of increase from age X to Y.[25]

We set the level of the awesome state $\bar{\epsilon}$, the rate of entry into that state λ^{in} and the rate of exit from it λ^{out} to match the observed top 5% income share of 36%, the top 1% wealth share of 36%, and the wealth share of percentiles 95 to 99 of 27% reported by Kuhn and Ríos-Rull (2025). This implies a top state encompassing 0.4% of the working age population. Matching these moments is important for the analysis because it affects the cost of raising tax revenue.

Tax and policy parameters. We set the parameter controlling the progressivity of income taxes, τ, to 0.137, and the flat capital income tax rate to 0.25, following Wu (2021), McDaniel (2007) and Guvenen et al. (2023). We set the social security replacement rate b^{SS} to 0.4.

Key to our analysis below is the calibration of UI benefits. We set the UI replacement rate to 0.5, a value very commonly used in the literature and very close to the average value of 0.52 measured by Birinci and See (2024). We set the fraction of those covered by UI upon job loss, p^{UI} to 0.135. This reflects the fact that upon job loss, two thirds of the attached individuals we study in the NLSY leave the labor force, and only a third enters unemployment.[26] Out of those, only 31 percent receive unemployment benefits (Birinci and See ????).[27]

Other policy parameters lack direct data counterparts and need to be set by matching moments. We set the lump sum transfer ι to match the fraction of transfers in GDP reported

[24]This modeling device was introduced by Castañeda, Díaz-Giménez, and Ríos-Rull (2003) and refined by Kindermann and Krueger (2022), among others. For a recent examination showing its excellent fit to the US joint distribution of earnings, income and wealth in a life cycle incomplete markets model, see Kaymak, Leung, and Poschke (????).

[25]We parameterize the initial distribution over the five regular states as $\left[\frac{1-\lambda_0}{6},\ \frac{1-\lambda_0}{3},\ \lambda_0,\ \frac{1-\lambda_0}{3},\ \frac{1-\lambda_0}{6}\right]$ and set λ_0 as described. No individual begins life in the awesome state.

[26]This proportion is similar in CPS data, as shown by e.g. Hall and Kudlyak (2022).

[27]These authors show that only 57% of those entering unemployment are eligible for benefits based on their earnings history. Among these, only 61% take up benefits. Wyse and Meyer (2025) show that takeup is also only partial for Medicaid, with an enrolment rate of the eligible of only about a quarter.

TABLE 6. Calibration of Endogenous Parameters

Symbol	Description	Homog. LMT	Heterog. LMT	Target	Model (Homog.)	Model (Heterog.)
Preferences						
β	Discount factor (annual)	0.942	0.94 (G1), 0.917 (G2), 0.972 (G3)	K/Y; relative capital	2.98	0.21 (G1), 0.54 (G2), 1.8 (G3)
					[3.0]	[0.23 (G1), 0.52 (G2), 1.82 (G3)
θ	Labor-disutility parameter	10.1 (G1), 7.1 (G2)	12.23 (G1), 9.85 (G2), 8.54 (G3)	Relative hours (H)	0.97 (G1), 1.04 (G2)	0.79 (G1), 1.01 (G2), 1.04 (G3)
					[0.97 (G1), 1.04 (G2)]	[0.77 (G1), 1.01 (G2), 1.04 (G3)
Labor-market transitions						
p^{los}	Probability of losing UI(quarterly)	0.6	0.57 (G1), 0.46 (G2), 0.24 (G3)	Benefit duration (weeks)	16.2	16.8 (G1), 15.9 (G2), 16.3 (G3)
					[16.0]	[16.0 (G1), 16.0 (G2), 16.0 (G3)
ζ	Job-finding rate (quarterly)	0.37	0.47 (G1), 0.58 (G2), 0.70 (G3)	Non-employment share	0.08	0.35 (G1), 0.06 (G2), 0.03 (G3)
					[0.08]	[0.32 (G1), 0.06 (G2), 0.03 (G3)
γ	Job-separation rate (quarterly)	0.03	0.26 (G1), 0.04 (G2), 0.02 (G3)	Employment spell (quarters)	22.3	3.7 (G1), 20.6 (G2), 29 (G3)
					[21.9]	[3.4 (G1), 20.8 (G2), 30.6 (G3)]
Fiscal and distributional parameters						
ι	Lump-sum transfer	0.06	0.058	TR/Y	2.5% [2.7%]	2.5% [2.7%]
$\bar{B}^{ss}$	Social Security benefit cap	0.47	0.45	SS/Y	5.5% [5.6%]	5.7% [5.6%]
$\bar{E}^{PR}$	Payroll-tax cap	3.78	3.78	Payroll tax rate	0.13 [0.124]	0.127 [0.124]
λ	Progressive earnings-tax scale	0.955	0.93	Y–MTR	0.34 [0.34]	0.34 [0.34]
G	Government expenditure	0.42	0.39	G/Y	0.17 [0.17]	0.17 [0.17]
$\bar{\epsilon}$	Super-earner threshold	55.5	50.5	Top 5% income share	0.41 [0.36]	0.4 [0.36]
$\lambda^{in}(\times 10^4)$	entry rate to $\bar{\epsilon}$	5	5	95–99% wealth share	0.29 [0.27]	0.26 [0.27]
λ^{out}	stay rate to $\bar{\epsilon}$	0.899	0.899	99–100% wealth share	0.33 [0.36]	0.28 [0.36]

Notes: LMT = labor-market type. G1 = low fixed effect (LFE–unstable), G2 = LFE–stable, G3 = high fixed effect (HFE–stable). Model-generated moments are reported in normal font, wi empirical targets shown in square brackets [ ].

in NIPA Table 3.12 of 2.7%. We set the social security benefit cap and the UI earnings cap to match the fraction of social security expenditure and UI expenditure to GDP of 5.6% and 0.2%, respectively, reported in the same table. We set the payroll tax cap $\bar{E}^{PR}$ so that the payroll tax rate in the model benchmark equals its empirical counterpart of 12.4%. We set G so that government spending net of UI, transfers and social security accounts for 17% of GDP.

4.2. Model fit

Table 6 shows model and data moments. Clearly, the model replicates targeted data moments well, including very pertinent moments like time spent non-employed, the duration of employment spells, and the tails of the distributions of income and wealth.

TABLE 7. Distribution Across Quintiles: Model vs Data

Quintile	**0–20**	**20–40**	**40–60**	**60–80**	**80–100**
Panel A: Wealth					
Model (Homog. LMT)	0.007	0.019	0.052	0.117	0.806
Model (Heterog. LMT)	0.001	0.011	0.024	0.09	0.874
Data	−0.007	0.006	0.032	0.098	0.870
Panel B: Earnings					
Model (Homog. LMT)	0	0.001	0.081	0.169	0.749
Model (Heterog. LMT)	0	0.003	0.09	0.175	0.732
Data	−0.001	0.030	0.104	0.202	0.665
Panel C: Income					
Model (Homog. LMT)	0.03	0.057	0.092	0.16	0.662
Model (Heterog. LMT)	0.03	0.059	0.1	0.164	0.649
Data	0.030	0.065	0.109	0.181	0.614
Panel D: Consumption					
Homog. LMT	0.0745	0.1101	0.1395	0.1914	0.4845
Heterg. LMT	0.0657	0.1032	0.1437	0.2097	0.4777

Notes: Each panel reports the share of total wealth, earnings, and income held by each quintile of the population. "Homog." and "Heterog." LMT denote the homogeneous and heterogeneous labor market type models, respectively.

Table 7 shows the fit of the model to the full empirical distributions of earnings, income and wealth. Despite not targeting them, the model replicates the distributions of earnings and income over quintiles of their respective marginal distributions very well, only slightly understating earnings and income in quintiles two to four, and overstating them in the top quintile. This results from the fact that our current calibration slighly overstates the top 5% income share. For our purposes, however, it is particularly important that the model fits earnings and income in the bottom quintile well.

The model wealth distribution also fits the data very closely. Most importantly, the model closely replicates the large share of the US population with wealth close to zero.

As we show in much more detail in Section 5.1 below, the model also fits empirical estimates of the consequences of job loss well. Birinci and See (2024) estimate that on average in the year of job loss plus the following year, consumption is 9.4% lower than before. Our estimates are very close, with an average consumption drop of 10% in the two years following job loss.

4.3. Consumption and saving behavior

The model also has implications for the distribution of consumption, and for consumption and savings rates across types. Table 7 shows the cross-sectional distribution of consumption. While less concentrated than that of earnings of income, it is nevertheless strongly concentrated. The bottom quintile of the population only consume about 7% of the total. The top quintile accounts for almost half of total consumption.

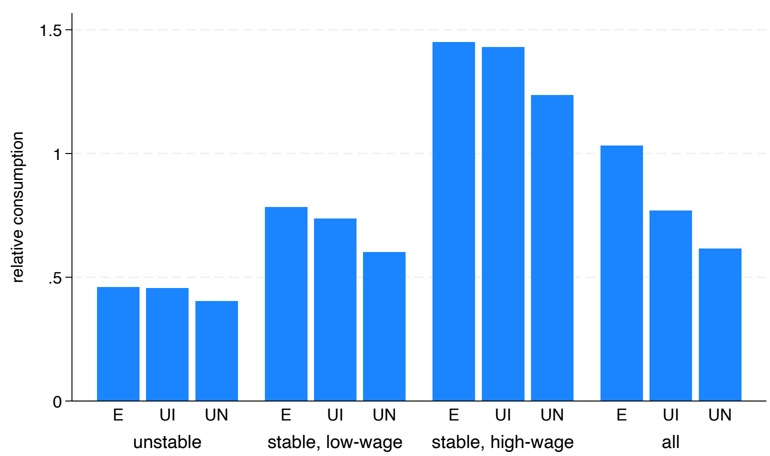


FIGURE 4. Consumption by type and state, relative to working-age mean

Note: States: employed (E), unemployed and insured (UI), unemployed uninsured (UN).

Consumption also differs strongly across types, as shown in Figure 4. When employed, unstable types consume only a third as much as stable high-wage types, and 40% less than stable low-wage types. This gap is much larger than the wage gap between the types. The low consumption of unstable types reflects three main factors. First, due to their lower wages, disposable income of the unstable is 12% lower compared to the stable low-wage type. Second, they are much more often not employed. Third, when employed, individuals of the unstable type engage in a lot of precautionary saving due to their much greater separation rate. As a group, they save around 30% of their disposable income. Their wealth nevertheless is much lower than that of the stable types due to their repeated episodes of non-employment, in which they draw down their wealth again, as shown below.[28]

Consumption also varies across labor market states. In the aggregate population, the insured non-employed consume 25% less than the employed, and the uninsured non-employed 40% less. Figure 4 also reveals that these large gaps result from type heterogeneity, which implies that the employed group consists mostly of stable types, whereas unstable types are over-represented among the non-employed. Conditional on type, the insured non-employed consume almost as much as their employed counterparts. The combination of UI and private saving thus provides strong insurance against job loss. The uninsured non-employed about 20% less than the employed of the same type. Private saving thus only undoes part of the consumption losses from non-employment.

Comparisons of means do not reveal the full welfare impact of employment fluctuations. Even if private insurance undoes some of the risk these fluctuations bring, this comes at the cost of saving more than intertemporal motives alone would call for.

5. The consequences of job loss and the welfare cost of employment fluctuations

In this section, we examine the consequences of job loss in the calibrated model, and use the model to compute the welfare cost of employment fluctuations. The former not only is a key ingredient for the latter. Examing the reaction of model agents to job loss and comparing them to the data also allows us to assess the model's performance in terms of capturing the extent of sources of insurance other than UI, in particular private savings. This is crucial for the welfare implications of job loss, as well as for the benefit of policies that aim to mitigate them.

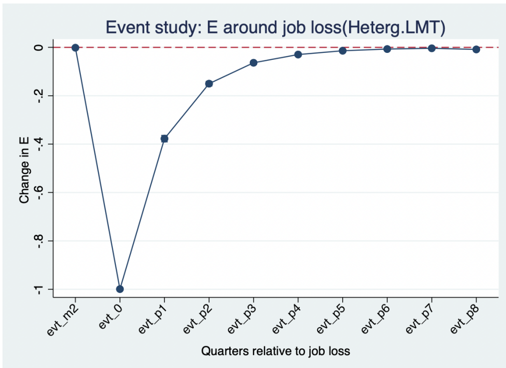
5.1. The consequences of job loss

Figure 5 shows the time path of employment following job loss. The top left figure shows results from an event study regression that captures the evolution of the average employment rate after job loss in the benchmark economy.[29] By construction, the employment

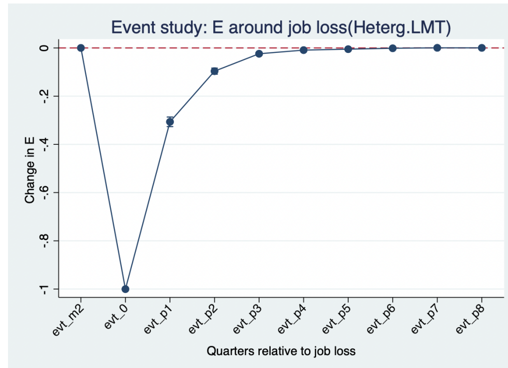
[28] A fourth factor is the difference in patience. The model requires a relatively low discount factor for individuals of the stable low-wage type to match the relateively low level of wealth (compared to wage differences) of that type.

[29] We regress employment (=1 if employed, =0 otherwise) on time dummies before and after job loss. Our convention is that job loss occurs in period 0, so period `px` (`mx`) is period x after (before) job loss. The period before job loss (`m1`) is the reference period and hence not shown in the graph. These event study estimates are for a treatment group of job losers relative to a control group, and include group fixed effects and a quadratic

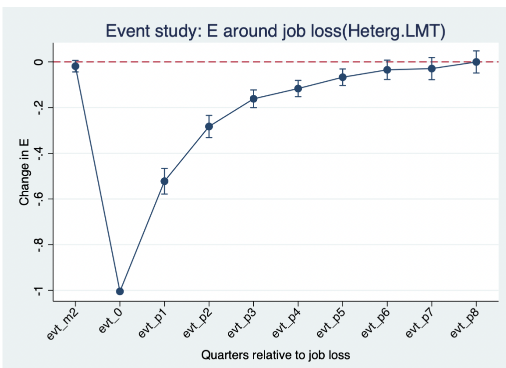
rate of the treatment group drops to zero in the quarter of job loss, time zero in the graph. Given large job finding rates, it recovers quickly. Four quarters after job loss, only a small percentage of the population remains out of employment.



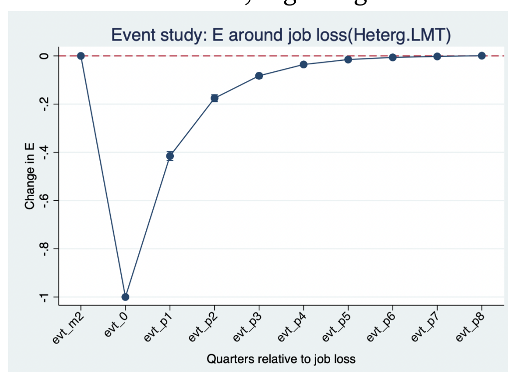
A. all



B. stable, high-wage



C. unstable type



D. stable, low-wage

FIGURE 5. Employment rates after job loss

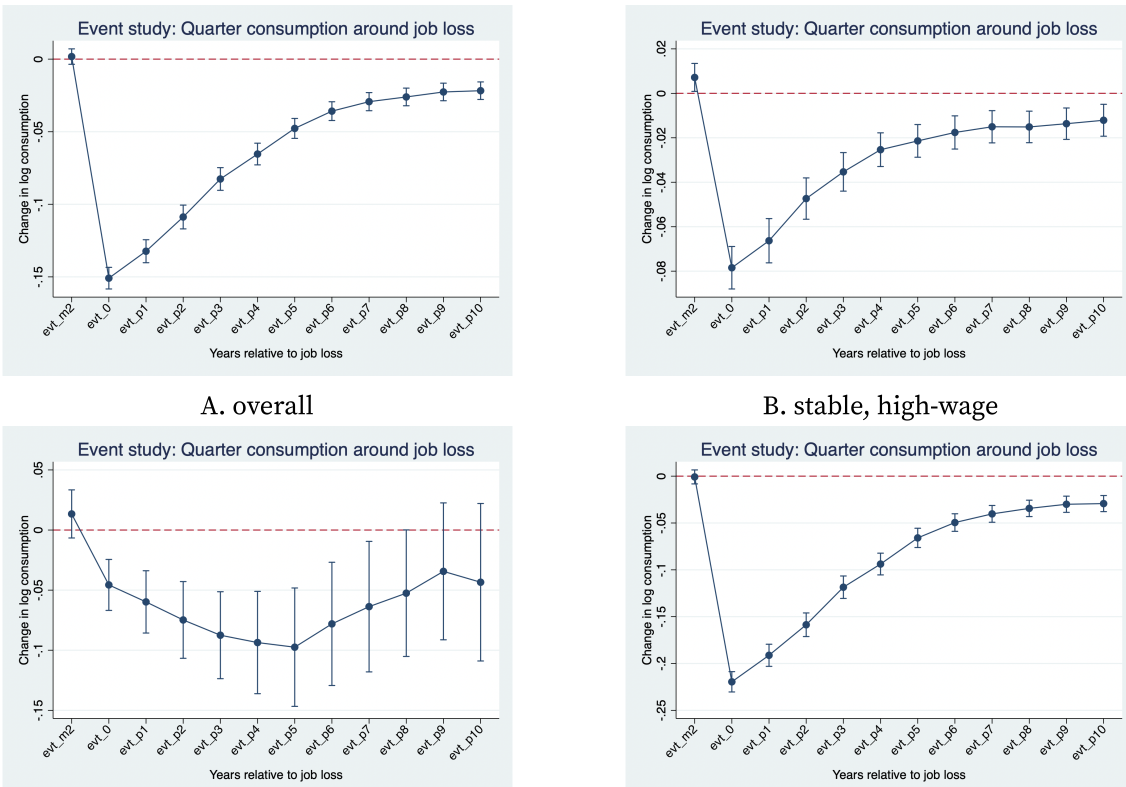
The two right panels of the Figure show that these dynamics are extremely similar for the two stable groups. The bottom left panel shows that the unstable group recovers much more slowly. Its non-employment rate remains around 13% four quarters after job loss. It takes this group seven quarters to reach employment levels that the other groups reached after only four quarters.

These dynamics of employment also drive consumption dynamics after job loss, shown in Figure 6. The top left figure shows the average consumption drop after job loss in the entire population.[30] Consumption drops by about 15% in the quarter of job loss. It then recovers quickly as job losers re-enter employment, but remains subdued for more than two years. As we will show, this arises because job losers draw down wealth to prop up consumption during non-employment. After they find a job again, they maintain low consumption for some time to build up wealth again.

in age.

[30]The regression parallels that for Figure 5, with log consumption as the dependent variable.

The remaining panels show consumption dynamics after job loss for each group separately. For the two stable groups, these are very similar to the aggregate pattern. The main difference is that consumption drops much more for the low-wage group. This reflects both its slighly lower job finding rate and its lower wealth compared to the high-wage group.



A. overall

B. stable, high-wage

C. unstable type

D. stable, low-wage

FIGURE 6. Consumption drop after job loss

The pattern is quite different for the unstable group. For this group, consumption drops less. Moreover, instead of the steep drop and quick recovery of consumption of the stable groups, the consumption drop progressively deepens. This reflects a different balance of the two factors governing consumption dynamics by the unemployed: Average consumption of job losers tends to rise with time since job loss as job losers find jobs again (this factor dominates for the stable types), but it tends to fall as job losers drawn down their wealth. The latter factor dominates for unstable types. These individuals thus can cushion the initial earnings loss using their accumulated wealth, but can do so less well as time progresses and wealth reserves are run down.

Figure 7 shows how consumption is financed in each state.[31] It reveals that for the

[31]The figure excludes individuals in the awesome state, whose large saving rate visually overwhelms the graph.

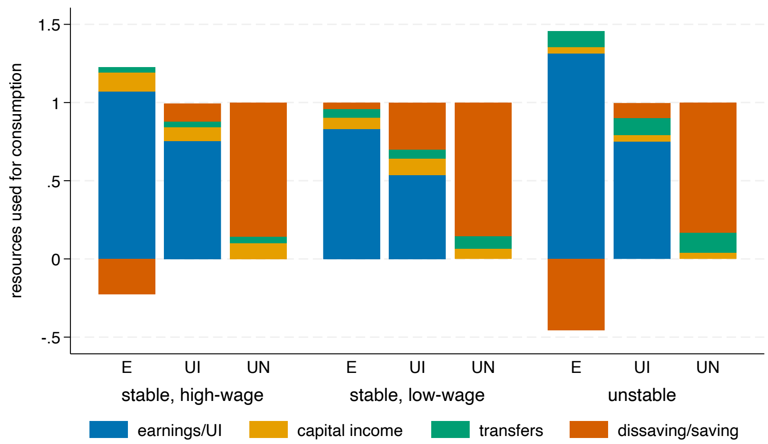


FIGURE 7. Sources of consumption after job loss, by type and labor market state

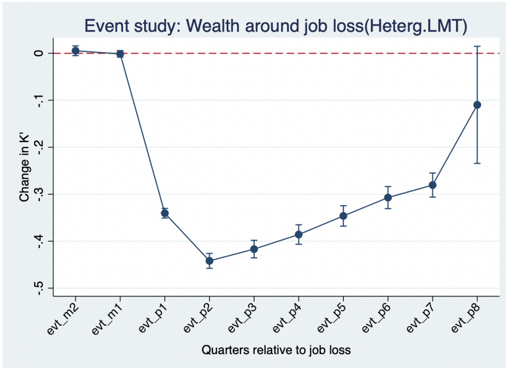
Note: States: employed (E), unemployed and insured (UI), unemployed uninsured (UN). Earnings/UI is after-tax earnings when employed, and UI benefits when unemployed and insured. Capital income is after taxes. Dissaving/saving is positive when $a' < a$ (dissaving) and negative otherwise (saving). For each source x_j, each bar element shows x_j/c by type and state. The sum of elements is 1 in all bars.

insured, UI benefits (blue) cover half (stable low) to three quarters (stable high and unstable) of their consumption in non-employment. Transfers make up little for the stable high type due to their high level of consumption, but cover 5% for the stable low type and 11% for the unstable type. Capital income similarly accounts for a small share of 20% (30%) [13.5%] for the stable high (stable low) [unstable] type. Stable low-wage types also strongly draw down their wealth when not employed, financing about 30% of consumption with it. In contrast, unstable types, who expect a significantly longer non-employment spell, only use their wealth to finance 10% of their consumption.

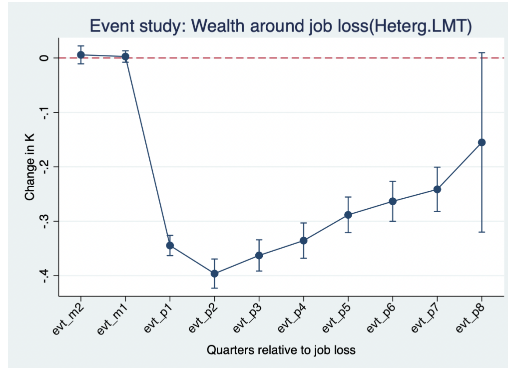
Those not receiving benefits consume less than the insured, as shown above. They finance a small share of around 15% of their consumption in non-employment with transfers and capital income. The remainder is financed by drawing down wealth.

Figure 8 shows the dynamics of wealth after job loss. The structure of the graph mirrors that of Figure 5, except that the choice of wealth is predetermined in the period of job loss itself (period zero), which hence is not shown. The first period in which wealth adjusts to job loss is period p1. For all groups, wealth dynamics are dominated by the uninsured, who make up a large majority of job losers. For the stable types and thus also on average, job losers spend around 35% of their wealth to sustain consumption in the first quarter of non-employment (p1). For the stable types, wealth bottoms out in the second quarter (p2) just slightly above half of the initial wealth level and then recovers, as employment rates pick up again.

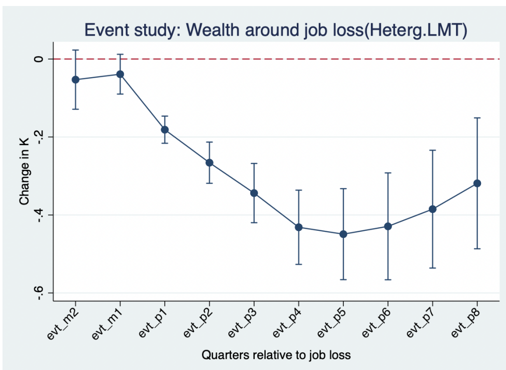
This pattern is very different for unstable types, who draw down their wealth much more slowly. Their wealth only bottoms out four to six quarters after job loss. Lower job



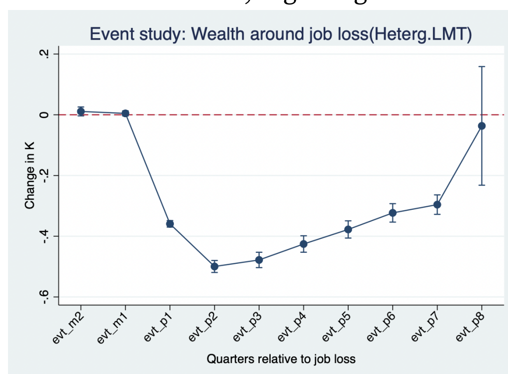
A. all



B. stable, high-wage



C. unstable type



D. stable, low-wage

FIGURE 8. Wealth dynamics after job loss

finding rates imply a greater need to smooth consumption out of wealth over time. This results in a consumption level in non-employment that must be lower than that of the other groups. Smoothing across states implies that the same holds when employed.

Overall, consumption of the stable types drops significantly when they are out of employment. Private saving cushions the impact of job loss on consumption, but at a significant hit to wealth holdings. Consumption falls more for stable low-wage types, who save less when employed. The overall welfare consequences of job loss may still be limited because for stable types since for them, non-employment is a rare, short event.

For unstable types in contrast, frequent non-employment episodes reduce consumption across states. Job loss does not only pull down their consumption after job loss, but their entire consumption profile. We next formally measure the welfare consequences of employment fluctuations.

5.2. The welfare cost of employment fluctuations

What is the cost of employment fluctuations, and how does it differ across types? To answer these questions, we compare welfare in the benchmark economy to that in a counterfactual economy without employment fluctuations, i.e. with permanent employment during working age. To do so, we compute the equivalent variation, or the constant λ by which consumption needs to be increased in all periods and states in the benchmark economy to equal welfare in the alternative economy. We do this overall, as well as separately by type.[32] To focus on the risk for individuals, we do this calculation in partial equilibrium. For comparison, the we also compute the mean difference in lifetime consumption between the two economies with and without employment fluctuations.

TABLE 8. The cost of employment fluctuations

	Heterog. LMT				**Homog. LMT**
CEV (%)	U	SL	SH	All	All
Welfare cost (consumption units)	35.1	7.7	3.5	8.7	10.7
Lifetime consumption cost	26.8	5.6	1.9	3.6	
Welfare comparison, unstable vs stable low-wage type					
Welfare difference (consumption units)	-36.70				–
...due to flows only	-23.30				–

Notes: U=unstable, S=stable, SL=stable low skill, SH=stable high skill. "Homog." and "Heterog." LMT denote the homogeneous and heterogeneous labor market type models, respectively.

Results are shown in Table 8. In the economy with common job flow rates, the welfare cost of employment fluctuations is equivalent to a reduction in consumption by 10.7% in all states. This is large, given that non-employment accounts only for 8% of working-age time (recall Table 2).

The table also shows that these costs are distributed extremely unequally across labor market types. For stable, high-wage individuals, the lifetime cost of non-employment is very small, corresponding to only 3.5% lower consumption. This cost is almost twice as large as the direct effect of employment fluctuations on consumption, which amounts to 1.9%. The cost is more than twice as large for stable, low-wage individuals. The cost is also in line with the time these two types spend non-employed – 3% and 6% of working age, respectively.

Losses are much larger for the unstable type. Their welfare loss is equivalent to slightly more than a third of consumption. This is four and a half times as large as the loss for stable, low-wage individuals. The loss is in line with the amount time these individuals spend non-employed (32%), and is significantly larger than the direct effect of employment fluctuations on consumption, which is only 27%. The difference arises from the frequent

[32] Recall that individuals of a given type only differ in initial employment status and initial transitory productivity. We average over transitory productivity, and focus on the employed to abstract from the direct effect of increasing the employment rate.

fluctuations of consumption arising with job loss, and from the cost of the precautionary savings individuals engage in to mitigate this risk.

The very unequal incidence of non-employment in the population thus also implies a very unequal welfare cost of non-employment. The unstable group accounts not only for a disproportionately large share of the non-employed, but also suffers much larger welfare losses.

This disproportionately large loss is hidden when computing the aggregate welfare cost of non-employment. At just shy of 9%, this is lower in the heterogeneous-flow model than in the common-flow one. This is because the welfare assessment in the common-flow scenario confounds heterogeneity across types with risk. The heterogeneous-flow model correctly captures that, while each type faces costly fluctuations, stable types do not face the risk of the unstable type's outcomes. This implies a smaller aggregate cost of employment fluctuations.

5.3. Welfare differences across types

Clearly, unstable types are less well off. By how much? How much does each of their different characteristics matter? The bottom panel of Table 8 addresses these questions, comparing the unstable type to the more similar stable, low-wage type.

These two types differ in labor market flow rates and in their wage levels, captured by their age-efficiency profiles.[33] Section 2 showed that wages of the unstable type are about 20% lower than those of the stable, low-wage type, and that the time spent working is 28% lower.

Table 8 shows that in terms of overall welfare, the unstable type is 37% less well off than the stable, low-wage type. The majority of this difference (a welfare difference of 23%, or 62% of the total) is due to the unstable type's worse flow rates. The remainder is due to the lower wage profile. (Both differences are cushioned by the presence of unemployment insurance and social security.) Their greater employment risk – the characteristic that defines them – is thus the dominant factor reducing the welfare of the unstable type compared to the stable low-wage type.

6. Type heterogeneity and policies

To complete our analysis, we explore what type of policy is best suited to mitigate the welfare cost of employment fluctuations. To assess the role of type heterogeneity, we

[33] They also differ in the discount rate. These directly affect welfare. To abstract from this effect, we conduct a comparison for a common discount rate, using the common discount rate from the common-flow calibration. We evaluate welfare by solving the problem of the low-stable and the unstable type, using this common discount rate.

contrast results for the benchmark model with type heterogeneity with those for the model with common flow rates.

We consider several types of policies that can insure against income fluctuations from loss of employment: not only changes to the UI system, but also changes to the progressivity of income taxes and changes to flat transfers. For reasons of computational complexity, we consider these policies individually, and do not search for the optimal combination of policy parameters, except for the two features of the UI system. We also assume that policies cannot condition on labor market type.[34]

6.1. Welfare measures

To analyze policies, we search for policies that maximize one of two welfare measures. Following Conesa, Kitao, and Krueger (2009), the first is the average welfare of an agent born into the stationary equilibrium implied by the policy, W. We refer to these individuals as "newborns".

Due to the concavity of preferences, this utilitarian welfare criterion favors not only efficiency gains and insurance, but also redistribution. Indeed, all the policies we consider have both insurance and redistributive consequences. To separate the two, we also consider a second welfare measure, which is a version of the aggregate efficiency criterion introduced by Bénabou (2002). It replaces an agent's stochastic consumption and labor sequence with its certainty equivalent, and aggregates those (rather than utilities) across agents. As a result, risk aversion is reflected in the certainty equivalent values, but not in their aggregation across agents. This welfare criterion, unlike W, thus abstracts from considerations of redistribution. Our implementation of the criterion follows Bakış, Kaymak, and Poschke (2015). We define the welfare criterion

(7)
$$W^E = \frac{1}{1-\sigma}\left(\int_{s_{-j}} \tilde{c}(s_{-j}, j=0)d\Gamma(s_{-j}, j=0)\right)^{1-\sigma} - \frac{\theta}{1+\phi}\left(\int_{s_{-j}} \tilde{n}(s_{-j}, j=0)d\Gamma(s_{-j}, j=0)\right)^{1+\phi}$$

where

$$V_0^c(s_{-j}, j=0) = \frac{1}{1-\beta}\frac{\tilde{c}(s_{-j}, j=0)^{1-\sigma}}{1-\sigma}$$
$$V_0^l(s_{-j}, j=0) = \frac{1}{1-\beta}\frac{\tilde{n}(s_{-j}, j=0)^{1+\phi}}{1+\phi}.$$

Here, V_0^c and V_0^l are the components of welfare reflecting utility from consumption and

[34] All policies have budgetary implications. We adjust the payroll tax rate so that the government's budget is balanced. All policy simulations are in general equilibrium.

disutility from labor, respectively. $\tilde{c}(s_{-j}, j = 0)$ and $\tilde{n}(s_{-j}, j = 0)$ are the certainty equivalent levels of consumption and hours for an individual entering the economy (age 0) with state s. This objective function allows us to assess efficiency and equity implications of different policies separately.[35] [36]

6.2. Policies

Table 9 shows optimal policies and the welfare gains they imply. The top part of the panel shows policy settings that maximize the welfare objective W and their consequences. The lower part shows policy settings that maximize W^E. Each panel shows the optimal level of the policy parameter for both the heterogeneous- and the common-flows model, as well as the welfare gains for each type and in the aggregate from the policies that are optimal in the heterogeneous-flow model.

The unemployment insurance replacement rate. It seems intuitive that the unemployment insurance replacement rate should be a promising policy parameter for mitigating the consequences of employment fluctuations. And indeed, in the heterogeneous-flow model, the optimal replacement rate is 80%, far in excess of the 50% in the benchmark economy. Yet, it turns out to not be the most beneficial policy.

The first reason is that the benefits from this policy are entirely due to redistribution. While a UI replacement rate of 0.8 maximizes welfare including the redistribution motive, it reduces the welfare function W^E that excludes that motive. In fact, the bottom panel shows that the optimal replacement rate in terms of efficiency and insurance only is just 42.5% – lower than the replacement rate in the benchmark economy. The unstable types are the least well-off in this economy, and UI benefits are a targeted way of redistributing resources towards them. But their insurance value is small.

Second, even the gains from redistribution are very small. Even unstable types gain only 0.8% of consumption from a very large increase in the UI replacement rate to 80%. This increase comes at the cost of the two stable groups. Aggregate welfare hardly changes. The small gain is in line with the observation that benefit recipients are already well insured in the benchmark economy. Only unstable types would favor a higher replacement rate. In contrast, almost all stable types favor the efficiency-maximizing policy that slightly reduces the replacement rate.

[35] This is clearest in a setting where only consumption is valued. Then, this objective function will increase with a redistributive policy only if this policy increases the aggregate of certainty equivalent levels of consumption.

[36] This analysis ignores welfare changes along the transition. It is known that these can matter. We intend for the analysis to reveal what types of policies are most beneficial in a setting with type heterogeneity, and leave a full optimal policy analysis, including transitional changes and interactions of policies, to future work.

TABLE 9. Optimal policy parameters and welfare gains

	UI replacement rate	UI coverage p^{UI}	UI coverage p^{UI} & replacement rate	Tax progressivity τ	Transfers ι
Maximize overall welfare W (all motives)					
Optimal policy parameter					
Heterogenous flows (bm)	0.8	0.4	0.4, 0.85	0.205	0.12
Common flows	0.4	0.4	0.4, 0.45	0.23	0.12
Welfare gain (consumption units, %)					
All	0.01	0.25	0.28	1.27	0.87
U	0.81	3.68	6.41	3.33	7.38
SL	-0.04	0.10	-0.03	2.70	2.59
SH	-0.13	-0.40	-0.84	-1.18	-3.10
Change in W^E (consumption units, %)					
All	-0.02	0.15	0.09	0.57	0.17
Population share in favor (%)					
Heterogenous flows (bm)	9.7	59	12.3	61.6	68.8
Common flows	95	96.3	96.3	61.7	68.5
Maximize W^E (only efficiency and insurance motives)					
Optimal policy parameter					
Heterogenous flows (bm)	0.425	0.4	0.4, 0.45	0.185	0.09
Common flows	0.425	0.4	0.4, 0.5	0.215	0.11
Welfare gain (consumption units, %)					
All	0.001	0.15	0.15	0.63	0.36
U	-0.22	3.72	3.18	2.74	3.96
SL	0.01	0.09	0.10	2.27	1.46
SH	0.03	-0.40	-0.33	-0.78	-1.43
Population share in favor (%)					
Heterogenous flows (bm)	89.4	59.0	59.0	61.6	69.2
Common flows	95	96.3	96.3	62.6	68.5

UI coverage p^{UI}. The main reason for this low gain is the low coverage rate of the UI system, which provides benefits to only 13% of the attached non-employed, or about a third of the unemployed, as discussed above. We next consider increasing this coverage rate. We consider values up to an upper bound of 40% which corresponds roughly to full coverage of the unemployed, but not those who are temporarily out of the labor force.

The optimal coverage rate, in terms of both welfare criteria, hits the upper bound of 40%. This policy yields a significantly larger welfare gain for unstable types, corresponding to more than 3% of consumption. At the same time, the policy slightly benefits stable low-wage types, and imposes a small cost on stable high-wage individuals. Aggregate welfare increases slightly, by 0.25%. While the policy clearly is redistributive, 60% of the gains from the policy do not depend on this motive.

Due to these positive outcomes, all unstable types and most stable low-wage types favor this policy.

UI coverage p^{UI} *and replacement rate.* It is natural to ask whether gains from changes in the replacement rate might be larger with a greater rate of coverage. The third column of the table shows outcomes for the combination of the coverage rate p^{UI} and the replacement rate that maximizes welfare, again bounding coverage at 0.4.

The optimal combination of the two policies is very similar to the individually optimal policies. The policy that maximizes W again features maximum coverage (40%), and a very large replacement rate of 85%. This policy results in a very large increase in welfare of unstable types, at a cost of almost 1% of consumption for high-wage types. The total welfare gain is very similar to that from only expanding coverage, and relies more strongly on redistribution. The optimal joint policy in terms of W^E implies increasing the coverage rate as much as possible, with only a small change in the replacement rate.

We conclude that increasing the replacement rate is mostly a redistributional policy, no matter the coverage rate. It results in large gains for unstable types, but also significant losses for the high-wage group. Expanding coverage instead can increase welfare more broadly. This policy benefits the unstable group at a smaller cost to the high-wage type, implying overall efficiency gains. This conclusion is in line with the consumption allocations shown in Figure 4, which already suggested greater welfare gains from expanding coverage than from greater generosity.

Tax progressivity τ. Progressive taxes also have an insurance effect. And indeed, by both welfare criteria, it is optimal to increase the progressivity of the tax system, from the benchmark value of τ of 0.137 to values around 0.2. Optimal τ is slightly larger, at 0.205 compared to 0.185, when redistribution is valued.

This policy change also increases welfare of unstable types by more than 3%, and welfare of the stable low-wage type almost as much. Although welfare of the stable high-wage type is reduced, aggregate welfare increases by more than 1 percent. About half of the welfare increase is due to insurance. All unstable types and most stable low-wage types favor this policy.

Transfers ι. Finally, higher flat transfers would also provide more insurance against job loss. The advantage is that they reach all the non-employed. The downside is that the policy is not targeted, implying a significant fiscal cost of providing transfers to all agents in order to reach just some.

The optimal value of transfers doubles transfers from the benchmark value of 0.06 model units. This corresponds to an increase from around 2.5 to about 5% of GDP. The policy has very heterogeneous welfare effects, with a very large increase in welfare of unstable types, and a large reduction of over 3% in welfare of high-wage types. As a result, overall welfare increases by less than one percent.

The optimal increase in transfers is only half as high when redistribution is not valued. This smaller change still generates large gains for unstable types and stable low-wage types, but significantly smaller losses for high-wage individuals. Both increases in transfers meet with approval from more than two thirds of newborns.

The role of type heterogeneity. Maybe surprisingly, optimal policies in the heterogeneous-flows model are not very different from those in the common-flows model. If anything, they are slightly less redistributive, apart from the UI replacement rate.

This pattern reflects the fact that the aggregate welfare cost of employment fluctuations is slightly lower once heterogeneity is accounted for and is not confounded with risk. Once these features are distinguished, efficiency-maximizing tax policies feature less redistribution. Tax policies are also a blunt tool for insuring a group of the population that stands out not due to wage fluctuations, but due to frequent job losses.

The main difference in optimal policies between the heterogeneous- and common-flows model is in the UI replacement rate. The UI replacement rate that maximizes W is higher in the heterogeneous-flow models because the common-flows model fails to recognize how concentrated job losses are in the population. If combined with expanded coverage, the replacement rate can be used to effectively redistribute towards the unstable group. Aggregate welfare effects remain small, because this policy tool does not affect the much larger stable low-wage group with its much higher job finding rate much.[37]

Which policy is best suited to improve the lot of unstable types, who face a large welfare cost of employment fluctuations? In the absence of type-specific policies, all

[37] Efficiency effects of greater benefits are similarly limited because of the presence of private insurance.

policies that benefit the unstable type redistribute to some extent.[38] In doing so, the best policies generate gains independently of distributional considerations. This is the case for an increase in tax progressivity, which increases both welfare measures by the greatest amount. This policy is less targeted at the unstable types and delivers broader benefits, at the cost of losses to the high-wage type. Extensions of UI coverage generate significant benefits to a small group (unstable types), at a limited cost to others. They are thus a well-targeted policy. Expansions in the UI replacement rate are less effective, since benefit recipients are already quite well insured, and the most important risk in this economy is job loss without insurance.

7. Conclusion

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[38] Clearly, policies that address the root causes of these fluctuations may also be very beneficial. See **?**. Such policies are beyond the scope of our analysis in this paper.

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